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**MULTI-SCALAR DRIVERS AND PATTERNS OF  
ABANDONED CROPLAND IN THE UNITED STATES:  
IMPLICATIONS FOR RENEWABLE ENERGY**

A Dissertation in

Geography

By

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## **ABSTRACT**

Scaling up renewable energy production, solar and biomass, will require a substantial area of land. Such land should ideally not be in competition with other uses such as agriculture, pasture, or urban development. Furthermore, converting this land to renewable energy should neither contribute to carbon emissions nor negatively impact habitat or ecosystem services. Recently abandoned cropland that has not converted to another use like urban development or pasture is presented here as an appropriate land opportunity.

This dissertation investigates abandoned cropland in three ways. First, it estimates how much usable abandoned cropland (UACL) there is in the United States. Usable abandoned cropland is an area recently in agricultural production but is not anymore and has not converted to another land use like urban development or pasture. Data from the Census of Agriculture, supplemented by information derived from the National Land Cover Dataset (NLCD), are used to calculate the amount of UACL that has emerged in the counties in the conterminous United States. Results show that between 5 and 15Mha of UACL exists in the United States, considering historical limits for when cropland was abandoned of 2007 and 1978 respectively. The relative contributions of these estimates to national energy consumption amount to only 3 to 8 percent of total light duty gasoline consumption, and make more significant contributions to other end uses, such as aviation.

Second, this dissertation explores the potential drivers of cropland abandonment. Random forest analysis is performed to see which of a suite of 22 variables of underlying characteristics is important to variation in levels of UACL in each county in the eastern United States. The western United States is excluded due to the prevalence of irrigation,

which is a stark difference from the east and would complicate analysis. Since many counties do not have a net increase in UACL, first, a classification analysis using Random Forest is performed to identify variables important to whether a county has UACL or not. Second, a regression analysis using Random Forest is performed to identify which variables are most important to the amount of net UACL that has emerged in each county that experiences an increase. Results show that the rent farmers pay to operate cropland and the value of farmland and buildings are among the most important variables influencing UACL. Interestingly, when viewing UACL in a binary form (counties with zero UACL versus counties with a non-zero value of UACL) it is the measure of change in rent and land value over time that is important, while a view of only those counties with a non-zero value of UACL reveal that static measures of rent and land value are most important. Regional analyses show that there are some differences in the drivers for counties in one part of the country versus another. However, the observations that measures of rent and land value change over time being most important to whether a county has net UACL or not and that static measures of rent and land value being most important to the amount of UACL in counties that experience a gain hold true for all regions.

Third, this dissertation downscales UACL from the county level to the 30m landscape level by using a spatially explicit land change model, Dyna-CLUE. Four counties, each of which is in a distinct agricultural region of the United States, are chosen as study areas. Using rates of increase in UACL from earlier chapters, the model projects UACL emergence over a 50-year period in each county. Patterns and distribution of UACL across each county are measured with landscape metrics to detect whether there



are differences among the counties and if some counties are more suitable for renewable energy production. Patterns that are favorable for renewable energy are those that have large, regular patches of UACL. Results show that there are differences in the metrics across the counties and that some emerge as more favorable for renewable energy. Interestingly, two counties that appear similar initially have starkly different patterns and suitability for renewable energy at year 50. This raises the question of whether this difference is due to the initial pattern and characteristics of the county landscape or an artifact of the modeling approach.

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## PREFACE

Chapter 2 of this dissertation is published in the *Annals of the American Association of Geographers* and co-authored with Kirby E. Calvert, former Penn State professor and dissertation committee member. Ryan E. Baxter is the lead author of the publication and performed all data preparation, analysis, cartography, and writing, except for some much-appreciated editorial contributions from Kirby E. Calvert. The work by Ryan E. Baxter in Chapter 2 is therefore substantial and integral to this dissertation. The reference to the publication is as follows:

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# **Chapter 1. Introduction**

## **1. Overview**

The overarching motivation of this research is to investigate abandoned cropland as an opportunity for the production of renewable energy, specifically utility-scale solar and biomass. These energy systems help mitigate the effects of anthropogenic climate change and are able to utilize land that does not compete with other uses. The land area requirements of these energy systems are large, and appropriate areas for production must be identified carefully. Abandoned cropland is explored, in part, to avoid the pitfalls of more common, generic classifications of land, like “marginal;” these pitfalls relate to the difficulty in defining what marginal land is, in a way that is objective, not biased by the view of the researcher, and not implying that particular land areas are of little value.

This dissertation addresses three primary questions: 1) How much abandoned cropland exists in the United States at a national scale that is available for renewable energy production, considering factors like urban development, forest growth, and pasture conversion? 2) What county-level factors are associated with national scale cropland abandonment? In other words, what might be the drivers of cropland abandonment? And 3) How suitable is abandoned cropland renewable energy production given its spatial configuration at the landscape level?

Prior research has estimated the quantity of renewable energy the United States is capable of producing. Biomass energy has potential to be integrated with existing regional agricultural systems (Chesapeake Bay Commission & Commonwealth of Pennsylvania, 2010), provide cellulosic biofuel products that can offset fossil sources nationwide (Lamers et al., 2021), and contribute to a global bioenergy system of

(Hoogwijk et al., 2003; Smeets et al., 2007). Solar has demonstrated particular promise in the United States as evidenced by spatially-explicit surveys of existing installations (Fujita et al., 2023; Tavakkoli et al., 2021). This potential includes utilizing solar for electricity generation (Brown & O'Sullivan, 2020; Tabassum et al., 2021), industrial applications (Schoeneberger et al., 2020), agrivoltaics (Lytle et al., 2021; Pascaris et al., 2023; Pascaris et al., 2021; Pascaris et al., 2020). Others have shown the potential for producing various types of renewable energy on marginal land (Milbrandt et al., 2014; Niblick & Landis, 2016; Stoof et al., 2015). Renewables are an important component of our future energy portfolio, whether reducing greenhouse gas emissions from fossil-based electricity generation or reducing our dependence on foreign and domestic oil (United States Energy Information Administration, 2023). These studies have established that the United States is capable of producing a meaningful quantity of renewable energy. A question that remains is *where* this energy may be effectively produced. The following sections introduce some theories and concepts that inform the process of where land use change occurs, the impacts of that change on the landscape, and the relevance of land change to renewable energy development.

## **2. Background**

### **2.1. Landscape Ecology**

Wiens (1995, p. 1) states that the underlying premise of landscape ecology is that “the explicit composition and spatial form of a landscape mosaic affect ecological systems in ways that would be different if the mosaic composition or arrangement were different.” This dissertation aims to extend this idea beyond ecological systems to the

realm of anthropogenic land change. Commonly, landscape ecology principles are applied to measure the impacts of human land use change on ecological systems. In this study, I explore the relationship between landscape ecology metrics and the land use change process itself. Concepts include how spatial pattern relates to land use processes and thresholds; how spatial landscape patterns are altered by the abandonment of cropland; and how landscape patterns may impact, either positively or negatively, the suitability of conversion to biofuel crops.

Landscapes possess characteristic states and behaviors, which are often self-regulating and driven by natural conditions, such as climate and biophysical structures. In fact, even when impacted by a disturbance, natural land covers commonly return to their pre-disturbance conditions or progression to a steady state (Bormann & Likens, 1979; Turner, 2010). However, human activity has the potential to force landscapes into new states outside of their natural tendencies (Foster et al., 1998). Measures of a landscape's pattern, such as heterogeneity, patchiness, patch configuration and inter-patch distance, can help elucidate such processes (Franklin & Forman, 1987). Previous research has investigated whether landscape patterns and change in patterns can help indicate criticality or tipping points in a system, which may indicate the point at which a landscape has been forced into a new state. Pascual & Guichard (Pascual & Guichard, 2005) observe that patchiness can indicate that an ecosystem is near a critical threshold. In the context of biofuel production, this can be extended to ask whether a landscape of a certain pattern, for example, the patchiness and connectedness of farms, is more or less suited to the yield and logistics of energy crops.

Wiens (1976) emphasizes patchiness as an important measure of landscape structure, and that the patches are defined and of relevance to environmental processes, in this case the production of renewable energy. Observing the change of patches over time can help indicate whether a landscape is evolving in a direction that is more conducive to energy crop production or crossing a threshold of diminishing returns or an unsustainable state. Raffa et al. (2008) extends this idea of thresholds by using landscape heterogeneity as a measure of landscape pattern, specifically observing that greater homogeneity increases the likelihood that a threshold will be crossed. Furthermore, thresholds can occur at different spatial scales, and consequently changes at a farm scale may not result in a system state shift, but at higher spatial scales the aggregate sum of many land use decisions may exceed a landscape's resilience and push it into a new state. There are many ways to measure the shape, configuration, and distribution of patches in a landscape, and these metrics have been used in many contexts, including natural and human systems (Cardille & Turner, 2017; Cushman & McGarigal, 2008; Kaminski et al., 2021).

Naveh (1988) discusses homeostasis (natural feedbacks) and homeorhesis (cultural regulation) as two mechanisms by which landscapes maintain their characteristic states. It is possible, however, to push a system beyond its capacity to self-regulate. This begs the question of whether the expansion of renewable energy can become widespread enough to dominate natural and cultural feedbacks and force landscapes into new states. Furthermore, it is not yet clear whether the increase in abandoned cropland within existing agricultural areas is itself a mechanism for maintaining a landscape's state.



## **2.2. Systems Theory**

The theoretical framework of Panarchy (Gunderson & Holling, 2002) acknowledges that systems (natural and human) are dynamic and that multiple stable states are possible. A state refers to the characteristic organisms, relationships, or processes within a given system. Given adequate disturbances, a system can be forced into a new state accompanied by the dissolution of some of its original characteristics. The ability of a system to maintain stability when confronted by disturbance is defined by its resilience (Berkes & Folke, 1994; Folke, 2006; Holling, 1973). As systems are increasingly managed (as is the case with agricultural land use) they can become rigid, dependent on multiple institutions to maintain stability and ultimately less resilient. The suitability of a landscape for energy crop production may be an important factor in assessing an area's resilience in the face of changing agricultural practices.

The transformation of system states, as defined by Panarchy, is highlighted by the progression from a state of disorganization and high resilience, typified by a nascent ecosystem or economy, to one of established structure and low resilience due to large amounts of stored capital or investment and the interdependent nature of the system's components (Gunderson & Holling, 2002). For a system to maintain stability it must manage its state transformations in a way that fosters novelty, allowing the system to gradually adapt to change and disturbance in a way that does not lead to a complete collapse and reorganization. Systems in a highly organized and managed state are often resistant to novelty. For example, an established agricultural economy may resist the rapid introduction of a new crop commodity. A system is resilient when it is able to reorganize its parts in subtle ways that cause it to evolve into a slightly different state but

avoiding crossing a threshold into collapse (Walker, 2020). Switchgrass production on newly abandoned cropland can be considered to be a novel land use within an existing agricultural landscape, representing the emergence of novelty in a highly organized system. Driving forces, such as energy demands and climate change, may force this novelty to occur and lead to a system transformation. Theoretically, if this transformation occurs while the system is at a highly connected, rigid state the consequences may be more extreme and unpredictable than if it occurs while the system is at a more loosely coupled state (Gunderson & Holling, 2002). Intentional design of a landscape system can help prevent collapse and, in fact, create a state that is more resilient and able to regenerate in a more sustainable manner (Smithwick et al., 2023).

### **2.3. Scale and Hierarchy**

Scale is critical to the study of land use processes (Allen & Starr, 1982; Delcourt et al., 1983; O'Neill, 1986). Scale can be defined as the spatial and temporal dimensions of an object or process (Turner et al., 2001), and it is important to recognize the scale at which data analyses are performed to better understand how the results fit within the complete system of land use change. Grain (the areal unit, or resolution, of analysis) and extent (the size of the study area region) are key aspects of scale and inform decisions of what data to include and how well the data models the objects and processes of interest.

This highlights a notion that can be framed within complex systems theory and hierarchy theory. Complex systems are those that contain a multitude of interrelated components, which challenge the comprehensive understanding of the whole system. This challenge is illustrated by Allen and Starr (1982) through the differentiation of systems into three broad types: first, Large-Number Systems, which contain a sufficiently

high number of components that makes a statistical average of them an appropriate treatment; second, Small-Number Systems, which contain few enough components to allow for each to be described specifically; and third, Middle-Number Systems, which possess an assortment of components numerous enough to preclude their individual treatment but few enough to make statistical averaging inappropriate. Such middle-number systems frequently characterize the realm of complexity found in human-environment systems and ecological systems, and consequently, methods are required that enable sufficient organization and simplification to support understanding while preserving the critical heterogeneity of the system. Simon (1973, p. 8) takes this a step further by stating that “all the very large systems will have hierarchic organization.” This generic view of complexity suggests that system components self-organize into different levels corresponding to the rate or scale of their dynamics. In this way, processes that proceed at a very high rate will appear as noise or an average value to processes at a higher level. Conversely, processes that proceed at a slow rate will appear constant to processes at a lower level. This separation of constituent parts allows for their individual treatment and requires the understanding of only minimal interaction between levels.

Simon’s hierarchical approach has been applied widely in the ecological and human-environment disciplines (Allen and Starr 1982; Gunderson and Holling 2002). Allen and Starr introduced hierarchy to ecological systems and suggested the debate between whether hierarchy is a purely heuristic tool with no basis in reality and whether ecological organisms and processes are physically organized in a hierarchical manner. Wiens (1995) argues that hierarchies are artificial constructs we impose on nature and may be more heuristic than operational. Others, however, show that hierarchy is a real

structure in nature and therefore approaching the system in this way is not just helpful, but necessary, to fully understand its behavior. Holling (1992) explicitly demonstrates the presence of hierarchy in nature by studying the body mass of organisms and observing that there is not a smooth increase in organism size, but rather a stepped distribution, where species' body masses tend to clump at similar sizes. Others have observed a more continuous increase in animal body mass, that is proportional to other components like metabolic rate and life span (West et al., 1997). Whether stepped or continuous, there are observed patterns in nature that vary with scale or size.

There is growing consensus that the use of hierarchy is appropriate and necessary for understanding land use land cover change, whether ecological, human, or integrated systems (O'Neill et al. 1999; Turner 1989; Urban, O'Neill, and Shugart 1987). (Gustafson, 1998, p. 151) states that the "scale of heterogeneity (patchiness) of the landscape" must be properly identified so that subsequent analyses are conducted at the appropriate scale. Some have gone as far as to specify the resolution of data relative to the features of interest; O'Neill et al. (1996) state that the spatial resolution of land use/land cover data should be two to five times finer than the size of the features so that patterns can be observed and not obscured and aggregated into coarse pixels. This body of literature illustrates the importance of the foundational concept of spatial resolution, or grain, in the study of landscapes and processes of change (Wiens, 1976).

Hierarchy theory and the concepts of resolution and grain help to frame chapters two and three of this dissertation by placing the county-level analysis at a level between higher-level government policy decisions and lower-level farm and field land use decisions. The pertinent information to be derived from this study are the driving forces

at the moderate, county level, which are most relevant to understanding regional patterns of land use. Conversely, local scale land use processes, i.e., decisions by individual landowners operate at a lower-level and a finer grain that are obscured by the scale of analysis in this study. Hierarchy theory helps to frame the current analysis at a moderate level of complexity that provides an appropriate amount of detail for the goal of regional decision-making, while still recognizing that actual land use processes are occurring at a lower, local level that are obscured by the aggregation into counties.

Crews (2008) argues that detecting patterns and subsequently inferring land change processes is dependent on the scale of observation and that the spatial unit of analysis should be unbiased rather than delineated by land characteristics. This supports the use of raster data models rather than vector polygons that require human interpretation when drawn. The choice of spatial units may be out of the researcher's hand, however, if data is only available in a specific form, for example, the county-level United States agricultural census. Changing scales and units of analysis by aggregating and disaggregating is cautioned because doing so may affect the relevance of the resulting data and hindering the interpretation of patterns and processes (Hill, 2008; Moody & Woodcock, 1994; Rutchey & Godin, 2009).

## **2.4. Land Use Change**

The modeling framework employed in Chapter 4 of this dissertation targets four theoretical concepts outlined by Verberg et al. (2002) as being important to land change: first, connectivity and topological relationships of landscape characteristics, which address the notion that behavior and properties of a location are impacted by properties of neighboring areas; second, hierarchy theory, which accounts for phenomena and driving

forces that operate and manifest at different scales (Easterling & Kok, 2002; Urban et al., 1987); third, the interplay between driving forces and proximate causes, which emphasize that land use change cannot be explained simply by relating it to underlying characteristics (driving forces); and finally, stability and resilience, which describe the ability of a system to sustain itself given a disturbance, either by maintaining its original form or evolving or adapting to a modified, yet still sustainable state (Holling, 1973).

The modeling procedure in this research is based largely on the approach of Hellmann and Verburg (2011) and addresses the four theoretical concepts described above. It involves a spatially explicit land change model (connectivity), including separate modules to separate driving forces at different hierarchical levels (hierarchy). In the case of biofuels, economic and policy drivers operate at a national level while land use change operates at a local/regional level. A multi-criteria evaluation component is coupled to help integrate the driving forces with proximate causes, such as social processes, decision-making, and individual behavior (integration). Although it is often impossible to identify all relevant driving forces (Lambin et al., 2001), one must integrate driving forces with social processes and constraints to gain a more complete picture. A conversion matrix of land change trajectories is utilized to account for resistance to and direction of change between particular land use types (stability & resistance). The modeling framework attempts to encapsulate the land change impacts of renewable energy expansion in an integrated systems approach to best represent the complex social and biophysical interactions involved and to observe the landscape response to increased biomass production on abandoned cropland.

Traditional land use change theories, like Ricardian (Lambin, 2012; Mendelsohn & Reinsborough, 2007) and von Thunen (Chisholm, 1962; Norton, 1979; Sinclair, 1967) provide understanding of how change ideally occurs and the spatial configuration of the resulting land use distribution. Ricardian theory emphasizes crop yield and profit as the primary motivators for decision-making by farmers. If there is a different crop or land use that would be more profitable, a landowner is likely to convert to that use. Likewise, if a current crop has low yield and proves to be unprofitable, land may be taken out of production and left idle rather than converting to another active use. Von Thunen is a complementary theory, with a nuanced difference that rather than profit being the primary driver of change, spatial proximity to markets is the dominant factor. In this case, locations closer to markets are generally allocated to the most profitable land use, while less profitable land uses are allocated to areas farther away from markets. This view can be extended to say that proximity to urban centers or higher population density impacts the land use chosen for a particular area. These theories are highly simplified models of reality and have received some criticism, but it is expected that decisions to abandon cropland will be made, to some degree, by its productivity and location (Harvey, 1981; Mendelsohn et al., 1994; Parr, 2015; Polsky, 2004; Polsky & Easterling III, 2001; Sinclair, 1967).

## **2.5. Climate Change Context**

The context for this research can be framed within two global challenges: the causes and effects of climate change and the supply and demand for energy. There is unequivocal scientific consensus that “human influence has warmed the atmosphere, ocean and land. Widespread and rapid changes in the atmosphere, ocean, cryosphere and

biosphere have occurred” (IPCC, 2021, p. 4). This change in climate has the potential to impose significant stress on natural and human systems. For example, rising sea levels may displace human populations; elevated temperatures and increased intensity of droughts and storms may challenge agricultural productivity and food production; and changes in the magnitude and timing of seasonal temperatures may stress marine and terrestrial biological systems in ways that exceed their resilience and ability to adapt.

Managed land areas, such as forestry, pastures, and crops, are of particular relevance to atmospheric CO<sub>2</sub> concentrations due to their role as terrestrial carbon sinks, and by association the land management practices that can lead to changes in land use and vegetation. For example, it is possible that a direct effort to adapt to climate change by converting land to biomass or solar production to offset fossil fuel use may result in a maladaptation, as the net carbon flux due to the land use change outweighs the benefit from reduced fossil fuel use (Fargione et al., 2008; Searchinger et al., 2008). In fact, the IPCC indicates that climate change may independently increase carbon storage on some managed lands, further compounding a potential loss of carbon sequestration if land use change occurs (IPCC, 2022a). Consequently, these scientific findings illustrate the importance of reducing human emissions of CO<sub>2</sub>, in particular finding alternatives for liquid fossil fuels that reduce direct carbon emissions while also minimizing undesired consequences of land use change. Field et al. (2020) find that, in fact, converting existing cropland or pasture to renewable energy production can have greater greenhouse gas emission mitigation potential than allowing former cropland or pasture return to natural vegetation. The IPCC finds that wind and solar have the greatest potential contribution to



net emission reductions of any mitigation effort and that biofuels have the greatest potential within the transportation sector (IPCC, 2022b).

## **2.6. Energy Context**

The demand for renewable energy in the United States has been increasing in recent years and is forecast to continue to grow in the coming decades (United States Energy Information Administration, 2023). Solar is expected to see particularly strong growth in the electricity sector, and biomass shows promise in the liquid transportation fuel sector.

Globally, solar energy production has increased by 41 percent since 2009 and the majority of this development has occurred on agricultural lands (Kruitwagen et al., 2021). In the United States solar is the third largest renewable source of electricity generation and its production capacity has increased by over 35 percent between 2022 and 2023 alone (United States Energy Information Administration, 2024). Consumer attitudes and demand for solar installations are often positive (Mamkhezri et al., 2020), although many farmers adopt solar energy production on their land under financial or social pressure (Spangler et al., 2024). This suggests the continued increase in need for land on which to build solar production facilities.

Although biomass has potential to contribute to the liquid fuel demands of the transportation sector, recent trends in the automotive industry have supplanted much of this demand with electric vehicles. Sales of electric vehicles globally have increased from 550,000 in 2015 to over 10 million in 2022 IEA (2023). The aviation industry is still a niche opportunity for the use of biomass energy as the industry has set a target of a 50% reduction in CO<sub>2</sub> emissions by 2050 (Detsios et al., 2023) and liquid fuel is likely to

continue to be a dominant renewable energy source due to the convenience of existing infrastructure and the challenges of electrifying aircraft (Su-ungkavatin et al., 2023).

The preceding discussion illustrates the importance of renewable energy to the energy portfolio of the United States and the need to study the impacts of their production. The impacts of renewables investigated in this dissertation pertain to the land change implications of expanding production. Despite the benefits and case made for renewable energy presented above, they present particular challenges related to the location and context of where they are produced.

### **2.6.1. Biomass**

Biofuel's advantage over fossil in terms of carbon sequestration is exemplified by its "feedstock uptake credit" (Searchinger et al., 2008). Biomass-derived fuels are considered carbon neutral as their combustion emissions are offset by the carbon absorbed via photosynthesis during the regrowth of the feedstock. However, this carbon neutrality is negated if land cleared to grow the initial fuel feedstock (e.g., switchgrass) was previously covered by vegetation (e.g., forest) that sequesters a greater quantity of carbon. The initial flux of carbon to the atmosphere due to the land use change is considered a "carbon debt" that may take decades to recoup (Fargione et al., 2008).

Ecosystem habitat health may be compromised by induced land use change. Instances of fragmentation, increasing homogeneity, and elimination of land cover types are examples of processes that can impair species' ability to survive and reduce valuable ecosystem services (Hasan et al., 2020; Martin et al., 2020). However, contradictory findings have demonstrated that, in some cases, a more fragmented landscape with small habitat patches can have advantages such as harboring more species in a smaller area

(Fahrig, 2020; Riva & Fahrig, 2022). Expansion of land area dedicated to the production of biofuel crops has the potential to interfere with the natural processes in place if not managed carefully. The decision to convert land to energy production can be viewed from the two perspectives of land sharing and land sparing (Baudron et al., 2021). Land sharing is the practice of putting land into agricultural land use, while maintaining other land functions and characteristics such as vegetation diversity and habitat conservation. The result is less energy production but improved ecosystem services. Land sparing, on the other hand, concentrates production and yield on a smaller amount of land, leaving other areas unaffected.

Induced land use changes caused by demand for biomass energy may incur indirect land use changes elsewhere (Fiorini et al., 2023). For example, non-agricultural land in other regions may be converted to food production to replace food sources displaced by energy crops. Many studies consider food to be inelastic (Jones et al., 2007; Searchinger et al., 2008; Smeets et al., 2007), and because of the conflict between food and fuel, it is appropriate to account for both direct and indirect land use changes. In the case of this dissertation, an assumption is made that food production totals will not be compromised, and that total agricultural land (food and fuel) will expand into previously non-agricultural land as necessary to accommodate both. Specifically, recent studies indicate that it is inappropriate to replace food crop production with energy crop production for economic and ethical reasons, and they suggest other means of increasing agricultural production, such as double cropping and utilizing non-competitive abandoned cropland (Baker & Griffis, 2009; Baxter et al., 2009; Chesapeake Bay Commission & Commonwealth of Pennsylvania, 2010). Furthermore, some cellulosic

biofuel crops, such as switchgrass, can grow adequately on less productive lands, where food crops would not otherwise be present (McLaughlin & Kszos, 2005; Sanderson & Adler, 2008; Tilman et al., 2006).

### **2.6.2. Solar**

Increased production of utility-scale solar will require the conversion of land. van de Ven et al. (2021) estimate that up to 5 percent of a country's land may need to be dedicated to solar installations if solar energy is to account for most of its total electricity generation mix. In the United States, it is estimated that over 4,400 utility-scale solar installations are in operation as of 2021 (Fujita et al., 2023). These estimates may, in fact, be an undercount as they are often derived from remotely sensed imagery that requires interpretation and may quickly become out of date and miss newer developments.

As the number and area of solar installations increase over time with increased demand for renewable electricity generation, thoughtful planning processes will be required to ensure that development proceeds in a way that maximizes production while avoiding negative land use change consequences within the context of the local area (Katkar et al., 2021). Furthermore, incorporating social factors in a multicriteria approach to siting solar facilities is likely necessary to arrive at an optimal solution (Sward et al., 2021). O'Shaughnessy et al. (2023) observe that the process of siting solar installations is typically driven by technoeconomic factors and may result in development that unjustly impacts communities by, for example, incurring environmental harm at the site of the solar installation while the generated electricity is transmitted to distant populations. Farming communities are at greater risk as opportunities for renewable energy development incentives changes to livelihoods and land use (Goldberg, 2023).

### **3. Research Approach**

This dissertation approaches the emergence of usable abandoned cropland as an opportunity for renewable energy production from two dominant perspectives: a multi-scale approach and spatially explicit modeling.

First, it has a multi-scalar focus. Chapter 2 of this dissertation estimates the amount of abandoned cropland that may be available for biomass production at a national scale. Chapter 3 explores the drivers of cropland abandonment at regional level by investigating how the factors influencing land change vary from one part of the country to another. Chapter 4 downscales the analysis further by modeling change at the local level using insights of the drivers obtained earlier to force the model and landscape characteristics to assess impacts.

Other studies of renewable energy transition, particularly on biofuels, have projected the potentials and impacts of biomass feedstocks typically at aggregated, national, or global scales (De La Torre Ugarte & Ray, 2000; Smeets et al., 2007; Strengers et al., 2004). Broad-scale research of this kind can be informative. However, when assessing land use decision-making, i.e., the decision to abandon cropland, a finer scale is more appropriate, because the process of land use and land cover change manifests at a local or landscape level. In general, it is optimal to match the scale and resolution of data and analysis to the scale of the phenomena being studied. Furthermore, human-environment systems involve complexities spanning multiple hierarchical scales, and it has been suggested that regional scale approaches are best suited for understanding this type of system (Easterling & Kok, 2002). Decisions by landowners to put land into agricultural production, remove land from agricultural production, or convert to a new

activity like renewable energy production are managed and governed at multiple scales. For example, the federal government directs national-scale policy; state governments and regional organizations assess meso-scale potential (Chesapeake Bay Commission & Commonwealth of Pennsylvania, 2010); and local land managers implement land use based on landscape characteristics and economic and provincial incentives. Studying this issue at multiple scales is therefore necessary, particularly when considering that the drivers of land use change and the relevance of spatial landscape pattern to those decisions may vary with spatial scale.

Second, the land change modeling framework employed in Chapter Four of this dissertation is spatially explicit. The impacts of energy crop production on abandoned cropland are inextricably connected to the spatial pattern of the landscape and the spatial manifestation of land use change processes. A spatial approach is particularly critical in biofuel studies, as the response to increased demand is influenced by the geographical location and proximity from which the demand originates (Kloverpris et al., 2008). Furthermore, to assess the relevance of spatial landscape pattern on the process and impacts of biofuel expansion, the modeling framework employed must be based on the spatial patterns of the underlying characteristics of the landscape. Non-spatial land change projections rely on prescriptive expert knowledge to drive models and are only able to assess results and impacts at gross aggregated levels, an approach inadequate for the proposed study.

While this dissertation utilizes statistics and modeling to understand and project land use change, it does not intend to imply that land use processes are completely explainable by the few factors included in the analysis nor does it suggest that complex

human decision-making and behavior are driven exclusively by quantifiable factors. Such an approach would suggest an adherence to antiquated theories, such as environmental determinism, where human behavior and cultural expression are shown to be controlled by the physical environment (Peet, 1985). Rather, this study aims to address land use change from a statistical perspective, relating both physical and cultural variables to the land change process, as a complement to other approaches grounded in critical social theory.

#### **4. Dissertation Outline**

Figure 1.1 illustrates the three following chapters of this dissertation and how they connect the primary research themes.

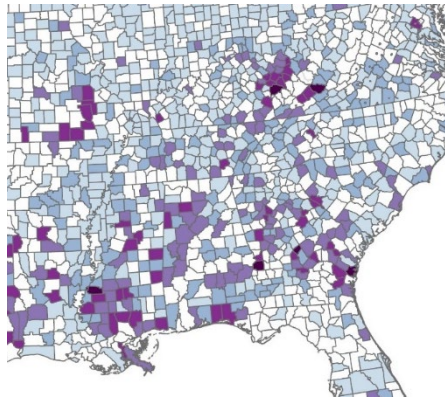
In Chapter 2, I utilize historical agricultural data to estimate the amount of abandoned cropland that is available for the production of energy crops, given three constraints: 1) avoiding abandoned cropland that may have had time to regrow mature forest cover and significant biomass that would incur a large carbon debt if cleared for switchgrass production; 2) avoiding land that may have converted to an urban land use and therefore unlikely to transition back to an agriculture; and 3) avoiding land that may have converted to a pasture land use.

In Chapter 3, I perform a statistical analysis to explore what county-level factors may contribute to the abandonment of cropland. Understanding these characteristics can help to identify regions of the country that have higher potential to experience future abandonment and opportunities for energy crop production, and therefore places that may be worth directing investments or incentives. The estimates of abandoned cropland developed in Chapter 2 are used as the dependent variable.

In Chapter 4, I downscale the occurrence of abandoned cropland to the landscape level to assess the patterns of available land and how they compare among counties in different types of landscapes. County-level estimates of abandoned cropland developed in Chapter 2 are used to inform how much abandonment to force onto the study area landscapes in a land change modeling exercise. The drivers identified in Chapter 3 provide a starting point for identifying variables relevant to the landscape-level changes in Chapter 4. The predictor variables in these two chapters are complementary, however, they differ due to differences in the scale of the analyses.

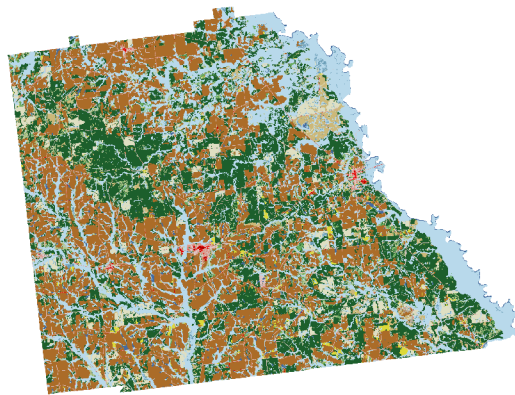
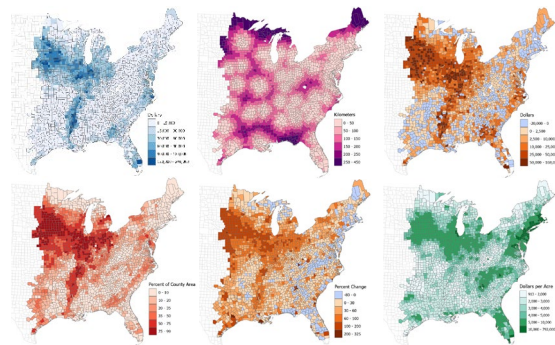
I conclude the dissertation in Chapter 5 by summarizing the results of the preceding chapters and discussing broader implications.





## *County Estimates of Abandoned Cropland* **Chapter 2**

## *Drivers of Cropland Abandonment* **Chapter 3**



## *Landscape Patterns of Abandoned Cropland* **Chapter 4**

**Figure 1.1.** Connections among themes and chapters of this dissertation.

## 5. References

- Allen, T. F. H., & Starr, T. B. (1982). *Hierarchy*. University of Chicago Press.
- Baker, J. M., & Griffis, T. J. (2009). Evaluating the potential use of winter cover crops in corn-soybean systems for sustainable co-production of food and fuel. *Agricultural and Forest Meteorology*, 149, 2120 - 2132.
- Baudron, F., Govaerts, B., Verhulst, N., McDonald, A., & Gérard, B. (2021). Sparing or sharing land? Views from agricultural scientists. *Biological Conservation*, 259, 109167. [https://doi.org/https://doi.org/10.1016/j.biocon.2021.109167](https://doi.org/10.1016/j.biocon.2021.109167)
- Baxter, R., Plakkat, A., Camargo, G., Dubin, M., A Rotz, C., Roth, G., & L Richard, T. (2009, October 11-14, 2009). *Biofuels for the bay: Cellulosic double crops in the chesapeake watershed* Bioenergy Engineering, Bellevue, Washington.
- Berkes, F., & Folke, C. (1994). Linking social and ecological systems for resilience and sustainability.
- Bormann, F. H., & Likens, G. E. (1979). Catastrophic disturbance and the steady state in northern hardwood forests: A new look at the role of disturbance in the development of forest ecosystems suggests important implications for land-use policies. *American Scientist*, 67(6), 660-669.
- Brown, P. R., & O'Sullivan, F. M. (2020). Spatial and temporal variation in the value of solar power across united states electricity markets. *Renewable & Sustainable Energy Reviews*, 121, Article 109594. <https://doi.org/10.1016/j.rser.2019.109594>
- Cardille, J. A., & Turner, M. G. (2017). Understanding landscape metrics. In S. E. Gergel & M. G. Turner (Eds.), *Learning landscape ecology: A practical guide to concepts and techniques* (pp. 45-63). Springer New York. [https://doi.org/10.1007/978-1-4939-6374-4\\_4](https://doi.org/10.1007/978-1-4939-6374-4_4)
- Chesapeake Bay Commission, & Commonwealth of Pennsylvania. (2010). *Chesapeake bay policies: Balancing energy, economy and environment*. <https://www.chesbay.us/library/public/documents/Policy-Reports/biofuels-report-3-Copy.pdf>
- Chisholm, M. (1962). *Rural settlement and land use*. Transaction Publishers. <https://doi.org/10.4324/9781315128832>

- Crews, K. A. (2008). Landscape dynamism: Disentangling thematic versus structural change in northeast thailand. In R. J. Aspinall & M. Hill (Eds.), *Land use change: Science, policy and management* (pp. 99 - 118). Taylor & Francis Group.
- Cushman, S. A., & McGarigal, K. (2008). Landscape metrics, scales of resolution. In *Designing green landscapes* (pp. 33-51). Springer.
- De La Torre Ugarte, D., & Ray, D. (2000). Biomass and bioenergy applications of the polysys modeling framework. *Biomass and Bioenergy*, 18, 291 - 308.
- Delcourt, H. R., Delcourt, P. A., & Webb, T. (1983). Dynamic plant ecology: The spectrum of vegetational change in space and time. *Quaternary Science Reviews*, 1, 153 - 175.
- Detsios, N., Theodoraki, S., Maragoudaki, L., Atsonios, K., Grammelis, P., & Orfanoudakis, N. G. (2023). Recent advances on alternative aviation fuels/pathways: A critical review. *Energies*, 16(4), 1904.  
<https://www.mdpi.com/1996-1073/16/4/1904>
- Easterling, W. E., & Kok, K. (2002). Emergent properties of scale in global environmental modeling - are there any? *Integrated Assessment*, 3(2 - 3), 233 - 246.
- Fahrig, L. (2020). Why do several small patches hold more species than few large patches? *Global Ecology and Biogeography*, 29(4), 615-628.  
<https://doi.org/10.1111/geb.13059>
- Fargione, J., Hill, J., Tilman, D., Polasky, S., & Hawthorne, P. (2008). Land clearing and the biofuel carbon debt. *Science*, 319, 1235-1238.
- Field, J. L., Richard, T. L., Smithwick, E. A. H., Cai, H., Laser, M. S., Lebauer, D. S., Long, S. P., Paustian, K., Qin, Z., Sheehan, J. J., Smith, P., Wang, M. Q., & Lynd, L. R. (2020). Robust paths to net greenhouse gas mitigation and negative emissions via advanced biofuels. *Proceedings of the National Academy of Sciences*, 117(36), 21968-21977. <https://doi.org/10.1073/pnas.1920877117>
- Fiorini, A. C. O., Angelkorte, G., Maia, P. L., Bergman-Fonte, C., Vicente, C., Morais, T., Carvalho, L., Zanon-Zotin, M., Szklo, A., Schaeffer, R., & Portugal-Pereira, J. (2023). Sustainable aviation fuels must control induced land use change: An

- integrated assessment modelling exercise for brazil. *Environmental Research Letters*, 18(1), 014036. <https://doi.org/10.1088/1748-9326/acae1>
- Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change*, 16(3), 253-267. <https://doi.org/10.1016/j.gloenvcha.2006.04.002>
- Foster, D., Motzkin, G., & Slater, B. (1998). Land-use history as long-term broad-scale disturbance: Regional forest dynamics in central new england. *Ecosystems*, 1, 96 - 119.
- Franklin, J., & Forman, R. (1987). Creating landscape patterns by forest cutting: Ecological consequences and principles. *Landscape Ecology*, 1(1), 5 - 18.
- Fujita, K. S., Ancona, Z. H., Kramer, L. A., Straka, M., Gautreau, T. E., Robson, D., Garrity, C., Hoen, B., & Diffendorfer, J. E. (2023). Georectified polygon database of ground-mounted large-scale solar photovoltaic sites in the united states [Article; Data Paper]. *Scientific Data*, 10(1), 14, Article 760. <https://doi.org/10.1038/s41597-023-02644-8>
- Goldberg, Z. A. (2023). Solar energy development on farmland: Three prevalent perspectives of conflict, synergy and compromise in the united states [Article]. *Energy Research & Social Science*, 101, 8, Article 103145. <https://doi.org/10.1016/j.erss.2023.103145>
- Gunderson, L. H., & Holling, C. S. (Eds.). (2002). *Panarchy: Understanding transformations in human and natural systems*. Island Press.
- Gustafson, E. J. (1998). Quantifying landscape spatial pattern: What is the state of the art? *Ecosystems*, 1, 143 - 156.
- Harvey, D. (1981). The spatial fix–hegel, von thunen, and marx. *Antipode*, 13(3), 1-12.
- Hasan, S. S., Zhen, L., Miah, M. G., Ahamed, T., & Samie, A. (2020). Impact of land use change on ecosystem services: A review. *Environmental Development*, 34, 100527. <https://doi.org/10.1016/j.envdev.2020.100527>
- Hellmann, F., & Verburg, P. H. (2011). Spatially explicit modelling of biofuel crops in europe. *Biomass and Bioenergy*, 35(6), 2411-2424. <https://doi.org/10.1016/j.biombioe.2008.09.003>

- Hill, M. (2008). Developing spatially dependent procedures and models for multicriteria decision analysis. In R. J. Aspinall & M. Hill (Eds.), *Land use change: Science, policy and management* (pp. 17 - 40). Taylor & Francis Group.
- Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 4, 1-23.
- Hoogwijk, M., Faaij, A., van den Broek, R., Berndes, G., Gielen, D., & Turkenburg, W. (2003). Exploration of the ranges of the global potential of biomass for energy. *Biomass and Bioenergy*, 25, 119 - 133.
- IEA. (2023). *Global ev data explorer* <https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer>
- IPCC. (2021). *Climate change 2021: The physical science basis. Contribution of working group i to the sixth assessment report of the intergovernmental panel on climate change*. C. U. Press.
- IPCC. (2022a). *Climate change 2022: Impacts, adaptation and vulnerability. Contribution of working group ii to the sixth assessment report of the intergovernmental panel on climate change*. C. U. Press.
- IPCC. (2022b). *Climate change 2022: Mitigation of climate change. Contribution of working group iii to the sixth assessment report of the intergovernmental panel on climate change*. C. U. Press.
- Jones, A., O'Hare, M., & Farrell, A. (2007). *Biofuel boundaries: Estimating the medium-term supply potential of domestic biofuels* [Working Paper]. Institutes of Transportation Studies, UC Berkeley Transportation Sustainability Research Center. <http://repositories.cdlib.org/its/tsrc/UCB-ITS-TSRC-RR-2007-4>
- Kaminski, A., Bauer, D. M., Bell, K. P., Loftin, C. S., & Nelson, E. J. (2021). Using landscape metrics to characterize towns along an urban-rural gradient. *Landscape Ecology*, 36(10), 2937-2956. <https://doi.org/10.1007/s10980-021-01287-7>
- Katkar, V. V., Sward, J. A., Worsley, A., & Zhang, K. M. (2021). Strategic land use analysis for solar energy development in new york state. *Renewable Energy*, 173, 861-875. <https://doi.org/10.1016/j.renene.2021.03.128>
- Kloverpris, J., Wenzel, H., Banse, M., Mila i Canals, L., & Reenberg, A. (2008). Conference and workshop on modeling global land use implications in the

- environmental assessment of biofuels. *The International Journal of Life Cycle Assessment*, 13(3), 178 - 183.
- Kruitwagen, L., Story, K. T., Friedrich, J., Byers, L., Skillman, S., & Hepburn, C. (2021). A global inventory of photovoltaic solar energy generating units. *Nature*, 598(7882), 604-610. <https://doi.org/10.1038/s41586-021-03957-7>
- Lambin, E. F. (2012). Global land availability: Malthus versus ricardo. *Global Food Security*, 1(2), 83-87. <https://doi.org/10.1016/j.gfs.2012.11.002>
- Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S., Angelsen, A., Bruce, J. W., Coomes, O. T., Dirzo, R., Fischer, G., Folke, C., George, P. S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E. F., Mortimore, M., Ramakrishnan, P. S., Richards, J. F., . . . Xu, J. (2001). The causes of land-use and land-cover change: Moving beyond the myths. *Global Environmental Change*, 11, 261 - 269.
- Lamers, P., T. Avelino, A. F., Zhang, Y., D. Tan, E. C., Young, B., Vendries, J., & Chum, H. (2021). Potential socioeconomic and environmental effects of an expanding u.S. Bioeconomy: An assessment of near-commercial cellulosic biofuel pathways. *Environmental Science & Technology*, 55(8), 5496-5505. <https://doi.org/10.1021/acs.est.0c08449>
- Lytle, W., Meyer, T. K., Tanikella, N. G., Burnham, L., Engel, J., Schelly, C., & Pearce, J. M. (2021). Conceptual design and rationale for a new agrivoltaics concept: Pasture-raised rabbits and solar farming [Article]. *Journal of Cleaner Production*, 282, 11, Article 124476. <https://doi.org/10.1016/j.jclepro.2020.124476>
- Mamkhezri, J., Thacher, J. A., & Chermak, J. M. (2020). Consumer preferences for solar energy: A choice experiment study. *The Energy Journal*, 41(5), 157-184. <https://doi.org/10.5547/01956574.41.5.jmam>
- Martin, A. E., Collins, S. J., Crowe, S., Girard, J., Naujokaitis-Lewis, I., Smith, A. C., Lindsay, K., Mitchell, S., & Fahrig, L. (2020). Effects of farmland heterogeneity on biodiversity are similar to—or even larger than—the effects of farming practices. *Agriculture, Ecosystems & Environment*, 288, 106698. <https://doi.org/10.1016/j.agee.2019.106698>

- McLaughlin, S. B., & Kszos, L. A. (2005). Development of switchgrass (*panicum virgatum*) as a bioenergy feedstock in the united states. *Biomass and Bioenergy*, 28, 515 - 535.
- Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The impact of global warming on agriculture: A ricardian analysis. *The American economic review*, 753-771.
- Mendelsohn, R., & Reinsborough, M. (2007). A ricardian analysis of us and canadian farmland. *Climatic Change*, 81(1), 9-17. <https://doi.org/10.1007/s10584-006-9138-y>
- Milbrandt, A. R., Heimiller, D. M., Perry, A. D., & Field, C. B. (2014). Renewable energy potential on marginal lands in the united states. *Renewable and Sustainable Energy Reviews*, 29, 473-481. <https://doi.org/10.1016/j.rser.2013.08.079>
- Moody, A., & Woodcock, C. E. (1994). Scale-dependent errors in the estimation of land-cover proportions; implications for global land-cover datasets. *Photogrammetric Engineering & Remote Sensing*, 60(5), 585 - 594.
- Naveh, Z. (1988). Biocybernetic perspectives of landscape ecology and management. In M. Moss (Ed.), *Landscape ecology and management*. Polyscience.
- Niblick, B., & Landis, A. E. (2016). Assessing renewable energy potential on united states marginal and contaminated sites. *Renewable and Sustainable Energy Reviews*, 60, 489-497. <https://doi.org/10.1016/j.rser.2015.12.045>
- Norton, W. (1979). The relevance of von thünen theory to historical and evolutionary analysis of agricultural land use. *Journal of Agricultural Economics*, 30(1), 39-47. <https://doi.org/10.1111/j.1477-9552.1979.tb01476.x>
- O'Neill, R. V. (1986). *A hierarchical concept of ecosystems*. Princeton University Press.
- O'Neill, R. V., Hunsaker, C. T., Timmins, S. P., Jackson, B. L., Jones, K. B., Riitters, K. H., & Wickham, J. D. (1996). Scale problems in reporting landscape pattern and the regional scale. *Landscape Ecology*, 11(3), 169-180.
- O'Shaughnessy, E., Wiser, R., Hoen, B., Rand, J., & Elmallah, S. (2023). Drivers and energy justice implications of renewable energy project siting in the united states [Article]. *Journal of Environmental Policy & Planning*, 25(3), 258-272. <https://doi.org/10.1080/1523908x.2022.2099365>

- Parr, J. B. (2015). Overlooked aspects of the von thünen system. *Spatial Economic Analysis*, 10(4), 471-487. <https://doi.org/10.1080/17421772.2015.1076577>
- Pascaris, A. S., Gerlak, A. K., & Barron-Gafford, G. A. (2023). From niche-innovation to mainstream markets: Drivers and challenges of industry adoption of agrivoltaics in the us [Article]. *Energy Policy*, 181, 12, Article 113694. <https://doi.org/10.1016/j.enpol.2023.113694>
- Pascaris, A. S., Schelly, C., Burnham, L., & Pearce, J. M. (2021). Integrating solar energy with agriculture: Industry perspectives on the market, community, and socio-political dimensions of agrivoltaics. *Energy Research & Social Science*, 75, 102023. <https://doi.org/https://doi.org/10.1016/j.erss.2021.102023>
- Pascaris, A. S., Schelly, C., & Pearce, J. M. (2020). A first investigation of agriculture sector perspectives on the opportunities and barriers for agrivoltaics [Article]. *Agronomy-Basel*, 10(12), 16, Article 1885. <https://doi.org/10.3390/agronomy10121885>
- Pascual, M., & Guichard, F. (2005). Criticality and disturbance in spatial ecological systems. *Trends in Ecology and Evolution*, 20(1), 88 - 95.
- Peet, R. (1985). The social origins of environmental determinism. *Annals of the Association of American Geographers*, 75(3), 309 - 333.
- Polsky, C. (2004). Putting space and time in ricardian climate change impact studies: Agriculture in the u.S. Great plains, 1969–1992. *Annals of the Association of American Geographers*, 94(3), 549-564. <https://doi.org/10.1111/j.1467-8306.2004.00413.x>
- Polsky, C., & Easterling III, W. E. (2001). Adaptation to climate variability and change in the us great plains:: A multi-scale analysis of ricardian climate sensitivities. *Agriculture, Ecosystems & Environment*, 85(1-3), 133-144.
- Raffa, K., Aukema, B., Bentz, B., Carroll, A., Hicke, J., Turner, M., & Romme, W. (2008). Cross-scale drivers of natural disturbances prone to anthropogenic amplification: The dynamics of bark beetle eruptions. *BioScience*, 58(6), 501 - 517.



- Riva, F., & Fahrig, L. (2022). The disproportionately high value of small patches for biodiversity conservation. *Conservation Letters*, 15(3), e12881.  
<https://doi.org/10.1111/conl.12881>
- Rutchev, K., & Godin, J. (2009). Determining an appropriate minimum mapping unit in vegetation mapping for ecosystem restoration: A case study from the everglades, USA. *Landscape Ecology*, 24, 1351-1362.
- Sanderson, M. A., & Adler, P. (2008). Perennial forages as second generation bioenergy crops. *International Journal of Molecular Sciences*, 9, 768 - 788.
- Schoeneberger, C. A., McMillan, C. A., Kurup, P., Akar, S., Margolis, R., & Masanet, E. (2020). Solar for industrial process heat: A review of technologies, analysis approaches, and potential applications in the united states. *Energy*, 206, 118083.  
<https://doi.org/https://doi.org/10.1016/j.energy.2020.118083>
- Searchinger, T., Heimlich, R., Houghton, R. A., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D., & Yu, T.-H. (2008). Use of u.S. Croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science*, 319, 1238-1240.
- Simon, H. A. (1973). The organization of complex systems. In H. Pattee (Ed.), *Hierarchy theory: The challenge of complex systems* (pp. 3 - 27). George Braziller.
- Sinclair, R. (1967). Von thünen and urban sprawl. *Annals of the Association of American Geographers*, 57(1), 72-87. <https://doi.org/10.1111/j.1467-8306.1967.tb00591.x>
- Smeets, E., Faaij, A., Lewandowski, I., & Turkenburg, W. (2007). A bottom-up assessment and review of global bio-energy potentials to 2050. *Progress in Energy and Combustion Science*, 33, 56 - 106.
- Smithwick, E. A. H., Baka, J., Bird, D., Blaszcak-Boxe, C., Cole, C. A., Fuentes, J. D., Gergel, S. E., Glenna, L. L., Grady, C., Hunt, C. A., Iulo, L. D., Kaye, J., & Keller, K. (2023). Regenerative landscape design: An integrative framework to enhance sustainability planning. *Ecology and Society*, 28(4), Article 5.  
<https://doi.org/10.5751/ES-14483-280405>
- Spangler, K., Smithwick, E. A. H., Buechler, S., & Baka, J. (2024). Just energy imaginaries? Examining realities of solar development on pennsylvania's

- farmland. *Energy Research & Social Science*, 108, 103394.  
<https://doi.org/https://doi.org/10.1016/j.erss.2023.103394>
- Stoof, C. R., Richards, B. K., Woodbury, P., B., Fabio, E. S., Brumbach, A. R., Cherney, J., Das, S., Geohring, L., Hansen, J., Hornesky, J., Mayton, H., Mason, C., Ruestow, G., Smart, L. B., Volk, T. A., & Steenhuis, T., S. (2015). Untapped potential: Opportunities and challenges for sustainable bioenergy production from marginal lands in the northeast USA. *Bioenergy Research*, 8, 482-501.
- Strengers, B., Leemans, R., Eickhout, B., de Vries, B., & Bouwmann, L. (2004). The land-use projections and resulting emissions in the ipcc sres scenarios as simulated by the image 2.2 model. *GeoJournal*, 61, 381 - 393.
- Su-ungkavatin, P., Tiruta-Barna, L., & Hamelin, L. (2023). Biofuels, electrofuels, electric or hydrogen?: A review of current and emerging sustainable aviation systems. *Progress in Energy and Combustion Science*, 96, 101073.  
<https://doi.org/10.1016/j.pecs.2023.101073>
- Sward, J. A., Nilson, R. S., Katkar, V. V., Stedman, R. C., Kay, D. L., Ifft, J. E., & Zhang, K. M. (2021). Integrating social considerations in multicriteria decision analysis for utility-scale solar photovoltaic siting. *Applied Energy*, 288, 116543.  
<https://doi.org/https://doi.org/10.1016/j.apenergy.2021.116543>
- Tabassum, S., Rahman, T., Islam, A. U., Rahman, S., Dipta, D. R., Roy, S., Mohammad, N., Nawar, N., & Hossain, E. (2021). Solar energy in the united states: Development, challenges and future prospects. *Energies*, 14(23), 8142.  
<https://www.mdpi.com/1996-1073/14/23/8142>
- Tavakkoli, S., Macknick, J., Heath, G. A., & Jordaan, S. M. (2021). Spatiotemporal energy infrastructure datasets for the united states: A review [Review]. *Renewable & Sustainable Energy Reviews*, 152, 10, Article 111616.  
<https://doi.org/10.1016/j.rser.2021.111616>
- Tilman, D., Hill, J., & Lehman, C. (2006). Carbon-negative biofuels from low-input high-diversity grassland biomass. *Science*, 314, 1598 - 1600.
- Turner, M. G. (2010). Disturbance and landscape dynamics in a changing world. *Ecology*, 91(10), 2833-2849. <https://doi.org/10.1890/10-0097.1>

- Turner, M. G., Gardner, R. H., O'Neill, R. V., & O'Neill, R. V. (2001). *Landscape ecology in theory and practice* (Vol. 401). Springer.
- United States Energy Information Administration. (2023). *Annual energy outlook 2023*.  
<https://www.eia.gov/outlooks/aeo/>
- United States Energy Information Administration. (2024). *Electric power monthly*.  
[https://www.eia.gov/electricity/monthly/current\\_month/february2024.pdf](https://www.eia.gov/electricity/monthly/current_month/february2024.pdf)
- Urban, D. L., O'Neill, R. V., & Shugart, H. H. (1987). Landscape ecology: A hierarchical perspective can help scientists understand spatial patterns. *BioScience*, 37(2), 119 - 127.
- van de Ven, D.-J., Capellan-Peréz, I., Arto, I., Cazcarro, I., de Castro, C., Patel, P., & Gonzalez-Eguino, M. (2021). The potential land requirements and related land use change emissions of solar energy. *Scientific Reports*, 11(1), 2907.  
<https://doi.org/10.1038/s41598-021-82042-5>
- Verberg, P., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., & Mastura, S. (2002). Modeling the spatial dynamics of regional land use: The clue-s model. *Environmental Management*, 30(3), 391 - 405.
- Walker, B. H. (2020). Resilience: What it is and is not. *Ecology and Society*, 25(2), Article 11. <https://doi.org/10.5751/ES-11647-250211>
- West, G. B., Brown, J. H., & Enquist, B. J. (1997). A general model for the origin of allometric scaling laws in biology. *Science*, 276(5309), 122-126.
- Wiens, J. A. (1976). Population responses to patchy environments. *Annual Review of Ecology and Systematics*, 7, 81 - 120.
- Wiens, J. A. (1995). Landscape mosaics and ecological theory. In L. Hansson, L. Fahrig, & G. Merriam (Eds.), *Mosaic landscapes and ecological processes* (pp. 1 - 26). Chapman & Hall.

## Chapter 2. Estimating Available Abandoned Cropland in the United States for Energy Crop Production

### 1. Abstract

Plans to produce significant energy crops at a scale that will achieve meaningful displacement of fossil fuels raise questions about the quantity of land that is available and the consequences of land conversion. Using the US as a case study, this paper assesses the potential of *abandoned cropland* to produce energy crops while avoiding some of the negative impacts of converting other types of land to such crops; for example, land cover change-induced carbon emissions and competition with food production. Abandoned cropland is a less ambiguous and context-dependent land resource than the more commonly considered *marginal land*. A methodology is developed to estimate available abandoned cropland (AACL) in the United States, accounting for conversion to forest cover, urban development, or permanent pasture. Estimates are derived for two scenarios: 1) land abandoned between 1978 and 2012, which represents the longest time period from the present that precludes forest regrowth; and 2) land abandoned between 2007 and 2012, which correspond to constraints imposed by the Renewable Fuel Standard. Results show that 15 and 4.9 Mha of AACL exist in the United States in the two scenarios respectively. The relative contributions of these estimates to national energy consumption amount to only 3 to 8 percent of total light duty gasoline consumption, and make more significant contributions to other end uses, such as aviation or ethylene. The policy implications of these findings and the need for future research are discussed.

## 2. Introduction

Concerns about the amount of land area that is required to produce a meaningful quantity of biomass for energy or fuel production (hereafter *energy crops*) underpin debates about whether bioenergy or biofuel systems are sustainable (Lynd, Laser, McBride, Podkaminer, & Hannon, 2007; Tilman, et al., 2009). Broadly speaking, these debates feature two issues: (1) environmental impacts such as habitat change and carbon sequestration as land is converted into energy crop production (Fargione, Hill, Tilman, Polasky, & Hawthorne, 2008); and (2) social impacts such as competition with food prices and large-scale land transfers from local subsistence to multinational corporations (i.e., land grabbing), most relevant to cases outside the United States (Nalepa & Bauer, 2012). Further complicating the sustainability and acceptance of energy crop production is the potential for indirect land use change, where land may be converted elsewhere to compensate for food crop production that was displaced by energy crop production (Searchinger, et al., 2008). Yet, biomass is the only renewable resource that can provide base-load heat or electricity without complex storage systems; the only renewable resource from which to produce non-energy products that are currently derived from petroleum (e.g., plastics); and the resource that is most likely to directly substitute for liquid fossil fuels in heavy-duty vehicles, shipping, and aviation in the near term. In this light, it is critical to locate and quantify land that might support energy crop production with minimal undesirable biophysical and social impacts (Calvert 2011).

Abandoned cropland is a possible alternative land type on which to produce energy crops (Kang, et al. (2013). Here, abandoned cropland is defined as land area that was once used for, or declared as, agricultural cropland, but is no longer (considered to

be) performing that function. In this sense, abandoned cropland is land that was once included within agricultural surveys, such as the USDA Census of Agriculture, and is no longer counted. Defined thusly, it is possible to estimate abandoned cropland using historical census data.

This paper contributes to the conceptual, methodological, and empirical foundations of estimating land potential for dedicated energy crop production, using the United States as a case study. The paper has four parts. First, the relationship between abandoned cropland and the concept of *marginal land* is discussed. Second, a review of existing estimates of abandoned cropland is undertaken. Building from this work, the paper then develops a methodology for calculating the quantity of available abandoned cropland (AACL) at the county-level in the United States. By AACL we refer to abandoned cropland that has not converted to another active use such as urban development, forest cover or permanent pasture. Before concluding, the implications on decision-making of how results are visualized cartographically are discussed. In sum, the paper argues that AACL is a more appropriate category than marginal agricultural land for quantifying and locating land that might support dedicated energy crop production with minimal social and ecological impacts. The US is shown to have a small amount of AACL relative to the area of land required to supply meaningful amounts of biomass, although regional opportunities exist.

### 3. Literature Review

#### 3.1. Abandoned Cropland as Economically Marginal Land

It is widely believed that the land use and food system impacts of energy crop production can be mitigated if they are grown on marginal land (Gopalakrishnan, Negri, & Snyder, 2011). Use of the label *marginal land* to identify potential land areas for energy crop production is problematic because it lacks a standard, unambiguous definition. Richards, et al. (2014) performed a review of 51 articles written between 2008 and 2012 that use the term *marginal* and found that only 53% of these articles provide an explicit definition, 31% provide an implicit definition that could be inferred from context, and 16% provide no definition at all. Ambiguity is further compounded by the fact that multiple terms are sometimes used interchangeably with *marginal*, including: “unproductive,” “waste,” “under-utilized,” “idle,” “abandoned,” “degraded,” “unused,” “suitable,” “free,” “spare,” “set aside,” “fallow,” “additional,” “appropriate,” (Kang, et al., 2013; Shortall, 2013).

Ambiguity breeds scientific deficiencies and exposes political value differences. Scientifically, conclusions drawn by studies which attempt to locate and quantify marginal land differ significantly depending on how *marginal* is defined. Lewis and Kelly (2014) performed a study of 21 articles from 2008 to 2013 that illustrates the impact of such variability on estimates of marginal land. Their results include five examples from China where differences in definitions produced marginal land estimates ranging from 2.80 to 22.26% of China’s total land area. Two of the most methodologically similar studies reviewed by Lewis and Kelly (2014) produced estimates of marginal land from 19.9 to 43.75 Mha. Most startling about this example is the fact

that each study relied on nearly identical input data. Politically, the lack of consensus around what defines land as marginal underpins actions by dominant actors (e.g., governments or corporations) which impose this land-use classification on a given plot of land for the purpose of attracting foreign investment (Baka, 2014).

Given the challenges and implications of the use of *marginal* as the underlying concept to identify land for energy crops, a more specific classification is advisable. Richards, et al. (2014) argue that the most effective classification will include economic and biophysical criteria. Building on these arguments, we propose *abandoned cropland* (ACL) as a more appropriate land resource to consider when trying to locate and quantify land that might support energy crops (see Figure 2.1). Here, ACL is defined as land that was once used for, or declared as, agricultural cropland, but is no longer supporting that function (see also Milbrandt, et al. (2014) and Zaragozi, et al. (2012)). Such land is by definition economically marginal, which might relate to the fact that it is also biophysically marginal relative to surrounding land but also to political-economic factors such as changing commodity markets, international competition, or the demographics of the landowner(s). ACL can be considered a subset of marginal land if one assumes that areas removed from active crop production are of a poorer quality than the lands remaining in production (see Pazur, et al. (2014)). This is not always the case however, as shown by Nalepa and Bauer (2012), who identify cases where land considered marginal is being used for primary agricultural activities. At the same time, key drivers of ACL are often socioeconomic factors, including emigration to urban areas by rural farmers, rather than land productivity per se (Rey Benayas, Martins, Nicolau, & Schulz, 2007). In some contexts, ACL emerges due to social conflict and fundamental political-economic



reforms (Pazur, Lieskovsky, Feranec, & Otahel, 2014). Researchers interested in locating and quantifying ACL for dedicated energy crop productions should not include ACL that has been abandoned for these reasons, since it is likely that under a peaceful set of conditions said land would be used for food production.

Consequently, the identification of abandoned cropland requires a different set of criteria and a different methodology from those used to identify marginal land. ACL implies a temporal change in land use, not a static characteristic of land cover or productivity (Munroe, van Berkel, Verburg, & Olson, 2013). Furthermore, ACL does not imply unused land. It is likely that land removed from crop production is under a new active land use, for example pasture or urban development. Zaragozi, et al. (2012) argue that a dynamic approach is more appropriate by considering land to be abandoned “if there is no current land use despite a recent history of farmland use, normally declining, over [the] last 10 years.” This type of definition is consistent with most usages in the literature and aligns with the approach presented in this paper. Here, we calculate the subset of abandoned cropland that has not converted to another active use and is therefore considered *available abandoned cropland* (AACL).

### **3.2. Estimating Abandoned Cropland**

The process of identifying abandoned land is based on a temporal analysis of changes in agricultural activity in a given area or for a specific plot of land. There are two predominant approaches to estimating ACL: 1) remote-sensing based, and 2) land-owner data based, derived from interviews and surveys. Although recent work has relied on a combination of these two, the distinction between remote-sensing based work and

survey-based research is determined by the data used to generate historical timelines and maps of agricultural land use.

Ramankutty and Foley conducted studies of cropland change at both global (1999a) and continental (1999b) extents. Their map of cropland abandonment in North America is most pertinent to the study presented in this paper. The authors take a hybrid approach to estimating ACL, combining remote sensing and agricultural survey data to produce a time series of cropland distribution. Historical cropland maps were produced by hindcasting from a baseline map for 1992. Hindcasting is the technique of extrapolating historical data patterns based on observations in a recent time period. The 1992 map was derived from the DISCover, 1km resolution land cover dataset, and the results were aggregated at the 5 minute / 10km resolution (Loveland & Belward, 1997). Agricultural land-cover was represented as a fraction of each pixel. Linear interpolation was used to develop annual values of cropland from Census of Agriculture data which are collected every 5 to 10 years. These values were used to adjust pixel fractions (Ramankutty & Foley, 1999b). Using this method, Ramankutty and Foley (1999b) found that 81 Mha of cropland have been abandoned in North America between 1850 and 1992.

This value is subject to some uncertainty for two primary reasons. First, understanding historic land use patterns by inference from current observations presumes the continuation of spatial patterns of cropland production and precludes capture of actual changes in land use that may occur beyond the extent of the 1992 cropland. In other words, the method would not be valid if it were replicated to generate estimates for present-day ACL. Second, and perhaps most importantly, 81 Mha is a gross total, since this study also does not explicitly account for conversions of abandoned cropland to

developed, forested or pastureland uses, and is therefore an inadequate estimate of AACL.

A recent study by Lark, et al. (2015) exemplifies a remote sensing methodology for assessing cropland change. In this study, the Cropland Data Layer (CDL), a 30m resolution land cover dataset (USDA NASS, 2015a), is used to classify land as *crop* or *non-crop*. Lark, et al. (2015) aggregate 107 unique cropland classes into a single *crop* class and 27 unique non-cropland classes into a single *non-crop* class. National-level CDL datasets from 2008 to 2012 are compared to measure the expansion or contraction of cropland over time.

Lark emphasizes the difference between gross change and net change over the 4-year period. *Gross change* is the sum of pixels that have changed to cropland plus the sum of pixels converting from cropland, whereas *net change* is the difference in the aggregated total cropland area between the two time periods. Recognition of the difference between these two measurements is important because the calculation of net change might undercount cropland abandonment in cases where land is abandoned in some areas but expands in different locations; for example, an area's net change may be zero when viewed in the aggregate (offsetting locations of cropland gain and loss), but its gross abandonment of cropland may be positive when viewed as the sum of individual pixels. Lark's results show a net increase of cropland area of 1.2 Mha from 2008 to 2012 and a gross abandonment of cropland of 1.76 Mha over the same period.

As a remote sensing-based study, the results from Lark et al. (2015) have two shortcomings. First, remote sensing platforms do not unambiguously distinguish between natural grassland, pastureland, and certain forage crops (Nalepa & Bauer, 2012), whereas

this distinction would be explicitly documented in a census or survey. For this reason, Lark, et al. (2015) aggregated the classes *Grassland/Pasture*, *Pasture/Hay* and *Other Hay/Non-Alfalfa* into their *non-crop* land class, despite the fact that some of those areas are most certainly cropland. This limitation might overestimate the amount of grassland that is being displaced for corn production (because pastureland is often converted to corn production due to market conditions, and this conversion may mistakenly be interpreted as grassland-to-corn). Second, remotely sensed datasets currently lack time series adequate to conduct historical trend analyses. Although they enable a calculation of gross change in recent years, they are unable to capture long-term trends that are observed by the US Census of Agriculture over decades. To make assessments for earlier time periods would require the use of proxy data (surveys, aerial photography, etc.) or extrapolations that may introduce error and uncertainty.

In contrast to remote sensing-based methodologies, survey/questionnaire-based approaches rely primarily on data directly from landowners, who directly provide data regarding their use of land. The analysis by Zumkehr and Campbell (2013) exemplifies such an approach, although, similar to Ramankutty and Foley (1999b), they rely on remote sensing data to account for unavailable land uses, such as forest regrowth and urbanization, that arise after cropland abandonment. Zumkehr and Campbell collect historical cropland data from Waisanen and Bliss (2002), which includes county-level values of total cropland in production for every five to ten years dating back to 1850. Zumkehr and Campbell calculate a gross estimate of abandoned cropland to be the difference between the current land in crop production (in the year 2000) and the maximum amount of land in crop production in any year since 1850. Their results find 45

Mha of abandoned cropland in the United States that are available for energy crop production.

Again, these results are subject to several uncertainties. First, Zumkehr and Campbell downscale the county-level cropland data to a grid of 5-minute pixels, assuming that the current spatial distribution of cropland is representative of the spatial arrangement of cropland in previous years using a hindcasting methodology from Ramankutty and Foley (1999b). This spatial allocation is critical because their subsequent steps to adjust for forest regrowth and urban development are explicitly dependent upon the spatial overlay of remote sensing data with historical cropland. To account for forest regrowth and urban expansion, Zumkehr and Campbell rely on MODIS satellite imagery to remove areas (at the 5-minute grid cell level) that are classified as *forest* or *developed*. This assumes that the classification of the imagery is accurate, and that the identification of pixels identified as abandoned cropland are accurately located. Any inconsistencies or errors in classification or spatial allocation of cropland will impact the accuracy of these calculations. Second, they do not account for conversion of pasture to cropland, and vice versa, even though land often converts between these two categories. Across the US, for example, between 1997 and 2012 the total national area of cropland has decreased by 22 Mha and the area of permanent pasture has increased by 7 Mha (USDA NASS, 2015b). It is likely that most or even all of the pasture increase is due to a direct conversion from cropland rather than the conversion of another land use such as forest, grassland or developed. Accordingly, to make a conservative estimate of the amount of usable abandoned cropland, the amount of increase in pasture should be removed from the estimate of abandoned cropland.

The preceding discussion illustrates that methodological choices have a profound impact on results. Key choices to consider are (1) determining the time scale across which to consider changes in land use, (2) accounting for the regrowth of vegetation and storage of carbon on lands that have been abandoned from active agricultural production, (3) accounting for the conversion of agricultural land to developed urban land uses, and (4) accounting for the conversion of cropland to and from pasture. The remainder of this paper presents a new methodology and results for the estimation of available abandoned cropland in the United States. Although trends in pastureland are considered, only increases in pasture at the expense of cropland are included. Pasture abandonment is not included because the focus here is on abandoned cropland, the type of land most likely to support dedicated energy crop production (see Bryngelsson and Lindgren (2013) for reasons why considering low-quality pasture land is not practical for energy crop production).

#### **4. Data and Methods**

Two scenarios were constructed in this study to guide estimates of ACL. The scenarios differ temporally. In the first scenario, we limit our time period to 34 years prior to the present day in order to avoid including abandoned agricultural land that would have had time to develop a mature forest cover, in order to limit the carbon debt that would be incurred due to large-scale conversion of forest to energy crops (Fargione et al., 2008) (our *carbon constraint* scenario). In the second scenario, we include only those lands that have been abandoned since 2007 to be consistent with rules set out in the Renewable Fuels Standard (RFS2) (our *regulatory constraint* scenario). In both scenarios, data on agricultural land-use are collected from landowners in agricultural

surveys executed and published by the USDA, and remote sensing data are used to locate and exclude areas that have converted to urban development and permanent pasture in order to arrive at a value of *available* abandoned cropland. Estimates are provided at the county-level for the contiguous United States (See Appendix A for detailed data processing procedures).

To estimate *available abandoned cropland (AACL)*, we follow the logic set out by Equation 1:

$$AACL_i = \max_{(pd-x) \leq t \leq pd} (TCL_{i,t}) - TCL_{i,pd} - UC_i - PC_i$$

Where  $AACL_i$  represents the calculated available abandoned cropland for each county (i).  $\max TCL_{i,t}$  represents the maximum total cropland in production for county (i) in any year (t) that occurs between present day and a historical limit of year (x), which is set at 1978 in scenario 1 and 2007 in scenario 2.  $TCL_{i,pd}$  represents the total cropland area in production for county (i) in the present day (pd), which is set at the date of the most recent agricultural census (in this case, 2012). UC and PC represent the quantity of abandoned cropland estimated to have transitioned into the land uses of urban development and permanent pasture respectively.

The sequence of subtractions described in Equation 1 can be subdivided into incremental equations describing each step. The first step calculates the Total Abandoned Cropland (TACL) by subtracting the current cropland area from the historical maximum cropland area (Equation 2).

$$TACL_i = \max_{(pd-x) \leq t \leq pd} (TCL_{i,t}) - TCL_{i,pd}$$

The primary data source to estimate total cropland over time is the US Census of Agriculture. Historical cropland area data are derived from Waisanen and Bliss (2002),

who produced a county-level compilation of population and agricultural data from 1790 to 1997. These data are updated using US Census of Agriculture reports for the years 1997, 2002, 2007 and 2012 (USDA NASS, 2015b), by extracting only *Total Cropland* and *Permanent Pastureland*. Total Cropland is represented by the entire circle labeled *Cropland* in Figure 2.2, and contains the sub-categories of Harvested Cropland, Cropland used for Pasture, and Other Cropland. Our definition of Permanent Pastureland excludes pastured woodland, and most notably Cropland used for Pasture, which would be double counted if included. Because historical data on pastureland are not included in the Waisanen and Bliss dataset, a digital archive of the 1978 Census of Agriculture was obtained from the Cornell Institute for Social and Economic Research (CISER) (U.S Census Bureau, 1978).<sup>1</sup>

In order to avoid counting cropland which has been reforested, this study sets the historical limit of analysis to 34 years (1978 – 2012) which is an appropriate national average (but does not reflect region-specific growth rates; thus, presenting an opportunity for future research). This method avoids the potentially significant sources of error when relying on current remote sensing imagery to track land cover change over several decades and aligning areas classified as forest with areas classified as cropland historically.

To account for immutable land-use conversions post-abandonment, such as to urban development and barren wasteland (e.g., quarries), the National Land Cover Database (NLCD) is utilized (Homer, et al., 2015). The NLCD is unique in that it is a 30m resolution land cover dataset for the entire United States and contains the specific

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<sup>1</sup> Values in the archive were validated by comparing a sample with respective county figures in the original 1978 Census of Agriculture report.



classes of agriculture and urban development required for this analysis. This permits the spatially explicit identification of locations that convert specifically from cropland to urban development or to other uses. More specifically, agriculture is represented by two classes, *cultivated crops* and *pasture/hay*. Based on the definitions of these two classes it is determined that the pasture/hay class more closely aligns with the Census of Agriculture category of cropland than permanent pasture. As pointed out by Laingen (2015), a class called *hay* might be considered grassland if viewed as a land cover but cropland if viewed as a land use, as it is in this analysis. Laingen's results also show that the combined NLCD classes of *cultivated crops* and *pasture/hay* are comparable to *total cropland* in the Census of Agriculture, which is the primary data value used in the current study. Consequently, *cultivated crops* and *pasture/hay* are both combined and treated as cropland.

Nation-wide NLCD datasets have been produced for the years 1992, 2001, 2006 and 2011. This study calculated change between the 2001 and 2011 datasets, which provide the greatest span of years with an acceptable level of classification accuracy.<sup>2</sup>

The quantity of land converting to an urban land use (UC) is calculated by observing changes between the raster datasets of 2001 and 2011 NLCD. First, a new dataset is created by selecting all pixels that transitioned from cultivated crops or pasture/hay to developed or barren classes. Second, a new dataset is created by selecting

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<sup>2</sup> The NLCD reports an accuracy of the agriculture classes to be approximately 43% in the 1992 dataset and 82% in the more recent ones **Invalid source specified**.. The poor level of confidence in the 1992 dataset compelled this study to focus instead on changes between 2001 and 2011 despite the fact that the 1992 data would provide a timespan that more closely matches the temporal extent of this analysis. Furthermore, Wickham, et al. (2013) indicate that accuracies of the observed changes in agriculture classes between 2006 and 2011 are quite low, likely due to the difficulty in distinguishing among grass-dominant land covers. This suggests caution in relying on NLCD for cropland change detection, however, the current paper focuses on change specifically from agriculture to developed classes, for which change accuracies are high.

all pixels that transitioned from cultivated crops or pasture/hay to any class. A Zonal Statistics function is applied to the new raster datasets to aggregate all selected pixels within each county and populate two new county attributes, which contain the number of pixels transitioning from agriculture to developed or barren ( $pixels_{AGtoDEV}$ ) and the number of pixels transitioning from agriculture to anything ( $pixels_{AGtoANY}$ ). The attributes are divided to derive for each county ( $i$ ) the fraction of its abandoned cropland that converts to an urban or barren land use versus any land use, setting any undefined values to zero (Equation 3).

$$UC_i = pixels_{AGtoDEV,i} \div pixels_{AGtoANY,i}$$

These fractions are multiplied against TACL to derive the quantity of abandoned cropland that is estimated to have converted to a developed land use, and that area is then subtracted from TACL. The assumption is made that the fraction of urban conversion calculated for the time period of 2001 to 2011 is representative of the time period of the entire study, 1978 – 2012. We discuss the validity of this assumption in the results section.

The final step is to remove abandoned cropland areas estimated to have converted to a permanent pastureland use. The assumption is made that an increase in permanent pastureland in each county will occur at the expense of cropland. Accordingly, an observed increase in permanent pastureland over the time period of analysis, 1978 – 2012, is deducted from the estimate of abandoned cropland. The total area of permanent pastureland (TPP) in 1978 is subtracted from the permanent pasture figures reported in the 2012 NASS data tables to calculate PC for each county (Equation 4).

$$PC_i = TPP_{i,2012} - TPP_{i,1978}$$

This value is then subtracted from each county's TACL to derive the quantity of abandoned cropland that is ultimately available for the production of energy crops. Conversion of cropland to pasture is assumed to be indicated by the total increase in permanent pastureland during the study period.

The data and methodology utilized in this study permit the running of scenarios of many time frames. The base scenario for this analysis spans from 1978 – 2012 to capture the greatest amount of AACL. A second scenario is performed for the time period of 2007 – 2012, which aligns with constraints imposed by the Renewable Fuel Standard (RFS), which limits the conversion of land to energy crops to only those areas that were in agricultural production sometime since December 19, 2007 (EPA 2010). In other words, biofuels generated from biomass grown on land that was abandoned prior to this date would not be eligible for production credits. This rule was established to restrict the conversion of non-agricultural land to energy crops, which could result in undesirable land use change consequences that may negate the benefit of the intended energy crops.

## **5. Results & Discussion**

### **5.1. Estimates of AAL**

The scenarios constructed in this study evaluated land change over the time periods from 1978 to 2012 and from 2007 to 2012 respectively. The results show 15 Mha of available abandoned cropland in the United States under the first scenario and 4.9 Mha under the second scenario. These estimates differ from those in other similar studies (see Table 2.1). Disagreement with Ramankutty & Foley (1999b) is likely due predominantly to the fact that Ramankutty & Foley incorporate cropland area figures dating back to

1850, when much more land was in production, and including all of North America. Furthermore, the Ramankutty & Foley methodology does not adjust for potential conversion of cropland to developed, forested or pasture uses. The study by Lark, et al. (2015), on the other hand, presents a much smaller estimate of available abandoned cropland of 1.76 Mha in the United States. Again, much of the disagreement with this study's estimate is due to differences in the time period under consideration. Lark, et al. only include the years between 2008 and 2012, which corresponds better with this study's *regulatory constraint* scenario. A second significant difference between these two studies is the reliance on agricultural census data versus remote sensing land cover data as the primary data source.

In contrast, the source data used in both Zumkehr and Campbell (2013) and this study are the same. And yet estimates of the national quantity of abandoned cropland differ significantly. Disagreement is due to three primary factors. First, Zumkehr and Campbell extend their historical view to 1850, relative to this study's limit of 34 years. Second, Zumkehr and Campbell account for forest regrowth by overlaying a spatially explicit map of abandoned cropland, at a 5-minute resolution, with current land cover map derived from satellite imagery. This introduces two sources of error: first, the process of downscaling of county-level cropland totals to 5-minute grid cells, and second, the interpretation of satellite imagery to delineate forest areas and the assumption that said-areas can confidently be overlaid with the downscaled cropland areas. Finally, Zumkehr and Campbell do not account for pasture conversion in their calculations, which likely results in higher estimates of abandoned cropland availability.

### **5.1.1. Energy crop production potential on AACL**

Estimates of AACL are useful for any number of rural policy domains (e.g., socioeconomic, land-use). In this study, we are primarily interested in AACL as a possible resource for energy crop production. Differences in estimates of AACL have important policy implications. For example, regional and national energy policies may be recommended or legislated based on production potentials communicated by the scientific community. In this case, policies related to the use of abandoned cropland for the production of energy crops may be implemented, or not, based on whether there is a meaningful amount of land available and ultimately whether there is potential to make significant contributions to energy demands. Developing confident and accurate estimates of land availability is critical, but also presenting consistent estimates is important to avoid confusion. The preceding discussion illustrates the great range of abandoned cropland estimates that can be obtained by making slight changes in data input and methodology, and that this variability can have serious consequences on the claimed contributions this energy feedstock can make to different energy sectors and, ultimately, the decisions that are made on energy policy.

To what extent might AACL in the US contribute to growing energy needs? In order to answer this question, energy crop production potential on AACL is estimated using average county-level switchgrass yields, calculated using the Wullschleger (2010) model. The Wullschleger model is based on a compilation of observations from field trials across the United States and defines yield as a function of annual average temperature, growing season precipitation and nitrogen fertilization. A continuous 800-meter resolution raster dataset of temperature and precipitation was obtained from

PRISM Climate Group (PRISM Climate Group, 2015). Two rasters were extracted containing 30-year average annual temperature and 30-year average growing season precipitation (April – September). For each pixel, the temperature and precipitation values were supplied as inputs to the switchgrass model to calculate yield. A Zonal Statistics function was applied to aggregate the pixel-level values into county-level yield averages. Multiplying each county's average switchgrass yield by its area of available abandoned cropland generated a county-level map of potential switchgrass production.

The results from this study indicate that under the *regulatory constraint* scenario only 2% of the United States' transportation fuel demand may be replaced by cellulosic ethanol produced from switchgrass on available abandoned cropland (Table 2.1). Values in this table are estimated using generic estimates of 10 Mg of switchgrass per hectare and 210 liters of fuel per dry ton of switchgrass. This figure increases to 6% under the *carbon constraint* scenario. Although insignificant relative to total fuel consumption in the US, AACL may provide a basis for specific sectors. For example, energy produced on this abandoned cropland may account for 81% of the aviation fuel consumed in the United States. This indicates that decision-makers may want to look not only at the total production numbers, but also to how they relate to different downstream uses that may be perceived as more appealing, feasible and meaningful.

### **5.1.2. Urban and pasture conversion**

The distribution of pasture increase between 1978 and 2012 is shown in Figure 2.3. The highest concentrations of pastureland expansion are found in Texas and extending northeast into Missouri. Additionally, individual counties with high densities of pastureland are scattered across the western plains. Low densities of pasture expansion

occur in the Cotton Belt, the Dakotas, and south of the Platte River and correspond to areas of high abandoned cropland density. This suggests that such areas are losing cropland and lack the incentives to replace the crop production with pasture operations.

Estimates of available abandoned cropland in this study are conservative in part because of the assumption that any increase in pasture is a result of decreasing cropland. It is possible that some new pasture production occurs on land not previously in crop production, for example converting grassland or forest land. However, it is difficult to determine from available data the fraction of pasture increase that is responsible for decreases in other specific land types, and this study assumes that the most common land interaction with pasture is the conversion to and from cropland.

Furthermore, pasture area totals are subject to changes in definitions of pastureland in the Census of Agriculture over time (particularly prior to 1978, which is outside the scope of this study's analysis) as well as privacy issues. For example, 99% of the land area in Kenedy County, Texas is reported as permanent pastureland in the 2012 Census of Agriculture, but no value is reported in the 1978 Census. This results in the calculation 369,188 ha of pasture increase between 1978 and 2012. However, it is very likely that there was pasture in production in 1978, but due to the requirements to protect respondent confidentiality the value was suppressed in the 1978 census report.

Estimates of cropland conversion to urban development are shown in Figure 2.4. Values of UC vary from county to county, ranging from zero in some areas to 100% in others, where urban and suburban expansion rates are high. A simple average of county-level fractions of abandoned cropland transitioning to a developed land use is approximately 38% across the entire United States and when weighting the values by

each county's area, the national average is 30%. Areas of high fractions of conversion from cropland to development are, not surprisingly, found in regions of high population: the northeast, pacific coast, rust belt, in addition to isolated pockets around urban centers, such as Salt Lake City, Denver and Houston. Prominently low fractions of conversion are visible in the cotton belt region in the southeast United States, which likely helps to explain why there is a relative abundance of available abandoned cropland in that area.

The calculated fractions of conversion of cropland to urban development play a significant role in the estimates of available abandoned cropland. Accordingly, these numbers were validated against other data sources to assess confidence in the results. Validating this result is challenging primarily because county-level data for agricultural conversion to urban development do not exist nation-wide. The USDA National Resources Inventory (NRI) (USDA 2010) provides the best data source available to validate the calculations of urban conversion. The NRI is a survey of sampled locations nationally and is administered primarily every five years. Land cover/use classes are identified by the NRI survey, including cropland, CRP land, pastureland, rangeland, forest land, other rural land, developed land and water areas & federal land. To most closely align with the classification scheme used in the NLCD and the Census of Agriculture, the NRI classes of cropland, CRP land and pastureland are combined and treated as cropland. Urban conversion fractions are calculated from the NRI data by summing the area converting from cropland, CRP land and pastureland to developed land, and dividing it by the sum of cropland, CRP land and pastureland converting to anything (Table 2.2). These numbers illustrate a reasonable agreement with the urban conversion fraction calculated from the NLCD. Differences may be due to the different



methods used to classify land as cropland versus pastureland, the fact that NRI is a sampled dataset, the fact that the NLCD is based on the interpretation of satellite imagery, or how data are aggregated into a national average.

### **5.1.3. Spatial Patterns of AAL**

Figures 2.5 and 2.6 illustrate the spatial distribution of the available abandoned cropland in both the 1978-2012 and 2007-2012 scenarios. The *regulatory constraint* results present a subtle spatial pattern; available abandoned cropland is distributed relatively evenly across the country with counties of higher concentrations scattered across the middle of the country in a band spanning from the Canadian border to Texas. The *carbon constraint* scenario, on the other hand, reveals a distinct spatial pattern in the distribution of available abandoned cropland. A concentration is visible in a crescent following the historic cotton belt in the southeast United States, and high concentrations are visible along the lower Mississippi River, near the Missouri River in the Dakotas, and south of the Platte River in Nebraska and Kansas. It is likely that regions with high concentrations of available abandoned cropland are those where economic conditions are not able to support existing agriculture and not sufficient to spur new active use of the land, either as urban development or pasture. A future study will study explanations of cropland abandonment and their persistence in greater detail

Spatial data can be visualized and communicated to decision-makers in many ways, and the choice of visualization method can have impacts on the conclusions drawn from the information. Furthermore, certain visualization options may be better suited for one audience than another. In the case of available abandoned cropland, four visualizations of the 1978-2012 scenario are presented in Figure 2.7. Map A is a

straightforward presentation of the county-level values of available abandoned cropland in hectares. Although a common approach presenting total values can be misleading. This is due to the fact that counties with a large spatial area are likely to have more hectares of cropland in them simply because of their size and their aggregation of many small values. Consequently, large counties often appear darker, suggesting high potential for energy crop production, despite the fact that such counties may be largely void of cropland. To correct for this phenomenon, values are normalized, by dividing each county's total value by the county's area to derive density values (Map B). For example, Elko County in northeast Nevada displays high amounts of available abandoned cropland in Map A, but when normalized by area in Map B, the county's lighter shading is more representative of the sparse concentration and relatively low quantity of abandoned cropland.

On the other hand, the agricultural community often presents crop commodities and production distributions as a density of total cropland area, rather than a density of total county area (Map C). This data visualization may be more familiar to an agricultural sciences audience but conveys a different message than the other maps. Nevada, Arizona and New Mexico provide a good example of this, as much of the states appear to have high values. In reality, all values are quite low, but the proportion of abandoned cropland to total cropland is high because there is little total cropland to begin with. Finally, data can be presented as total hectares in the form of a dot density map as seen in Map D. This is also a common visualization method in the agricultural community. This technique allows for the display of total hectares without normalization and would be familiar to individuals who interact with crop production maps often seen in USDA reports. Dot

density maps are an effective way to see general distribution patterns but can be a poor tool for deriving values for particular locations.

The audiences for the results of this study are not necessarily agricultural scientists or farmers. Rather, these results are primarily intended to inform policy decision-makers and government officials who operate at a broad scale and make determinations of the value in enacting regulations to pursue the generation of energy crops. Accordingly, it is most relevant to present land resource totals as a density of total county area, so policymakers can see what regions of the country might be most productive and where the greatest concentrations of available land are located. The other visualizations may be valuable for the agricultural community to assess the relative contribution of abandoned cropland to other agricultural activities, but they may be less appropriate for broad scale energy policy decisions.

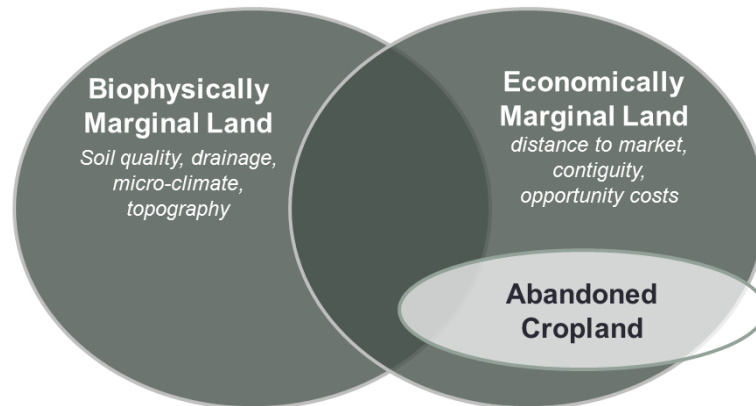
## **6. Conclusion**

This study develops and applies a methodology to estimate and map abandoned cropland across the United States at the county level. Rather than focusing on *marginal* land, this study targets abandoned cropland that has neither had time to develop mature forest nor converted to urban development or pasture. This enables a more precise and appropriate estimate of land that might be immediately available to support dedicated energy crop production with minimal social and ecological impacts. Agricultural census data is the primary source of cropland data, rather than remote sensing; cropland abandonment is a *land use* process, which landowner surveys like the USDA Census of Agriculture directly capture, in contrast to *land cover*, which is fundamentally what remote sensing instruments measure and which requires further interpretation to deduce

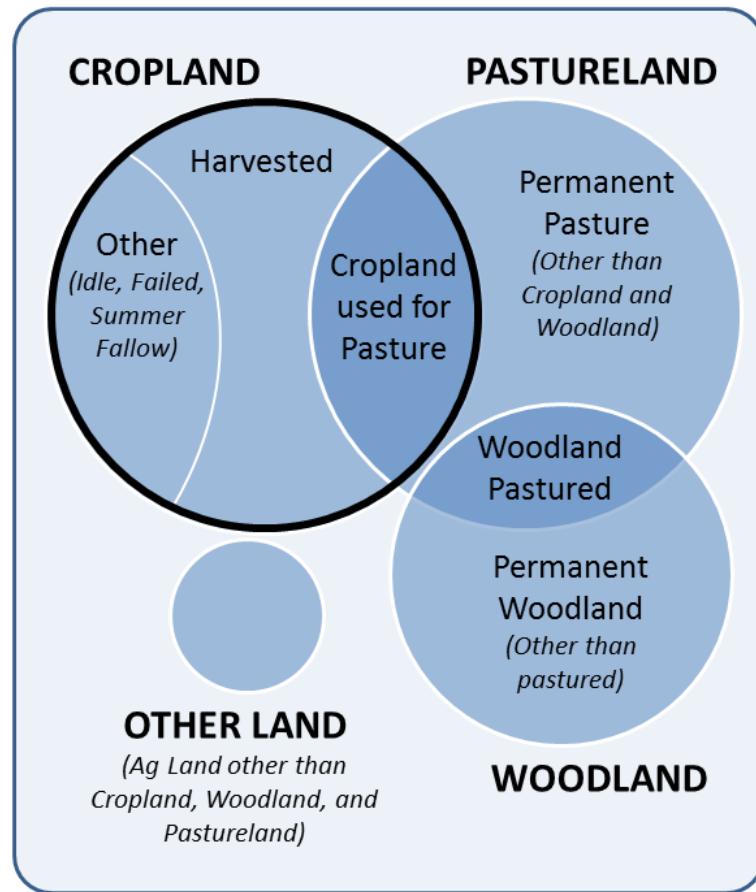
land use. The methodological framework developed in this study for estimating and mapping AACL is flexible, replicable and encourages future research and customized scenarios. As new data are released by the Census of Agriculture and the NLCD, new urban conversion fractions can be developed, pasture conversion amounts updated, and final results refined. Additionally, this framework allows for scenarios to be run for any time frames, which may be useful for decision-makers when comparing trends over time or evaluating different policy environments, such as relaxed rules on the use of abandoned cropland for energy crop production.

The *carbon constraint* scenario developed in this study suggests that 15 Mha of AACL is available. When considering limitations on the use of AACL for energy crop production set by the RFS in the *regulatory constraint* scenario, the area drops to 4.9 Mha. Although potentially significant at regional scales, these numbers are not significant at national scales, as they could potentially supplement only 3-8 percent of total light duty gasoline consumption. That said, the existing quantity of AACL might be capable of producing enough biomass to support specific sectors, such as aviation or ethylene, and future policy might consider targeting biofuel production in these areas to match production with consumption. At the same time, rates of AACL are driven by increased international trade, increased yield on other lands due to greater use of synthetic fertilizers, and other features of a fossil-fuel based economy. Future research should aim to understand drivers of land abandonment including the extent to which these lands are abandoned due to the more intensive use of fossil fuels in the first place. Future research should also aim to understand and explain the persistence of agricultural land abandonment, and how landowners and land managers envision these land resources.

## Marginal Land and Abandoned Cropland



**Figure 2.1.** The definition of Abandoned Cropland within the biophysical and economic dimensions of Marginal Land.



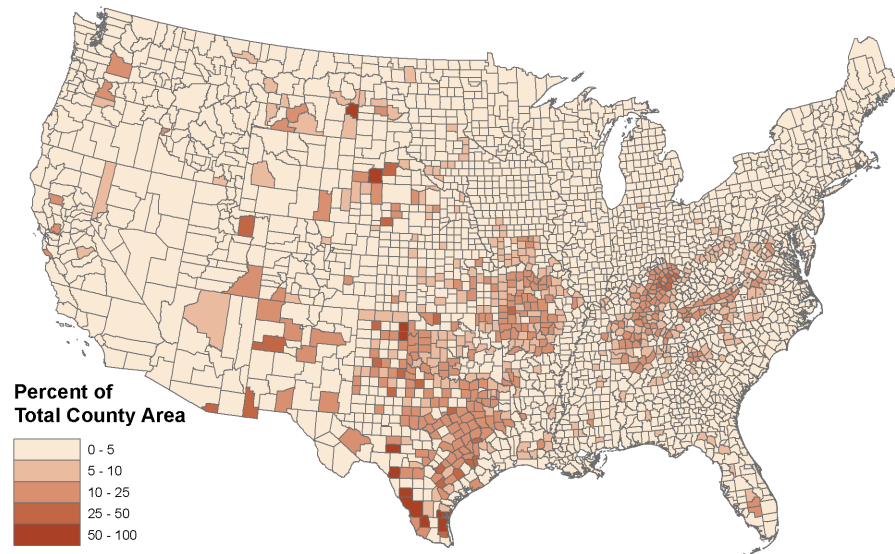
**Figure 2.2.** The intersections of variables defined in the US Census of Agriculture. The dark-outlined circle labeled “cropland” is the primary data category used in this study to assess cropland abandonment.

**Table 2.1.** Liquid fuel production from switchgrass grown on different estimates of abandoned cropland, and the percent of the total US demand for various fuel sectors each would offset. Total = total liquid transportation fuel, LDV = Light Duty Vehicles, Aviation = aviation fuel, Ethylene = chemical production. \* Estimate for North America; all other estimates for the United States.

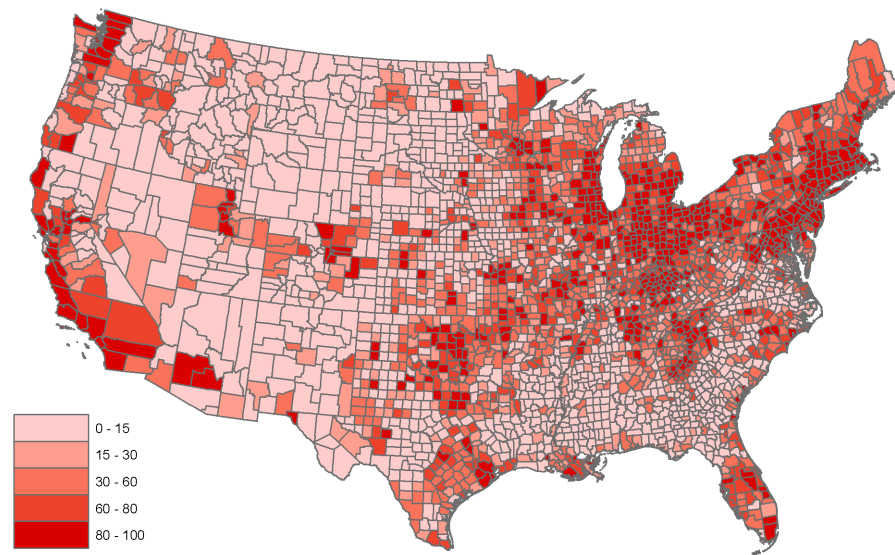
	<i>Time Frame</i>	<i>Area (Mha)</i>	<i>Millions of Liters</i>	<i>% Total</i>	<i>% LDV</i>	<i>% Aviation</i>	<i>% Ethylene</i>
<i>Baxter &amp; Calvert, Scenario 1</i>	1978 - 2012	15	38,648	6	8	81	39
<i>Baxter &amp; Calvert, Scenario 2</i>	2007- 2012	4.9	12,834	2	3	27	13
<i>Ramankutty &amp; Foley (1999)</i>	1850 -1992	81*	170,100	25	36	358	174
<i>Lark, et al. (2015)</i>	2008 – 2012	1.76	3,696	1	1	8	4
<i>Zumkehr &amp; Campbell (2013)</i>	1850 - 2000	45	94,500	14	20	200	96

**Table 2.2.** Estimates of the fraction of cropland converting to urban development based on analyses of the NLCD and NRI over different time periods.

	<i>NLCD 2001-2011</i>	<i>NRI 1997-2002</i>	<i>NRI 2002-2007</i>	<i>NRI 2007-2010</i>	<i>NRI 1982-2010</i>
<i>Fraction of Cropland Converting to Development</i>	.30	.22	.26	.24	.27

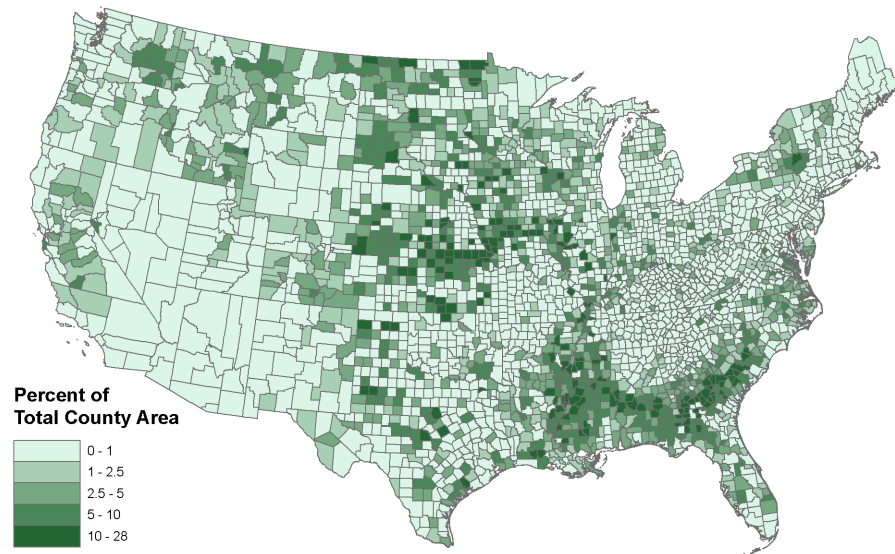


**Figure 2.3.** Pasture area increase between 1978 and 2012 presented as a density of total county area.

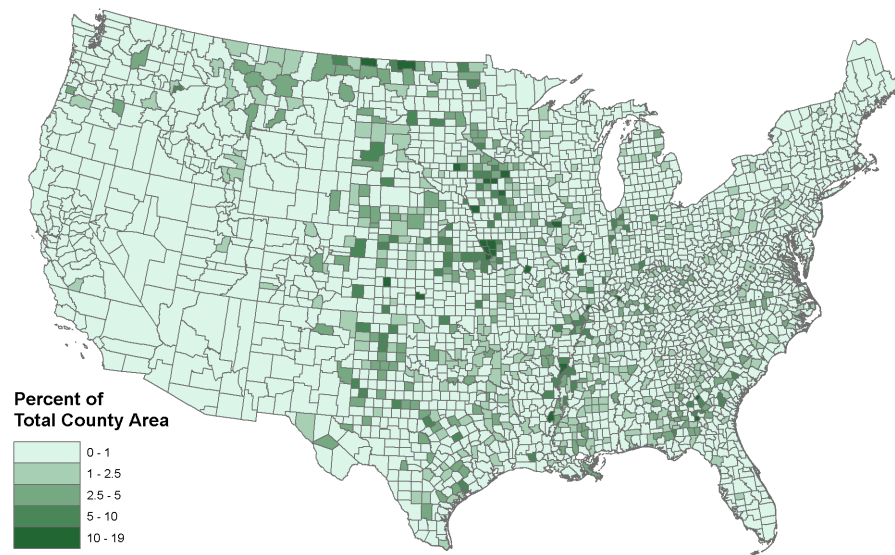


**Figure 2.4.** Fraction of abandoned cropland area that transitions into a developed or barren land use. The national average weighted by county area is 30%. In other words, this is a map of urban expansion.

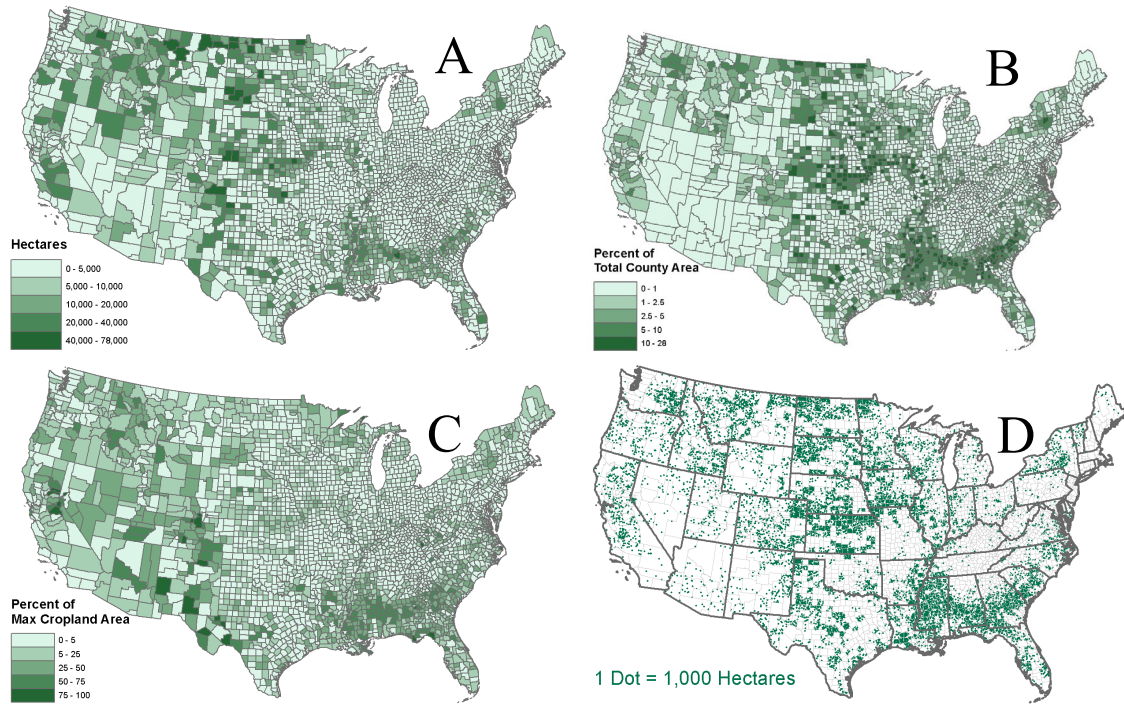




**Figure 2.5.** Available Abandoned Cropland for Scenario 1 presented as a density of total county area.



**Figure 2.6.** Available Abandoned Cropland for Scenario 2 presented as a density of total county area.



**Figure 2.7.** Available Abandoned Cropland visualized using four different methods. Map A: total hectares. Map B: density of total county area. Map C: density of maximum cropland area. Map D: dot density.

## 7. References

- Baka, Jennifer. 2014. "What Wastelands? A Critique of Biofuel Policy Discourse in South India." *Geoforum* 54: 315-323.
- Bryngelsson, David K., and Kristian Lindgren. 2013. "Why Large-Scale Bioenergy Production on Marginal Land is Unfeasible: A Conceptual Partial Equilibrium Analysis." *Energy Policy* 55: 454-466.
- Calvert, K. 2011. "Geomatics and bioenergy feasibility assessments: taking stock and looking forward." *Renewable and Sustainable Energy Reviews* 15: 1117-1124.
- Cope, Miriam A., Sara McLafferty, and Bruce L. Rhodes. 2011. "Farmer Attitudes Toward Production of Perennial Energy Grasses in East Central Illinois: Implications for Community-Based Decision Making." *Annals of the Association of American Geographers* 101 (4): 852-862.
- EPA. 2010. "Regulation of Fuels and Fuel Additives: Changes to Renewable Fuel Standard Program: Final Rule," 40 CFR Part 80. Federal Register 75(58): 14669-15320.
- ESRI. 2015. *ArcGIS for Desktop version 10.2.2*. Redlands, CA: Environmental Systems Research Institute.
- Fargione, Joseph, Jason Hill, David Tilman, Stephen Polasky, and Peter Hawthorne. 2008. "Land Clearing and the Biofuel Carbon Debt." *Science* 319: 1235-1238.
- Gopalakrishnan, G., C. M. Negri, and S. W. Snyder. 2011. "A Novel Framework to Classify Marginal Land for Sustainable Biomass Feedstock Production." *Journal of Environmental Quality*, 40: 1593-1600.
- Homer, C. G., J. A. Dewitz, L. Yang, S. Jin, P. Danielson, G. Xian, J. Coulston, N. D. Herold, J. D. Wickham, and K. Megown. 2015. "Completion of the 2011 National Land Cover Database for the Conterminous United States-Representing a Decade of Land Cover Change Information." *Photogrammetric Engineering and Remote Sensing* 81 (5): 345-354. Accessed April 2015. <http://www.mrlc.gov/finddata.php>.
- Houghton, R. A., J. L. Hackler, and K. T. Lawrence. 1999. "The U.S. Carbon Budget: Contributions from Land-Use Change." *Science* 285: 574-578.

- Kang, Shujiang, Wilfred M. Post, Jeff A. Nichols, Dali Wang, Tristram O. West, Varaprasad Bandaru, and Roberto C. Izaurralde. 2013. "Marginal Lands: Concept, Assessment and Management." *Journal of Agricultural Science* 5 (5): 129-139.
- Laingen, Chris. 2015. "Measuring Cropland Change: A Cautionary Tale." *Papers in Applied Geography* 1(1): 65-72.
- Lark, Tyler J., J. Meghan Salmon, and Holly K. Gibbs. 2015. "Cropland Expansion Outpaces Agricultural and Biofuel Policies in the United States." *Environmental Research Letters* 10: 044003.
- Lewis, Sarah M., and Maggi Kelly. 2014. "Mapping the Potential for Biofuel Production on Marginal Lands: Differences in Definitions, Data and Models across Scales." *ISPRS International Journal of Geo-Information* 3: 430-459.
- Li, Tania Murray. 2014. "What is Land? Assembling a Resource for Global Investment." *Transactions of the Institute of British Geographers* 39: 589-602.
- Loveland, T. R., and A. S. Belward. 1997. "The International Geosphere Programme Data and Information System Global Land Cover Dataset (DISCover)." *Acta Astronautica* 41 (4): 681-689.
- Lynd, Lee R., Mark S. Laser, John McBride, Kara Podkaminer, and John Hannon. 2007. "Energy Myth Three - High Land Requirements and an Unfavorable Energy Balance Preclude Biomass Ethanol from Playing a Large Role in Providing Energy Services." In *Energy and American Society - Thirteen Myths*, by B.K. Sovacool and M.A. Brown, 75-101. New York: Springer Publishing Company.
- Milbrandt, Anelia R., Donna M. Heimiller, Andrew D. Perry, and Christopher B. Field. 2014. "Renewable Energy Potential on Marginal Lands in the United States." *Renewable and Sustainable Energy Reviews* 29: 473-481.
- Munroe, Darla K., Derek B. van Berkel, Peter H. Verburg, and Jeffrey L. Olson. 2013. "Alternative Trajectories of Land Abandonment: Causes, Consequences and Research Challenges." *Current Opinion in Environmental Sustainability* 5 (5): 471-476.
- Nalepa, Rachel A., and Dana Marie Bauer. 2012. "Marginal Lands: the Role of Remote Sensing in Constructing Landscapes for Agrofuel Development." *The Journal of Peasant Studies* 39 (2): 403-422.

- Pazur, Robert, Juraj Lieskovsky, Jan Feranec, and Jan Otahel. 2014. "Spatial Determinants of Abandonment of Large-Scale Arable Lands and Managed Grasslands in Slovakia During the Periods of Post-Socialist Transition and European Union Accession." *Applied Geography* 54: 118-128.
- PRISM Climate Group. 2015. *30-Year Normals*. Oregon State University. Accessed January 2014. <http://prism.oregonstate.edu>.
- Ramankutty, Navin, and Jonathan A. Foley. 1999a. "Estimating Historical Changes in Global Land Cover: Croplands from 1700 to 1992." *Global Biogeochemical Cycles* 13 (4): 997-1027.
- . 1999b. "Estimating Historical Changes in Land Cover: North American Croplands from 1850 to 1992." *Global Ecology and Biogeography* 8: 381-396.
- Rey Benayas, Jose M., Ana Martins, Jose M. Nicolau, and Jennifer J. Schulz. 2007. "Abandonment of Agricultural Land: an Overview of Drivers and Consequences." *Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources* 2 (57).
- Richards, Brian K., Cathelijne R. Stoof, Ian J. Cary, and Peter B. Woodbury. 2014. "Reporting on Marginal Lands for Bioenergy Feedstock Production: a Modest Proposal." *BioEnergy Research* 7: 1060-1062.
- Searchinger, Timothy, Ralph Heimlich, R.A. Houghton, Fengxia Dong, Amani Elobeid, Jacinto Fabiosa, Simla Tokgoz, Dermot Hayes, and Tun-Hsiang Yu. 2008. "Use of U.S. Croplands for Biofuels Increases Greenhouse Gasses Through Emissions from Land-Use Change." *Science* 319: 1238-1240.
- Shortall, O. K. 2013. "'Marginal Land' for Energy Crops: Exploring Definitions and Embedded Assumptions." *Energy Policy* 62: 19-27.
- Tilman, David, Robert Socolow, Jonathan A. Foley, Jason Hill, Eric Larson, Lee Lynd, Stephen Pacala, et al. 2009. "Beneficial Biofuels - The Food, Energy, and Environment Trilemma." *Science* 325: 270-271.
- U.S Census Bureau. 1978. "1978 Census of Agriculture." *Cornell Institute for Social and Economic Research, Data Archive: Online Catalog*. Accessed April 2015. [https://ciser.cornell.edu/ASPs/search\\_athena.asp?IDTITLE=116](https://ciser.cornell.edu/ASPs/search_athena.asp?IDTITLE=116).

- USDA. 2013. "Summary Report: 2010 National Resources Inventory." Natural Resources Conservation Service, Washington, DC, and Center for Survey Statistics and Methodology, Iowa State University, Ames, IA.
- USDA NASS. 2002. "2002 Census of Agriculture." *2002 Census Publications*. Accessed April 2015. <http://www.agcensus.usda.gov/Publications/2002/>.
- . 2012. "2012 Census of Agriculture." *2012 Census Publications*. Accessed April 2015. <http://www.agcensus.usda.gov/Publications/2012/>.
- . 2015a. "Published crop-specific data layer." *USDA National Agricultural Statistics Service Cropland Data Layer*. Accessed April 2015. <http://nassgeodata.gmu.edu/CropScape/>.
- . 2015b. "Quick Stats." *USDA National Agricultural Statistics Service, Census of Agriculture*. Accessed April 2015. <http://quickstats.nass.usda.gov/>.
- Waisanen, Pamela J., and Norman B. Bliss. 2002. "Changes in Population and Agricultural Land in Conterminous United States Counties, 1790 to 1997." *Global Biogeochemical Cycles* 16 (4): 1137.
- Wickham, J. D., S. V. Stehman, J. A. Fry, J. H. Smith, and C. G. Homer. 2010. "Thematic Accuracy of the NLCD 2001 Land Cover for the Conterminous United States." *Remote Sensing of Environment* 114: 1286-1296.
- Wickham, J. D., S. V. Stehman, L. Gass, J. Dewitz, J. A. Fry, and T. G. Wade. 2013. "Accuracy Assessment of NLCD 2006 Land Cover and Impervious Surface." *Remote Sensing of Environment* 130: 294-304.
- Wulschleger, S. D., E. B. Davis, M. E. Borsuk, C. A. Gunderson, and L. R. Lynd. 2010. "Biomass Production in Switchgrass Across the United States: Database Description and Determinants of Yield." *Agronomy Journal* 102 (4): 1158-1168.
- Zaragozi, B., A. Rabasa, J. J. Rodriguez-Sala, J. T. Navarro, A. Belda, and A. Ramon. 2012. "Modelling Farmland Abandonment: a Study Combining GIS and Data Mining Techniques." *Agriculture, Ecosystems and Environment* 155: 124-132.
- Zumkehr, A., and J. E. Campbell. 2013. "Historical U.S. Cropland Areas and the Potential for Bioenergy Production on Abandoned Croplands." *Environmental Science & Technology* 47: 3840-3847.

## **Chapter 3. Drivers of Cropland Abandonment**

### **1. Introduction**

The current chapter investigates the process of cropland abandonment and specifically the emergence of usable abandoned cropland (UACL). Usable abandoned cropland is defined to be land that had been in agricultural production sometime since 2007 but is no longer in production and has not converted to another immutable land use, such as urban development, permanent pasture, or mature forest. The 2007 threshold is a constraint specified in the Renewable Fuel Standard to avoid the carbon debt incurred by clearing non-agricultural land (e.g., mature forest) for energy production (United States Environmental Protection Agency, 2022b). Usable Abandoned Cropland (UACL) differentiates itself from Available Abandoned Cropland (AACL) discussed in the previous chapter, in that AACL can be calculated to any historical limit while UACL is specifically limited by the 2007 constraint.

Abandoned cropland has been suggested as a potential opportunity for renewable energy production, much of which is land intensive. But only “usable” abandoned cropland is truly available for such subsequent uses. Conversely, on average, nearly 40% of the cropland abandoned in the United States converts to some sort of urban development, whether residential, commercial, or industrial (Baxter & Calvert, 2017). In some counties, particularly surrounding the northeast metro areas, rates of abandonment converting to urban development are 100%. These types of abandoned cropland are not usable for renewable energy production as they have actively converted to a land use that is likely irreversible and precludes the development of biomass, wind, or utility-scale

solar energy production. Whereas active abandonment is characterized by conversion directly to another use like urban development, passive abandonment is characterized by land that is abandoned for other reasons without an intended subsequent use and consequently left unmanaged (Hart, 1968). The potential for passive abandonment to result in usable land for energy production has been quantified previously across the US (Baxter & Calvert, 2017). However, the processes that drive patterns of this abandonment are not clear, and likely heterogeneous across the US.

This study explores the process by which cropland is abandoned and the economic, demographic, and biophysical factors that contribute to the landscape patterns of usable abandoned cropland. Understanding these factors can help identify potential land opportunities for other activities beyond food production. Specifically, an emphasis is placed on usable abandoned cropland as a potential land base on which to produce renewable energy, whether biomass (Fargione et al., 2008; Field et al., 2020; Hellmann & Verburg, 2011; Searchinger et al., 2008), solar (Daniels, 2023; Hoffacker et al., 2017; Katkar et al., 2021; Nordberg et al., 2021), or wind (Alonso Serna, 2022; Dabiri et al., 2015; Diffendorfer et al., 2019), to satisfy production and sustainability requirements. Ultimately, the decision about whether agricultural land stays in production or not, a local-scale process that takes place at the farm and field level, involving the intended land use decisions made by landowners or farmers about how to utilize their land. These proximate causes are defined by Geist and Lambin (2002, p. 143) as “human activities or immediate actions at the local level, such as agricultural expansion, that originate from intended land use and directly impact [land] cover.” These proximate causes may include, for example, retiring from farming and allowing fields to return to an unmanaged state,



investing in real estate opportunities and converting farms to suburban housing developments, or shifting production practices from crops to pasture due to changes in farmer interest or economic profitability.

The factors driving landowner decisions are influenced by driving forces operating at the county, state, or national levels. These driving forces constrain and control the local processes that occur beneath them and establish an environment or set of conditions that influence local-scale decisions (Allen & Starr, 1982). Geist and Lambin (2002) define driving forces as “fundamental social processes, such as human population dynamics or agricultural policies, that underpin the proximate causes and either operate at the local level or have an indirect impact from the national or global level.” Therefore, by conducting this current analysis at the county level, rather than at the local field level or broad national level, I am investigating driving forces that influence the process of cropland abandonment.

Lambin and Geist (2006) caution that oversimplification of land change systems can be helpful but misleading. Generalization and variable selection are unavoidable and must be interpreted within the context and scale of the research. In the current study, all variables are aggregate measures of the economic, demographic, geographic and biophysical conditions of each county in the United States. Results of this analysis can help indicate which of these variables is likely to represent a driver underlying cropland abandonment.

## **1.1. Drivers of Cropland Abandonment**

Land use land cover (LULC) change has been studied from different perspectives. Foley et al. (2005) take a global perspective, with the understanding that land use is a

local phenomenon that has global implications as it is aggregated. In addition to this recognition of the importance of spatial scale, Foley et al. (2005) asserts that a temporal component is relevant too, in that there are potentially different impacts in the short term versus the long term. Some studies take a regional perspective and use statistical relationships with underlying land characteristics to project future land use patterns (Gellrich et al., 2007; Mahiny & Clarke, 2012; Temme & Verburg, 2011; Veldkamp & Fresco, 1996; Verberg et al., 2002; Verburg et al., 2006; Verburg & Overmars, 2007; Verburg & Overmars, 2009).

Some studies have investigated the development of a specific type of land cover or land use, for example, using spatially explicit models to project future distribution of bioenergy crops (Hellmann & Verburg, 2011). Others assess the impacts of land change on different phenomena like carbon emissions and climate (Houghton et al., 1999; Searchinger et al., 2008; Strengers et al., 2004), land availability and global food security (Lambin, 2012), water resources (Näschen et al., 2019), earthquake risk assessment (Nath et al., 2020), and ecosystem services (Yirsaw et al., 2017). Many such studies group the predictor variables in their studies into categories such as economic, institutional, technological, cultural, and demographic, as defined in Geist and Lambin (2002).

Within this larger body of research, some studies have specifically investigated the process of cropland abandonment using a similar set of predictor variables. Gurgel et al. (2021) take a broad, global view of cropland abandonment and groups possible driving factors into economic, population, food demand, and climate categories, concluding that economic and population factors dominate. van Vliet et al. (2015) performed a meta-analysis of cropland change research in Europe and classified drivers

into the following categories: farmer characteristics, demographic, economic, technological, institutional, sociocultural, and location factors. Their findings show that institutional characteristics, farmer characteristics, and economic drivers are the most important, followed by location. A recurring theme in this literature is that certain drivers are dominant, particularly socio-economic, with other factors playing lesser roles that act as mediating forces or catalysts of change (Zaragozi et al., 2012).

Rey Benayas et al. (2007) perform a meta-analysis of the literature and observed that the most decisive factors in explaining farmland abandonment are: first, socio-economic factors; followed by factors related to poor management; and finally, physical variables. They state that "abandonment is mainly a human process" and, furthermore, that "usually, some of these [socio-economic] drivers are mediators of large-scale or macro-driving forces of change, representing, ultimately, new economic opportunities" (Rey Benayas et al., 2007, p. 2). They find that at the global level rural-urban migration in areas where new economic opportunities are offered to rural people is the number one driver. Even when approaching cropland from different scales, the socio-economic drivers appear to dominate and be facilitated by other factors. "Agricultural land whose production is limited by ecological factors such as fertility or precipitation is more prone to be abandoned if socio-economic factors act" (Rey Benayas et al., 2007, p. 2). This reiterates the observation above that some factors serve as catalysts when the underlying socio-economic factors occur.

A particular socio-economic process that is significant to cropland abandonment in the literature is the decline in economic competitiveness. Hart (1968) studies the eastern United States and finds that a potential factor is the "loss of major crop." For

example, many counties in the South, where cotton was dominant, struggled to compete with other areas of production due to poor land quality. Consequently, land may have been abandoned as the major crop (cotton) moved to other regions. Some land may have continued to produce other crops, but the loss of a major crop could contribute to abandonment. Napton et al. (2010) studies the southeastern United States and finds that increasing demand for commercial forest products coincided with farming becoming less competitive, in addition, there were federal programs that subsidized the conversion of cropland to forest land. Even dating back to the 19<sup>th</sup> and 20<sup>th</sup> centuries, degradation of soil quality coupled with the opening of new productive croplands elsewhere led to existing cropland, particularly in the northeastern United States, losing competitiveness and leading to abandonment (Stoof et al., 2015).

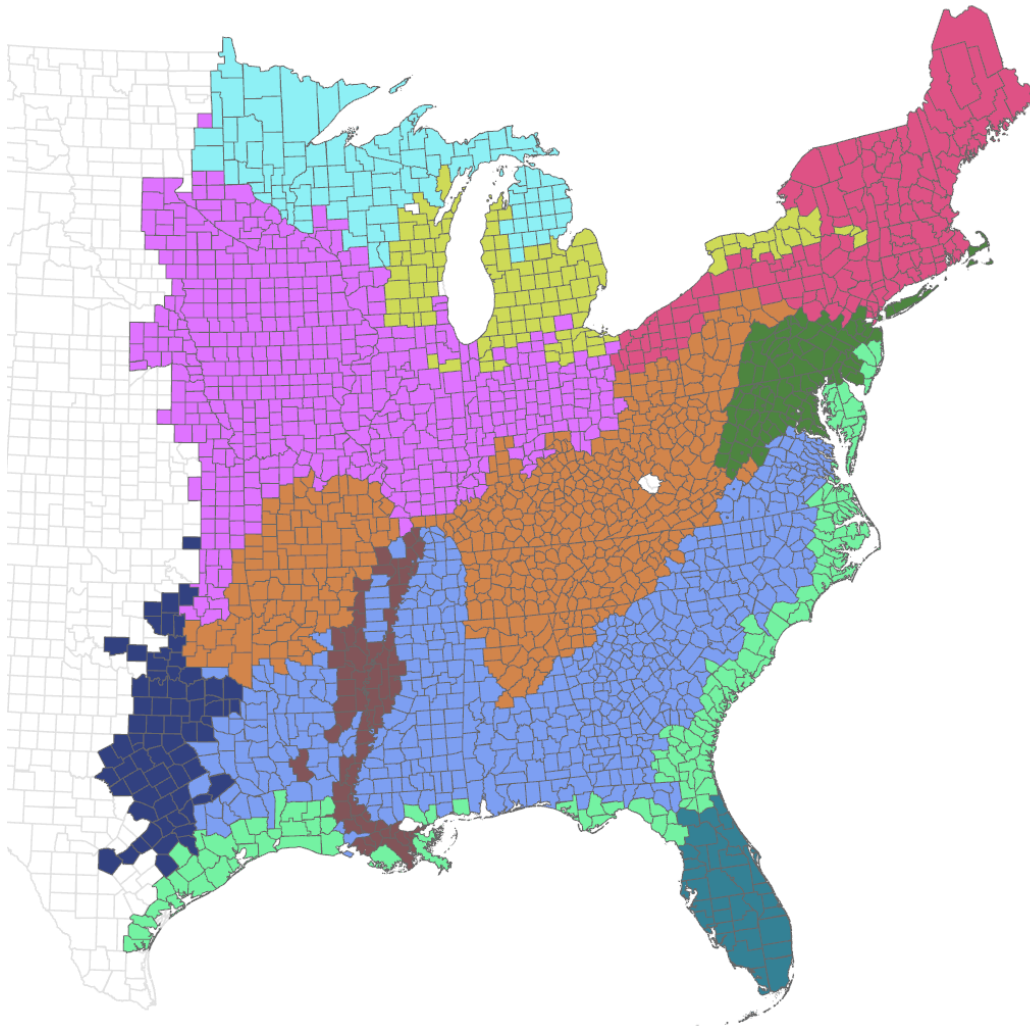
Munroe et al. (2013) echo many of the above observations and assert that land abandonment is not an end state but rather part of a continuous cycle of land change. Abandonment typically takes place on remote, less productive, and less profitable land, although it has been observed on land not considered marginal. Ultimately, the underlying drivers of change, however, are primarily socio-economic. Examples that Munroe et al. (2013) provide from around the globe include competition with more profitable land opportunities in the western United States leading to abandonment in the east (Ramankutty et al., 2010), aging farm populations in Europe (MacDonald et al., 2000), adjusting economies in post-soviet Eastern Europe (Müller & Munroe, 2008), rural-to-urban migration in Latin America (Aide et al., 2013), and resource conservation efforts in Africa (Hartter et al., 2010).

Several studies focus specifically on mountainous regions, which are similar to the East & Central Farming region in the eastern United States. These found that mountainous regions with fragmented farms that are far from population centers experience more abandonment. The importance of proximity to urban areas is a finding unique to mountainous areas (MacDonald et al., 2000; Mottet et al., 2006; Müller et al., 2009; Pazúr et al., 2014).

## **1.2. Study Area**

The study area for this research is the eastern United States. The 100<sup>th</sup> parallel is roughly the western extent of the study area and represents a demarcation to the west of which agricultural land is largely arid and highly irrigated and to the east of which irrigation is less common or necessary. This difference between east and west is noticeable and complicates the effort to try and develop a single model to explain land use decisions. Eastern and western counties are inherently different due to these conditions. Consequently, this study only focuses to the east of the 100<sup>th</sup> parallel to simplify the analysis and remove irrigation and aridity as substantial, complicating factors.

To more precisely define the western extent of the study area, the US Department of Agriculture (USDA) land resource regions (LRRs) are utilized. LRRs are delineated areas that are each characterized by common physiography, geology, climate, water resources, soils, biological resources, and land use (United States Department of Agriculture, 2022). The entire United States consists of 28 LRRs, and this study includes 11 regions in the eastern part of the country (Figure 3.1).



**Figure 3.1.** Entire study area and the Land Resource Regions (LRRs) within it.

### 1.3. Research Questions

To investigate the drivers of usable abandoned cropland, this study poses two research questions:

1. Are there different factors that influence (1) whether a county will experience a gain in UACL or not versus (2) how much UACL exists in counties that experience a positive gain?

2. What are the regional differences in the factors that drive the emergence of usable abandoned cropland?

To address these research questions, three hypotheses are tested:

1. A unique set of factors are important to the binary classification of counties with a positive gain versus those with no gain (H1).
2. A unique set of factors are important to the amount of UACL in counties that experience a non-zero gain (H2).
3. The factors most important to the emergence of usable abandoned cropland in the counties of one region are different than the factors important to counties in other regions (H3).

## **2. Data and Methods**

### **2.1. Dependent Variable**

The target variable in this study is the amount of net usable abandoned cropland that has emerged between 2007 and 2017. 2017 is set as the current time because it represents the latest year available in the Census of Agriculture, as of the date of this writing. 2007 is set as the historical maximum to abide by constraints imposed by the Renewable Fuel Standard (RFS), which amended the Clean Air Act (United States Environmental Protection Agency, 2022a). The RFS regulations state that only existing agricultural land may be utilized for producing biofuel feedstock. This land is defined as land “that was cleared or cultivated prior to December 19, 2007” and not forested (United States Environmental Protection Agency, 2022b). Cropland that had been abandoned

earlier than 2007 would not be considered cultivated and may have had time to grow forest cover and is therefore not eligible for conversion to energy crop production.

Enforcement of this constraint is made only by observing the net change in agricultural land relative to the amount of cropland as of 2007 (Larson, 2014). It is possible that areas not cultivated prior to 2007 were converted to energy crop production while other cropland areas were abandoned to other uses, such as urban development. In this way, expansion into disallowed land may be obscured due to abandonment in other areas. Only if expansion of energy crop production exceeds abandonment would enforcement take place.

Using the methodology developed by Baxter and Calvert (2017), the area of net usable abandoned cropland (UACL) in each county in the United States between 2007 and 2017 is calculated. This method utilized the Census of Agriculture as its primary data source and the National Land Cover Dataset (NLCD) to account for cropland estimated to have transitioned into an urban land use. This is in contrast to other studies that have estimated abandoned cropland using different methods and relying on other primary data sources such as the Cropland Data Layer (CDL) (Lark et al., 2015; Plassin et al., 2021), global remote sensing imagery (Campbell et al., 2008; Ramankutty & Foley, 1999a, 1999b), and a combination of census data and remote sensing to hindcast the amount and distribution of cropland back into the 1800s (Zumkehr & Campbell, 2013). UACL areas are divided by the total cropland area of each county to normalize results and account for the variable range of county sizes (See Appendix B for detailed data processing procedures).



When performing the initial subtraction of cropland between 2007 and 2017, some counties show an increase in cropland, or in other words, a negative value of abandoned cropland. These negative values are treated as zeros. Treating negative values as zero explicitly focuses the analysis on opportunities for new energy production activities, which only occur on UACL, making areas of cropland expansion irrelevant. Additionally, a negative value for “usable” abandoned cropland is nonsensical because usable abandoned cropland excludes other types of abandoned cropland, i.e., cropland that actively converted to another land use, such as urban development. This research is studying land opportunities for future production, not general agricultural land use change which may benefit from including both expansion and abandonment. Thus, it is sufficient to know whether a county has abandonment or not, and to know the actual value of net positive UACL area.

It is possible for a county in this study with zero abandoned cropland to have experienced abandonment in some places and be negated by cropland expansion in other places. Consequently, some abandoned cropland area changes within counties may be obscured. However, the emphasis on net abandonment at the county-level in this study reflects the opportunity to identify counties and, subsequently, regions with the greatest potential for available land for producing renewable energy. County-level and regional-level estimates of UACL are relevant to state and federal level policies that would benefit from information about where best to focus renewable energy investments.

## **2.2. Predictor Variables**

This study does not include all potential forces influencing the decisions of farmers to abandon cropland. This is due in part to practical concerns, i.e., some factors

are not available or representable in a spatial data format at the county level. Also, the current analysis investigates how the driving forces of agricultural land use change vary across space, from county to county. Accordingly, the statistical analysis excludes variables that are constant nationwide, such as commodity prices, national policies, and national and international market conditions. Although these factors influence decisions to abandon cropland the data is not resolved at this scale. Rather, this analysis includes variables that have resolution at the county-level (a moderate hierarchical level) to identify factors that are relevant and contribute to regional land use patterns.

A suite of independent variables describing the economic, demographic, geographic and biophysical characteristics of each county is prepared. Data regarding farm economics and farmer demographics are obtained from the United States Census of Agriculture for the years 2007, 2012, and 2017 (United States Department of Agriculture, 2017). The Census of Agriculture is administered by the US Department of Agriculture every 5 years using surveys of every farm in the United States that makes at least \$1000 in revenue. The Census of Agriculture aggregates its data to the county level, so no additional processing is required. 2017 is the latest year data from the Census of Agriculture are available and 2007 marks the historical extent of the study; these datasets are used to calculate variables of change over time. Data from 2012 are used to represent conditions at a single point in time, and 2012 is the midpoint of the study's temporal extent.

Data regarding economics and demographics of the general population are derived from the United States Population Census conducted by the United States Census Bureau in 2010 and 2017 (United States Census Bureau, n.d.). The Population Census

aggregates its data to the county level, so no additional processing is required. Variables representing conditions at a single point in time are taken from the 2010 decennial census, which is the closest time frame of available data to the 2012 data used from the Census of Agriculture. The decennial census is an enumeration of the population by surveying every household in the country. The 2012 Census of Agriculture data and the 2010 Population Census are treated the same in the analysis to represent the approximate midpoint of the study timeframe. More recent data is derived from the American Community Survey conducted in 2017, which aligns with the time extent in the study and data from the Census of Agriculture. The American Community Survey is conducted in years between each decennial census and is based on a sample of the population, unlike the decennial census which is a direct enumeration of every household. Some variables, however, are only available in the American Community Survey, which necessitates its use despite the potential reduction in accuracy due to it being a sample rather than a direct count of the entire population.

Road and rail network data are obtained from the US Department of Transportation (United States Department of Transportation, 2012). These vector datasets are used to calculate sums of the total length of all road or rail lines in each county, which are then divided by the county's total area to derive rail and road density figures. Climate data represents 30-year normal for temperature and precipitation developed by PRISM (PRISM Climate Group, 2023). This raster data has a spatial resolution of 4km, and values are aggregated to the county level by taking the average of all pixels within each county. Slope is calculated by utilizing a 1/3 arc second (approximately 10m) spatial resolution digital elevation model (DEM) from the United State Geological Survey

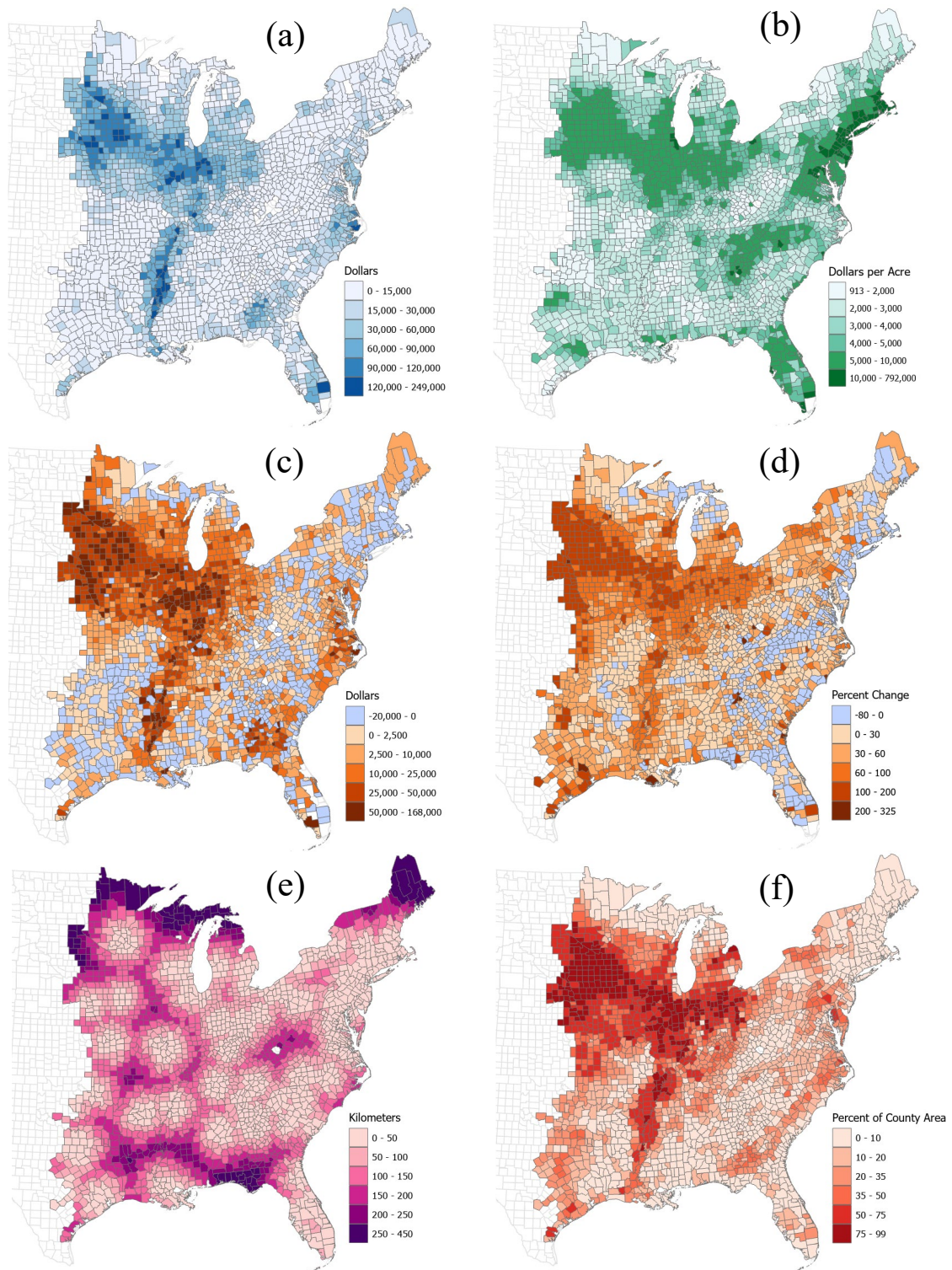
(United States Geological Survey, 2023). ArcGIS Pro software (Esri, 2023) is used to calculate a slope value for every pixel in the dataset from the elevation values in the DEM. These pixel values are then averaged to determine an aggregate value for each county. Crop productivity is calculated to be the average of the values of the National Commodity Crop Productivity Index (NCCPI) from the 90m gSSURGO dataset from the United States Department of Agriculture, Natural Resource Conservation Service (NRCS) (United States Department of Agriculture, 2023). The NCCPI rates “soils according to their inherent capacity to produce dryland (non-irrigated) commodity crops” (Albers et al., 2022). Table 3.1 lists the final predictor variables selected for analysis, and Table 3.2 shows summary statistics across the entire study area. Figure 3.2 contains maps of six of the predictor variables, which emerge as some of the most important in the results.

**Table 3.1.** Predictor variables and units.

<b>Variable</b>	<b>Units</b>
<i>Average value of farmland and buildings in 2012</i>	\$/ac
<i>Percent change in average value of farmland and buildings between 2007 and 2017</i>	%
<i>Average rent paid by farmers in 2012</i>	\$/farm
<i>Change in average rent paid by farmers between 2007 and 2017</i>	\$
<i>Median housing value in 2010</i>	\$
<i>Percent change in median housing value between 2010 and 2017</i>	%
<i>Median household income in 2010</i>	\$
<i>Percent change in median household income between 2010 and 2017</i>	%
<i>Median household age in 2010</i>	age in years
<i>Average age of principal farm operator in 2012</i>	age in years
<i>Unemployment rate in 2010</i>	% of population
<i>Change in unemployment rate between 2010 and 2017</i>	%
<i>Mean annual precipitation</i>	mm
<i>Mean annual temperature</i>	degrees C
<i>Average crop productivity</i>	NCCPI index
<i>Average slope</i>	angular degrees
<i>Distance to nearest urban area</i>	m
<i>Percent of population living in an urban area in 2010</i>	% of population
<i>Population density in 2010</i>	persons/ha
<i>Density of road networks</i>	total road length/ha
<i>Density of rail networks</i>	total rail length/ha
<i>Percent of county in cropland</i>	% of county area

**Table 3.2.** Predictor variable summary statistics (minimum value, maximum value, mean, and standard deviation) for the entire study area.

<b>Variable</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>SD</b>
<i>Average value of farmland and buildings in 2012</i>	913.0	35660	4214	2834
<i>Percent change in average value of farmland and buildings between 2007 and 2017</i>	-82.46	324.6	42.64	40.30
<i>Average rent paid by farmers in 2012</i>	454.6	248600	28380	33550
<i>Change in average rent paid by farmers between 2007 and 2017</i>	-74370	104800	1070	19110
<i>Median housing value in 2010</i>	44400	507800	125800	64700
<i>Percent change in median housing value between 2010 and 2017</i>	-34.24	55.22	7.908	11.90
<i>Median household income in 2010</i>	20080	1156	44070	1215
<i>Percent change in median household income between 2010 and 2017</i>	6.572	104.4	47.600	13.125
<i>Median household age in 2010</i>	25.00	55.90	40.07	4.041
<i>Average age of principal farm operator in 2012</i>	47.80	65.70	58.46	2.036
<i>Unemployment rate in 2010</i>	1.900	23.00	8.144	2.885
<i>Change in unemployment rate between 2010 and 2017</i>	0.224	3.156	8.144	0.2784
<i>Mean annual precipitation</i>	634.9	1933	1193	223.8
<i>Mean annual temperature</i>	3.508	24.48	13.30	4.180
<i>Average crop productivity</i>	0.08194	0.9132	0.4617	0.1664
<i>Average slope</i>	0.270	24.76	4.783	4.197
<i>Distance to nearest urban area</i>	0	448100	85310	68090
<i>Percent of population living in an urban area in 2010</i>	0	0.9998	0.4267	0.2907
<i>Population density in 2010</i>	0.01555	18.59	0.7123	1.396
<i>Density of road networks</i>	0	7.237	1.484	0.8290
<i>Density of rail networks</i>	0	4.767	0.5980	0.5276
<i>Percent of county in cropland</i>	0.1623	99.87	29.29	0.2639



**Figure 3.2.** Maps of some important predictor variables: (a) mean rent in 2012, (b) value of farmland and buildings in 2012, (c) change in average rent per farm between 2007 and 2017, (d) percent change in value of farmland and buildings between 2007 and 2017, (e) distance to urban areas, and (f) percent of county area in cropland.

### **2.2.1. Outlier and Missing Values**

Thirteen counties have values in at least one variable that are outliers relative to the other counties. For example, Nantucket, Massachusetts and New York, New York have average housing values of \$1,000,000 and \$825,200, respectively, that strongly skew the distribution of values that have a mean of \$127,676 and a standard deviation of \$74,026. Of the outlier counties, most have either no cropland at all or predictor values have been redacted to protect the identities of the very small number of farmers in the area. Of the 1,302 remaining counties in the study area, 29 have missing values, most commonly due to redaction in order to protect the privacy of farmers in counties that contain only one or a few farms and are removed from the analysis.

### **2.2.2. Collinearity**

Of all the remaining variables, a correlation matrix illustrates if any pairs of variables show relationships between them. Variable collinearity is a condition that violates an assumption of regression models. Table 3.3 shows the variable pairs with a correlation coefficient greater than 0.6 to highlight the strongest relationships. These relationships can be explained mostly by reasonable commons sense; population density shows a strong relationship with road and railroad density, road and railroads are related to each other, and housing value is related to land value and household income. Similar studies use higher thresholds (0.7, 0.8 or above) above which variables should be considered for removal (Mahan et al., 2010; Spangler et al., 2022). Although some of the variables in this study are correlated at levels above 0.6, all variables are retained, in part due to the demonstrated use of higher thresholds in other studies and because the random



forest statistical method used in this study is not sensitive to correlated predictors, unlike traditional parametric regression techniques.

**Table 3.3.** Independent variable correlation coefficients greater than 0.6.

<i>Variable 1</i>	<i>Variable 2</i>	<i>Correlation</i>
<i>Housing value 2010</i>	<i>Land value 2012</i>	0.67
<i>Household income 2010</i>	<i>Land value 2012</i>	0.60
<i>% Land in cropland</i>	<i>Average rent paid 2012</i>	0.79
<i>Change in land value 07-17</i>	<i>Average rent paid 2012</i>	0.61
<i>Change in rent paid 07-17</i>	<i>Average rent paid 2012</i>	0.76
<i>Road density</i>	<i>% population in urban areas 2010</i>	0.60
<i>Road density</i>	<i>Population density 2010</i>	0.81
<i>Household income 2010</i>	<i>Housing value 2010</i>	0.85
<i>Rail density</i>	<i>Road density</i>	0.63
<i>Crop productivity</i>	<i>% Land in cropland</i>	0.69
<i>Change in land value 07-17</i>	<i>% Land in cropland</i>	0.70
<i>Change in rent paid 07-17</i>	<i>% Land in cropland</i>	0.74
<i>Mean temperature</i>	<i>Mean precipitation</i>	0.68

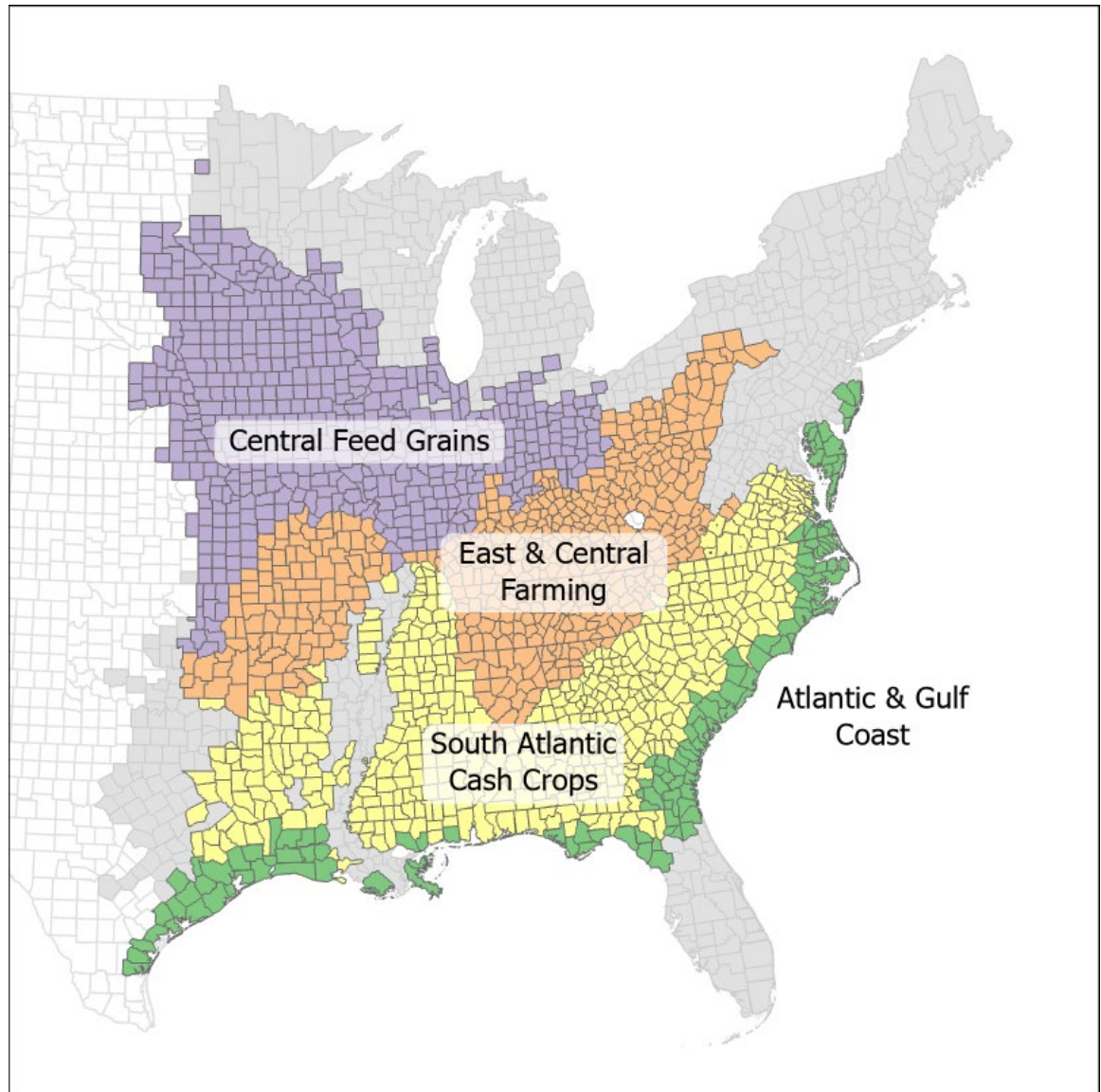
### 2.2.3. Spatial Autocorrelation

Spatial autocorrelation is a characteristic of geographic data where observations present a correlation with each other based on their spatial proximity (Anselin, 1988; Legendre & Fortin, 1989), in other words, observations that are spatially close to each other have values that are more similar than to observations that are far away. These correlations may be inconsequential or may indicate a functional process whereby a location's value is directly influenced by the values of its neighbors. If the latter case is true, it is necessary to identify it and account for it in any statistical models. Furthermore, a requirement in many statistical methods is that observations be independent of each other and not related in space; thus, the presence of spatial autocorrelation precludes the use of such methods or calls their results into question.

Using ArcGIS Pro software, a Morans-I analysis of UACL produces a value of 0.21. This indicates a slight expression of spatial autocorrelation. A Morans-I value of 1 indicates high spatial autocorrelation with similar features clustering near each other, a value of 0 indicates a random arrangement, and a value of -1 indicates a checkerboard pattern where dissimilar features are near each other. This small expression of spatial autocorrelation is not surprising, as national crop production follows broad distributions similar to those of climate and geology, which are spatially autocorrelated. However, the Morans-I value is low, which indicates that the expression of UACL is largely not spatially autocorrelated and that the process of cropland abandonment resulting in usable land is not dependent on spatial proximity. Perhaps at the local level (e.g., land parcels) there is a process at work where a landowners decide to abandon cropland due to a neighbor doing so, i.e., spatial autocorrelation, but at the county level, which is the scale of UACL in this study, a causal process due to spatial proximity is unlikely thus resulting in the low Morans-I. It is therefore not necessary to control for spatial autocorrelation in the model.

### **2.3. Region Selection**

In addition to performing analyses of the entire eastern United States study area, comparisons are made across four LRRs (Figure 3.3). These include Central Feed Grains, East & Central Farming, South Atlantic Cash Crops, and Atlantic & Gulf Coast. These regions are selected due to their relatively large extent and number of counties and represent distinct topographical and agricultural characteristics. These regions also perform well in the statistical analysis, as explained in the following section.



**Figure 3.3.** LRRs selected for analysis.

## **2.4. Statistical Analysis**

Given the large number of zero values in the dependent variable of UACL, traditional regression techniques are not well suited. The large number of zero observations in the dependent variable suggests that there is a meaningful process that influences whether a county has zero UACL versus non-zero UACL and a process that

influences the magnitude of UACL in counties that have a non-zero value. These realizations call for statistical methods that address the preponderance of zero observations and the bounded nature of the dataset. Generalized linear regression models assume that data are normally distributed and are not bounded. The UACL values in this study are not normal, given the long tail of zeros in its histogram, and are bounded by zero and one since the values are fractions representing percents. Furthermore, this analysis aims to determine variable significance, or importance, rather than a model intended to make predictions of the dependent variable.

Random forest is chosen as the statistical method for this study and has been employed in similar research (Peeler & Smithwick, 2018; Prasad et al., 2006; Spangler et al., 2022). Prasad et al. (2006) is of particular relevance as the data in that study contains a substantial number of observations with a value of zero, leading to the same complications encountered in this study with regard to regression model fitness assumptions. Other methods exist that account for a preponderance of zero values and a bounded range in the dependent variable, such as fractional regression, but are not employed here (Breiman, 2001; Papke & Wooldridge, 1996; Ramalho et al., 2011).

Random forest is a collection of many tree-structured classifiers each consisting of nodes at which a randomly selected independent variable is used to split a sample population (Breiman, 2001). This pattern repeats recursively with other randomly selected variables and split values until the population is ultimately split into groups of observations that are the most similar within the group and most different from other groups. By randomly selecting variables and iterating through many trees, no a priori knowledge of variable significance or relationship needs to be known nor does the data

need fit to a certain distribution, as is the case for other methods like linear regression. Furthermore, data covering a large geographic area can be problematic for traditional regressions as independent variables' influence may vary from one region to another. The randomized tree approach allows for more flexible results that are not bound to particular distribution curves, allowing for a more exploratory analysis that reveals patterns that may have otherwise been obscured (Prasad et al., 2006).

The dependent variable in a random forest analysis can be nominal (e.g., land cover classes) or ratio (e.g., values of population density). random forest can therefore be run in two different forms: classification or regression. The difference is how nodes are split and aggregated to develop an overall result for the model. In either case, independent variables can be measured for their importance in predicting the dependent variable regardless of the predictive power of the model (Prasad et al., 2006).

To test the first hypothesis regarding whether a county experiences a net gain in UACL or not, random forest is run in classification mode. This run is similar to a logistic regression in the sense that the dependent variable is classified into two classes: counties with a value of zero UACL and counties with a non-zero value of UACL. This binary form of the dependent variable allows the analysis to determine which variables are important in distinguishing counties that experience UACL and those that do not. To test the second hypothesis regarding the magnitude of UACL in counties that have a non-zero value, random forest is run in regression mode. To test the third hypotheses, both the classification and regression modes of random forest described above are run for just the counties in each region.

The measure of percent variance explained, which is an output from random forest that is similar to  $R^2$  in traditional regression analysis, are very low for some sub regions (Table 3.4). A test run of a random forest regression is performed twice: first against all counties (including those with a UACL value of zero) within each sub region and second against only those counties with a non-zero UACL value. Regions with a percent variance explained value above 20 in the non-zero test performed relatively well and are selected for further analysis.

**Table 3.4.** Percent variance explained by random forest analysis of each study area region.

<b><i>Region</i></b>	<b><i>UACL</i></b>	<b><i>Non-Zero UACL</i></b>
<i>Entire Study Area</i>	24.18	42.96
<i>Atlantic and Gulf Coast</i>	10.53	24.73
<i>Central Feed Grains</i>	-12.07	30.06
<i>East and Central Farming</i>	22.33	12.91
<i>Florida Subtropical Fruit</i>	2.28	-10.82
<i>Lake States Fruit</i>	0.06	16.52
<i>Mississippi Delta Cotton</i>	-12.84	-17.93
<i>Northeastern Forage</i>	4.94	19.14
<i>Northern Atlantic Slope</i>	-35.6	38.11
<i>Northern Lake States</i>	15.23	10.10
<i>South Atlantic Cash Crops</i>	14.17	23.77
<i>Southwestern Prairies Cotton</i>	4.66	-33.46

The Central Feed Grains region performed poorly in the test of all counties (-12.07) but was retained in the analysis because of its of particular importance in the agricultural landscape in the eastern United States. Such low percent variance explained values for many of these regions suggests that there are other predictors involved that are missing. They may also indicate that the factors that are included do an inadequate job at explaining the dependent variable and, therefore, the model should be discarded. This is not necessarily the case, however. First of all, a single measure of model fitness, like percent variance explained or  $R^2$ , does not define whether there is value in a model. Such measures can be quite low and still describe a model that contains useful information (Moriassi et al., 2015; Spiess & Neumeyer, 2010). Secondly, the purpose of the random forest application in this study is not to develop a predictive model, for which a measure of fitness may be more relevant. Rather, this study aims to elucidate variable importance. A low measure of fitness does not negate information about variables' relative importance to variation in the dependent variable.

Prior to running the random forest models, two parameters (nTree and mTry) are tuned to achieve the highest performance. Some assert that the default model values of mTree=500 and nTry=7 are optimal for most cases but that increasing the number of trees can help to achieve stable importance values (Grömping, 2009; Probst et al., 2019; Spangler et al., 2022). Several combinations of these parameters are tested to determine the values to utilize in all model cases.

The first parameter is nTree, which specifies the total number of random trees that will be generated. Increasing this number helps ensure that every variable will likely be used to split a node and therefore assessed for its importance. If a study has many

predictor variables, but likely only a few that are important, more trees is better to help the model identify those most important ones. However, it is possible that a few dominant variables may be selected over and over, resulting in them obscuring the importance of slightly lesser, but still important, variables.

nTree is tested with values of 250, 500, 1000, 2000, 4000, and 8000 (Table 3.5). When testing different nTree values for UACL and All Counties, overall model accuracy (percent variance explained) peaks at around 24.27% 4000 trees. Accuracy increases from a value of 250 and plateaus at around 24% at 500, with a slight dip at 1000, returning to 24% at 2000 with little change beyond that value. 2000 was selected as the nTree value to use in all model cases as a good compromise between accuracy and computation time.

**Table 3.5.** Variable Importance to the classification of zero versus non-zero UACL counties in the entire study area.

<i>nTree</i>	<i>Percent Variance Explained</i>
250	23.54
500	24.09
1000	23.81
2000	24.05
4000	24.27
8000	24.05

The second parameter is mTry, which specifies the number of randomly selected variables that will be available to perform the split at each node. For example, if mTry is set to seven, seven predictors will be randomly selected at a given split. The model will iterate through those variables to determine which produces the optimal segregation of the data into two groups. Only that one chosen variable performs the split. At each



subsequent node, a new random selection of 7 variables is selected, and one of those is chosen as the most optimal splitter.

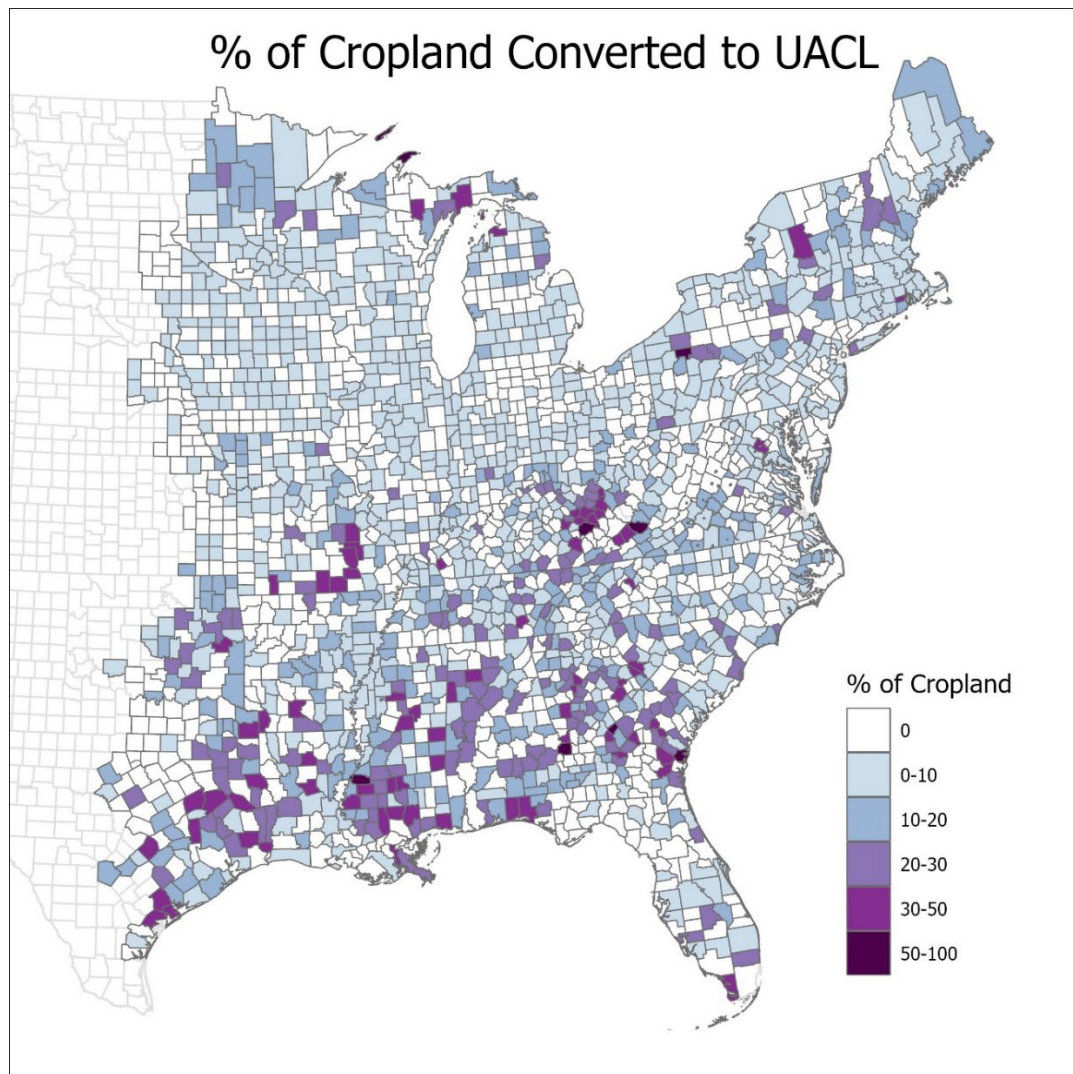
Holding nTree constant at 2000, mTry is tested with values of 4, 7, 14, and 20. All mTry values resulted in essentially the same percent variance explained. Furthermore, each run results in the same variable listed as the most important and the next five or six variables were the same with only slight differences. Since varying mTry does not affect the variable importance results in the model and did not improve overall accuracy, the default value of 7 is selected.

To address the hypotheses stated earlier, three separate runs of random forest are performed. The first classifies counties in the entire study area into two classes: one consisting of counties with a value of zero UACL, and one consisting of counties with a non-zero value of UACL. Random forest is run in classification mode to determine which predictor variables are most important in distinguishing counties that experienced a net increase in usable abandoned cropland versus those that did not. The second run excludes all counties with a value of zero UACL and only includes counties with a non-zero value. The actual values of UACL are retained and random forest is run in regression mode to determine which predictor variables are most important to the magnitude of usable abandoned cropland in counties that experienced a net gain. The third run compares both the classification of zero versus non-zero UACL counties and the magnitude of non-zero UACL counties for each of the four regions. Doing so allows for the observation of differences among the regions of the eastern United States.

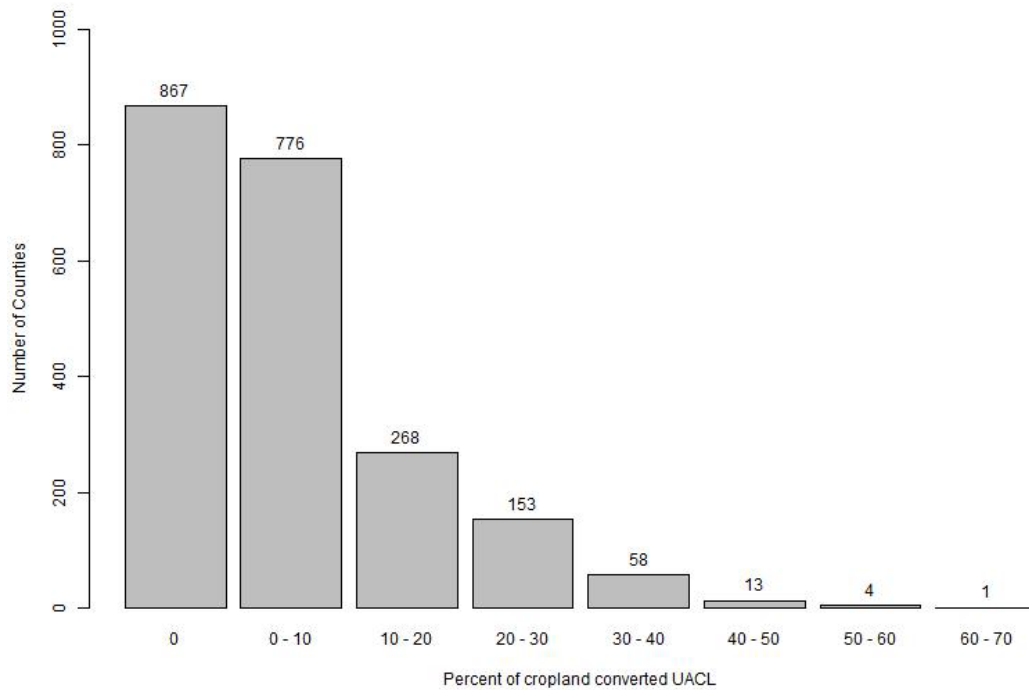
### **3. Results**

#### **3.1. Usable Abandoned Cropland**

Using the methodology from Baxter and Calvert (2017), UACL is calculated for counties in the eastern United States between the years of 2007 and 2017 (Figure 3.4). Of the 2140 total counties selected for the analysis, 867 have a value of zero UACL (Figure 3.5). This represents approximately 40% of the counties in the eastern United States that have no net increase in usable abandoned cropland. These and other counties with low amounts of UACL appear to be concentrated in the Central Feed Grains region, although they are scattered throughout the entire study area. Higher values of UACL are concentrated in the East & Central Farming and southeastern regions of the United States.



**Figure 3.4.** Usable abandoned cropland (UACL) over the 2007 – 2017 timeframe.

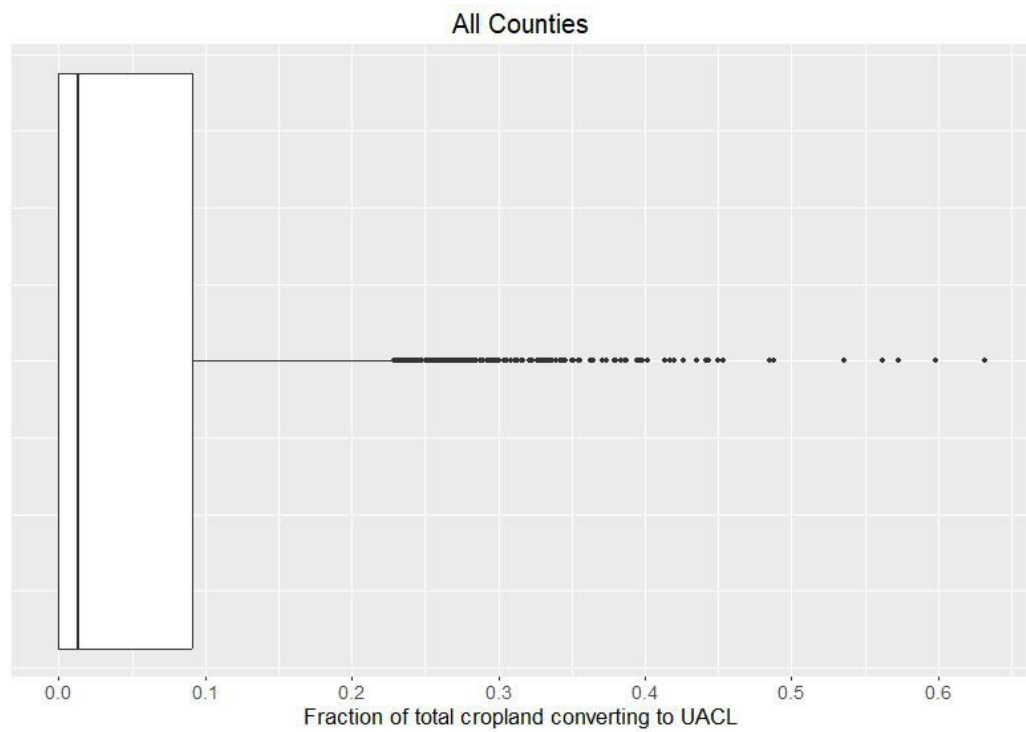


**Figure 3.5.** Histogram of UACL values for counties across the entire study area.

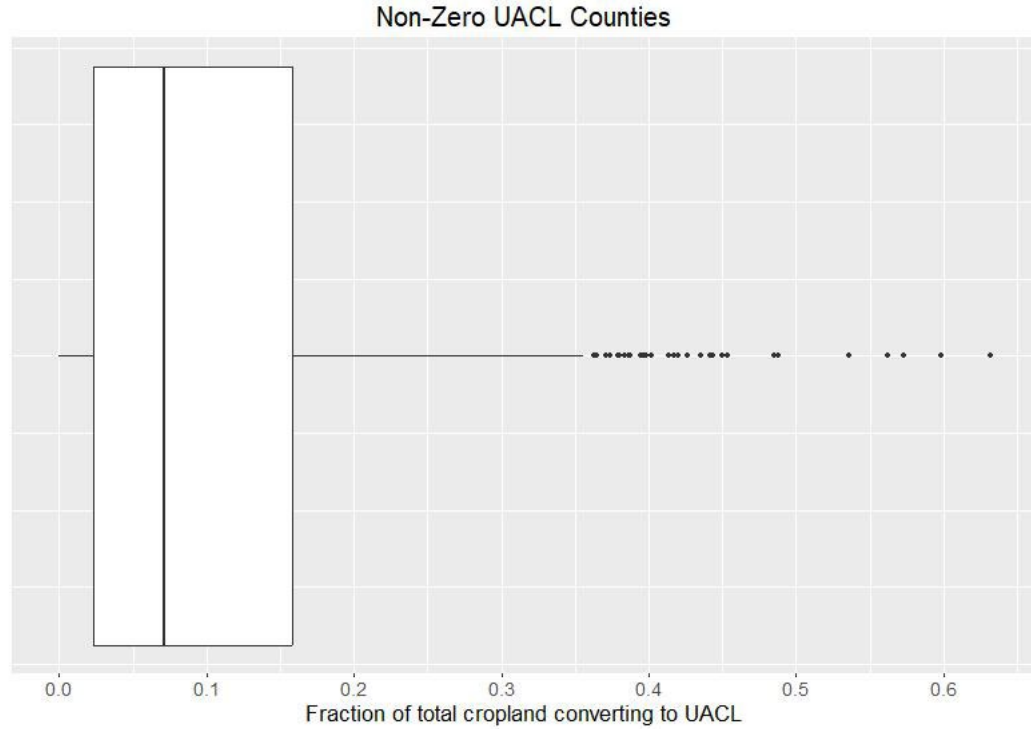
The range of values in the usable abandoned cropland dataset is a minimum of zero and a maximum of approximately 0.63. The median value is approximately 0.013 and an interquartile range from 0.0 to 0.09 (Figure 3.6). These figures illustrate that 75% of the counties saw less than 10% of their total cropland convert to usable abandoned cropland. Only 25% of counties saw between approximately 10 and 63% of their total cropland convert to UACL.

When looking only at counties with a non-zero value of UACL, the median is approximately 0.07 and an interquartile range from approximately 0.02 to 0.16 (Figure 3.7). Even when excluding all counties with zero net gain in usable abandoned cropland, 75% of counties see less than only 16% of total cropland convert to UACL. For the majority of counties in the eastern United States with a net gain in usable abandoned

cropland, this land opportunity represents a small fraction of the county's total cropland area.



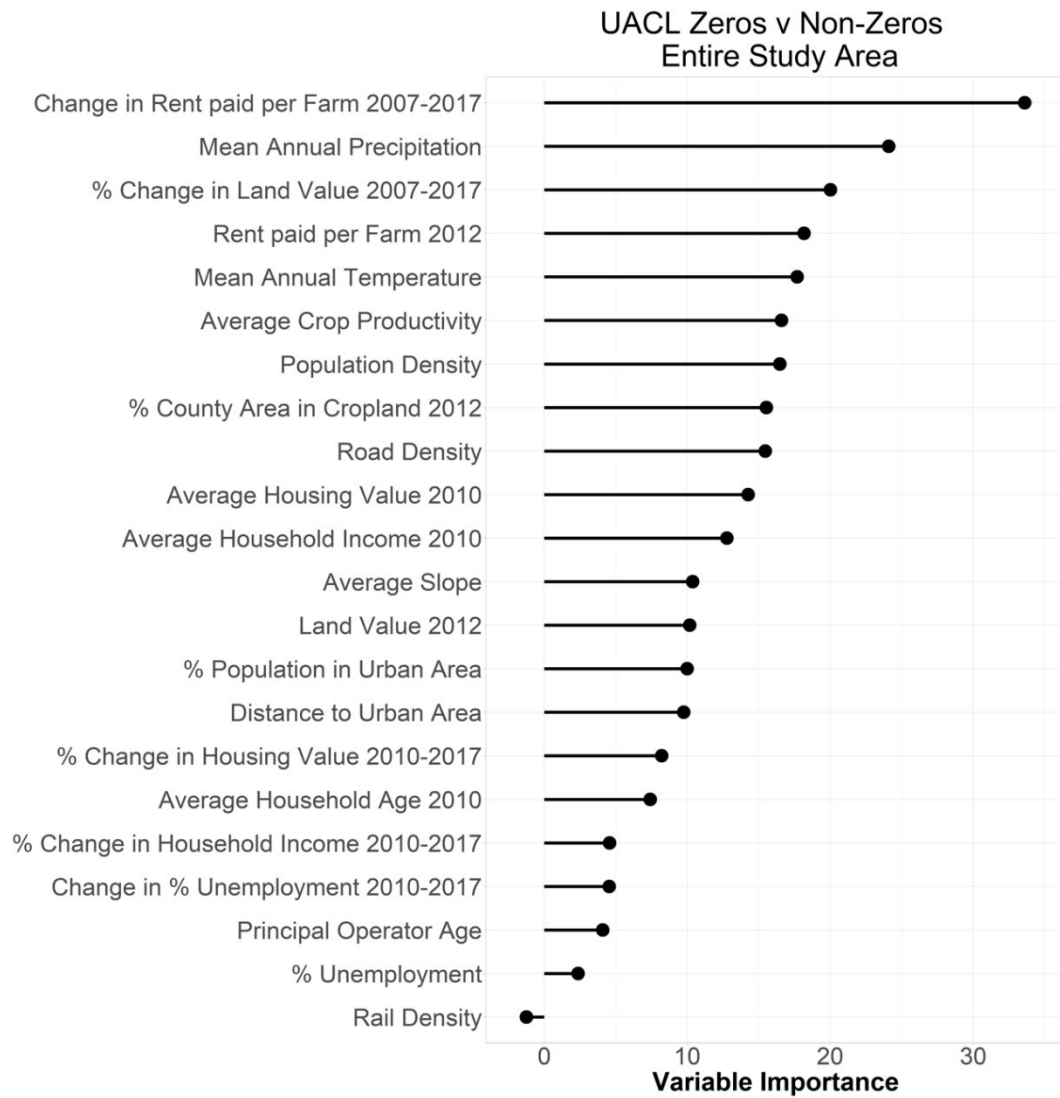
**Figure 3.6.** Box plot of UACL values including all counties in the entire study area.



**Figure 3.7.** Box plot of UACL values of only those counties with a non-zero value.

### 3.2. Drivers of UACL – Binary Classification of Counties (H1)

The change in Rent Paid per Farm from 2007 to 2017 has the highest variable importance in determining whether or not abandoned cropland is available (Figure 3.8). Mean Annual Precipitation is the next most important followed by Percent Change in Land Value from 2007 to 2017. It is notable that two of these three most important predictor variables represent *change* in economic conditions over time. Important variables measuring change over time are unique to the binary analysis testing Hypothesis 1 (H1). One variable describes how rents that farmers pay to work their farms changes and the other describes how the value of the farmland and its buildings changes over time. Other economic variables that represent the absolute rents and values at a single time period are also present in the model but show less importance.

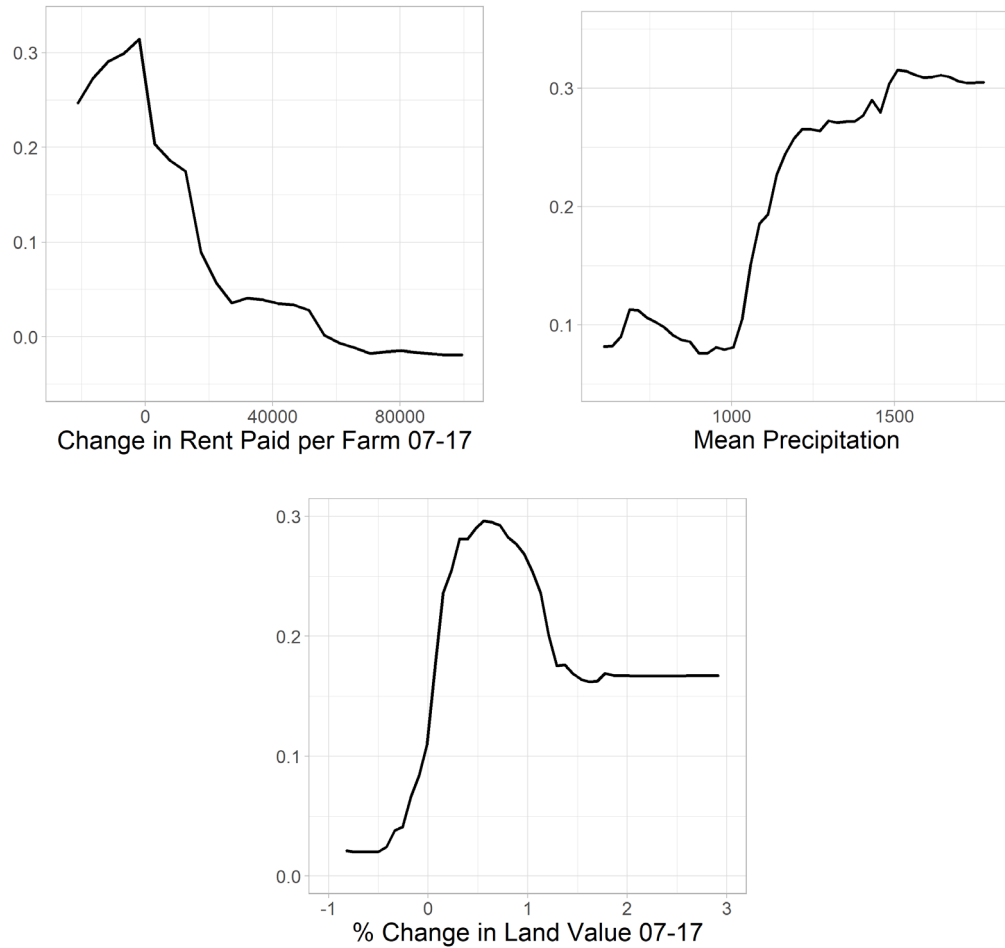


**Figure 3.8.** Variable Importance to the classification of zero versus non-zero UACL counties in the entire study area.

The relationship between each predictor variable and UACL is illustrated in partial dependence plots. The pattern of relationship between Change in Rent Paid per Farm from 2007 to 2017 and UACL shows a positive relationship for rent values that decrease over time and a negative relationship for rents that increase over time (Figure

3.9). This suggests that counties where rent values are stable or decrease over time experience the greatest increase in UACL, and counties with larger increases in rent over time produce less UACL. Mean Precipitation shows a relationship where UACL increases slightly with low precipitation values and increases steeply as precipitation grows beyond 1000 mm, levelling off at around 1500 mm (Figure 3.9). There is a greater likelihood that a county will produce a net increase in UACL if it experiences more than 1000 mm precipitation per year. The relationship between Percent Change in Land Value from 2007 to 2017 and UACL shows a threshold around zero, below which there is nearly no increase in UACL and above which there is a steep increase in UACL ultimately leveling off at around 100%, which is equivalent to a doubling of land value over time (Figure 3.9).



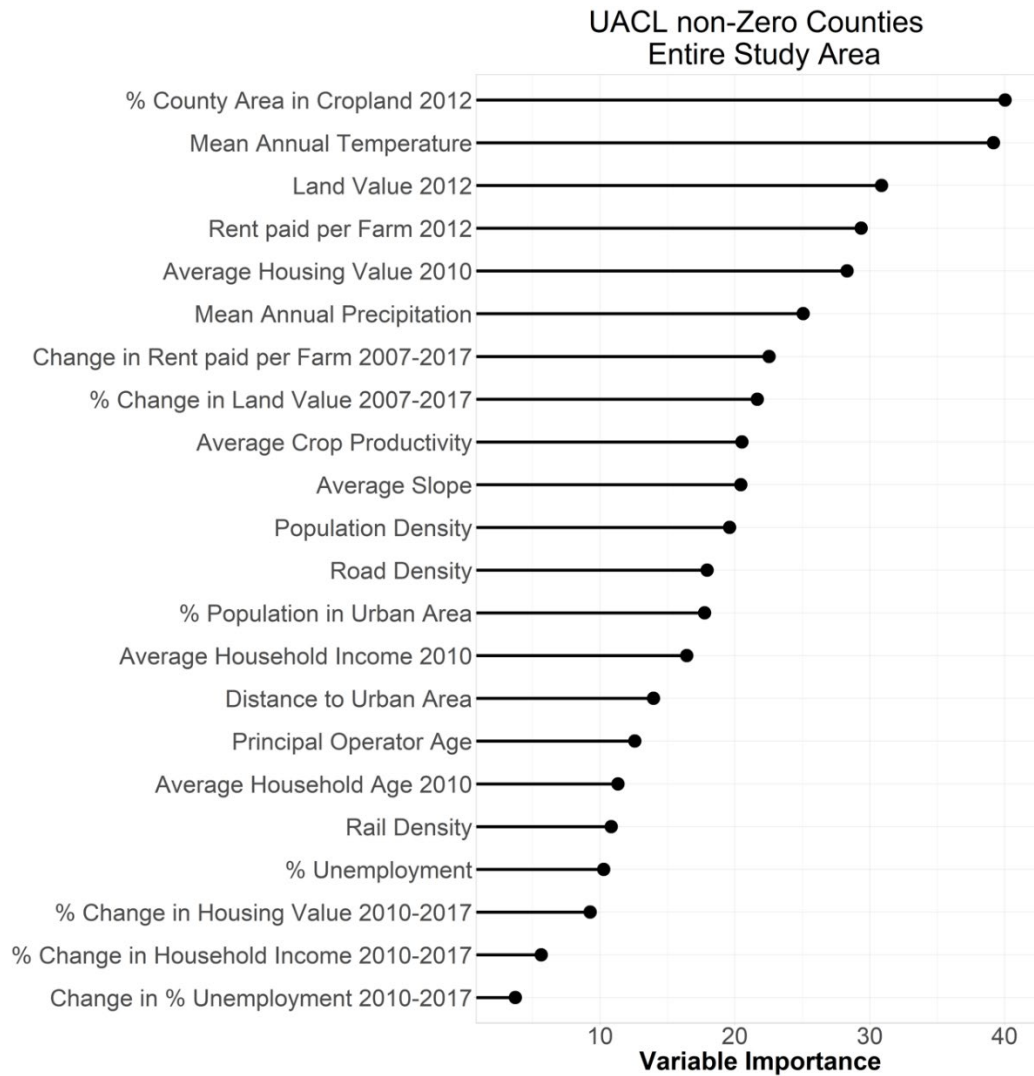


**Figure 3.9.** Relationships between three predictor variables and the classification of zero versus non-zero UACL counties in the entire study area.

The economic variables of rent and land value change over time show strong, but opposite, relationships with UACL. Increasing rent leads to decreasing UACL, while increasing land value leads to increasing UACL.

### **3.3. Drivers of UACL – Positive Gain Counties (H2)**

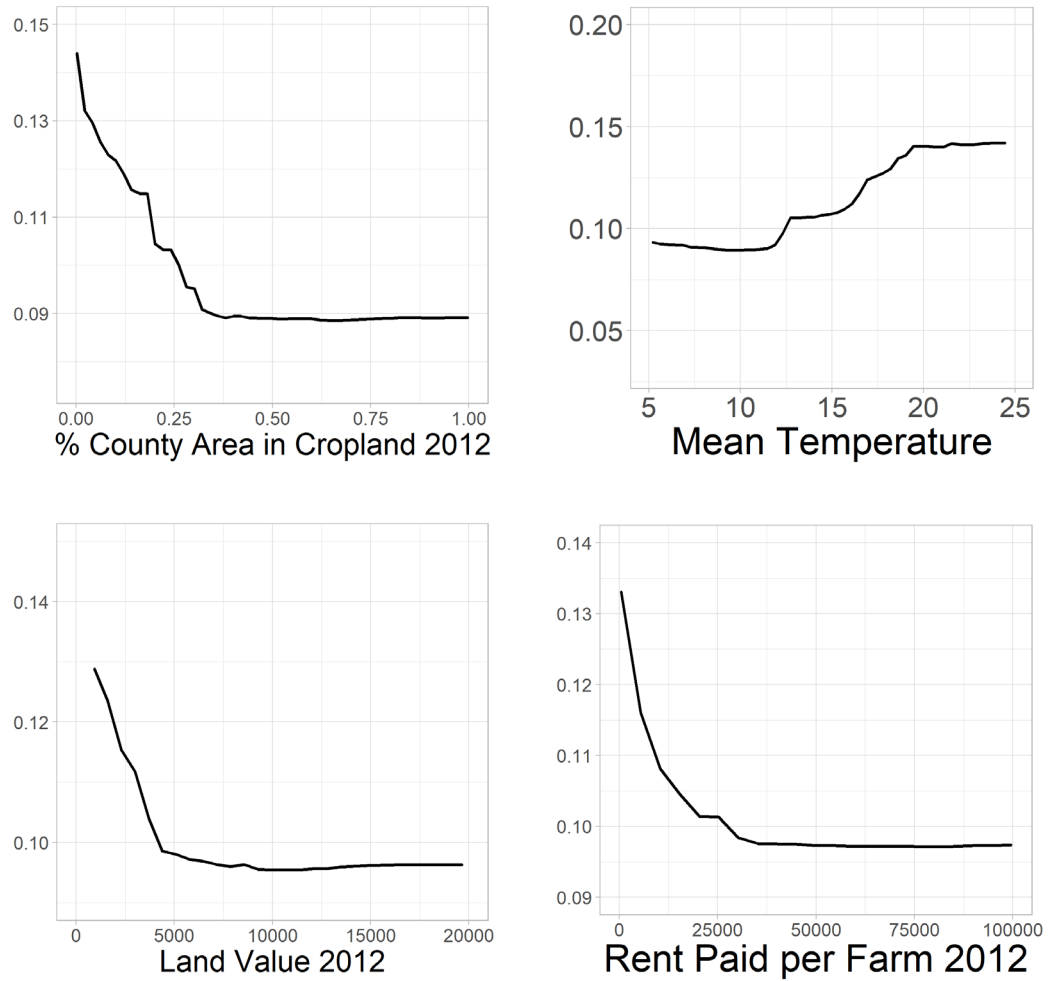
Two variables stand out as the most important to the magnitude of non-zero UACL counties: percent of the county's area that is cropland in 2012 and mean annual temperature (Figure 3.10). Land value in 2012 and average rent paid in 2012 are the next most important variables. Like the classification analysis of zero versus non-zero counties (H1), a biophysical variable is among the most important, however in this case it is temperature rather than precipitation. A notable contrast with H1 is that, in the case of only the non-zero counties, three of the top four most important variables are values for a single year rather than their change over time. Cropland area, land value, and rent represent economic and geographic conditions at a particular time and indicate that measure of such factors at a single point in time influences the magnitude of UACL in counties that have a net gain. Important variables measuring conditions at a single point in time are unique to the non-zero analysis test of Hypothesis 2 (H2).



**Figure 3.10.** Variable importance to the regression of non-zero UACL counties in the entire study area.

Partial dependence plots for the non-zero counties in the entire study area show how important each predictor variable is in affecting variation in UACL. The percentage of a county's total area that is cropland shows a negative relationship with UACL (Figure 3.11). This variable is normalized by county area, so county size should not skew the findings. Counties with little area in cropland experience a greater rate of usable abandoned cropland while counties with increasing amounts of their area in cropland

experience more usable abandoned cropland. The decrease in UACL with increasing percentage of cropland plateaus at around 25% of county area. Mean annual temperature shows a positive relationship with usable abandoned cropland (Figure 3.11). Below approximately 10 °C UACL is steady, then increases until approximately 20 °C when it again plateaus. This suggests a threshold between 10 and 20 °C above which counties may experience a greater increase in usable abandoned cropland. Land value and rent paid in 2012 both show negative relationships with usable abandoned cropland (Figure 3.11). In each case UACL decreases until a threshold value at which it levels off. For land value in 2012 the threshold is approximately \$5,000 and for rent paid the threshold is approximately \$25,000. These two relationships suggest that as rents increase, likely due to high agricultural productivity, and land value increases, due to opportunities to sell land to developers, land either remains in agricultural production or is sold to developers for urban development. In both cases, little land is abandoned and left usable for other purposes.



**Figure 3.11.** Relationship between four predictor variables and the non-zero UACL counties in the entire study area.

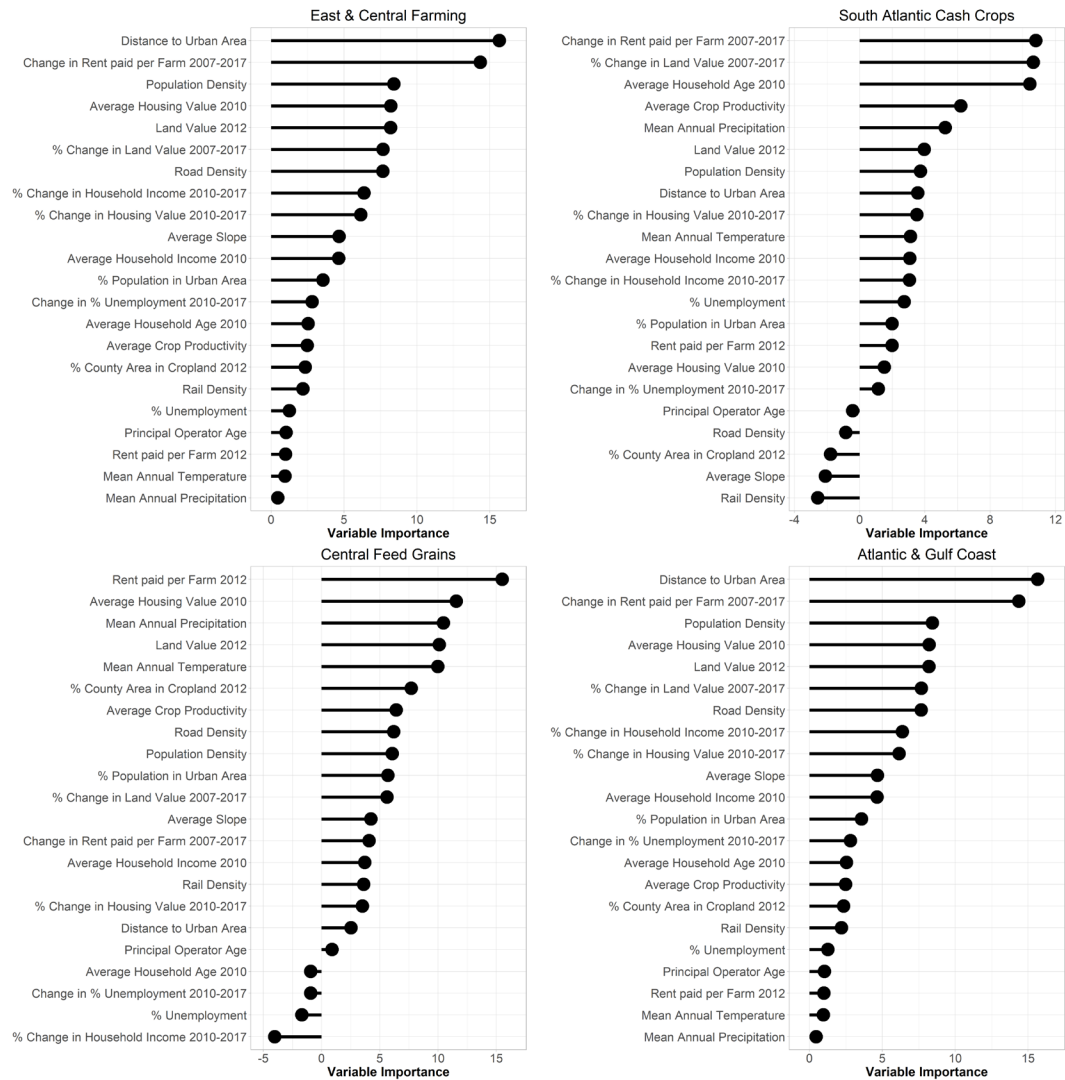
### 3.4. Regional Differences in Drivers of UACL (H3)

To test the hypothesis regarding differences among regions in the eastern United States (H3), random forest is run separately including only the counties within each region. Random forest is run in both classification and regression modes to investigate the process influencing whether a county experiences a net increase in usable abandoned cropland (i.e., counties with a UACL value of zero versus counties with a non-zero value

of UACL) and the factors that influence the magnitude of usable abandoned cropland in counties that experience a net increase.

### **3.4.1. Binary Classification of Counties in Each Region**

In the classification case of counties with zero UACL versus counties with a non-zero value of UACL the variable that is distinctly the most important across the entire study area (change in rent paid between 2007 and 2017) also emerges as the first or second most important variable in three of the four regions (Figure 3.12). Only in the Central Feed Grains region is change in rent not among the most important factors. Furthermore, change in land value between 2007 and 2017 is among the most important factors for the same regions. These observations reinforce that change in economic conditions over time is an important factor in the development of usable abandoned cropland across the majority of the entire study area. Interestingly, three of the top four most important variables for the Central Feed Grains region are economic conditions at a single point in time: average rent paid in 2012, average housing value in 2010, and land value in 2012.



**Figure 3.12.** Variable importance for regions in the study area in the classification analysis of counties with zero UACL versus counties with a non-zero value.

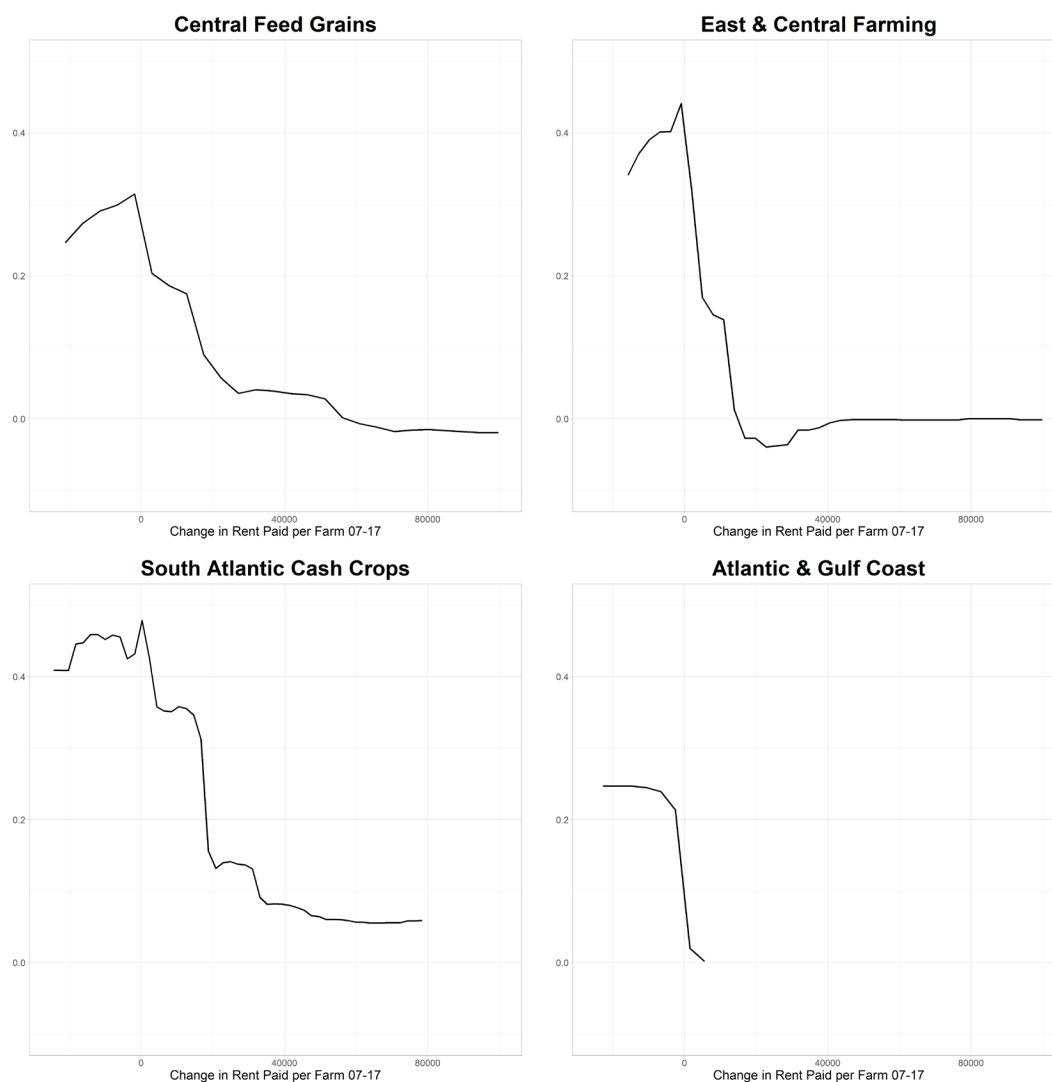
The biophysical variable of average annual precipitation stand out as the second-most important variable to the entire study area. However, it does not stand out as having particular importance to any sub region, only appearing in the top five for two regions. In fact, mean annual precipitation is either the very lowest or among the least important variables for two regions: it is the least important variable in the East & Central Farming region and is seventh least important variable in the Atlantic & Gulf Coast region.

Accompanying precipitation, mean annual temperature is the second-least important variable in the East & Central Farming region.

Two other observations of regional differences in important factors relate to the East & Central Farming and South Atlantic Cash Crops regions. First, the very most important variable in The East & Central Farming region is distance to urban areas. This variable measures the distance from each county's centroid to the nearest urban area. This, along with the differences in biophysical variables, sets The East & Central Farming region apart from all other regions. Second, average household age in 2010 is among the most distinctly important variables in the South Atlantic Cash Crops region. In no other region does a demographic variable stand out as being particularly important.

Figure 3.13 illustrates the relationship between change in rent between 2007 and 2017 and whether a county has a net increase in usable abandoned cropland in each of the regions. Each region shows a similar threshold at zero change in rent. When rents decrease over time, more UACL is likely to occur, and when rents increase over time, less UACL is likely to occur.





**Figure 3.13.** Relationship between change in rent between 2007 and 2017 and usable abandoned cropland in each region.

Figure 3.14 illustrates the relationship between precipitation and usable abandoned cropland. Excluding The East & Central Farming and the Atlantic & Gulf Coast, where this variable is not important, precipitation shows a similar positive relationship in the Central Feed Grains and South Atlantic Cash Crops regions. A notable difference is that the threshold at which UACL increases with increasing annual

precipitation is higher in the South Atlantic Cash Crops region than it is in the Central Feed Grains region. At 1000 mm of precipitation in the Central Feed Grains region,

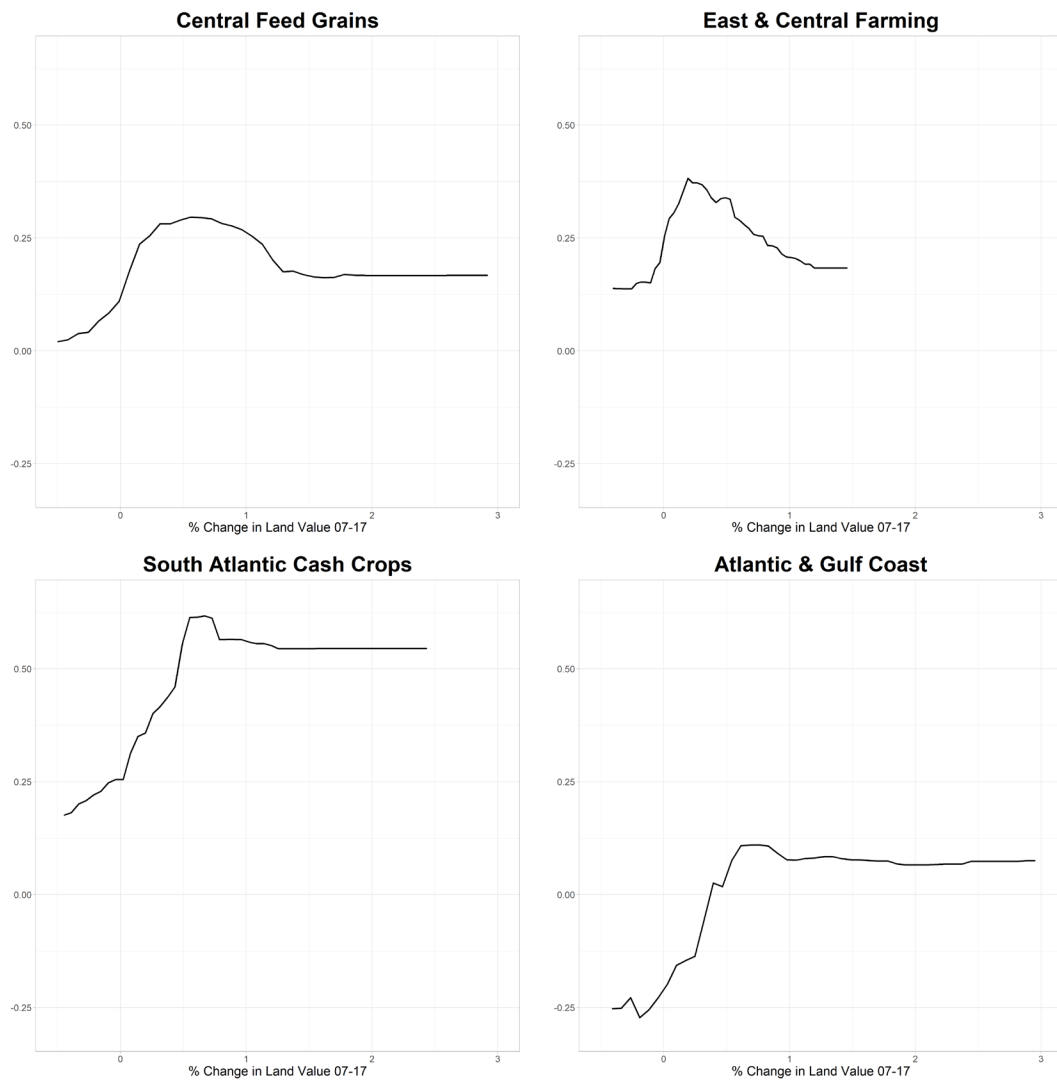


**Figure 3.14.** Relationship between mean annual precipitation and usable abandoned cropland in each region.

UACL values increase steeply, which in the South Atlantic Cash Crops region the increase occurs at 1500 mm of precipitation. Furthermore, the amount of change in UACL influenced by precipitation is higher in the South Atlantic Cash Crops region than

in the Central Feed Grains region, indicating a 60% change and a 20% change respectively.

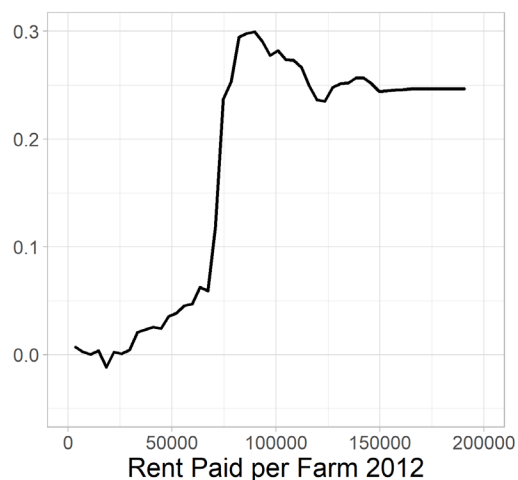
Figure 3.15 illustrates the relationship between change in land value over time and usable abandoned cropland. Again, excluding the Central Feed Grains region, each



**Figure 3.15.** Relationship between change in land value between 2007 and 2017 and usable abandoned cropland in each region.

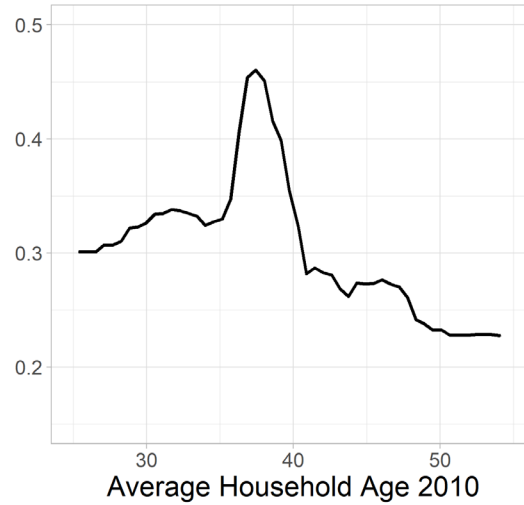
region shows a similar pattern of increasing UACL with increasing land values that levels off, or decreases in the case of The East & Central Farming region, above approximately 1% change.

Three variables stand out as being of distinct importance to only one of the regions. Central Feed Grains is the only region in which average rent paid in 2012 is most important. Figure 3.16 shows the relationship between rent and usable abandoned cropland. UACL increases steeply above a threshold of approximately \$75,000.



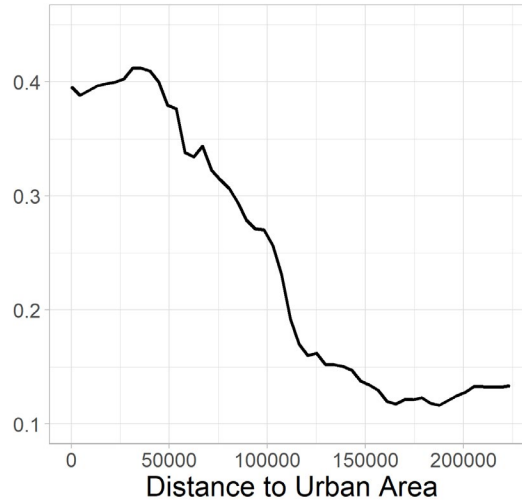
**Figure 3.16.** Relationship between average rent paid by farmers in 2012 and usable abandoned cropland in the Central Feed Grains region.

South Atlantic Cash Crops is the only region in which average household age in 2010 is distinctly important. UACL increases across all ages with a spike at approximately 40 years of age (Figure 3.17).



**Figure 3.17.** Relationship between average household age in 2010 and usable abandoned cropland in the South Atlantic Cash Crops region.

Distance to urban areas is only important in the East & Central Farming region and it shows a negative relationship with usable abandoned cropland. UACL changes at a 40% for counties nearer to urban areas and decreases starting at a distance of approximately 50,000 m to almost zero change as distances exceed approximately 200,000 m (Figure 3.18).



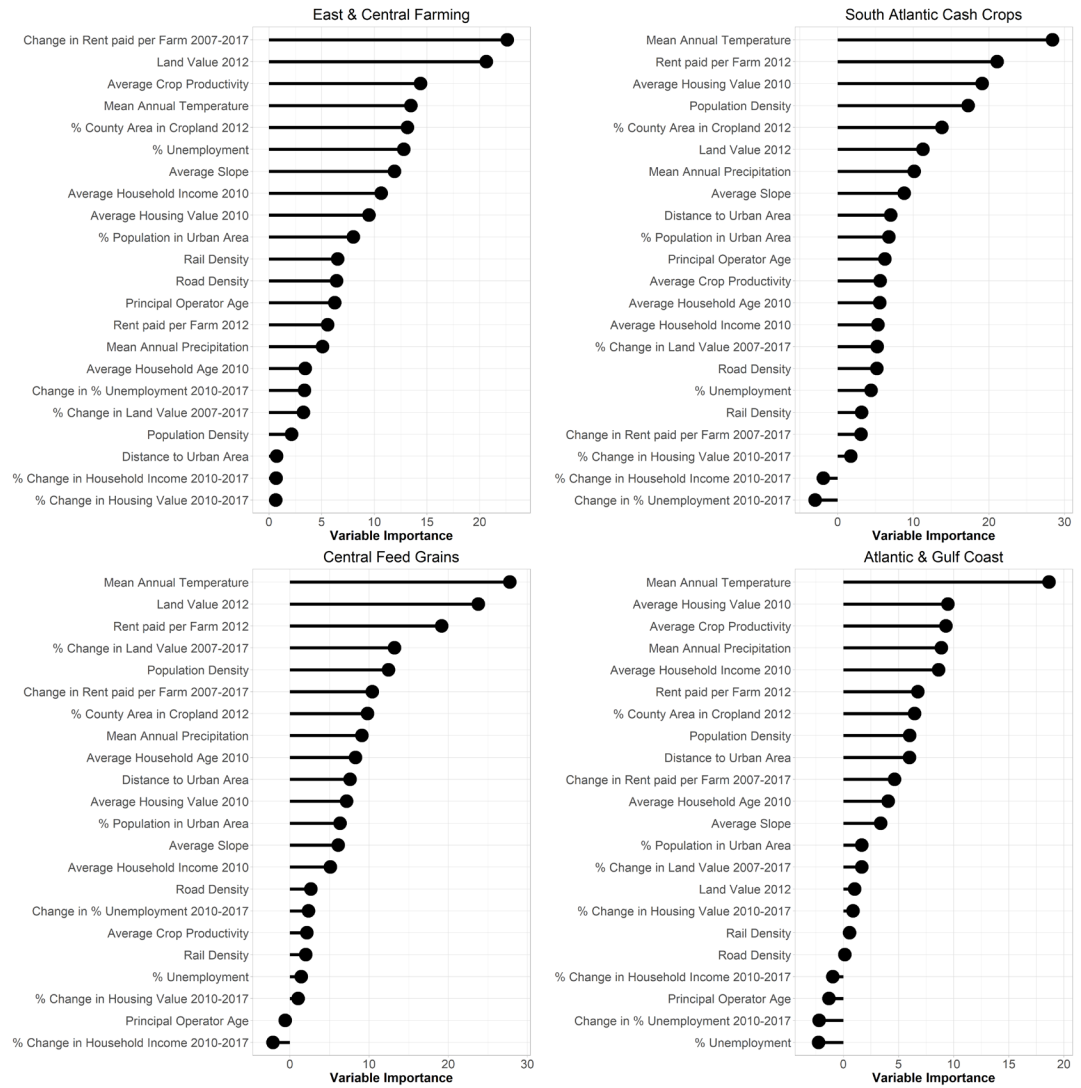
**Figure 3.18.** Relationship between distance to urban areas and usable abandoned cropland in The East & Central Farming region.

### 3.4.2. Positive Gain Counties in Each Region

In the regression analysis of only those counties with a non-zero value of UACL, regional variable importance mirrors the entire study area for the most part (Figure 3.19). Percent of county area in cropland, which is the topmost important variable in the entire study area, is not a particularly important variable in any of the regions, but is among the top seven in all regions. Mean annual temperature is the single most important variable to three of the regions, except for The East & Central Farming region where it is the fourth most important variable. A final observation is that average rent paid in 2012 is among the most important variables in each region except for The East & Central Farming region, where it is in the lower half of variables when sorted by importance. Interestingly, in The East & Central Farming region, it is change in rent between 2007 and 2017 that is the very most important variable. As is the case when observing the classification

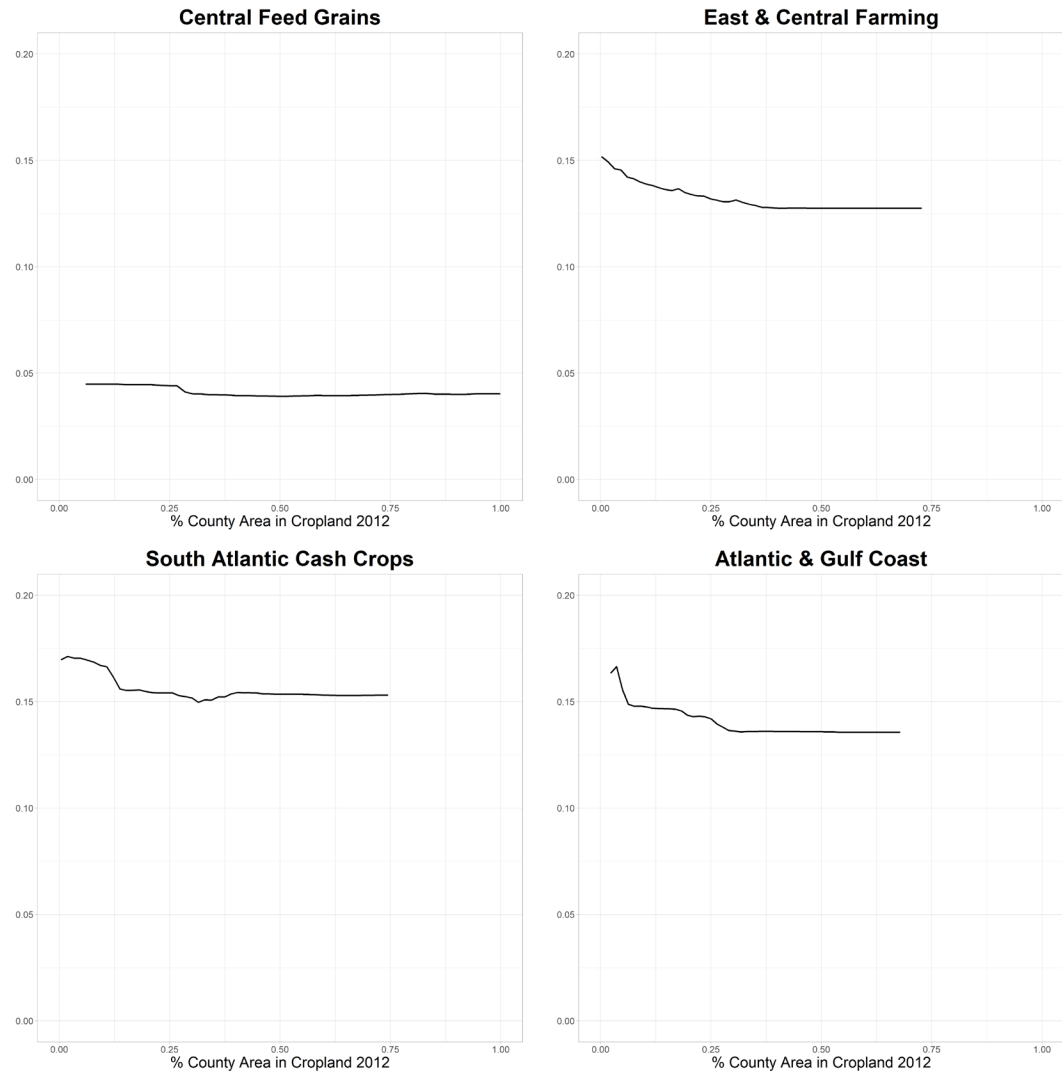
analysis of zero versus non-zero counties, The East & Central Farming region appears to differentiate itself from the other regions.

Figures 3.20 - 3.23 show partial dependence plots for four of the overall most important variables for each of the regions. In all cases, the relationship between the variables and the magnitude of usable abandoned cropland in counties where there is a net increase are similar. A notable difference across all four variables is that, in the Central Feed Grains region, the amount of change in UACL is overall lower than in the other regions, suggesting that these variables are important but do not lead to as much change as in the other regions. Another observation is that The East & Central Farming region has a slightly different pattern than the other regions for mean temperature and land value in 2012. For these two variables, the relationship between them and the magnitude change in net UACL shows a decrease at lower values of the variables, while the other regions remain relatively flat (Figures 3.21 and 3.22). These results suggest that the Central Feed Grains and East & Central Farming regions are unique in some ways relative to the rest of the study area.

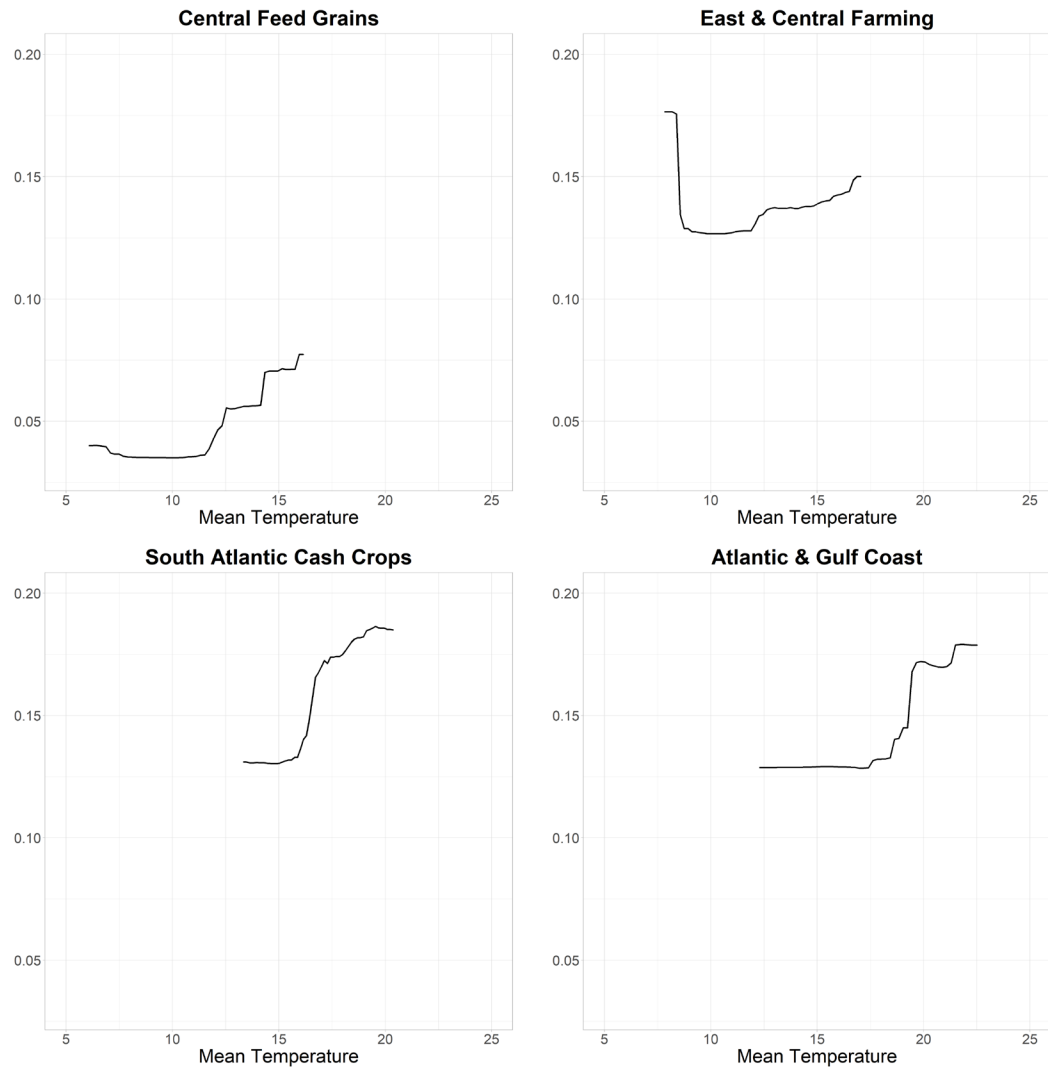


**Figure 3.19.** Variable importance for regions in the study area in the regression analysis of counties with a non-zero value of UACL.

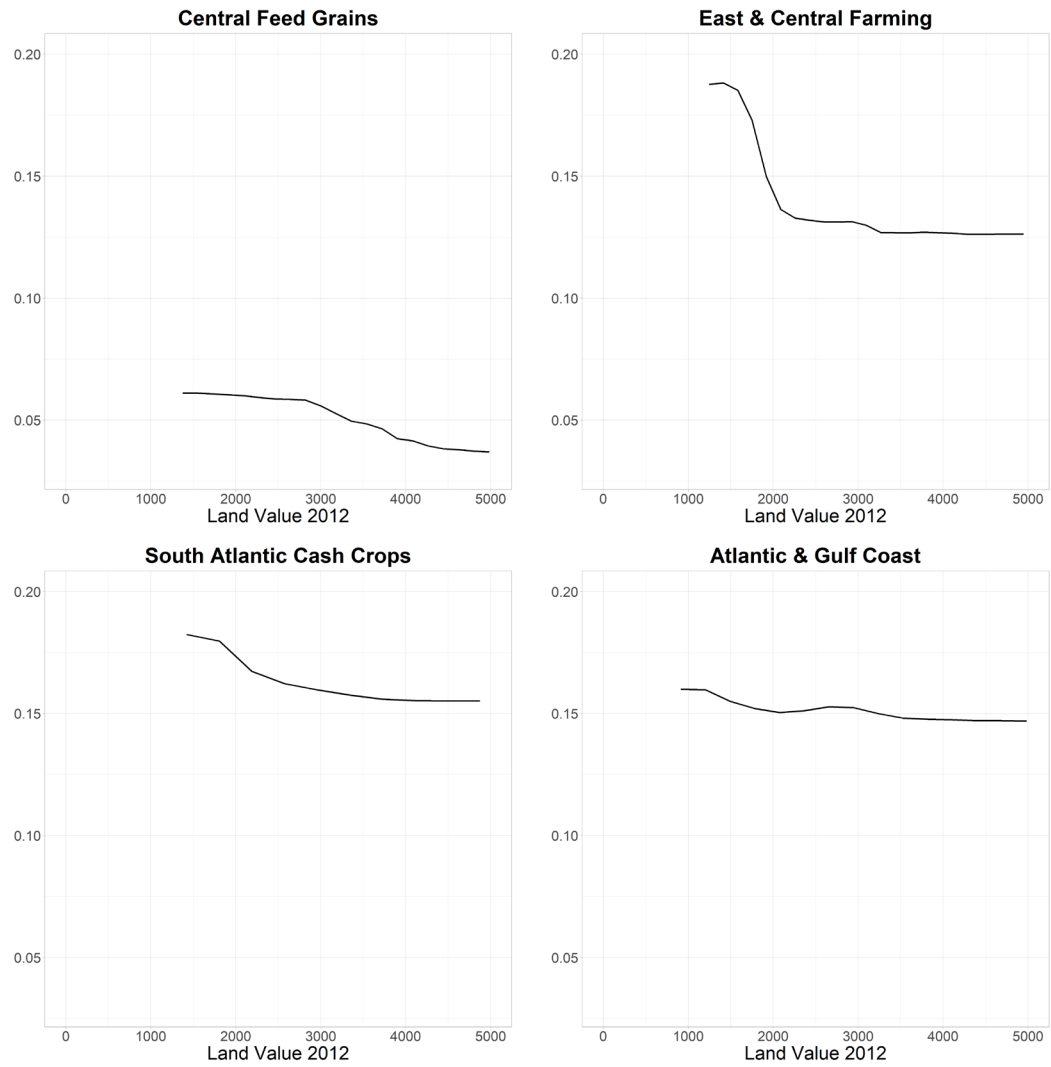




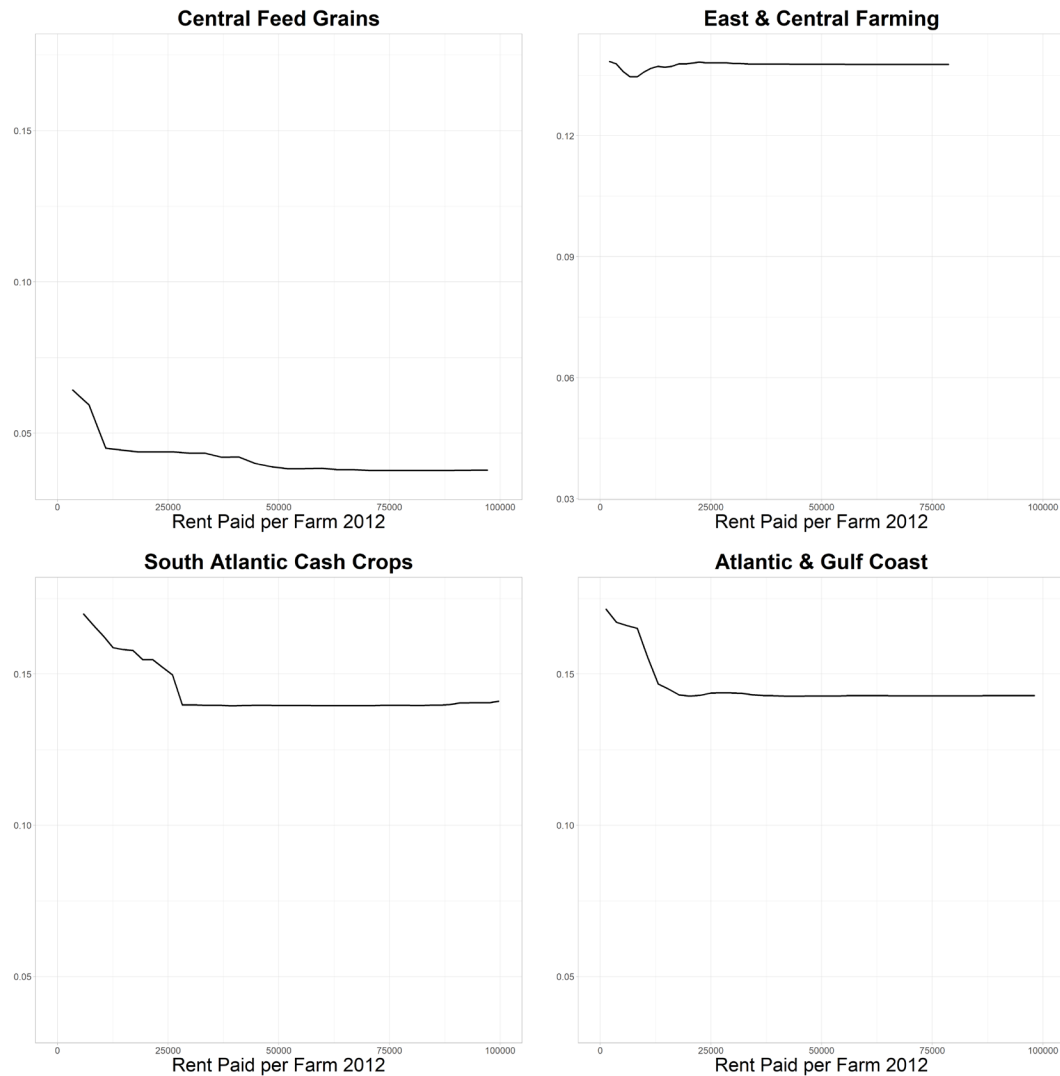
**Figure 3.20.** Relationship between percent of county area in cropland and usable abandoned cropland in each region.



**Figure 3.21.** Relationship between mean temperature and usable abandoned cropland in each region.



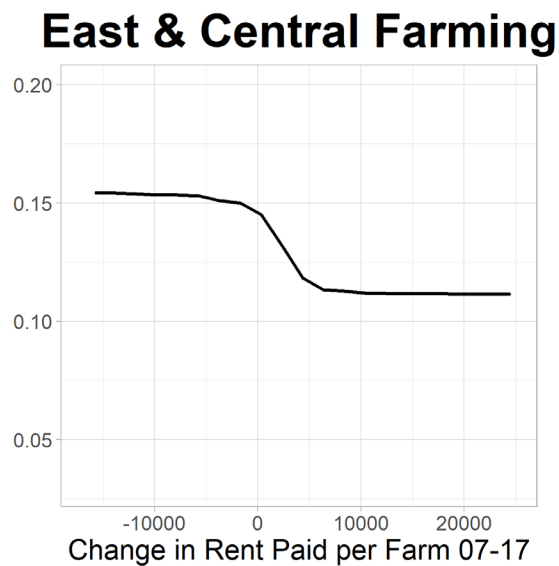
**Figure 3.22.** Relationship between land value in 2012 and usable abandoned cropland in each region.



**Figure 3.23.** Relationship between average rent paid per farm in 2012 and usable abandoned cropland in each region.

In the analysis of the magnitude change in counties with a non-zero value of UACL, The East & Central Farming region is also unique in that its most important variable is change in rent between 2007 and 2017, whereas in the other regions this variable is much less important. Figure 3.24 illustrates the relationship between this variable and the change in amount of UACL in counties that experience a net increase.

There is a threshold at zero change in rent, below which there is an increase in UACL and above which there is less of an increase in UACL. In The East & Central Farming region, decreasing rents result in more usable abandoned cropland and increasing rents result in less usable abandoned cropland.



**Figure 3.24.** Relationship between change in average rent paid between 2007 and 2017 and usable abandoned cropland in The East & Central Farming region.

#### 4. Discussion

These results suggest that hypotheses one (H1) and two (H2) are accepted: that there is a different set of factors that are most important when comparing UACL as a binary classification across all counties and UACL only in those that have a positive value. The same general observation is made when looking at the entire eastern US or each of the regions separately. The most important factors related to whether a county has a gain in UACL or not are largely variables measuring change in conditions over time,

while the most important factors in the case of counties with a positive gain are largely variables measuring conditions at a single point in time.

This dichotomy between temporal and static variables suggests that there are two processes influencing the emergence of UACL. Temporal variables measuring changes in rent and land value over time have an important role in determining whether a county will have a net gain in UACL or not. This observation is of particular importance to this study given that there are a substantial number of counties that have no net gain in UACL between 2007 and 2017. The counties with a value of zero UACL are evenly scattered across the entire eastern US (Figure 3.4). Comparing this spatial distribution with the rent and land value change over time variables, which are most important, reveals a somewhat similar pattern.

Change in rent over time and change in land value over time show somewhat scattered patterns of counties with zero or negative change (Figure 3.2c and d). These patterns are more scattered than the static variables of rent and land value (Figure 3.2a and b). Local conditions likely contribute to these changes in rent and land value over time and, consequently, to whether a county will experience a net gain in UACL.

Changing rent and land value variables have opposite relationships with UACL. The negative relationship between changing rents over time and UACL suggests that the agricultural productivity of land is high enough for landowners to charge more for farmers to operate it and to continue keeping the land in agricultural production. Whereas the positive relationship between changing land values over time suggests that there are more opportunities to sell land to developers which would result in cropland abandonment. However, since this results in an increase in *usable* abandoned cropland,

the land values are high enough to compel a landowner to sell, but not high enough or in a location desirable enough for the land to convert to an urban land use, thereby leaving the land available for other purposes.

Static variables of rent and land value in 2012 present more clustered and gradual spatial distributions. Clusters are most notable in the Central Feed Grains region and some pockets to the southeast. There is more alignment with these factors and the non-zero UACL counties, which present a pattern of less UACL in the Central Feed Grains region and more in pockets to the southeast. Broader forces at the regional or national level are likely to contribute to the static rent and land value conditions and, consequently, the amount of UACL that emerges in counties that experience a net gain.

Both the static measure of rent and land value have the same relationship with UACL, unlike the scenario with the multi-temporal variables. These variables generally have a negative relationship with UACL which indicates that higher rents and higher land values lead to farmers to either keep their land in agricultural production or sell their land to developers. Increasing rents could be taken as a proxy for profitability, which logically explains why a farmer would remain in production. Increasing land value is more curious because its relationship with UACL is different in the two cases (binary classification of counties and regression of just the positive-gain counties). Increasing land value suggests greater opportunities for selling to developers, and logically the reason more counties would not see a gain in UACL. Increasing land value also exerts influence on counties that do experience a net gain in UACL by moderating the amount that ultimately remains over time. Increasing rent over time does not appear to have the same moderating effect.

Prior research and modeling studies show that the value of farmland and rental rates are closely related to each other and that a rise in one is coincident with a rise in the other (Buchholz et al., 2022; Gutierrez et al., 2007; Nickerson & Zhang, 2014; Robison et al., 1985). Others, however, show some disagreement between the two factors, for example, different rates of change or lags in time when changes occur (Clark et al., 1993; Hanson & Myers, 1995; Ibendahl, 2013). Among the variables included in this dissertation analysis, only Change in Land Value between 2007 and 2017 and Average Rent Paid in 2012 were correlated at a level above 0.6. This indicates a relationship between land value and rent; however, it is not a strong signal, which would have been evidenced by a high correlation between variables such as land value and rent in the same year.

Results also show that hypothesis three (H3) is accepted: that different factors are important in some regions and not others. For the most part, the important variables are similar across regions. For example, in the case of counties with a net gain in UACL, mean annual temperature is the most important factor in three regions and in the top four in the other.

However, despite these limited overarching trends, regional variation among drivers is evident. For example, Central Feed Grains is different from the other regions in the classification case in terms of the importance of economic drivers. For the entire study area and the other three regions, variables of economic change over time (rent and land value) are among the most important, whereas for the Central Feed Grains region, static economic conditions at a particular point in time were most important, suggesting fundamental differences in the process of land use change. The Central Feed Grains



region is certainly a highly productive agricultural region, more so than the three other regions in this analysis. Furthermore, the diversity of crops produced is more narrowly focused on corn and soybeans in a landscape comprised of relatively large, flat, and continuous farms.

The East & Central Farming region is similarly unique in the case of net-gain counties. It is the only region for which change in rent over time is most important, while static rent in 2012 is most important to all other regions. Additionally, it is the only region for which distance to urban areas is important. These two notable differences suggest unique processes at work in the East & Central Farming region that aren't at play elsewhere. The map of distance to urban areas (Figure 3.2e) illustrates that there is a large portion in the interior of the East & Central Farming region that is relatively far from urban centers.

Other studies (MacDonald et al., 2000; Mottet et al., 2006; Müller et al., 2009; Pazúr et al., 2014) have shown that in rural areas, the distance to urban areas is a significant factor in the feasibility of agricultural production. The East & Central Farming region is characterized by variable terrain and relatively low economic conditions. These factors may explain why the East & Central Farming region is unique, but in a different manner than the Central Feed Grains region suggests. There is a threshold of around 50 km below which there is some increase in UACL and above which there is a sharp decrease. It's possible that farms more than this distance from population centers don't have much agricultural production to begin with or continue their farming practices perhaps for subsistence or local community markets. In this region and others in the southeast there are likely other forces at play. Napton et al. (2010) studies the

southeastern United States and finds that increasing demand for commercial forest products coincided with farming becoming less competitive, in addition, there are federal programs that subsidize the conversion of cropland to forest land. Future work should investigate these types of regionally targeted forces and how they might affect cropland abandonment.

Across the board, some form of rent (static or multi-temporal) is among the most important factors influencing the emergence of usable abandoned cropland. In 2017, 482,214 farms are rented out of a total of 2,042,220 farms in the United States. For comparison, in 1997, 485,512 farms are rented out of a total of 1,911,859 total farms. This amounts to 25% of farms in the United States renting to operators steadily over at least the last 20 years and corresponds to approximately 50% of the total farmland acreage in the United States (Kirwan, 2009). The impact of rents on decisions to keep land in production or abandon it is a topic that demands further investigation.

Renter-landowner relationships are important. In a qualitative study, Qiu et al. (2021) found that renting out land does not generally improve a landowner's sense of well-being. However, the study does observe an increase in well-being in the specific case of renting to an acquaintance. This suggests that from whom a farmer rents farmland has a qualitative effect on their sense of well-being, and consequently a potential impact on their decision to continue farming or abandon land. It is possible that abandonment is less likely in areas where land is predominantly rented from local landowners versus large agribusinesses with no local connection to the land beyond its value as an investment property. Future work should investigate the relationship between the rates of abandonment and the types of relationships between renter and landowner.

Allen and Borchers (2016) find that over the past 20 years, there has been an increase in cash rent versus sharecropping arrangements between renters and landowners. This results in more of a business-only relationship between farmer and landowner. This may come at the expense of relationships in which the farmer and landowner are acquaintances and work collaboratively. A study by Swinton et al. (2017) found that farmers in the Great Lakes region of the US were largely unwilling to rent farmland they consider to be marginal, largely due to environmental concerns and worries about how an unacquainted renter would maintain the property. This suggests that even if land is not otherwise profitable, landowners are often not interested in renting their land even when rental rates are high.

Land management and soil conservation practices are related to land tenure. Leonhardt et al. (2019) finds that farmers who rent land in short-term agreements tend to manage their land less carefully than if they owned it. Furthermore, if the farmer does not have a personal relationship with the landowner, practices such as fertilization and soil conservation are worse. Sawadgo et al. (2021) found that practices of cover crops, buffer strips, and sediment basins were implemented less frequently on rented farmland. Ranjan et al. (2022) performed a qualitative study that observed that renting farmland hinders conservation behavior. These findings suggest that the type of rental arrangement affects farmers' practices, which may in turn lead to decisions to abandon, particularly if land is less well cared for. Other studies, however, have found that land tenure does not have an impact on some specific practices, such as weed management (Frisvold et al., 2020).

Farmer age is related to the decision to rent farmland. A study by Sun et al. (2023) investigated the relationship between elderly care and farmland rental practices. Elderly

farmers are shown to be more likely to rent out their land if they are in a more stable financial and medical situation. This may suggest that in places of economic uncertainty and inadequate retirement funds, farmers may be more likely to continue operating their farms and ultimately abandon them. Furthermore, Buchholz et al. (2022) find that the only factor statistically significant to the willingness to rent land is the age of the farmer. They report that in 2017 the average age of farmers in the US is 58 years old.

Stevens and Wu (2022) find that renting is associated with higher net farm income for younger farmers. In other words, young farmers who rent some or all of the land they operate have higher levels of production and profit than those who own their land. Renting may increase flexibility to invest in improvements on the farm, whereas inheriting farmland may present few incentives to implement efficient practices (Stevens & Wu, 2022). Further research into the rates of ownership because of family inheritance versus renting or purchasing from unacquainted landowners may elucidate whether either scenario leads to increased rates of abandonment.

Burchfield et al. (2022) find that, on average, farms in the US are generating less net income than in earlier years. Despite rising subsidies from the federal government, many farmers see less profit. This may be due in part because landowners increase rents in step with the subsidies resulting in the farmers not seeing any of the increased government payments. This practice of raising rents commensurate with increased subsidies may also be a consequence of less personal and unacquainted relationships between renter and landowner. The overall reduction in net income is particularly apparent in areas within Texas, Appalachia, and the Southeast (Burchfield et al., 2022). These trends of increasing farmer age, financial insecurity, and renter-landowner

relationship may contribute to decisions to rent farmland or simply abandon it, particularly in some regions of the country.

## **5. Conclusion**

This study explores the emergence of usable abandoned cropland (UACL) between 2007 and 2017 and the potential drivers of this land change. A random forest analysis of UACL reveals that the rent farmers pay to operate cropland and the value of farmland and buildings are among the most important variables. Interestingly, when viewing UACL in a binary form (counties with zero UACL versus counties with a non-zero value of UACL) it is the measure of change in rent and land value over time that is important, while a view of only those counties with a non-zero value of UACL reveal that static measures of rent and land value are important.

These results suggest that there are different processes at work: one that affects whether a county will experience a net gain in UACL or not, and one that affects the amount of UACL that emerges in counties where there is a net gain. Because temporal variables of changing land value and rent over time are spatially scattered, it is likely that local conditions play an important role in determining whether a county will experience a gain in UACL or not. Whereas static measures of land value and rent at one point in time are more spatially clustered, suggesting that broader regional factors play an important role in the amount of UACL that emerges in counties with a net gain. With this information, policymakers may be able to identify regions of renewable energy potential based on quantitative economic characteristics and qualitative assessments of farmer-landowner relationships.

## 6. References

- Aide, T. M., Clark, M. L., Grau, H. R., López-Carr, D., Levy, M. A., Redo, D., Bonilla-Moheno, M., Riner, G., Andrade-Núñez, M. J., & Muñiz, M. (2013). Deforestation and reforestation of Latin America and the Caribbean (2001–2010). *Biotropica*, 45(2), 262-271.
- Albers, M. A., Dobos, R. R., & Robotham, M. P. (2022). User guide for the national commodity crop productivity index (nccpi). <https://www.nrcs.usda.gov/sites/default/files/2023-01/NCCPI-User-Guide.pdf>
- Allen, D. W., & Borchers, A. (2016). Conservation practices and the growth of us cash rent leases [Article]. *Journal of Agricultural Economics*, 67(2), 491-509. <https://doi.org/10.1111/1477-9552.12153>
- Allen, T. F. H., & Starr, T. B. (1982). *Hierarchy*. University of Chicago Press.
- Alonso Serna, L. (2022). Land grabbing or value grabbing? Land rent and wind energy in the isthmus of Tehuantepec, Oaxaca. *Competition & Change*, 26(3-4), 487-503.
- Anselin, L. (1988). *Spatial econometrics: Methods and models* (Vol. 4). Springer Science & Business Media.
- Baxter, R. E., & Calvert, K. E. (2017). Estimating available abandoned cropland in the United States: Possibilities for energy crop production. *Annals of the American Association of Geographers*, 107(5), 1162-1178. <https://doi.org/10.1080/24694452.2017.1298985>
- Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5-32. <https://doi.org/10.1023/a:1010933404324>
- Buchholz, M., Danne, M., & Musshoff, O. (2022). An experimental analysis of German farmers' decisions to buy or rent farmland [Article]. *Land Use Policy*, 120, 9, Article 106218. <https://doi.org/10.1016/j.landusepol.2022.106218>
- Burchfield, E. K., Schumacher, B. L., Spangler, K., & Rissing, A. (2022). The state of US farm operator livelihoods [Article]. *Frontiers in Sustainable Food Systems*, 5, 22, Article 795901. <https://doi.org/10.3389/fsufs.2021.795901>

- Campbell, J. E., Lobell, D. B., Genova, R. C., & Field, C. B. (2008). The global potential of bioenergy on abandoned agriculture lands. *Environmental Science & Technology*, 42(15), 5791-5794.
- Clark, J. S., Fulton, M., & Scott Jr., J. T. (1993). The inconsistency of land values, land rents, and capitalization formulas. *American Journal of Agricultural Economics*, 75(1), 147-155. <https://doi.org/10.2307/1242963>
- Dabiri, J. O., Greer, J. R., Koseff, J. R., Moin, P., & Peng, J. (2015). A new approach to wind energy: Opportunities and challenges. *AIP Conference Proceedings*, 1652(1), 51-57. <https://doi.org/10.1063/1.4916168>
- Daniels, T. L. (2023). The development of utility-scale solar projects on us agricultural land: Opportunities and obstacles. *Socio-Ecological Practice Research*, 5(2), 205-213. <https://doi.org/10.1007/s42532-023-00139-9>
- Diffendorfer, J. E., Dorning, M. A., Keen, J. R., Kramer, L. A., & Taylor, R. V. (2019). Geographic context affects the landscape change and fragmentation caused by wind energy facilities. *PeerJ*, 7, e7129.
- Esri. (2023). *Arcgis pro*. In (Version 3.1.3)
- Fargione, J., Hill, J., Tilman, D., Polasky, S., & Hawthorne, P. (2008). Land clearing and the biofuel carbon debt. *Science*, 319, 1235-1238.
- Field, J. L., Richard, T. L., Smithwick, E. A. H., Cai, H., Laser, M. S., Lebauer, D. S., Long, S. P., Paustian, K., Qin, Z., Sheehan, J. J., Smith, P., Wang, M. Q., & Lynd, L. R. (2020). Robust paths to net greenhouse gas mitigation and negative emissions via advanced biofuels. *Proceedings of the National Academy of Sciences*, 117(36), 21968-21977. <https://doi.org/10.1073/pnas.1920877117>
- Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., & Snyder, P. K. (2005). Global consequences of land use. *Science*, 309, 570-574.
- Frisvold, G. B., Albright, J., Ervin, D. E., Owen, M. D. K., Norsworthy, J. K., Dentzman, K. E., Hurley, T. M., Jussaume, R. A., Gunsolus, J. L., & Everman, W. (2020). Do farmers manage weeds on owned and rented land differently? Evidence from

- us corn and soybean farms [Article]. *Pest Management Science*, 76(6), 2030-2039. <https://doi.org/10.1002/ps.5737>
- Geist, H. J., & Lambin, E. F. (2002). Proximate causes and underlying driving forces of tropical deforestation: Tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. *BioScience*, 52(2), 143-150.
- Gellrich, M., Baur, P., Koch, B., & Zimmermann, N. E. (2007). Agricultural land abandonment and natural forest re-growth in the swiss mountains: A spatially explicit economic analysis. *Agriculture, Ecosystems & Environment*, 118(1), 93-108. <https://doi.org/10.1016/j.agee.2006.05.001>
- Grömping, U. (2009). Variable importance assessment in regression: Linear regression versus random forest. *The American Statistician*, 63(4), 308-319. <https://doi.org/10.1198/tast.2009.08199>
- Gurgel, A. C., Reilly, J., & Blanc, E. (2021). Agriculture and forest land use change in the continental united states: Are there tipping points? *iScience*, 24(7), 102772. <https://doi.org/10.1016/j.isci.2021.102772>
- Gutierrez, L., Westerlund, J., & Erickson, K. (2007). Farmland prices, structural breaks and panel data. *European Review of Agricultural Economics*, 34(2), 161-179. <https://doi.org/10.1093/erae/jbm018>
- Hanson, S. D., & Myers, R. J. (1995). Testing for a time-varying risk premium in the returns to u.S. Farmland. *Journal of Empirical Finance*, 2(3), 265-276. [https://doi.org/https://doi.org/10.1016/0927-5398\(95\)00006-G](https://doi.org/https://doi.org/10.1016/0927-5398(95)00006-G)
- Hart, J. F. (1968). Loss and abandonment of cleared farm land in the eastern united states. *Annals of the Association of American Geographers*, 58, 417-440.
- Hartter, J., Southworth, J., & Binford, M. (2010). Parks as a mechanism to maintain and facilitate recovery of forest cover: Examining reforestation, forest maintenance and productivity in uganda. *Reforesting landscapes: Linking pattern and process*, 275-296.
- Hellmann, F., & Verburg, P. H. (2011). Spatially explicit modelling of biofuel crops in europe. *Biomass and Bioenergy*, 35(6), 2411-2424. <https://doi.org/10.1016/j.biombioe.2008.09.003>



- Hoffacker, M. K., Allen, M. F., & Hernandez, R. R. (2017). Land-sparing opportunities for solar energy development in agricultural landscapes: A case study of the great central valley, ca, united states. *Environmental Science & Technology*, 51(24), 14472-14482. <https://doi.org/10.1021/acs.est.7b05110>
- Houghton, R. A., Hackler, J. L., & Lawrence, K. T. (1999). The u.S. Carbon budget: Contributions from land-use change. *Science*, 285(5427), 574 - 578.
- Ibendahl, G. G., Terry. (2013). The connection between cash rents and land values. *Journal of ASFMRA*, 239-247.
- Katkar, V. V., Sward, J. A., Worsley, A., & Zhang, K. M. (2021). Strategic land use analysis for solar energy development in new york state. *Renewable Energy*, 173, 861-875. <https://doi.org/10.1016/j.renene.2021.03.128>
- Kirwan, Barrett E. (2009). The incidence of u.S. Agricultural subsidies on farmland rental rates. *Journal of Political Economy*, 117(1), 138-164. <https://doi.org/10.1086/598688>
- Lambin, E. F. (2012). Global land availability: Malthus versus ricardo. *Global Food Security*, 1(2), 83-87. <https://doi.org/10.1016/j.gfs.2012.11.002>
- Lambin, E. F., & Geist, H. J. (2006). *Land-use and land-cover change*. Springer.
- Lark, T. J., Salmon, J. M., & Gibbs, H. K. (2015). Cropland expansion outpaces agricultural and biofuel policies in the united states. *Environmental Research Letters*, 10(4), 044003.
- Larson, B. (2014). *How epa is letting the rfs become a driver of land conversion*. [https://www.nwf.org/~media/PDFs/Wildlife/RFS\\_factsheet\\_v3\\_09-10-14.pdf](https://www.nwf.org/~media/PDFs/Wildlife/RFS_factsheet_v3_09-10-14.pdf)
- Legendre, P., & Fortin, M. J. E. (1989). Spatial pattern and ecological analysis. *Vegetatio*, 80(2), 107-138. <https://doi.org/10.1007/bf00048036>
- Leonhardt, H., Penker, M., & Salhofer, K. (2019). Do farmers care about rented land? A multi-method study on land tenure and soil conservation [Article]. *Land Use Policy*, 82, 228-239. <https://doi.org/10.1016/j.landusepol.2018.12.006>
- MacDonald, D., Crabtree, J. R., Wiesinger, G., Dax, T., Stamou, N., Fleury, P., Gutierrez Lazpita, J., & Gibon, A. (2000). Agricultural abandonment in mountain areas of europe: Environmental consequences and policy response. *Journal of*

- Environmental Management*, 59(1), 47-69.  
<https://doi.org/10.1006/jema.1999.0335>
- Mahan, C. G., Bishop, J. A., Steele, M. A., Turner, G., & Myers, W. L. (2010). Habitat characteristics and revised gap landscape analysis for the northern flying squirrel (*glaucomys sabrinus*), a state endangered species in pennsylvania. *The American Midland Naturalist*, 164(2), 283-295, 213. <https://doi.org/10.1674/0003-0031-164.2.283>
- Mahiny, A. S., & Clarke, K. C. (2012). Guiding sleuth land-use/land-cover change modeling using multicriteria evaluation: Towards dynamic sustainable land-use planning. *Environment and Planning B: Planning and Design*, 39(5), 925-944. <https://doi.org/10.1068/b37092>
- Moriasi, D., Gitau, M., Pai, N., & Daggupati, P. (2015). Hydrologic and water quality models: Performance measures and evaluation criteria. *Transactions of the ASABE*, 58(6), 1763-1785. <https://doi.org/10.13031/trans.58.10715>
- Mottet, A., Ladet, S., Coqué, N., & Gibon, A. (2006). Agricultural land-use change and its drivers in mountain landscapes: A case study in the pyrenees. *Agriculture, Ecosystems & Environment*, 114(2), 296-310. <https://doi.org/10.1016/j.agee.2005.11.017>
- Müller, D., Kuemmerle, T., Rusu, M., & Griffiths, P. (2009). Lost in transition: Determinants of post-socialist cropland abandonment in romania. *Journal of Land Use Science*, 4(1-2), 109-129. <https://doi.org/10.1080/17474230802645881>
- Müller, D., & Munroe, D. K. (2008). Changing rural landscapes in albania: Cropland abandonment and forest clearing in the postsocialist transition. *Annals of the Association of American Geographers*, 98(4), 855-876. <https://doi.org/10.1080/00045600802262323>
- Munroe, D. K., van Berkel, D. B., Verburg, P. H., & Olson, J. L. (2013). Alternative trajectories of land abandonment: Causes, consequences and research challenges. *Current Opinion in Environmental Sustainability*, 5(5), 471-476.
- Napton, D. E., Auch, R. F., Headley, R., & Taylor, J. L. (2010). Land changes and their driving forces in the southeastern united states. *Regional Environmental Change*, 10, 37-53

<https://doi.org/10.1007/s10113-009-0084-x>

- Näschen, K., Diekkrüger, B., Evers, M., Höllermann, B., Steinbach, S., & Thonfeld, F. (2019). The impact of land use/land cover change (lulcc) on water resources in a tropical catchment in tanzania under different climate change scenarios. *Sustainability*, 11(24), 7083. <https://doi.org/10.3390/su11247083>
- Nath, B., Wang, Z., Ge, Y., Islam, K., P. Singh, R., & Niu, Z. (2020). Land use and land cover change modeling and future potential landscape risk assessment using markov-ca model and analytical hierarchy process. *ISPRS International Journal of Geo-Information*, 9(2), 134. <https://doi.org/10.3390/ijgi9020134>
- Nickerson, C. J., & Zhang, W. (2014). Modeling the determinants of farmland values in the united states. In J. M. Duke & J. Wu (Eds.), *The oxford handbook of land economics* (pp. 0). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199763740.013.005>
- Nordberg, E. J., Julian Caley, M., & Schwarzkopf, L. (2021). Designing solar farms for synergistic commercial and conservation outcomes. *Solar Energy*, 228, 586-593. <https://doi.org/10.1016/j.solener.2021.09.090>
- Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, 11(6), 619-632.
- Pazúr, R., Lieskovský, J., Feranec, J., & Oľahel', J. (2014). Spatial determinants of abandonment of large-scale arable lands and managed grasslands in slovakia during the periods of post-socialist transition and european union accession. *Applied Geography*, 54, 118-128. <https://doi.org/10.1016/j.apgeog.2014.07.014>
- Peeler, J. L., & Smithwick, E. A. H. (2018). Exploring invasibility with species distribution modeling: How does fire promote cheatgrass (*bromus tectorum*) invasion within lower montane forests? *Diversity and Distributions*, 24(9), 1308-1320. <https://doi.org/10.1111/ddi.12765>
- Plassin, S., Koch, J., Wilson, M., Neal, K., Friedman, J. R., Paladino, S., & Worden, J. (2021). Multi-scale fallow land dynamics in a water-scarce basin of the u.S. Southwest. *Journal of Land Use Science*, 16(3), 291-312. <https://doi.org/10.1080/1747423X.2021.1928310>

- Prasad, A. M., Iverson, L. R., & Liaw, A. (2006). Newer classification and regression tree techniques: Bagging and random forests for ecological prediction. *Ecosystems*, 9(2), 181-199. <https://doi.org/10.1007/s10021-005-0054-1>
- PRISM Climate Group. (2023). *Prism gridded climate data*. <https://prism.oregonstate.edu>
- Probst, P., Wright, M. N., & Boulesteix, A. L. (2019). Hyperparameters and tuning strategies for random forest. *WIREs Data Mining and Knowledge Discovery*, 9(3), e1301. <https://doi.org/10.1002/widm.1301>
- Qiu, T. W., He, Q. Y., & Luo, B. L. (2021). Does land renting-out increase farmers' subjective well-being? Evidence from rural china [Article]. *Applied Economics*, 53(18), 2080-2092. <https://doi.org/10.1080/00036846.2020.1855315>
- Ramvalho, E. A., Ramalho, J. J., & Murteira, J. M. (2011). Alternative estimating and testing empirical strategies for fractional regression models. *Journal of Economic Surveys*, 25(1), 19-68.
- Ramankutty, N., & Foley, J. A. (1999a). Estimating historical changes in global land cover: Croplands from 1700 to 1992. *Global biogeochemical cycles*, 13(4), 997-1027.
- Ramankutty, N., & Foley, J. A. (1999b). Estimating historical changes in land cover: North american croplands from 1850 to 1992: Gcte/lucc research article. *Global Ecology and Biogeography*, 8(5), 381-396.
- Ramankutty, N., Heller, E., & Rhemtulla, J. (2010). Prevailing myths about agricultural abandonment and forest regrowth in the united states. *Annals of the Association of American Geographers*, 100(3), 502-512. <https://doi.org/10.1080/00045601003788876>
- Ranjan, P., Arbuckle, J. G., Church, S. P., Eanes, F. R., Floress, K., Gao, Y. L., Gramig, B. M., Singh, A. S., & Prokopy, L. S. (2022). Understanding the relationship between land tenure and conservation behavior: Recommendations for social science research [Article]. *Land Use Policy*, 120, 6, Article 106161. <https://doi.org/10.1016/j.landusepol.2022.106161>
- Rey Benayas, J. M., Martins, A., Nicolau, J. M., & Schulz, J. J. (2007). Abandonment of agricultural land: An overview of drivers and consequences. *CAB Reviews*:

*Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, 2, 1/14.

- Robison, L. J., Lins, D. A., & VenKataraman, R. (1985). Cash rents and land values in u.S. Agriculture. *American Journal of Agricultural Economics*, 67(4), 794-805. <https://doi.org/https://doi.org/10.2307/1241819>
- Sawadgo, W. P. M., Zhang, W., & Plastina, A. (2021). What drives landowners' conservation decisions? Evidence from iowa [Article]. *Journal of Soil and Water Conservation*, 76(3), 211-221. <https://doi.org/10.2489/jswc.2021.00115>
- Searchinger, T., Heimlich, R., Houghton, R. A., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D., & Yu, T.-H. (2008). Use of u.S. Croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science*, 319, 1238-1240.
- Spangler, K., Schumacher, B. L., Bean, B., & Burchfield, E. K. (2022). Path dependencies in us agriculture: Regional factors of diversification. *Agriculture, Ecosystems & Environment*, 333, 107957. <https://doi.org/10.1016/j.agee.2022.107957>
- Spiess, A.-N., & Neumeyer, N. (2010). An evaluation of  $r^2$  as an inadequate measure for nonlinear models in pharmacological and biochemical research: A monte carlo approach. *BMC Pharmacology*, 10(1), 6. <https://doi.org/10.1186/1471-2210-10-6>
- Stevens, A. W., & Wu, K. R. (2022). Land tenure and profitability among young farmers and ranchers [Article]. *Agricultural Finance Review*, 82(3), 486-504. <https://doi.org/10.1108/afr-04-2021-0048>
- Stoof, C. R., Richards, B. K., Woodbury, P., B., Fabio, E. S., Brumbach, A. R., Cherney, J., Das, S., Geohring, L., Hansen, J., Hornesky, J., Mayton, H., Mason, C., Ruestow, G., Smart, L. B., Volk, T. A., & Steenhuis, T., S. (2015). Untapped potential: Opportunities and challenges for sustainable bioenergy production from marginal lands in the northeast USA. *Bioenergy Research*, 8, 482-501.
- Strengers, B., Leemans, R., Eickhout, B., de Vries, B., & Bouwmann, L. (2004). The land-use projections and resulting emissions in the ipcc sres scenarios as simulated by the image 2.2 model. *GeoJournal*, 61, 381 - 393.

- Sun, J. H., Cheng, P., & Liu, Z. X. (2023). Social security, intergenerational care, and cultivated land renting out behavior of elderly farmers: Findings from the china health and retirement longitudinal survey [Article]. *Land*, 12(2), 22, Article 392. <https://doi.org/10.3390/land12020392>
- Swinton, S. M., Tanner, S., Barham, B. L., Mooney, D. F., & Skevas, T. (2017). How willing are landowners to supply land for bioenergy crops in the northern great lakes region? [Article]. *Global Change Biology Bioenergy*, 9(2), 414-428. <https://doi.org/10.1111/gcbb.12336>
- Temme, A. J. A. M., & Verburg, P. H. (2011). Mapping and modelling of changes in agricultural intensity in europe. *Agriculture, Ecosystems & Environment*, 140(1), 46-56. <https://doi.org/10.1016/j.agee.2010.11.010>
- United States Census Bureau. (n.d.). *Data.Census.Gov*. Retrieved from [data.census.gov](https://data.census.gov)
- United States Department of Agriculture. (2017). *Census of agriculture*. Retrieved from [www.nass.usda.gov/Publications/AgCensus](https://www.nass.usda.gov/Publications/AgCensus)
- United States Department of Agriculture. (2022). *Land resource regions and major land resource areas of the united states, the caribbean, and the pacific basin*. (Agriculture Handbook 296).
- United States Department of Agriculture. (2023). *Gridded soil survey geographic (gssurgo) database*. Natural Resources Conservation Service. <https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database>
- United States Department of Transportation. (2012). *National transportation atlas database*. Retrieved from <https://rosap.ntl.bts.gov/view/dot/7544>
- United States Environmental Protection Agency. (2022a, 2/22/2022). *Overview for renewable fuel standart*. Retrieved 11/07/2022 from <https://www.epa.gov/renewable-fuel-standard-program/overview-renewable-fuel-standard>
- United States Environmental Protection Agency. (2022b). *Regulation of fuels and fuel additives, 40 cfr part 80*. Retrieved from <https://www.ecfr.gov/current/title-40/chapter-I/subchapter-C/part-80#part-80>

- United States Geological Survey. (2023). *National elevation database*.  
<https://www.usgs.gov/publications/national-elevation-dataset>
- van Vliet, J., de Groot, H. L. F., Rietveld, P., & Verburg, P. H. (2015). Manifestations and underlying drivers of agricultural land use change in europe. *Landscape and Urban Planning*, 133, 24-36. <https://doi.org/10.1016/j.landurbplan.2014.09.001>
- Veldkamp, A., & Fresco, L. O. (1996). Clue-cr: An integrated multi-scale model to simulate land use change scenarios in costa rica. *Ecological Modelling*, 91(1), 231-248. [https://doi.org/10.1016/0304-3800\(95\)00158-1](https://doi.org/10.1016/0304-3800(95)00158-1)
- Verberg, P., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., & Mastura, S. (2002). Modeling the spatial dynamics of regional land use: The clue-s model. *Environmental Management*, 30(3), 391 - 405.
- Verburg, P., Kok, K., Pontius Jr., R. G., & Veldkamp, A. (2006). Modeling land-use and land-cover change. In E. F. Lambin & H. J. Geist (Eds.), *Land-use and land-cover change: Local processes and global impacts*. Springer-Verlag.
- Verburg, P. H., & Overmars, K. P. (2007). Dynamic simulation of land-use change trajectories with the clue-s model. In *Modelling land-use change* (pp. 321-337). Springer Netherlands. [https://doi.org/10.1007/978-1-4020-5648-2\\_18](https://doi.org/10.1007/978-1-4020-5648-2_18)
- Verburg, P. H., & Overmars, K. P. (2009). Combining top-down and bottom-up dynamics in land use modeling: Exploring the future of abandoned farmlands in europe with the dyna-clue model. *Landscape Ecology*, 24(9), 1167-1181. <https://doi.org/10.1007/s10980-009-9355-7>
- Yirsaw, E., Wu, W., Shi, X., Temesgen, H., & Bekele, B. (2017). Land use/land cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of china, the su-xi-chang region. *Sustainability*, 9(7), 1204. <https://doi.org/10.3390/su9071204>
- Zaragozi, B., Rabasa, A., Rodriguez-Sala, J. J., Navarro, J. T., Belda, A., & Ramon, A. (2012). Modelling farmland abandonment: A study combining gis and data mining techniques. *Agriculture, Ecosystems & Environment*, 155, 124-132.
- Zumkehr, A., & Campbell, J. E. (2013). Historical u.S. Cropland areas and the potential for bioenergy production on abandoned croplands. *Environmental Science & Technology*, 47(8), 3840-3847. <https://doi.org/10.1021/es3033132>

## **Chapter 4. Patterns of Emergent Usable Abandoned Cropland**

### **1. Introduction**

Previous chapters have estimated the amount of usable abandoned cropland (UACL) there is in the United States and some of the factors that influence the process of abandonment. The current chapter explores the occurrence of abandoned cropland further by downscaling it from the county level to the landscape level to assess the suitability of these lands for the production of renewable energy. A spatially explicit land use change model is utilized to project where on the landscape abandoned cropland may occur. Suitability is assessed within the context of the logistics of energy production. Patches of UACL that are larger, closer to each other, and more regularly shaped are considered more suitable given the challenges and efficiencies of installing, harvesting, or transporting renewable energy.

While many previous studies explore land change using a variety of methods, few have specifically studied novel land types (i.e., those that were not previously present on the landscape) or the specific case of abandoned cropland for renewable energy production. Among the methods used to model land change, spatially explicit models are among the most effective. For example, Nath et al. (2020) and Yirsaw et al. (2017) utilized a cellular automata approach to model future landscape risk in earthquake-prone regions and changes to ecosystem services respectively. Mahiny and Clarke (2012) present an example of using multi-criteria evaluation to project urban expansion in Iran based on Landsat imagery. Some studies specifically perform land use projections for the purpose of assessing suitability of some activity or phenomenon. Sahoo et al. (2018)



project the future suitability of areas to be considered agricultural zones in India. Kienast et al. (2012) predict areas suitable for the development of recreation in Swiss cities using correlations between locations specified by residents and underlying characteristics of the landscape to drive a spatial model. Fonderflick et al. (2015) develop a habitat suitability model based on the presence of foraging bats and correlate it with 17 underlying Mediterranean landscape variables.

Commonly, land change modeling exercises perform multiple scenarios to observe how landscapes change under different drivers and conditions, particularly climate regimes. Näschen et al. (2019) runs different climate scenarios to observe possible impacts to agriculture and water resources in Tanzania. The Intergovernmental Panel on Climate Change (IPCC) develops a suite of emission scenarios (SRES) or narratives of how the world may unfold in the future. These narratives have been used to project future carbon emissions and resulting climate change. Strengers et al. (2004) extends these projections to explicitly include land use change. Their analysis is global in scope and has a spatial resolution of 0.5 degrees, much coarser than land change models that operate at the landscape level.

A gap in the research literature that the current study addresses is the application of land change modeling to find opportunities for renewable energy production in a novel land type, e.g., places where abandoned cropland was not previously present but is starting to emerge as an opportunity. In this case, projecting where usable abandoned cropland emerges on the landscape over time and measuring where these emergent lands may be the most favorable for the production of energy like biomass or utility-scale solar. Furthermore, the current study utilizes a data structure with a 30 m pixel resolution,

which is a greater level of detail than many previous efforts. This fine spatial resolution facilitates the measurement of landscape pattern and composition that is necessary for the assessment of suitability for energy production placement.

Landscape metrics can be applied to data at this resolution to derive quantitative measures of the spatial configuration of usable abandoned cropland and ultimately assess its utility. Metrics have traditionally been used to measure the configuration and composition of various land types in the context of ecological process and wildlife habitat (Gergel et al., 2002; Heilman et al., 2002; Jones et al., 2001; Mladenoff et al., 1995; Riitters et al., 2000; Wiens, 2002). Land managers can use information derived from such studies to understand better the form of land that best supports biota and ecosystem services and make more informed decisions about how to alter or utilize land. The current study applies such landscape measurement techniques using metrics not to assess habitat or ecological function, but rather the human process of renewable energy production.

To investigate the patterns of usable abandoned cropland and its utility for renewable energy production, this study poses two research questions:

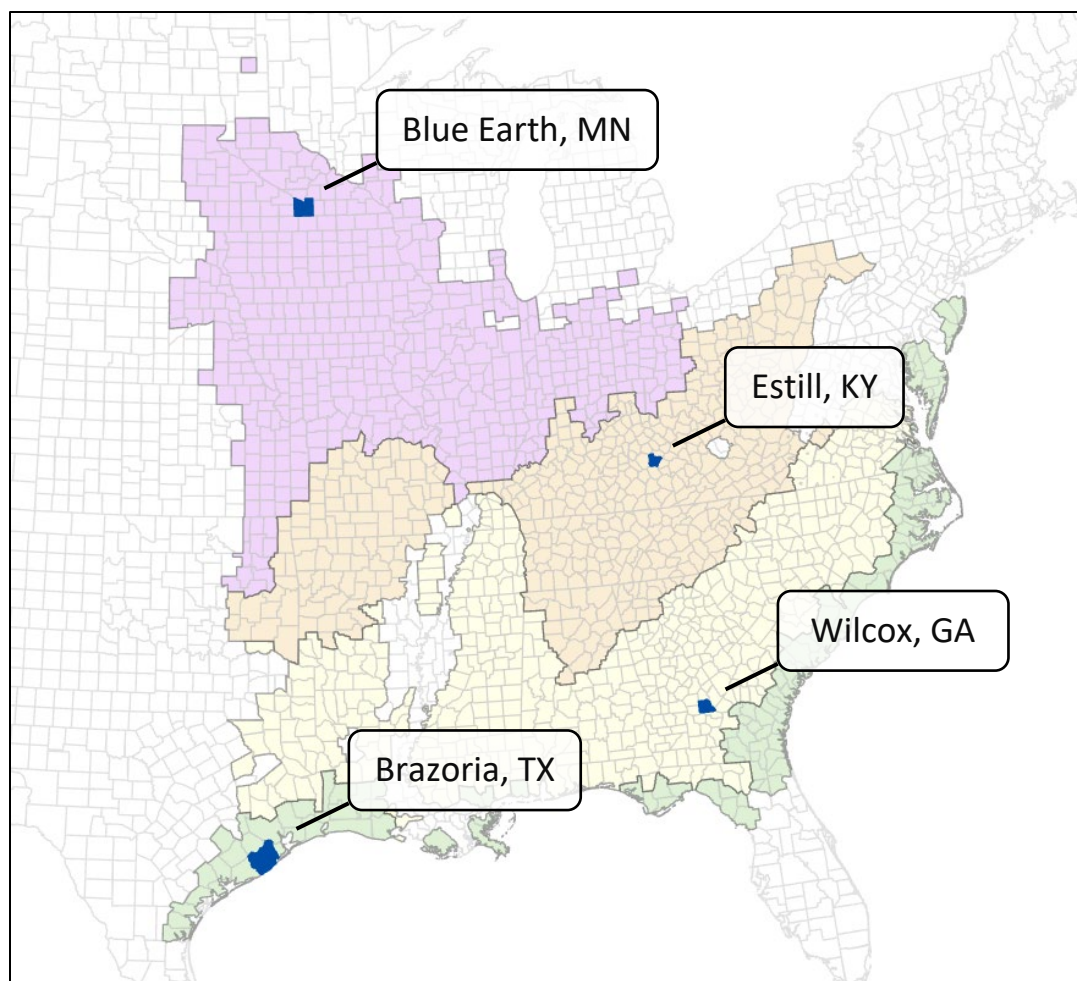
1. Does usable abandoned cropland emerge in different spatial patterns in different regional landscapes of the United States when projected over 50 years?
2. Are the spatial patterns of emergent usable abandoned cropland in some regions of the United States more favorable to renewable energy production?

To address these research questions, two hypotheses are tested:

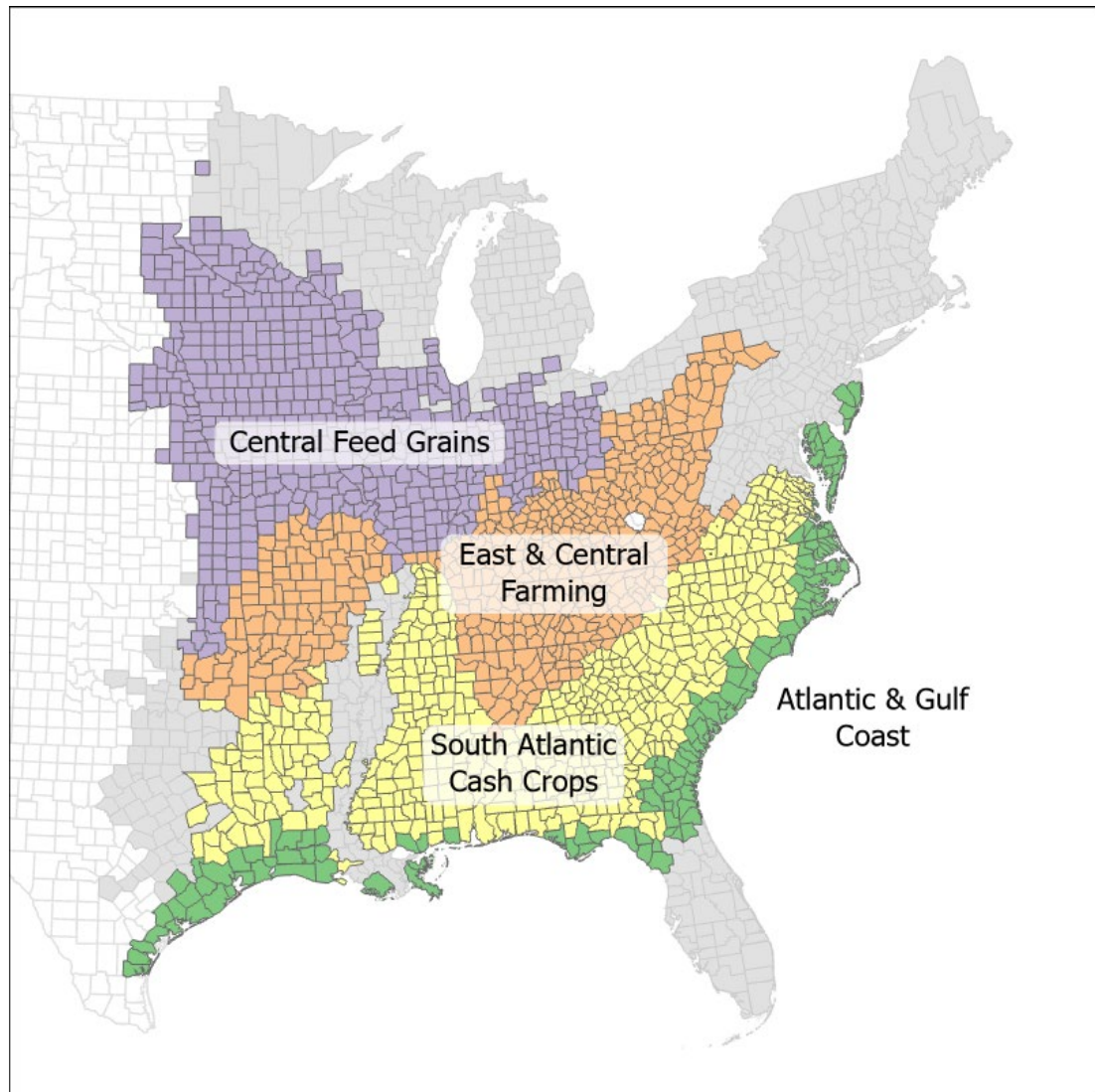
1. Counties in different regions in the United States present unique patterns of emergent usable abandoned cropland (H1).
2. The patterns of usable abandoned cropland in some counties are more favorable for renewable energy production than counties in other regions (H2).

## **1.1. Study Area**

Four counties in the United States are selected for analysis in this study. These counties are Blue Earth, Minnesota Brazoria, Texas, Estill, Kentucky, and Wilcox, Georgia (Figure 4.1). These counties are chosen because they each occur within one of the four regions studied in the previous chapter. The four regions are distinct agricultural zones defined by the USDA Land Resource Region (LRR) map (FIGURE 4.2). Other criteria for selecting counties are that they have above average amounts of UACL (i.e., a total UACL area greater than the mean for all counties in the region) and where the fraction of the counties' total area that is cropland is greater than the mean percentage for all counties in the region. The mean values for UACL and percent of county area in cropland are shown in Table 4.1. Counties were also selected based on where the NLCD trend in cropland aligned with the Census of Agriculture; Blue Earth, Brazoria, and Wilcox counties show general agreement between the two datasets but Estill shows an inverse trend in cropland change.



**Figure 4.1.** County study areas.



**Figure 4.2.** Land Resource Regions included in this study.

**Table 4.1.** Mean values of UACL (fraction of total cropland area) and amount of cropland (fraction of total county area that is cropland) for each region.

<i>Region</i>	<i>UACL</i>	<i>Cropland</i>
<i>Central Feed Grains (Blue Earth, MN)</i>	0.0226	0.6824
<i>East &amp; Central Farming (Estill, KY)</i>	0.1052	0.1368
<i>South Atlantic Cash Crops (Wilcox, GA)</i>	0.1426	0.1038
<i>Atlantic &amp; Gulf Coast (Brazoria, TX)</i>	0.1068	0.1292

## 1.2. Modeling Framework

Projections of future land use patterns are performed using a spatial land change model that projects the expansion of abandoned agricultural land, and implicitly accounts for direct and indirect land use changes. The spatial model chosen here is the Dynamic Conversion of Land Use and its Effects at Small regional extent (Dyna-CLUE) model (Verburg & Overmars, 2009). Different versions of this model have been widely used to project land use change under different scenarios, drivers, and underlying conditions (Easterling & Kok, 2002; Hellmann & Verburg, 2011; Veldkamp & Fresco, 1996; Verburg & Overmars, 2007; Waiyasusri & Wetchayont, 2020).

The Dyna-CLUE model is chosen because it best addresses the theoretical criteria discussed in earlier chapters. Accordingly, the model falls into the following relevant categories: it is spatially explicit, relying on existing land use and landscape characteristics to explain future change in land use; it follows a top-down approach, which is appropriate here, as the primary driver of change originates at a high hierarchical level in the form of the county-level estimates of usable abandoned cropland (UACL) from previous chapters along with national/regional demands for biofuel in response to climate change and energy demand; it is descriptive, in that it is based on the actual land use and the processes that operate within it, as opposed to prescriptive models that aim to produce optimized land use configurations that meet a set of criteria and objectives; and finally, it is dynamic by incorporating competition among land uses, irreversibility, path dependence and fixed land use trajectories (P. Verburg et al., 2006).

The National Land Cover Dataset (NLCD) (Dewitz, 2021) is used as the initial land cover map input to the Dyna-CLUE model. The NLCD is produced every ten years,

most recently in 2016. It would be possible to simply compare multiple years of NLCD land cover maps to determine how much and where cropland is abandoned; cultivated crops is one of the land cover types included in the NLCD. This would be a reasonable approach; however, it has two disadvantages. First, NLCD cannot be used on its own to project future land use, but rather only to compare previous changes. The current study aims to project future cropland abandonment and measure its pattern and configuration. This would not be possible with the NLCD. Second, the reported accuracy of NLCD raises questions about its reliability as a definitive source of land change information and is a primary reason for not relying on it entirely.

Wickham et al. (2021) details the accuracies of both the 2006 and 2016 NLCD products. Overall accuracies of land type classifications are 83.6 and 86.4% respectively for 2006 and 2016. The cultivated crops class itself has accuracies of 86 and 89% respectively. These numbers are quite high and suggest confidence in the NLCD to present land cover in each year. However, when identifying pixels that change from one class to another, the NLCD is less accurate. The accuracy of identifying pixels that change to agriculture (cultivated crops or pasture) from 2006 to 2016 is 33% and pixels that change from agriculture to another class between 2006 and 2016 is 27%. As a static representation of LULC at a point in time, NLCD provides a reasonable data source. However, the NLCD's ability to accurately identify changes in a pixel's LULC from one time period to another is quite poor, particularly for the agriculture classes.

NLCD is good at classifying the bulk of pixels in a particular land class because the majority of pixels in each class do not transition to another class; the majority of pixels in a class remain in that class between time periods. It is the pixels at the margins,

which convert to another class, for which NLCD has poor accuracy. The pixels converting from one class to another represent a small fraction of the total pixels in each class, so this poor accuracy does not significantly impact NLCD's overall accuracy measures. However, it is precisely these marginal pixels that the current study is interested in. Therefore, NLCD is a reliable source for observing the general distribution of land types but not their change in quantity or spatial configuration, thus supporting the use of a land change model, like Dyna-CLUE, to determine locations of change.

Comparing images, and derived products like the NLCD, from the same remote sensing instrument, like Landsat, across multiple time periods is an example of homogeneous change detection (Homo-CD) (Lv et al., 2022). A potential area for future research from the current study is to use imagery from different sensors across time periods to detect land change, or heterogeneous change detection (Hete-CD). An advantage of Hete-CD is that imagery is more likely available at a greater variety of time periods, whereas a single remote sensing product may only be available at regular time intervals that do not coincide with the needs of the study. Hete-CD has been shown to be an effective method and has advantages that complement the strengths of traditional Homo-CD techniques (Ayhan & Kwan, 2019; Lei et al., 2022; Lv et al., 2022; Touati et al., 2018). This approach may be an improvement over simply comparing multiple years of a dataset like the NLCD.

Another complication for the NLCD is its disagreement with land change quantities with the Census of Agriculture (United States Department of Agriculture, 2017). For example, Estill, KY had 13,041 acres of Harvested Cropland in 2007 and 11,062 acres in 2017, based on the US Census of Agriculture (Table 4.2). This is a



reduction in cropland of 1,979 acres. NLCD, on the other hand, shows 6,813 pixels (14,777 acres) of Cultivated Crops in 2006 and 8,605 pixels (19,137 acres) in 2016, which represents an increase of 4,360 acres. This illustrates the challenge of identifying LULC types from remote sensing data sources, which the NLCD does. Discriminating among classes such as cultivated crops, pasture, and grassland is particularly challenging and is likely the reason that the NLCD acreages for cropland differ from the Census of Agriculture.

**Table 4.2.** Comparison of cropland areas reported by the NLCD and the Census of Agriculture from 2006 to 2016. (Census of Agriculture dates are in parentheses. The Census is conducted every five years and 2007 and 2017 are the closest dates that match the NLCD.)

<i>Estill County, KY</i>	<i>Census of Agriculture</i>	<i>NLCD</i>
<i>2006 (2007)</i>	13,041	14,777
<i>2016 (2017)</i>	11,062	19,137
<b><i>Net Change</i></b>	<b>-1,979</b>	<b>4,360</b>

NLCD acknowledges that its accuracy in identifying locations of change in agricultural classes is particularly poor (Wickham et al., 2021). Baxter and Calvert (2017) argue that data from the Census of Agriculture is more accurate than remote sensing-based datasets. Furthermore, studies have shown that landscape patterns and composition are influenced by error in the underlying land cover data (Burnicki, 2012). The inaccuracies in the NLCD, particularly its representation of land change, may lead to erroneous measures of landscape pattern, which is a critical component of the current study. For these reasons, the current study utilizes NLCD as the initial land cover map

but relies on the Census of Agriculture to derive rates of change of agricultural areas and on Dyna-CLUE to determine the locations of change.

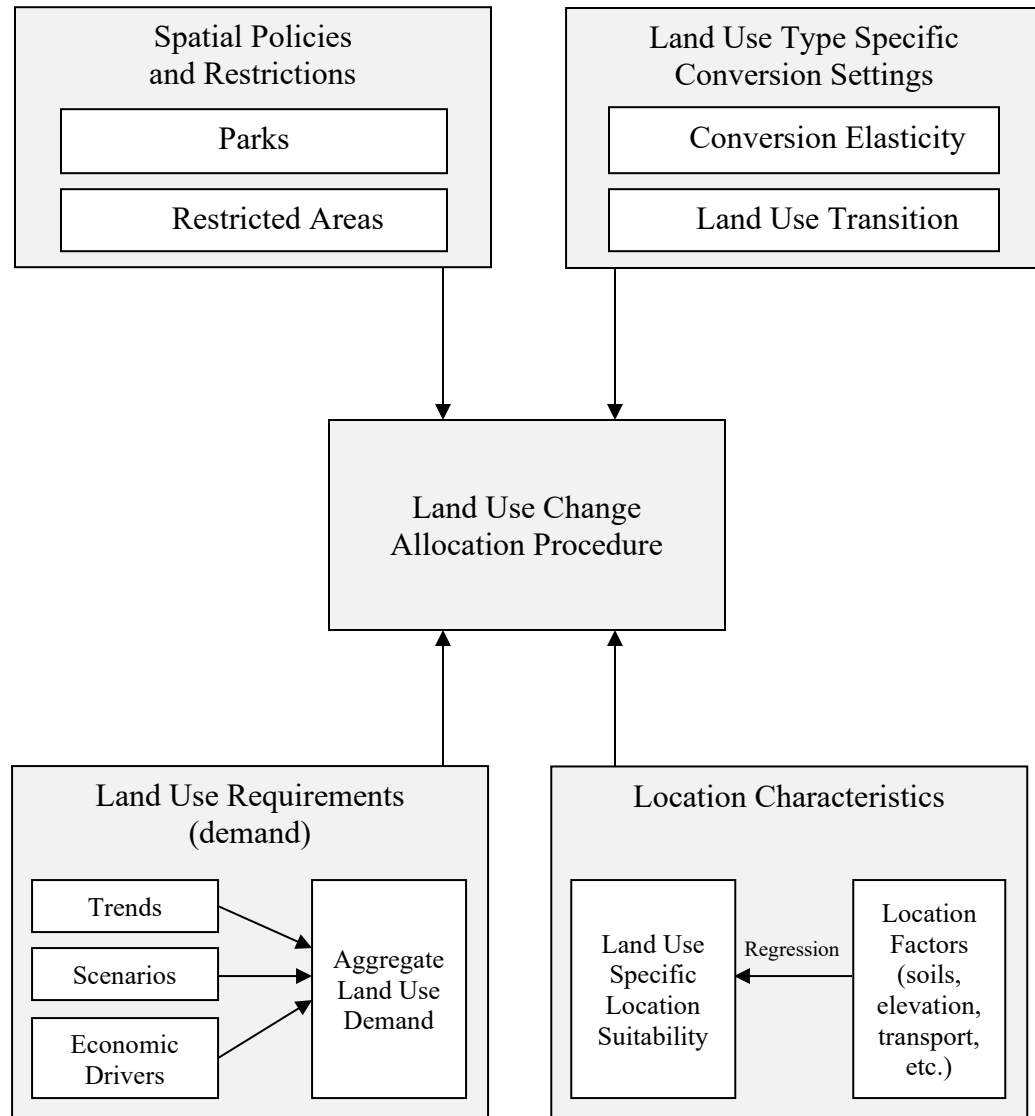
### **1.3. Model Description**

The Conversion of Land Use and its Effects modeling framework (CLUE) (Veldkamp & Fresco, 1996; Verburg et al., 1999) is developed to simulate land use change using empirically quantified relations between land use and its driving factors in combination with dynamic modeling of competition between land use types. The model is initially intended for national and continental levels and applications. For study areas with such a large extent the spatial resolution for analysis is coarse and, as a result, each land use is represented by assigning the relative cover of each land use type to each pixel. In contrast, land use studies of smaller spatial extents are typically based on land use maps or remote sensing images that represent land use types by assigning a single land type to each pixel, indicating the dominant land type in that location. To reflect this fundamental difference in data structure and spatial extent, the modelling approach has been modified and renamed CLUE-S (the Conversion of Land Use and its Effects at Small regional extent). CLUE-S is specifically developed for the spatially explicit simulation of land use change based on an empirical analysis of location suitability combined with the dynamic simulation of competition and interactions between the spatial and temporal dynamics of land use systems. The most recent version of the CLUE model includes autonomous developments through bottom-up simulation (Verburg, 2007). This version is called Dyna-CLUE and is what the current study employs.

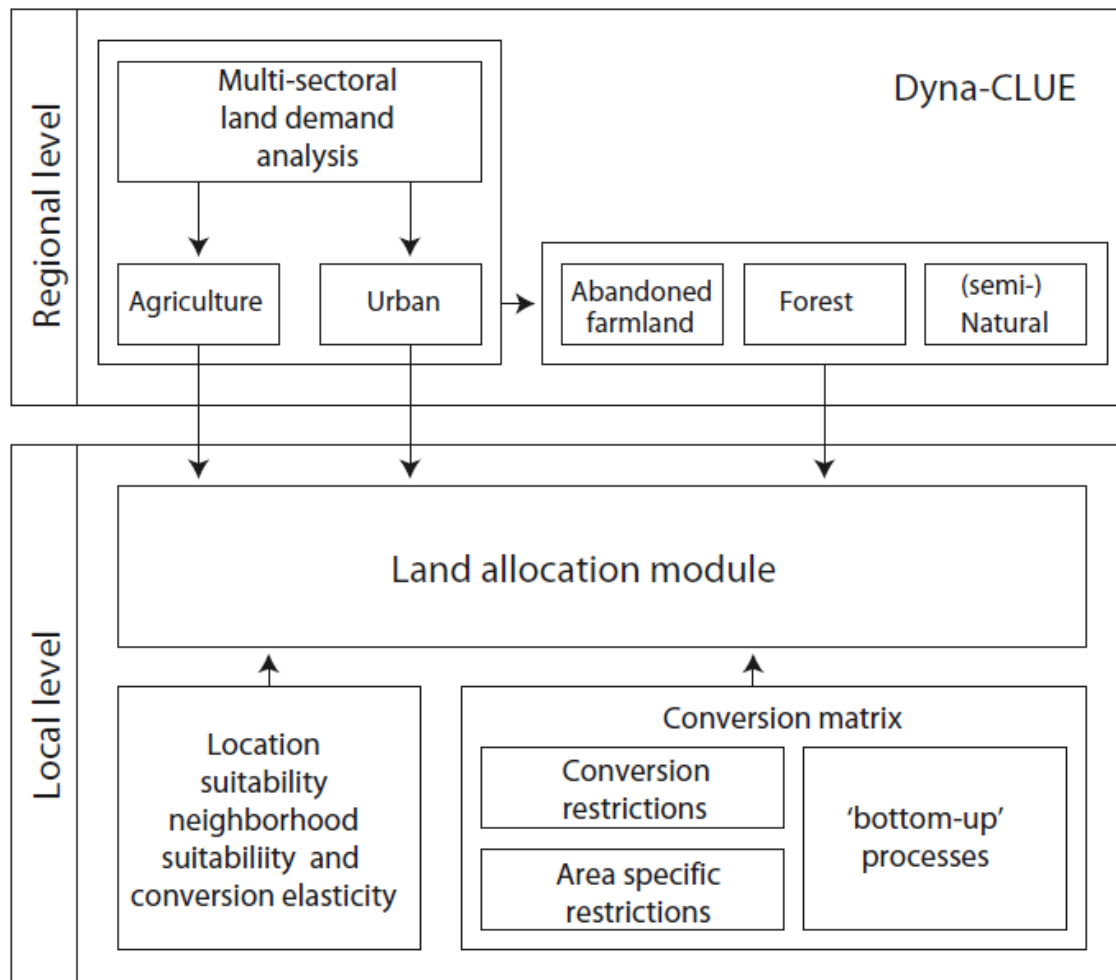
There are two primary components to the Dyna-CLUE model: a non-spatial demand component, and a spatial land use allocation component. The demand component

provides the model the quantity of land cover types on a yearly basis that must be allocated across the spatial landscape. I use scenarios of the quantity of UACL derived in the earlier analysis as the net change of agricultural land use over the entire time period, the total amount of which will be divided by the number of years to derive the annual increments.

The lower two boxes of Figure 4.3 illustrate the demand (non-spatial) and location suitability (spatial allocation) components of the model. The demand component forces annual changes to the amounts of each land cover type, while the location suitability component guides where on the landscape the changes will occur. The Dyna-CLUE model differs from its predecessor, CLUE-S, in part because the area change for some land cover types is not required to be explicitly stated in the demand module (Verburg & Overmars, 2009) (see Figure 4.4). Land cover types that are not specified are grouped into a single category for the purposes of the land allocation process and allowed to convert to those land classes defined in the demand module. Location suitability is determined by an analysis of the land cover types and other underlying factors by performing a regression to determine the relative impact of each factor on land use. The underlying factors are correlated to land cover using a logistic regression that predicts whether a pixel is likely to convert from one land cover type to another. Using the relationships derived by logistic regression, the model can determine the most likely land use conversion at each pixel.



**Figure 4.3.** Overview of the CLUE-S land allocation procedure (Adapted from P. H. Verburg et al. (2006).



**Figure 4.4.** Overview of the inputs to the land allocation module of the Dyna-CLUE model (Verburg & Overmars, 2009).

The model can be parameterized to account for restrictions or requirements for certain land use conversions. The upper two boxes of Figure 2 illustrate some of these configuration options. Parameters include: the ability to restrict certain areas from converting to certain land use types, for example parks or protected areas; specific land transition sequences, for example agriculture always converting first to grassland and only to forest after a certain amount of time has elapsed; and conversion elasticities, which define how likely it is for a land type to convert at all, for example, it is very

unlikely that an urban land cover type will undergo a conversion to forest or grassland, whereas it is relatively likely that forest or grassland might convert to an agricultural land use.

Land use sequences are defined in a matrix that specifies whether each land use type is allowed or not allowed to convert to each other land use type. See Figure 4.5 for the scenario used in this study where only a conversion from cropland to grassland is allowed. Additionally, time constraints that restrict certain land conversions only after a specified period of time has elapsed can be specified. The model runs at a yearly interval. For each yearly step, the model first identifies pixels that can convert to another land use, excluding ones that are in a protected area or are not able to convert due to time constraints. The model iterates through all possible pixels to determine the likelihood of each to convert to another land type, based on the regressions with underlying factors, and assigns new land types to the most likely candidate. The model continues to iterate until the total amounts of each land cover type determined by non-spatial demand component have been allocated on the map. In this study, the model is parameterized such that demand for UACL is specified as an explicit increase in a grassland category and will be configured in the conversion matrix to specifically replace cropland pixels.

	Open Water	Dev. Open Space	Dev. Low Intensity	Dev. Medium Intensity	Dev. High Intensity	Bare Rock	Deciduous Forest	Evergreen Forest	Mixed Forest	Shrub/Scrub	Grasslands	Pasture/ Hay	Cultivated Crops	Woody Wetlands	Emergent Herb. Wetlands
Open Water	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dev. Open Space	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Dev. Low Intensity	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Dev. Medium Intensity	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Dev. High Intensity	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Bare Rock	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Deciduous Forest	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Evergreen Forest	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Mixed Forest	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Shrub/Scrub	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Grasslands	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Pasture/Hay	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Cultivated Crops	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
Woody Wetlands	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Emergent Herb. Wetlands	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

**Figure 4.5.** Land type conversion matrix. 1 = land conversion is allowed, 0 = land conversion is not allowed. Initial land type along the left, destination land type across the top.

## 2. Data and Methods

### 2.1. Data

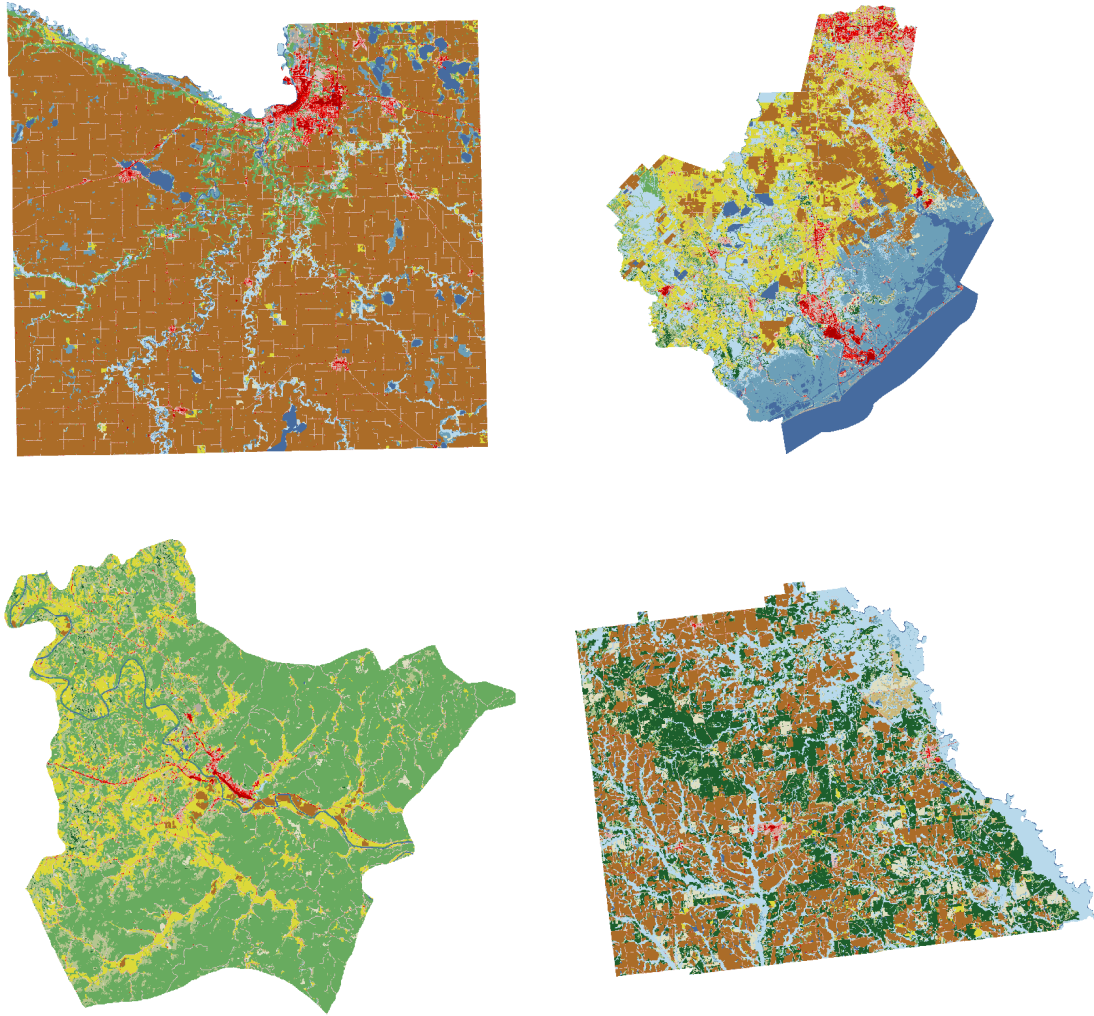
The Dyna-CLUE model is run to project the future distribution of land uses across the landscape. The data inputs to this model consist of spatial layers at a 30-meter

resolution, representing the land cover and predictor variables, which adequately matches the scale of the core process (agricultural land use) being studied. The National Land Cover Database (NLCD) is the map of land use types that serves as the foundation of the modeling exercise (Dewitz, 2021). Among the land classes included in the NLCD is Agriculture (Cultivated Crops); it is the target land class that this study is interested in as the model forces changes to the quantity of this land use in the study area and ultimately reveals the location and configuration of abandoned cropland. See Figure 4.6 for a legend of the land classes included in the NLCD and Figure 4.7 for maps showing the initial NLCD land cover in the four counties in 2006.



**Figure 4.6.** NLCD Land Cover Types (Dewitz, 2021).





**Figure 4.7.** 2006 NLCD land cover. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right). (Maps are not to scale.)

A suite of additional variables that describe the landscape are converted to rasters at the same 30-meter resolution as the NLCD land cover map. These layers represent potential underlying drivers of land use. Slope is calculated from the USGS National Elevation Database (United States Geological Survey, 2023), demographic variables (median age, household size, percent of the population that is non-white, population density, and percent of households that are renting) come from the US Census Bureau

(United States Census Bureau, n.d.), and soils data (crop productivity (NCCPI), drought vulnerability, flooding frequency, soil organic matter, and soil water availability) come from the USDA gSSURGO database (United States Department of Agriculture, 2023). See Appendix C for definitions of the gSSURGO variables. A challenge of statistical models, such as the one employed here, is that the factors included in the model must be carefully selected to avoid spurious correlations with irrelevant factors and to avoid inadvertently excluding factors of importance. These 11 factors are not a comprehensive list of every potential driver of cropland abandonment but represent a sample of such factors. Tables 4.3 – 4.6 shows summary statistics of each predictor variable within each region and Appendix D show maps of each factor for each study region.

**Table 4.3.** Summary statistics for predictor variables in Blue Earth County, MN.

<b>Variable</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>SD</b>
<i>Slope (%)</i>	0.000007	50.74	2.052	3.727
<i>NCCPI (0 – 1, low – high productivity)</i>	0.06	0.925	0.7261	0.1718
<i>Median Age (age)</i>	5.5	94.5	46.11	13.87
<i>Household Size (people)</i>	1	8	2.556	0.8013
<i>Drought vulnerability (0 – 1, slightly – severely)</i>	2	6	4.405	0.8377
<i>Flooding Frequency (1 – 6, none – very frequent)</i>	1	6	1.218	0.9314
<i>% Non-White (fraction)</i>	0	1	0.01799	0.0802
<i>Pop Density (people per square mile)</i>	0.4842	1253	85.66	665.6
<i>Soil Organic (% weight)</i>	0.65	90	3.971	6.510
<i>Soil Water (cm)</i>	5.5	68.40	31.27	7.716
<i>% Renting (fraction)</i>	0	1	0.1174	0.1984

**Table 4.4.** Summary statistics for predictor variables in Brazoria County, TX.

<b>Variable</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>SD</b>
<i>Slope (%)</i>	0	34.31	0.3329	1.213
<i>NCCPI (0 – 1, low – high productivity)</i>	0.002	0.706	0.3662	0.1168
<i>Median Age (age)</i>	3.8	96.5	43.457	10.10
<i>Household Size (people)</i>	1	8	2.6817	0.6510
<i>Drought vulnerability (0 – 1, slightly – severely)</i>	2	6	2.527	0.8008
<i>Flooding Frequency (1 – 6, none – very frequent)</i>	1	7	1.956	1.245
<i>% Non-White (fraction)</i>	0	1	0.8075	0.2060
<i>Pop Density (people per square mile)</i>	0.1618	105100	325.1	1130.9
<i>Soil Organic (% weight)</i>	0.11	3.5	1.815	0.8238
<i>Soil Water (cm)</i>	3.04	39.02	25.54	7.228
<i>% Renting (fraction)</i>	0	1	0.1530	0.1884

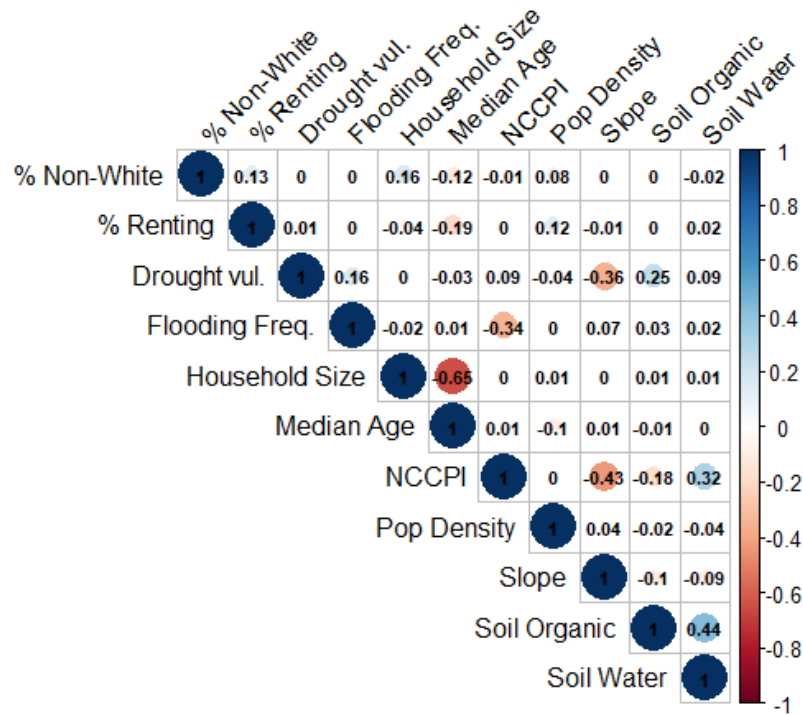
**Table 4.5.** Summary statistics for predictor variables in Estill County, KY.

<b>Variable</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>SD</b>
<i>Slope (%)</i>	0.000005	61.32	14.92	9.461
<i>NCCPI (0 – 1, low – high productivity)</i>	0.04	0.929	0.2835	0.2225
<i>Median Age (age)</i>	12	80.5	42.68	6.063
<i>Household Size (people)</i>	1	8	2.462	0.2900
<i>Drought vulnerability (0 – 1, slightly – severely)</i>	2	6	3.394	0.8204
<i>Flooding Frequency (1 – 6, none – very frequent)</i>	1	6	1.285	0.9895
<i>% Non-White (fraction)</i>	0	1	0.02130	0.0734
<i>Pop Density (people per square mile)</i>	0.8924	5330	47.70	123.9
<i>Soil Organic (% weight)</i>	0.34	3.61	1.347	1.056
<i>Soil Water (cm)</i>	3.12	40.45	20.16	8.339
<i>% Renting (fraction)</i>	0	1	0.1992	0.1169

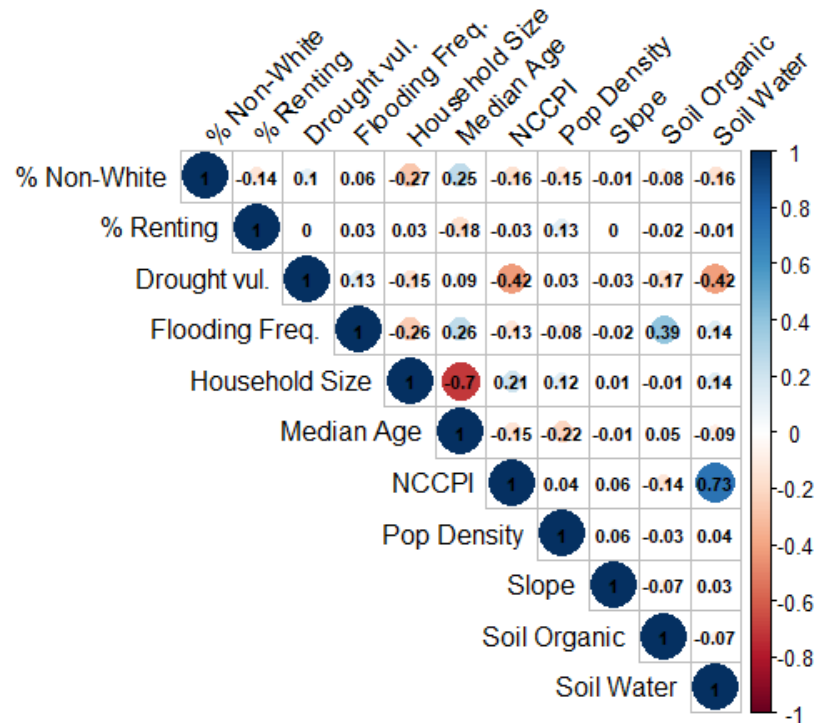
**Table 4.6.** Summary statistics for predictor variables in Wilcox County, GA.

<b>Variable</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>SD</b>
<i>Slope (%)</i>	0.000001	23.99	1.925	1.546
<i>NCCPI (0 – 1, low – high productivity)</i>	0.19	0.766	0.4756	0.1356
<i>Median Age (age)</i>	5.5	88.5	43.55	13.71
<i>Household Size (people)</i>	1	6	2.518	0.7027
<i>Drought vulnerability (0 – 1, slightly – severely)</i>	2	5	3.257	1.001
<i>Flooding Frequency (1 – 6, none – very frequent)</i>	1	6	1.590	1.561
<i>% Non-White (fraction)</i>	0	1	0.1517	0.2617
<i>Pop Density (people per square mile)</i>	0.5249	121300	29.30	861.9
<i>Soil Organic (% weight)</i>	0.16	2.06	0.3747	0.3023
<i>Soil Water (cm)</i>	10.2	31.1	19.94	4.583
<i>% Renting (fraction)</i>	0	1	0.1585	0.2200

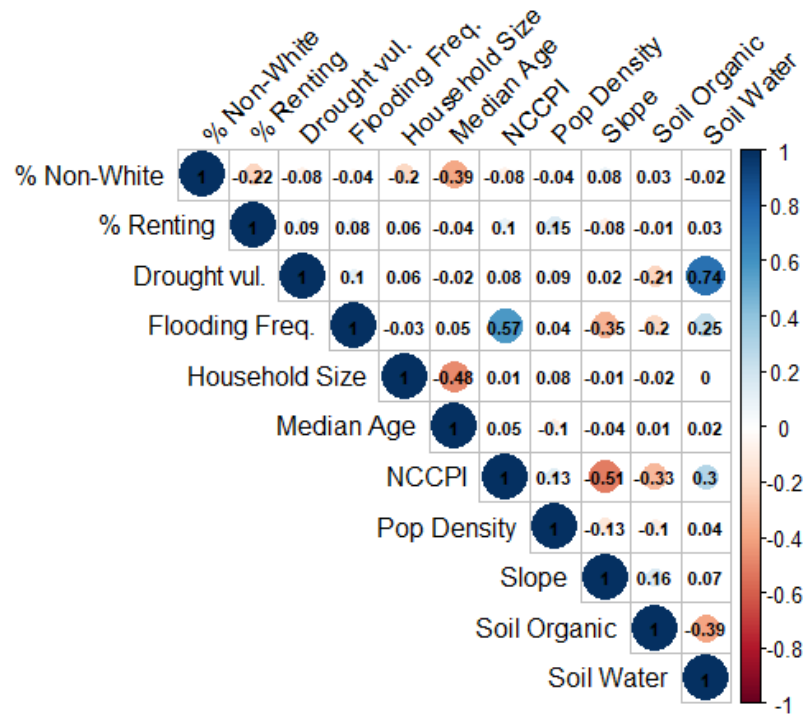
Correlations between each pair of predictors show little collinearity among the variables. Figures 4.8 – 4.11 show variable correlation matrices of predictor variables for each of the analysis counties. Household size and median age show a larger correlation than most other pairs of variables. This is true across all regions, but to a lesser degree in Estill, KY. A few physical characteristics, like soil water availability, show collinearity with other variables but not to a great degree. Because only a few variables show some collinearity, correlation coefficients are only above 0.6 in a few cases, and no variables are correlated above 0.6 in every county, all variables are retained in the logistic regression analysis.



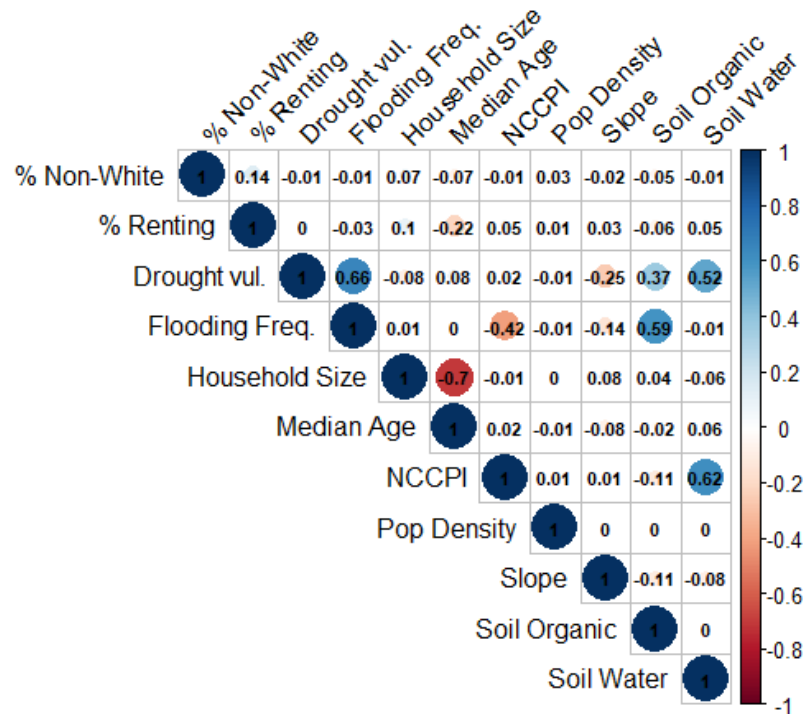
**Figure 4.8.** Predictor variable correlation matrix for Blue Earth County, MN



**Figure 4.9.** Predictor variable correlation matrix for Brazoria County, TX.



**Figure 4.10.** Predictor variable correlation matrix for Estill County, KY.



**Figure 4.11.** Predictor variable correlation matrix for Wilcox County, GA.

## 2.2. Pattern Analysis

Areas of usable abandoned cropland are the interest of this study. As such, metrics at the class level are appropriate, rather than those at the patch or landscape level. The class level measures the composition and pattern of one land type, whereas patch-level metrics measure the properties of individual patches and landscape-level metrics measure the composition and distribution of all land types across the entire landscape. Previous studies have found that a select few metrics adequately describe landscape patterns (Li & Reynolds, 1995; Li & Reynolds, 1994; McGarigal, 1995; Riitters et al., 1995).

Riitters et al. (1995), for example, studied fifty-five metrics and determined their pair-wise correlation coefficients based on their measurements of eighty-five land cover maps. Metrics with a coefficient above 0.9 were grouped together. From each group, one metric was chosen as its representative, and all others were removed. A factor analysis identified five unique characteristics of landscapes: average patch perimeter-area ratio, contagion, average patch area, patch perimeter-area scaling, and number of attribute classes. Some of these characteristics are more appropriate at the landscape level rather than the class level, and therefore not appropriate to the current study. Cushman et al. (2008) performed a similar study and identified seven class-level metrics they determined to be consistent across many regions of the United States. These metric categories align well with the metrics chosen in the current study.

From these categories of metrics, I selected ones that are relevant to the ultimate end use of usable abandoned cropland proposed in this study: renewable energy, in the form of either industrial-scale solar or biomass production. I made these selections based

on my own assessment of the metrics' appropriateness and fitness for assessing the impact of landscape pattern on energy production.

The logistics and productivity of biomass and solar energy production suggest preferable patterns of available land (Ali et al., 2019; Anwarzai & Nagasaka, 2017; Caputo et al., 2005; Liu et al., 2017; Pillot et al., 2020; Ribeiro et al., 2016; Richard, 2010; Ruiz et al., 2013; Uyan, 2013; Watson & Hudson, 2015). Areas that are large, compact, regularly shaped, and close to each other simplify the installation, harvesting and transmission/transport of these energy types. Also, the overall usable area in a county, measured as a percent of the total county's area, suggests greater potential energy production. In light of these observations, I selected the following metrics for inclusion in the analysis: average patch area (AREA\_MN), largest patch index (LPI), edge density (ED), connectance index (CONNECT), patch density (PD), mean perimeter-area ratio (PARA\_MN), aggregation index (AI), and percentage of landscape (PLAND).

To test hypothesis 1 (H1), metrics measuring the spatial patterns of UACL are calculated using Fragstats software (McGarigal et al., 2023). For each region in the analysis, metrics are calculated for each of the 50 years in the scenario. Metrics may be correlated with each other and therefore redundant in an analysis (Cushman et al., 2008; Eigenbrod et al., 2011; Riitters et al., 1995). However, these correlations are observed when comparing metrics across many different regions rather than across different time periods within the same region, making it difficult to calculate correlations in the current study. Recognizing this potential redundancy, all eight metrics are included for comparison across the regions. Cardille and Lambois (2010) demonstrated that including



many metrics, even those that may appear to be redundant, can help to characterize landscapes and distinguish unique landscape types.

To assess the relative suitability of usable abandoned cropland in each region for renewable energy production and test hypothesis 2 (H2), the outputs from the CLUE model are measured using each metric over a 50-year modeling period. The values of each metric are assessed based on how preferable they likely are for energy production (Table 4.7). I made my own assessment of whether a higher or lower value of each metric represents a more favorable landscape pattern. These preferences generally aim toward large, simply shaped patches that are close together.

**Table 4.7.** Landscape metric preference for renewable energy production.

<b>Metric</b>	<b>Renewable Energy Production Preference</b>	<b>Landscape Characteristic</b>
<i>Average Patch Area (AREA_MN)</i>	Higher values	Size and Quantity
<i>Largest Patch Index (LPI)</i>	Higher values	Size and Quantity
<i>Percentage of Landscape (PLAND)</i>	Higher values	Size and Quantity
<i>Edge Density (ED)</i>	Lower values	Shape Complexity
<i>Mean Perimeter-Area Ratio (PARA_MN)</i>	Lower values	Shape Complexity
<i>Connectance (CONNECT)</i>	Higher values	Clustering and Proximity
<i>Patch Density (PD)</i>	Lower values	Clustering and Proximity
<i>Aggregation Index (AI)</i>	Higher values	Clustering and Proximity

AREA\_MN, LPI, and PLAND indicate how large the patches of usable abandoned cropland are and how much of the region they comprise. ED and PARA\_MN indicate how complex the shapes of the patches are; lower values of these metrics mean that the patches are more regularly shaped. CONNECT, PD, and AI indicate how clustered and near to each other the patches of usable abandoned cropland are. Lower values of PD are

preferable in that fewer, large patches are easier to manage in an energy production setting than many, small patches. Rather than attempt to combine these metrics into a single index of renewable energy suitability, as has been done in other contexts like wildlife habitat (Brooks, 1997; Theuerkauf & Lipcius, 2016), this study will compare them individually since there may not be a definitive combination of these measures that is universally preferable across all regions.

### **2.3. Analysis Procedure**

Dyna-CLUE requires several data inputs and parameters. Required data include an ASCII map of the initial NLCD land cover, ASCII maps of each of the 11 predictor variables, the logistic regression coefficients, a conversion matrix of each land type, and the land change demand. (See Appendix E for detailed data processing steps.)

For each study region, data for the predictor variables are converted to a raster data model with a cell size and alignment that matches the 2006 NLCD using ArcGIS Pro software (Esri, 2023). Data obtained from the US Census Bureau are aggregated to census blocks. This is the smallest areal unit at which these data variables are available. Census blocks are much larger than 30m pixels, so the resulting rasters contain large homogenous patches of pixels. There is likely some variation within these patches but it is obscured by the resolution of the source data. Rasters are then exported to an ASCII format to prepare them for statistical analysis. Using the File Convert tool provided by the CLUE model, all predictor rasters along with the NLCD land cover raster are converted into a single text table in which each row is a pixel and each column represents a predictor variable or land cover type. The table contains all cells from the source rasters.

Using R statistical analysis software (R Core Team, 2022) a logistic regression is performed on the table for each region where a land cover type is the dependent variable, and the 11 predictors are the independent variables. For each region, a separate regression equation is generated for each of the 15 land cover types in the NLCD. These regression coefficients are used as inputs to the Dyna-CLUE model.

The conversion matrix specifies to which land types each initial land type is allowed to convert. For example, agriculture is only allowed to convert to grassland; agriculture is not allowed to convert to forest or open water. This study is only interested in the emergence of usable abandoned cropland, all other land conversions are not allowed and only the conversion of cropland to grassland is allowed (Figure 4.5). This simplifies the model and removes conversion detail that is superfluous. For example, knowing the locations where cropland converts to urban development is unnecessary because it does not represent locations of usable abandoned cropland. Also, knowing other conversions such as forest areas that convert to or from grassland is not necessary in this study.

The land change demand input is a list of each year in the model scenario, 50 years in the case of this study, and the explicit land area for each of the 15 land types. In each row (year) of the demand input, the sum of all land types must equal the total area of the entire region. Quantities of each individual land type can vary as long as they still add up to the same total. Appendix F shows the demand input for each region in the current study. All land types are held constant over time, except for a reduction in cropland and an increase in grassland. The amount of decrease in cropland, and commensurate increase

in grassland, is calculated using the rate of emergence of UACL developed in Baxter and Calvert (2017)

Other parameters include conversion elasticities and allowable allocation deviation. Conversion elasticities, on a scale from 0 to 1, specify how likely, or easily, each land type changes. In the current study, all land types are set to 1 to enforce that they will not change, except for cropland and grassland which are both set to 0. Certainly, if the purpose of a land change modeling exercise is interested in the dynamics of other land types, these elasticities would not be parametrized so strictly. Finally, the maximum deviation from the demanded land areas is specified as a percent of the demanded land area. For example, during each annual iteration of the Dyna-CLUE model, pixels are changed in sequence based on the suitability factors in the regression coefficients and the other model parameters until the area of each land type matches the values in the demand input. If the allocated area in the iteration is within the percentage specified in the deviation parameter, the model will consider the allocation complete and move on to the next year. In the current study, for example, the Dyna-CLUE model for Wilcox County, GA has an allowable deviation parameter of 2 percent maximum in any year.

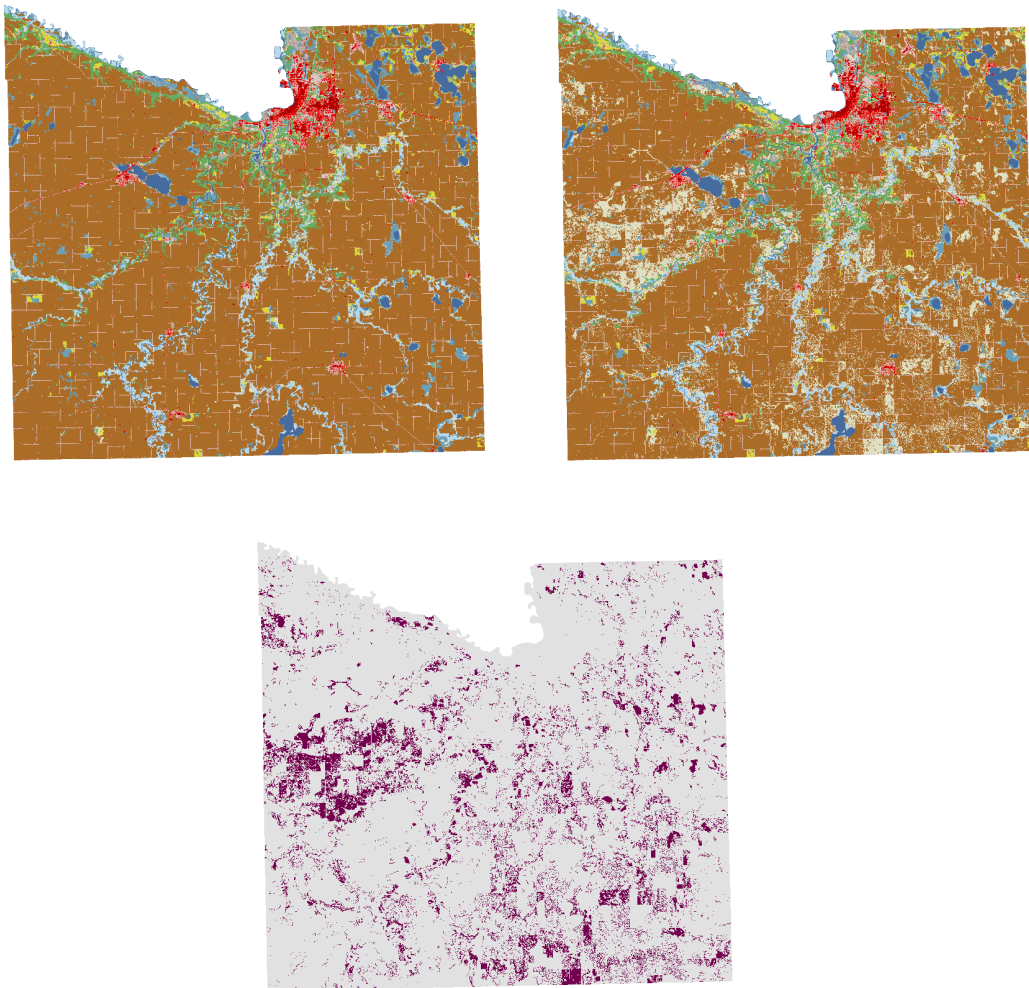
The resulting land cover maps for 2056 are queried using ArcGIS Pro software to select pixels that converted from cropland to grassland to produce a map of UACL for each of the regions. These maps are exported to TIFF images for pattern analysis in Fragstats software (McGarigal et al., 2023).

### **3. Results**

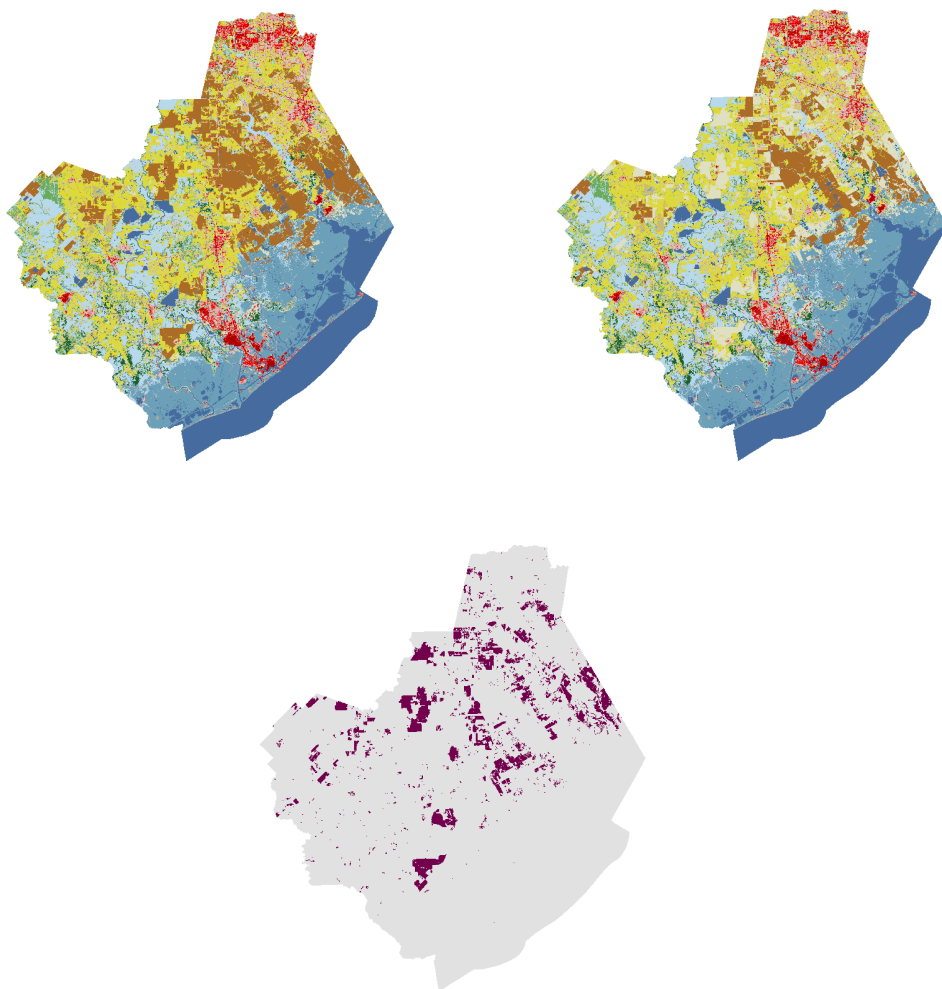
The logistic regression analysis in R produced results where nearly all predictor variables are statistically significant in the prediction of every land type in all regions. All

variables are included for all land cover types. Regression results for each land type in the four regions are presented in Appendix G.

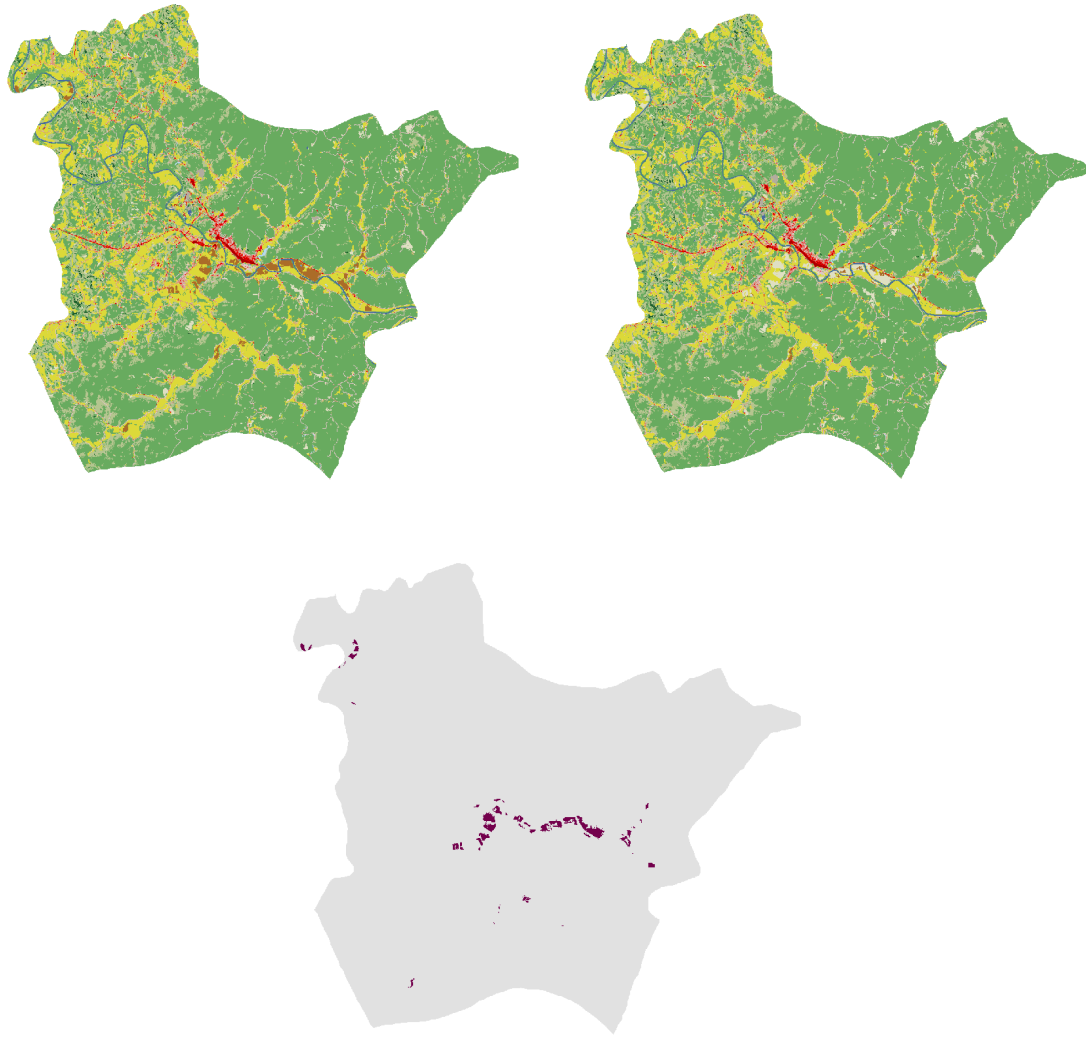
Figures 4.12 – 4.15 illustrate the initial land cover map in 2006, the projected map for 2056, and the areas of emergent UACL for each region. Figure 4.16 shows graphs of each landscape metric calculated for each year of the model scenario in each region.



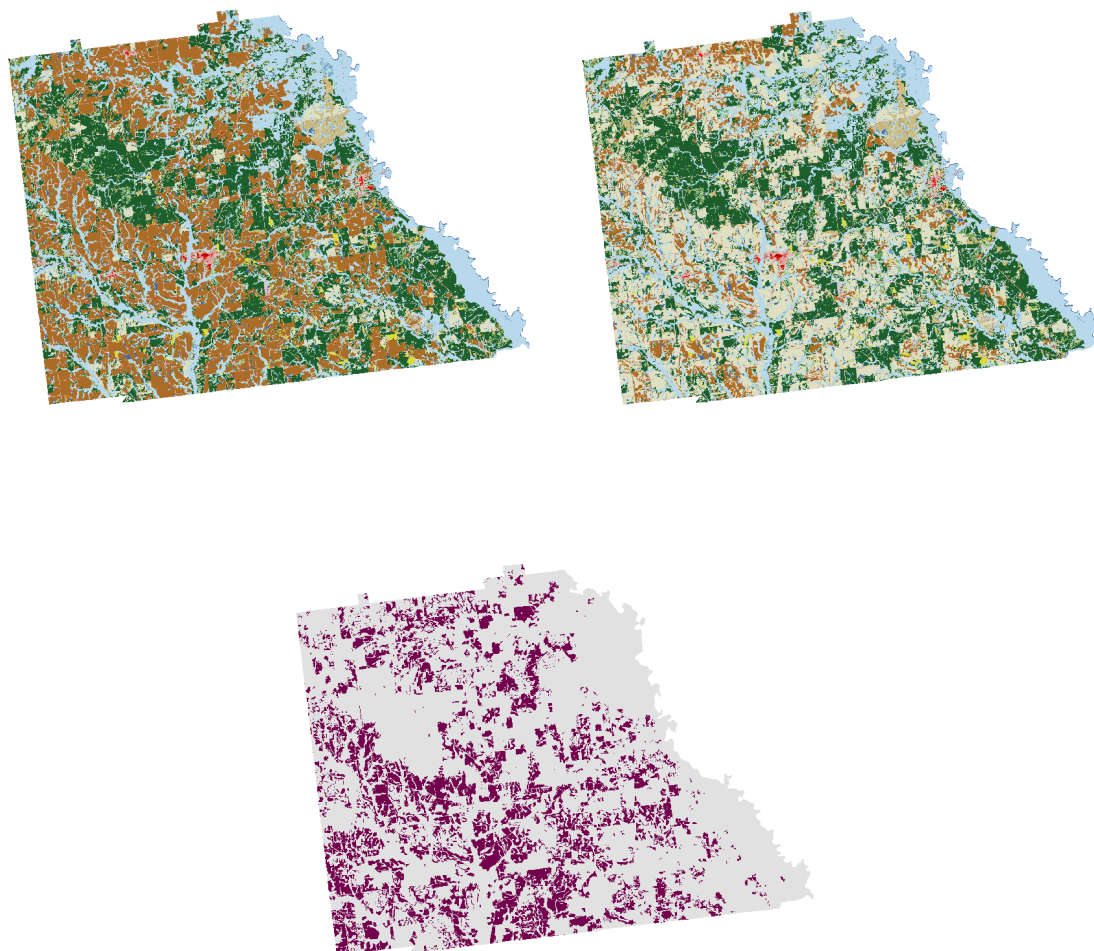
**Figure 4.12.** Blue Earth County, MN. Upper left: initial NLCD land cover map in 2006. Upper right: Modeled 2056 land cover map. Lower: dark areas represent the emergent UACL between 2006 and 2056.



**Figure 4.13.** Brazoria County, TX. Upper left: initial NLCD land cover map in 2006. Upper right: Modeled 2056 land cover map. Lower: dark areas represent the emergent UACL between 2006 and 2056.

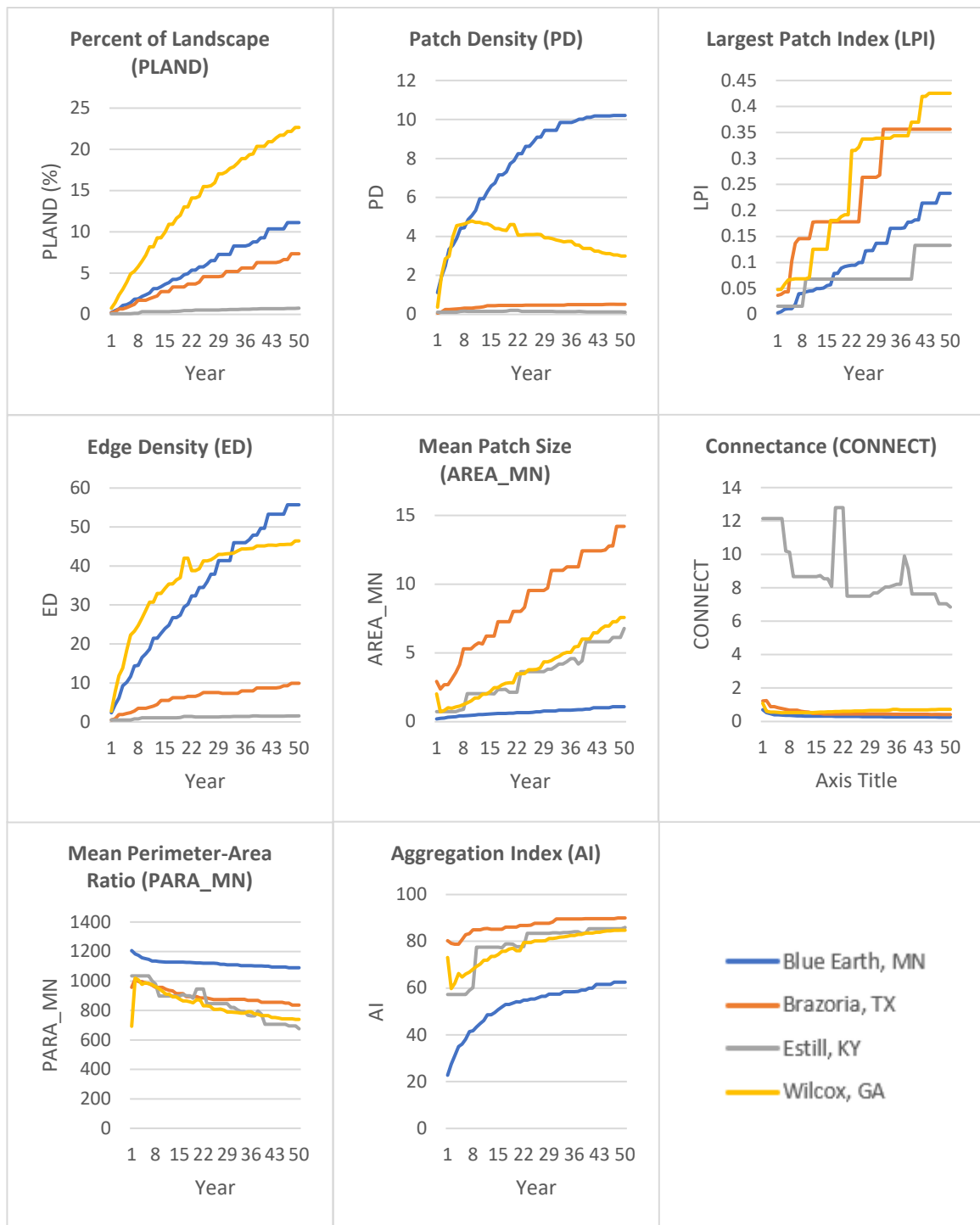


**Figure 4.14.** Estill County, KY. Upper left: initial NLCD land cover map in 2006. Upper right: Modeled 2056 land cover map. Lower: dark areas represent the emergent UACL between 2006 and 2056.



**Figure 4.15.** Wilcox County, GA. Upper left: initial NLCD land cover map in 2006. Upper right: Modeled 2056 land cover map. Lower: dark areas represent the emergent UACL between 2006 and 2056.





**Figure 4.16.** Landscape metrics of UACL plotted over the 50-year modeling scenario for each region.

Several metrics showed similar patterns for each region. AI, PARA\_MN show the closest agreement across regions. In these two cases, however, Blue Earth County, MN is slightly different than the others; its perimeter-area ratio is a bit higher, and its aggregation index is a bit lower. This suggests that the patches of UACL in Blue Earth County, MN are a bit more complexly shaped and distributed more widely. Estill County, KY is more divergent than other regions in some metrics, due in large part to the fact that there is less cropland to begin with relative to the other counties. Interestingly, the CONNECT metric shows much greater connectance, or proximity between UACL patches, in Estill than all other counties. A possible cause of this outlier is that all UACL, and cropland for that matter, is concentrated in a single valley, whereas the other counties have cropland distributed more evenly across the entire landscape.

Patch density (PD), which is a measure of how many patches exist per area of the county, shows some regional differences. Blue Earth County, MN shows the greatest density of patches among the regions, and its value increases over time before levelling off. Wilcox County, GA, on the other hand, initially increases in patch density but then begins to decrease after year ten and continues to decrease steadily through year 50 of the scenario.

All counties show an increase in mean patch size (AREA\_MN) over time. Brazoria County, TX shows the greatest increase while Blue Earth County, MN shows the least increase. This metric along with the aggregation index (AI) suggests that the patches of UACL become larger and more clustered over time. Interestingly, Blue Earth County, MN shows very little increase in mean patch size, suggesting that UACL emerges in small, disjointed patches rather than agglomerating onto existing patches.

A final observation is that Blue Earth County, MN and Brazoria County, TX show an increase in edge density (ED) over time which Estill County, KY and Wilcox County, GA show very little. Edge density is a measure of the complexity of patches' shapes. Blue Earth and Brazoria's patches of UACL develop more complexity while Estill and Wilcox retain more simply shaped patches of UACL. Edge density is calculated by summing the lengths of all patch edges and dividing them by the total area of the county. Interestingly, Blue Earth and Brazoria are the two largest of the four counties. On their own, these large areas would tend to make the calculation of edge density result in lower values. Rather, these counties have higher values of edge density which suggests that the patches of UACL are particularly complex in shape relative to those in Estil and Wilcox counties.

Table 4.8. shows a summary of the relative favorability of each metric in each region. Metric favorability is determined by ranking the 50-year value as higher or lower than the other regions and whether the ordinal value (relatively high or low) aligns with the preferred magnitude of each metric. Brazoria, TX, Estill, KY, and Wilcox, GA aligned with 6, 5, and 4 metric preferences respectively. Blue Earth, MN, however, does not rate more favorably relative to the other regions for any metric.

**Table 4.8.** 50-year projected UACL metrics and preference for renewable energy. “low” and “high” are ordinal rankings of a county’s metric value relative to the other regions. The shading indicates that the ranking aligns with the metric’s preferability for renewable energy production.

Metric	Preference	Blue Earth, MN	Brazoria, TX	Estill, KY	Wilcox, GA
<i>Average Patch Area (AREA_MN)</i>	Higher values	low	high	med	med
<i>Largest Patch Index (LPI)</i>	Higher values	med	high	low	high
<i>Percentage of Landscape (PLAND)</i>	Higher values	med	med	low	high
<i>Edge Density (ED)</i>	Lower values	high	low	low	high
<i>Mean Perimeter-Area Ratio (PARA_MN)</i>	Lower values	high	low	low	low
<i>Connectance (CONNECT)</i>	Higher values	low	low	high	low
<i>Patch Density (PD)</i>	Lower values	high	low	low	med
<i>Aggregation Index (AI)</i>	Higher values	med	high	high	high
<b>Total Aligned Preferences</b>		<b>0</b>	<b>6</b>	<b>5</b>	<b>4</b>

## 4. Discussion

Hypothesis 1 (H1) is accepted based on the results of this study. The landscape metrics measured for the 50-year projected UACL are different for each region. This is true for essentially all eight of the metrics selected for this analysis. Rarely are the plots of metrics for multiple regions exactly the same. The metrics vary both in their rate of change over the 50-year period and in their magnitude in year 50.

Trends in metrics over time follow the same sign of change for all regions with one exception: Wilcox County, GA experiences a decrease in patch density after year 10

while all other regions continue to increase. This suggests that new patches of UACL in Wilcox County initially emerge in isolation from each other, similar to the other regions, but after year 10 new areas of UACL emerge adjacent to existing patches. This results in larger, aggregated patches, more so than the other regions that experience an increase in smaller separate patches. A contributing factor to this difference may be that a larger percentage of the overall landscape in Wilcox County is comprised of UACL. At year 50, Wilcox County is over 20% comprised by UACL while the other regions are around 10% or less.

Hypothesis 2 (H2) is accepted because the favorability of metrics for renewable energy production varies from region to region. This cursory inspection of the metrics results suggests that three of the four regions (Brazoria County, TX, Estill County, KY, and Wilcox County, GA) may be well suited for renewable energy efforts. It is notable that Blue Earth County, MN did not rank more preferably than the other regions for any landscape metric. More research is needed to determine which of these metrics is the most important measure of an area's suitability for renewable energy. It may be the case that some metrics for which regions in this study were favorable are not relevant, perhaps due to poor metric selection or incorrect assumptions about their relevance to renewable energy. Furthermore, since it is likely that only some of the metrics included in this study are relevant or important, the regions that scored preferably in certain metrics may ultimately not be good candidates for renewable energy investment. Despite these potential shortcomings, these results, along with the national level results in the previous chapters, indicate that there is variability across space and scale that is of consequence to renewable energy.

Brazoria County, TX emerges as the region ranking favorably across the most landscape metrics. This county is large in total area, relatively flat terrain, and has large plots of cropland that are abandoned in aggregated portions. Blue Earth County, MN is similarly large with flat terrain. However, the emergence of usable abandoned cropland occurs in a more scattered pattern rather than in large, aggregated areas like in Brazoria. Whether this is an artifact of the model or methodology in this study, or a reflection of the underlying drivers and landscape characteristics requires further investigation. A notable observation is that the edge density of UACL patches in Brazoria County, TX is much lower than the densities in Blue Earth County, MN. This likely due in part to the fact that Blue Earth has many, small patches rather than large, contiguous patches as in Brazoria, but it is also a reflection that the shapes of the usable abandoned cropland areas in Brazoria County, TX are more simple and therefore more favorable for renewable energy production.

## **5. Conclusion**

This study projected the emergence of usable abandoned cropland within four distinct regions of the eastern United States. The projection was based on a spatially explicit land change model that relies on relationships with underlying landscape characteristics to allocate change in the places where it is most likely to occur. Results indicate that each of the four regions exhibits different patterns of UACL. Furthermore, measurements of the size, quantity, shape, and clustering of the emergent areas of UACL show that some regions are more favorable for renewable energy production based on spatial pattern alone. Brazoria County, TX ranked most favorable across more metrics than the other regions. Blue Earth County, MN, on the other hand, did not rank most

favorable in any of the landscape metrics. On the surface, both counties appear to have great potential for renewable energy production on their emergent UACL, but the results of this study suggest that there may be other factors operating in those regions that make them less favorable. Future work is needed to identify which, if any, landscape metrics are good measures of energy production suitability, and whether there are other underlying characteristics or factors that contribute to areas being more or less appropriate for renewable energy. The variability in patterns of usable abandoned cropland across regions and scales presents intriguing insights into the suitability of renewable energy.

## 6. References

- Ali, S., Taweekun, J., Techato, K., Waewsak, J., & Gyawali, S. (2019). Gis based site suitability assessment for wind and solar farms in songkhla, thailand. *Renewable Energy*, 132, 1360-1372. <https://doi.org/10.1016/j.renene.2018.09.035>
- Anwarzai, M. A., & Nagasaka, K. (2017). Utility-scale implementable potential of wind and solar energies for afghanistan using gis multi-criteria decision analysis. *Renewable and Sustainable Energy Reviews*, 71, 150-160. <https://doi.org/10.1016/j.rser.2016.12.048>
- Ayhan, B., & Kwan, C. (2019, 10-12 Oct. 2019). A new approach to change detection using heterogeneous images. 2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON),
- Baxter, R. E., & Calvert, K. E. (2017). Estimating available abandoned cropland in the united states: Possibilities for energy crop production. *Annals of the American Association of Geographers*, 107(5), 1162-1178. <https://doi.org/10.1080/24694452.2017.1298985>
- Brooks, R. P. (1997). Improving habitat suitability index models. *Wildlife Society Bulletin (1973-2006)*, 25(1), 163-167. <http://www.jstor.org/stable/3783299>
- Burnicki, A. C. (2012). Impact of error on landscape pattern analyses performed on land-cover change maps. *Landscape Ecology*, 27(5), 713-729. <https://doi.org/10.1007/s10980-012-9719-2>
- Caputo, A. C., Palumbo, M., Pelagagge, P. M., & Scacchia, F. (2005). Economics of biomass energy utilization in combustion and gasification plants: Effects of logistic variables. *Biomass and Bioenergy*, 28(1), 35-51.
- Cardille, J., & Lambois, M. (2010). From the redwood forest to the gulf stream waters: Human signature nearly ubiquitous in representative us landscapes. *Frontiers in Ecology and the Environment*, 8, 130 - 134.
- Cushman, S. A., McGarigal, K., & Neel, M. C. (2008). Parsimony in landscape metrics: Strength, universality, and consistency. *Ecological indicators*, 8(5), 691-703.



- Dewitz, J. a. U. S. G. S. (2021). National land cover database (nlcd) 2019 products (ver. 2.0, june 2021): U.S. Geological survey data release.  
<https://doi.org/10.5066/P9KZCM54>
- Easterling, W. E., & Kok, K. (2002). Emergent properties of scale in global environmental modeling - are there any? *Integrated Assessment*, 3(2 - 3), 233 - 246.
- Eigenbrod, F., Hecnar, S. J., & Fahrig, L. (2011). Sub-optimal study design has major impacts on landscape-scale inference. *Biological Conservation*, 144(1), 298-305.
- Esri. (2023). *Arcgis pro*. In (Version 3.1.3)
- Fonderflick, J., Azam, C., Brochier, C., Cosson, E., & Quékenborn, D. (2015). Testing the relevance of using spatial modeling to predict foraging habitat suitability around bat maternity: A case study in mediterranean landscape. *Biological Conservation*, 192, 120-129. <https://doi.org/10.1016/j.biocon.2015.09.012>
- Gergel, S. E., Turner, M. G., Miller, J. R., Melack, J. M., & Stanley, E. H. (2002). Landscape indicators of human impacts to riverine systems. *Aquatic Sciences*, 64(2), 118-128. <https://doi.org/10.1007/s00027-002-8060-2>
- Heilman, G. E., Strittholt, J. R., Slosser, N. C., & Dellasala, D. A. (2002). Forest fragmentation of the conterminous united states: Assessing forest intactness through road density and spatial characteristics: Forest fragmentation can be measured and monitored in a powerful new way by combining remote sensing, geographic information systems, and analytical software. *BioScience*, 52(5), 411-422. [https://doi.org/10.1641/0006-3568\(2002\)052\[0411:Ffotcu\]2.0.Co;2](https://doi.org/10.1641/0006-3568(2002)052[0411:Ffotcu]2.0.Co;2)
- Hellmann, F., & Verburg, P. H. (2011). Spatially explicit modelling of biofuel crops in europe. *Biomass and Bioenergy*, 35(6), 2411-2424.  
<https://doi.org/10.1016/j.biombioe.2008.09.003>
- Jones, K. B., Neale, A. C., Nash, M. S., Van Remortel, R. D., Wickham, J. D., Riitters, K. H., & O'Neill, R. V. (2001). Predicting nutrient and sediment loadings to streams from landscape metrics: A multiple watershed study from the united states mid-atlantic region. *Landscape Ecology*, 16(4), 301-312.  
<https://doi.org/10.1023/A:1011175013278>

- Kienast, F., Degenhardt, B., Weilenmann, B., Wäger, Y., & Buchecker, M. (2012). Gis-assisted mapping of landscape suitability for nearby recreation. *Landscape and Urban Planning*, 105(4), 385-399.  
<https://doi.org/10.1016/j.landurbplan.2012.01.015>
- Lei, L., Sun, Y., & Kuang, G. (2022). Adaptive local structure consistency-based heterogeneous remote sensing change detection. *IEEE Geoscience and Remote Sensing Letters*, 19, 1-5. <https://doi.org/10.1109/LGRS.2020.3037930>
- Li, H., & Reynolds, J. (1995). On definition and quantification of heterogeneity. *Oikos*, 280-284.
- Li, H., & Reynolds, J. F. (1994). A simulation experiment to quantify spatial heterogeneity in categorical maps. *Ecology*, 75(8), 2446-2455.
- Liu, W., Wang, J., Richard, T. L., Hartley, D. S., Spatari, S., & Volk, T. A. (2017). Economic and life cycle assessments of biomass utilization for bioenergy products. *Biofuels, Bioproducts and Biorefining*, 11(4), 633-647.  
<https://doi.org/10.1002/bbb.1770>
- Lv, Z., Huang, H., Li, X., Zhao, M., Benediktsson, J. A., Sun, W., & Falco, N. (2022). Land cover change detection with heterogeneous remote sensing images: Review, progress, and perspective. *Proceedings of the IEEE*, 110(12), 1976-1991.  
<https://doi.org/10.1109/JPROC.2022.3219376>
- Mahiny, A. S., & Clarke, K. C. (2012). Guiding sleuth land-use/land-cover change modeling using multicriteria evaluation: Towards dynamic sustainable land-use planning. *Environment and Planning B: Planning and Design*, 39(5), 925-944.  
<https://doi.org/10.1068/b37092>
- McGarigal, K., Cushman, S. A., & Ene, E. (2023). *Fragstats v4: Spatial pattern analysis program for categorical maps*. In <https://www.fragstats.org>
- McGarigal, K. M., B. J. (1995). *Fragstats: Spatial pattern analysis program for quantifying landscape structure*.
- Mladenoff, D. J., Sickley, T. A., Haight, R. G., & Wydeven, A. P. (1995). A regional landscape analysis and prediction of favorable gray wolf habitat in the northern great lakes region. *Conservation Biology*, 9(2), 279-294.  
<https://doi.org/10.1046/j.1523-1739.1995.9020279.x>

- Näschén, K., Diekkrüger, B., Evers, M., Höllermann, B., Steinbach, S., & Thonfeld, F. (2019). The impact of land use/land cover change (lulcc) on water resources in a tropical catchment in tanzania under different climate change scenarios. *Sustainability*, 11(24), 7083. <https://doi.org/10.3390/su11247083>
- Nath, B., Wang, Z., Ge, Y., Islam, K., P. Singh, R., & Niu, Z. (2020). Land use and land cover change modeling and future potential landscape risk assessment using markov-ca model and analytical hierarchy process. *ISPRS International Journal of Geo-Information*, 9(2), 134. <https://doi.org/10.3390/ijgi9020134>
- Pillot, B., Al-Kurdi, N., Gervet, C., & Linguet, L. (2020). An integrated gis and robust optimization framework for solar pv plant planning scenarios at utility scale. *Applied Energy*, 260, 114257. <https://doi.org/10.1016/j.apenergy.2019.114257>
- R Core Team. (2022). *A language and environment for statistical computing*. In (Version R version 4.2.2 (2022-10-31 ucrt)) R Foundation for Statistical Computing.
- Ribeiro, A. E. D., Arouca, M. C., & Coelho, D. M. (2016). Electric energy generation from small-scale solar and wind power in brazil: The influence of location, area and shape. *Renewable Energy*, 85, 554-563. <https://doi.org/10.1016/j.renene.2015.06.071>
- Richard, T. L. (2010). Challenges in scaling up. *Science*, 329, 793-796.
- Riitters, K., Wickham, J., O'Neill, R., Jones, B., & Smith, E. (2000). Global-scale patterns of forest fragmentation. *Conservation Ecology*, 4(2). <http://www.jstor.org/stable/26271763>
- Riitters, K. H., O'Neill, R. V., Hunsaker, C. T., Wickham, J. D., Yankee, D. H., Timmins, S. P., Jones, K. B., & Jackson, B. L. (1995). A factor analysis of landscape pattern and structure metrics. *Landscape Ecology*, 10(1), 23-39. <https://doi.org/10.1007/BF00158551>
- Ruiz, J. A., Juárez, M. C., Morales, M. P., Muñoz, P., & MENDÍVIL, M. A. (2013). Biomass logistics: Financial & environmental costs. Case study: 2 mw electrical power plants. *Biomass and Bioenergy*, 56, 260-267. <https://doi.org/10.1016/j.biombioe.2013.05.014>
- Sahoo, S., Sil, I., Dhar, A., Debsarkar, A., Das, P., & Kar, A. (2018). Future scenarios of land-use suitability modeling for agricultural sustainability in a river basin.

- Journal of Cleaner Production*, 205, 313-328.  
<https://doi.org/10.1016/j.jclepro.2018.09.099>
- Strengers, B., Leemans, R., Eickhout, B., de Vries, B., & Bouwmann, L. (2004). The land-use projections and resulting emissions in the ipcc sres scenarios as simulated by the image 2.2 model. *GeoJournal*, 61, 381 - 393.
- Theuerkauf, S. J., & Lipcius, R. N. (2016). Quantitative validation of a habitat suitability index for oyster restoration [Original Research]. *Frontiers in Marine Science*, 3. <https://doi.org/10.3389/fmars.2016.00064>
- Touati, R., Mignotte, M., & Dahmane, M. (2018, 7-10 Oct. 2018). Change detection in heterogeneous remote sensing images based on an imaging modality-invariant mds representation. 2018 25th IEEE International Conference on Image Processing (ICIP),
- United States Census Bureau. (n.d.). *Data.Census.Gov*. Retrieved from [data.census.gov](http://data.census.gov)
- United States Department of Agriculture. (2017). *Census of agriculture*. Retrieved from [www.nass.usda.gov/Publications/AgCensus](http://www.nass.usda.gov/Publications/AgCensus)
- United States Department of Agriculture. (2023). *Gridded soil survey geographic (gssurgo) database*. Natural Resources Conservation Service. <https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database>
- United States Geological Survey. (2023). *National elevation database*. <https://www.usgs.gov/publications/national-elevation-dataset>
- Uyan, M. (2013). Gis-based solar farms site selection using analytic hierarchy process (ahp) in karapinar region, konya/turkey. *Renewable and Sustainable Energy Reviews*, 28, 11-17. <https://doi.org/10.1016/j.rser.2013.07.042>
- Veldkamp, A., & Fresco, L. O. (1996). Clue-cr: An integrated multi-scale model to simulate land use change scenarios in costa rica. *Ecological Modelling*, 91(1), 231-248. [https://doi.org/10.1016/0304-3800\(95\)00158-1](https://doi.org/10.1016/0304-3800(95)00158-1)
- Verburg, P., Kok, K., Pontius Jr., R. G., & Veldkamp, A. (2006). Modeling land-use and land-cover change. In E. F. Lambin & H. J. Geist (Eds.), *Land-use and land-cover change: Local processes and global impacts*. Springer-Verlag.
- Verburg, P. H. (2007). *Dyna-clue*. In Land Dynamics Group, Wageningen University.

- Verburg, P. H., De Koning, G., Kok, K., Veldkamp, A., & Bouma, J. (1999). A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use. *Ecological Modelling*, 116(1), 45-61.
- Verburg, P. H., & Overmars, K. P. (2007). Dynamic simulation of land-use change trajectories with the clue-s model. In *Modelling land-use change* (pp. 321-337). Springer Netherlands. [https://doi.org/10.1007/978-1-4020-5648-2\\_18](https://doi.org/10.1007/978-1-4020-5648-2_18)
- Verburg, P. H., & Overmars, K. P. (2009). Combining top-down and bottom-up dynamics in land use modeling: Exploring the future of abandoned farmlands in europe with the dyna-clue model. *Landscape Ecology*, 24(9), 1167-1181. <https://doi.org/10.1007/s10980-009-9355-7>
- Verburg, P. H., Schulp, C. J. E., Witte, N., & Veldkamp, A. (2006). Downscaling of land use change scenarios to assess the dynamics of european landscapes. *Agriculture, Ecosystems & Environment*, 114(1), 39-56. <https://doi.org/10.1016/j.agee.2005.11.024>
- Waiyasusri, K., & Wetchayont, P. (2020). Assessing long-term deforestation in nam san watershed, loei province, thailand using a dyna-clue model. *Geography, Environment, Sustainability*, 13(4), 81-97.
- Watson, J. J. W., & Hudson, M. D. (2015). Regional scale wind farm and solar farm suitability assessment using gis-assisted multi-criteria evaluation. *Landscape and Urban Planning*, 138, 20-31. <https://doi.org/10.1016/j.landurbplan.2015.02.001>
- Wickham, J., Stehman, S. V., Sorenson, D. G., Gass, L., & Dewitz, J. A. (2021). Thematic accuracy assessment of the nlcd 2016 land cover for the conterminous united states. *Remote Sensing of Environment*, 257, 112357. <https://doi.org/10.1016/j.rse.2021.112357>
- Wiens, J. A. (2002). Riverine landscapes: Taking landscape ecology into the water. *Freshwater Biology*, 47, 501 - 515.
- Yirsaw, E., Wu, W., Shi, X., Temesgen, H., & Bekele, B. (2017). Land use/land cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of china, the su-xi-chang region. *Sustainability*, 9(7), 1204. <https://doi.org/10.3390/su9071204>

## **Chapter 5. Conclusion**

This dissertation explores abandoned cropland as a land opportunity for renewable energy production. The first chapter presents relevant background context and theoretical concepts. Chapter 2 develops a methodology for calculating how much abandoned cropland exists in the United States. This methodology accounts for forest regrowth, conversion to pasture, and conversion to urban development to determine how much abandoned cropland is still available for other uses, such as biomass production or utility-scale solar. This methodology is flexible and allows the user to specify a historical extent to limit how old the time of abandonment may be. Estimates are calculated with historical limits of 1978 and 2007 to represent scenarios limited by forest regrowth and the renewable fuel standard respectively. This methodology and analysis are performed nationally with the county as the spatial unit of analysis.

Chapter 3 explores the drivers of cropland abandonment. The specific time scenario of 2007 – 2017 is used to determine how much usable abandoned cropland emerges in each county over that timeframe. A suite of other variables representing the economic, demographic, and biophysical characteristics of each county are examined for their correlations with usable abandoned cropland. Four distinct agricultural regions of the United States are chosen as study areas. Random forest regressions are performed to determine which underlying county characteristics are most important to the emergence of usable abandoned cropland. Results show that measures of the rent farmers pay to work their land and the value of the land itself are the most important across all regions. In some cases, it is the static measure of rent and land value in 2007 that is most

important, and in other cases it is the change in rent and the change in land value over time that are most important.

Chapter 4 downscales the exploration of usable abandoned cropland to a 30m spatial resolution within four counties, one selected from each of the four study areas in Chapter 3. A spatially explicit land change model (Dyna-CLUE) is used to project the spatial expression of usable abandoned cropland on the landscape using the rate of abandonment developed in Chapter 2 as the driver of change. The resulting maps are analyzed using metrics that measure the spatial pattern, shape, and distribution of usable abandoned cropland patches. Results show that each county develops a different set of spatial characteristics of the pattern of usable abandoned cropland. The two largest counties, Blue Earth County, MN and Brazoria County, TX, present a contrast of results. Both counties appear to have similar initial underlying characteristics including large parcels of cropland and flat terrain. Blue Earth, however, produces metric values unfavorable to renewable energy production relative to the other counties, and Brazoria produces several metric values that are relatively favorable. These results indicate that the potential land opportunities for renewable energy production on abandoned cropland vary from region to region, and that some characteristic regions may be better suited than others, despite how they may appear on the surface.

This dissertation successfully produces three sets of results: 1) estimates of how much usable abandoned cropland may exist in the United States, 2) what the drivers of usable abandoned cropland may be, and 3) the spatial patterns of emergent usable abandoned cropland in different regions of the country. These results, in and of themselves, represent useful findings that could be used by land managers and

policymakers to assess the potential for renewable energy production on abandoned cropland. Future work is required to expand on these findings in several ways.

First, land change scenarios, like the one employed in Chapter 4, should include other conversion trajectories. In the current study, only cropland was allowed to change to grassland; no other land type conversions are allowed for the purpose of running a simple model for baseline results. Although the conversion from cropland to grassland between year one and the final year of any scenario is the ultimate interest of the analysis, allowing conversions among other land types may influence the ultimate spatial allocations of abandoned cropland. Furthermore, allowing pixels to make multiple conversions over time may introduce complexity that influences the ultimate spatial pattern of abandoned cropland. It is possible that a pixel begins as cropland in year one and converts to grassland, then back to cropland, then to pasture, and then back to grassland over the intervening years.

Second, running complex scenarios requires more expert knowledge of the region of study in order to appropriately parameterize the model. Ultimately, this modeling exercise helps to understand the context within which land change is occurring. Each location exists within a story involving economics, politics, climate, demographics, health, hazards, and many other factors that contribute to the process and patterns of land change. Modeling ideally integrates the known aspects of this story while at the same time helps to reveal other aspects that were previously unknown. It is also possible that extreme events take place in one of two regions that are otherwise similar. Hurricanes, earthquakes, economic crises, and other such events may cause traumatic shifts in the characteristics and trajectories of a place which would influence the ability to completely



understand the processes at work. Simplified models like the ones developed in Chapters 3 and 4 are the first steps in achieving this.

Finally, this study is an exploration of scale and hierarchy. By explicitly spanning from the national to local scales between Chapters 2 and 4, this dissertation investigates the relevance of scale to the process of land change. Factors at broader scales (national/regional), such as the net change in cropland area, influence changes at local scales (county/landscape) by forcing change in the relative areas of each land type. And the underlying characteristics of places guide and influence where and how the changes manifest on the landscape. The drivers explored in Chapter 3 operate at a higher hierarchical level than the underlying forces in Chapter 4. This study explores each level somewhat separately. A more complete systems approach would be required to fully integrate the operators at each scale. This dissertation provides a foundation upon which to build more complex and integrated models to understand the process of cropland abandonment, its drivers, and the potential for emergent lands to support critical new land uses like renewable energy production.

## Appendix A. Data Processing Procedures for UACL Calculation

These procedures include steps for calculating UACL (or AACL) for any time range.

Sections toward the bottom include steps for calculating UACL specifically for 2006 – 2016.

Shapefile called AbandonedCropLandSince1969and1850.shp contains all calculations below.

20141010 – Migrating shapefile to a geodatabase with separate tables for attributes. All of the variables named below should still exist as they are currently named, some in tables starting with “REB” to indicate that they are for my use only. Newer model runs and results will be performed in their own self-contained tables that indicate the range of years for which the analysis is run.

The following is a link to an ESRI document regarding working with Excel files in ArcGIS:

- <http://support.esri.com/es/knowledgebase/techarticles/detail/31793>
- Summary: To add an Excel doc to ArcGIS, the table must conform to the following:
  - Fields being joined must be of the same type (double, text, short, integer)
  - Name of the .xls or .xlsx file must have:
    - No spaces
    - No special characters (only underscores allowed)
    - Not begin with a number
  - The first row of the table must contain the field names:
    - No spaces
    - No special characters (only underscores allowed)
    - Not begin with a number
  - Tabs or worksheets must conform to the same as above.

### 1) Switchgrass on Recently Abandoned (Potential) Cropland

1. Begin with shapefile of counties in the US
  - a. Dissolve features by FIPS code(rejoin attributes from original shapefile, export and rename to make permanent)
  - b. Bring the attribute table (.dbf) into Excel and convert the FIPS\_1 column to numbers
    - i. This is necessary to remove leading spaces from the values
    - ii. Open the table in Access and export back to DBASE4 and replace original .dbf
  - c. Add a new field (Max1969) to store the max crop land value since 1969, which is approximately 40 years prior to the ‘current’ year of 2007.
    - i. Do this by bringing the attribute table into Excel
    - ii. Save the table as AbandonedCropLandSince1969.xlsx

- iii. Use the Max() function to assign the max value from IFC1969M2 to IFC1997M2
    - iv. Copy and paste the new column to itself As Values to remove the function.
    - v. Delete all fields except FIPS\_1 and Max1969 and join back to the shapefile (directly do the join from the .xlsx)
    - vi. Perform the export/join/rename procedure to store the values and remove the join.
  - d. Create a new field (Max69\_ha) to store the values as hectares
    - i. Calculate the field by multiplying Max1969 by .0001
2. Download current (2007) Crop Land area from the 2007 Ag stats (this is considered to be the ‘current’ year, which is approximately 40 years following 1969).
  - a. Use NASS Quick Stats site
    - i. Census, Economics, Farms & Land & Assests, Ag Land, Area, “Ag Land, Cropland – Acres”
  - b. Data manipulated and converted to hectares in TotalCropLandChesBay.xlsx
  - c. New value stored in CurLndHa
  - d. Note: a value of “(D)” in the Ag Census data indicates that the value has been restricted due to privacy concerns. This represents a situation where an individual producer may possibly be identified, for example if they are the only one in the county.
3. Join Ag Stats table to shapefile
  - a. Perform the export/join/rename procedure to store the values and remove the join.
4. Create new field (Aban1969) to store the area of potential crop land abandoned since 1969
  - a. Calculate by subtracting CurLndHa from Max69\_ha (THIS INCLUDES NEGATIVE NUMBERS) (thru 2007)
5. Create new field (1969noNeg) by converting all negative values in Aban1969 to zero.
6. NLCD UPDATE FOR 2012 – SEE NEW PROCEDURE AT END OF DOCUMENT.....
7. Acquire NLCD 1992/2001 Change Product Raster
  - a. All Areas
  - b. Merge the grids into a single raster dataset (Raster dataset in a File Geodatabase NationalNLCD)
8. (The following steps are required as a workaround because Arc cannot run Zonal Stats on large rasters)
9. Clip the National NLCD into 16 smaller blocks using the ClipBlock shapefile.
10. Reclassify each of the 16 grids into two new grids:
  - a. Using the Reclassify tool, create a new grid (Ag2Urb01 - Ag2Urb16) where pixels with value 62 (Ag to Urban) have a value of 1 and all else is 0

- b. Using the Reclassify tool, create a new grid (Ag2Els01 - Ag2Els16) where pixels with values of 61,63,64,65,67,68 (Ag to anything else) have a value of 1 and all else is 0
  - c. NOTE: the agriculture category in the NLCD retrofit dataset includes the pasture/hay classification, which is not intended to be included in the cropland calculation. However, since this analysis calculates the % of agriculture that transitioned to urban, we can assume that the % of true agriculture land uses will be the same as the % of total ag/pasture/hay that transitions.
  - d. ALSO NOTE: since this category includes both cropland and pastureland, we can use this percentage to adjust the amount of abandoned cropland and permanent pastureland in subsequent steps to derive the grand total of Abandoned Agricultural Land.
11. Use the Zonal Statistics tool to calculate the sum of pixels in each raster dataset and create a .dbf table (Ag2Urb01 - Ag2Urb16 and Ag2Els01 - Ag2Els16) for each block.
12. Create a new table (nlcdJoin.dbf) that has the identical county records as the AbandonedCropLandSince1969 shapefile
13. One at a time, join each of the 32 .dbf tables to it and use Calculate Field to write the SUM from the block table to a new field (UrbSum01 - UrbSum16 and ElsSum01 - ElsSum16)
14. Join nlcdJoin.dbf to the AbandonedCropLand shapefile
15. Create two new fields in the county shapefile (AgToUrbn, AgToElse)
16. Use the calculate Field option to sum all 16 Urb values into the AgToUrbn field and all 16 Els values into the AgToElse field
17. Create new field in the county shapefile (AgToAll) as the total Ag change and the sum of AgToUrbn + AgToElse
18. Create new field in the county shapefile (PctUrbCh) to represent the fraction of changed Ag land that went to urban v. anything else by dividing AgToUrban/AgToAll.
19. Create a new field (69toUrbn) to show the portion of abandoned crop land that went to urban by multiplying by the percent of ag land change that transitioned to urban v. total ag land change (PctUrbCh).  $69toUrbn = Aban1969 * PctUrbCh$ .
20. Create a new field (Potent69) to show the amount of cropland abandoned since 1969 that has not transitioned to urban and is therefore a potential resource for switchgrass production.  $Potent69 = Aban1969 - 69toUrbn$ . (Convert any negative numbers to 0.) (thru 2007)
21. Create new attributes for nominal switchgrass yield (Mg/ha) assuming 0 Nitrogen and 100 Nitrogen applied (SGYDN0, SGYDN100)
  - a. Using the updated switchgrass yield model from Dartmouth, produce a raster dataset of switchgrass yield for the CB region.
    - i. PRISM climate data includes normals from 1971-2000.
    - ii. Extracted the Temp and Prcp layers from the Chesapeake Bay analysis folder and imported to a new file geodatabase in the national folder
  - b. Run the model separately for upland and lowland ecotypes.

- c. Export the two grids to the TempGrids file geodatabase
  - d. (May need to close ArcMap to perform the following steps)
  - e. In ArcCatalog, Use the Copy Raster tool to duplicate the lowland grid to the Yields filegeodatabase and name it with the final name (e.g., yldN100)
  - f. Use the Mosaic tool to mosaic the upland grid into the final grid using the MAXIMUM option.
  - g. Calculate Statistics.
  - h. Use this maximum raster in the zonal stats step below.
  - i. Use the Zonal Statistics tool to calculate the average nominal switchgrass yield for each county and populate the new yield attribute in the county layer
22. Create new attributes for the total switchgrass production (Mg) on recently abandoned cropland corresponding to 0, 100 and 200 N applied (SGPDABN0,SGPDABN1,SGPDABN2)
- a. Multiply the failed cropland area by the switchgrass yield to calculate the total switchgrass production ( $\text{Potent69} * \text{SGYDN0} = \text{SGPDABN0}$ ,  $\text{Potent69} * \text{SGYDN100} = \text{SGPDABN1}....$ )
  - b. Convert any negative values to 0.
23. NEW (20140307) Calculations to incorporate calculations back to 1850
24. Repeat steps from sections 1c and d above for calculating the max going all the way back to 1850
- a. Export the attribute table from AbandonedCropLandSince1969.shp and bring into Excel
  - b. Save the table as tempTableFor1850MaxCalc.xlsx
  - c. Create a new field called Max1850
  - d. Use the Max() function to assign the max value from IFC1850M2 to IFC1997M2
  - e. Copy and paste the new column to itself As Values to remove the function.
  - f. Create a new field called Mx1850ha to store the values as hectares
    - i. Calculate the field by multiplying Max1850 by .0001
  - g. Delete all fields except FIPS\_1, Max1850 and Mx1850ha and join back to the shapefile (directly do the join from the .xlsx – THIS DID NOT WORK, had to convert to csv first)
  - h. Export the shapefile to a new one to make join permanent
    - i. New shapefile called: AbandonedCropLandSince1850.shp
25. Create new field (Aban1850) to store the area of potential crop land abandoned since 1850
- a. Calculate by subtracting CurLndHa from Mx1850ha (THIS CONTAINS NEGATIVE NUMBERS)
26. Create new field (1850noNeg) by converting all negative values in Aban1850 to zero.
27. Create a new field (1850toUr) to show the portion of abandoned crop land that went to urban by multiplying by the percent of ag land change that transitioned to urban v. total ag land change (PctUrbCh).  $1850\text{toUr} = \text{Aban1850} * \text{PctUrbCh}$ .

28. Create a new field (Pot1850) to show the amount of cropland abandoned since 1850 that has not transitioned to urban and is therefore a potential resource for switchgrass production.  $Pot1850 = Aban1850 - 1850toUr$ . (Convert any negative numbers to 0.)

**Numbers for current year 2002 (looking back thru 1964, which is approximately 40 years) \*\*this is the best time period to compare against Z&C, who calculate thru 2000:**

1. Create new field, Max1964, to hold the max cropland area that occurred in any year between 1964 and 1997 (in the historical spreadsheet), see above for procedure. 1964 is chosen because it is the closest year in the record to the 40-year time period we established.
2. Create new field, Mx64\_ha, to convert Max1964 to hectares.
3. Create new field, CrpLnd02, to hold the cropland totals for the year 2002 from the USDA NASS Ag Census. (This is in hectares. The files called, 2002Acres.xlsx, are the download from NASS in acres.)
4. Create new field, Aban2002, to hold the abandoned cropland between 1964 and 2002 ( $Max64\_ha - CrpLnd02$ )
5. Create new field, 2002noNeg, to equal Aban2002 with all negative numbers converted to zeros.
6. Create new field, 02toUrbn, to represent the amount of the abandoned cropland estimated to have converted to urban;  $2002noNeg * PctUrbCh$ .
7. Create new field, Potent02, to be the potential abandoned cropland including deduction of the amount estimated to have transitioned to urban since 1964;  $2002noNeg - 02toUrbn$ .

**Numbers for current year 2012 (looking back thru 1974, which is approximately 40 years) \*\*this is the time period for presenting our most up-to-date numbers:**

1. Create new field, Max1974, to hold the max cropland area that occurred in any year between 1974 and 1997 (in the historical spreadsheet), see above for procedure. 1974 is chosen because it is the closest year in the record to the 40-year time period we established.
2. Create new field, Mx74\_ha, to convert Max1974 to hectares.
3. Create new field, CrpLnd12, to hold the cropland totals for the year 2012 from the USDA NASS Ag Census. (This is in hectares. The files called, 2012Acres.xlsx, are the download from NASS in acres.)
4. Create new field, Aban2012, to hold the abandoned cropland between 1974 and 2012 ( $Max74\_ha - CrpLnd12$ )
5. Create new field, 2012noNeg, to equal Aban2012 with all negative numbers converted to zeros.
6. Create new field, 12toUrbn, to represent the amount of the abandoned cropland estimated to have converted to urban;  $2012noNeg * PctUrbCh$ .
7. Create new field, Potent12, to be the potential abandoned cropland including deduction of the amount estimated to have transitioned to urban since 1974;  $2012noNeg - 12toUrbn$ .

8. To calculate Potential Switchgrass Production on the most current abandoned land estimates, create a new field, SGPD12N1, to hold the production totals based on Nitrogen of 100 k/ha on the 2012 land estimate ( $SGYDN100 * Potent12$ )

### **Correction for 1940 – 1945 Definition Change:**

#### **UPDATE:**

Create a new table in the Geodatabase called, “HistoricCroplandUSGS1940Adjusted”, that contains cropland numbers from 1850 to 1997 where values prior to 1945 have been adjusted for the definition change in the Census as Z&C did.

1. Create separate spreadsheet:  
AbandonedCropLandSince1969and18501940Adjust.xlsx
2. Copy all M2 columns
3. Rename the pre-1954 columns with a trailing “c” to indicate that they are corrected.
4. Create new field, 40\_45Dif, to hold the difference between 1940 and 1945 ( $1940 - 1945$ ).
5. Create new field, 4045NoNg, to convert all negative values to zeros.
6. Calculate the “c” columns by subtracting the 4045NoNg values from the original M2 values.
7. In all “c” columns, convert negative values to zeros.
8. Create a new column, Mx1850\_HAc, to hold the Max occurring value in all years dating back to 1850 including the corrected columns. (multiply by .0001 to convert to Hectares)
9. Create a new column, Aban18502002c, to hold the difference between the 1850 Max and the current 2002 cropland ( $Mx1850\_HAc - CrpLnd02$ ) and convert all negative values to zeros at the same time.
10. Create a new column, 1850to2002toURBNc, to hold the % of abandoned cropland that transitioned to urban. ( $Aban18502002c * PctUrbCh$ ).
11. Create a new column, Potent18502002c, to hold the potential abandoned cropland after urban is removed. ( $Aban18502002c - 1850to2002toURBNc$ ).
12. Create a new column, Aban18502012c, to hold the difference between the 1850 Max and the current 2012 cropland ( $Mx1850\_HAc - CrpLnd12$ ) and convert all negative values to zeros at the same time.
13. Create a new column, 1850to2012toURBNc, to hold the % of abandoned cropland that transitioned to urban ( $Aban18502012c * PctUrbCh$ ).
14. Create a new column, Potent18502012c, to hold the potential abandoned cropland after urban is removed. ( $Aban18502012c - 1850to2012toURBNc$ ).

### **Integration with Campbell Data:**

Source data Downloaded from

<https://eng.ucmerced.edu/campbell/AbandonedAG/download.html>

\*\*Repeat the following for the 1964 – 2002 numbers above to get the best comparison with Z&C.....

1. Need to join the Campbell tables to my shae file.
2. Create a new field in shapefile, STABBV, to hold the state abbreviation in order to match Campbell's usage. (used the script in StateNameTranslation.txt)
3. Create new field, CNTYJOIN, in Campbell's and my tables that is the state abbreviation [STABBV] appended to the county name [CNTY\_NAME].
4. Create new field, cntyJnLo, to hold the /county combined names in all LOWERCASE letters.
5. In all tables (my attribute table, noSub and Sub):
  - a. Delete all spaces in cntyJnLo.
  - b. Delete all underscores in cntyJnLo.
  - c. Delete all periods in cntyJnLo.
  - d. Delete all single quotes in cntyJnLo.
6. Change the following counties manually:
  - a. FL, Dade (Miami-Dade) "flmiamidade"
  - b. Alabama, De Kalb to "aldekalb".
7. Join the tables based on cntyJnLo.
  - a. Several 'counties' in Virginia don't exist in Campbell list
  - b. Pinellas county in FL does not exist in Campbell's list
8. Create two new fields, ZC\_SUB and ZC\_noSub, to hold Z&C's abandoned cropland values (with and without urban/forest subtraction)
9. Create new field, CNTYAREA, to hold the total area of each county (ha). Use Calculate Geometry function to populate the values.
10. Create a new field, Pot69\_D, to hold the density of abandoned cropland in each county according to Baxter. Populate it with the calculation:  
Potent69/CNTYAREA.
11. Create a new field, **Pot02\_D**, to hold the density of abandoned cropland in each county according to Baxter. Populate it with the calculation:  
Potent02/CNTYAREA.
12. Create a new field, ZC\_sub\_D, to hold the density of abandoned cropland in each county according to Z&C. Populate it with the calculation: ZC\_sub/CNTYAREA.
13. Create a new field, DensDiff, to hold the difference between ZC\_sub\_D and Pot69\_D. This is the difference in our estimates of abandoned cropland density.
14. Create a new field, **D\_Diff02**, to hold the difference between ZC\_sub\_D and Pot02\_D. This is the difference in our estimates of abandoned cropland density.
15. Create a new field, AreaDiff to hold the difference between ZC\_sub and Potent69. This is the difference in our estimates of abandoned cropland area.
16. Create a new field, **A\_Diff02** to hold the difference between ZC\_sub and Potent02. This is the difference in our estimates of abandoned cropland area.
17. Create a new field, 1850Diff, to hold the difference between ZC\_noSub and 1850noNeg. This is the difference between our estimates going back to 1850 without any adjustments.
18. To compare with his NOSUB numbers, create a new variable, 185097Ha, to be my estimate of abandoned cropland between the max cropland dating back to 1850 and 1997 ((Max1850 - IFC1997M2) \* .0001)



19. Create new field, NSb97Dif, To show the difference between Z&C's noSub estimates and my estimate dating back to 1850 and only up to 1997 to be comparable to the dates used in Z&C. (ZC\_noSub – 185097Ha) (a positive value indicates a higher estimate from Z&C) (Not useful. It appears that the data in Z&C's table already adjusts for the 1940 reclassification of ag land, resulting in a drop from approx. 90 MHa to 60MHa)
20. Calculate Switchgrass Production on Z&C land estimates:
  - a. Create new field, SGPDN1ZC, to be (SGYDN100 \* ZC\_sub)

Processing Historic Ag Census Files From CISER (to get historic Pasture numbers):

1. Acquire data file from  
[http://ciser.cornell.edu/ASPs/browse\\_ath.asp?CATEGORY=100](http://ciser.cornell.edu/ASPs/browse_ath.asp?CATEGORY=100)
2. Ideally, get a .trn file, which can be processed with SAS
3. Copy the .trn file to the Work folder in GPFS using SSH
4. Open SAS:
5. In the Program Editor window paste the following code and edit with the appropriate file names (“libraryName” is the name of a SAS library that will hold the imported table. “ag6974ad” is the name of the table to be loaded):

```
libname libraryName '/gpfs/home/reb186/work/Data';
libname ag6974ad xport '/gpfs/home/reb186/work/Data/ag6974ad.trn';
PROC COPY in=ag6974ad out=agCensus;
run;
```

6. In the Program Editor window paste the following code and edit with the appropriate file names (“libraryName” is the name of a SAS library that will hold the imported table. “ag6974ad” is the name of the table to be loaded):

```
PROC EXPORT DATA= libraryName.ag6974ad
OUTFILE=
"/gpfs/home/reb186/work/DataAg_census.csv"
DBMS=CSV REPLACE;
PUTNAMES=YES;
RUN;
```

7. Import the .csv to a new table in ArcGIS called “AgCensus1978” (of course changing the year accordingly).
  - a. In the 1978 table, the Permanent Pasture attribute is called, “V218”.
  - b. In the 1978 table, the Total Cropland attribute is called, “V50”.
  - c. To determine which attribute column in the csv is desired, refer to the cag003\_codebook.pdf. Count the number of variable values occur in the document starting with “Farms” moving across columns and down each row until you encounter the value you want. For example, to get Total Cropland in Acres, there are 8 columns of values in the pdf and Total Cropland is in the 7<sup>th</sup> row. So count the first 6 rows (each with 8 variables)

up to 48 and then count two more until you arrive at Total Copland in Acres.

### **Integration of Pasture data and full Cropland data from NASS**

1. In the HistoricCroplandUSGS table, create a new set of columns that contain the cropland areas in hectares.
  - a. Calculate the new fields by multiplying the corresponding 'M2' fields by .0001.
2. Acquire any updated NASS data:
  - a. Download data from the NASS QuickStats site for the years 1997 – 2017.
    - i. C:\data\PhD\Chapter2\_Data\CropAndPastureDataNASS
  - b. Save the files as .xlsx in Excel (confirm naming conventions described in link above)
  - c. Create a new column that matches the FIPS\_1 field in the shapefile for use when joining.
    - i. FIPS\_1 combines the two-digit state code with the three-digit county code
    - ii. State code has no leading zero (therefore some counties are four digits and others five)
    - iii. Calculate new column by multiplying State by 1000 and adding the County
  - d. Delete the following columns:
    - i. Program, Year, Period, Week Ending, Geo Level, Ag District, Ag District Code, Zip Code, Region, Watershed, Commodity, Domain, Domain Category and all "CV (%)" columns
  - e. Rename all columns to match conventions described in the link above.
    - i. Remove spaces
    - ii. Remove special chars
    - iii. Include the appropriate year in each variable name (e.g., 97)
      1. aglnxCPW97ac      Ag Land (excl crop & past & wood) - NASS
      2. cropTot97ac      Cropland Total - NASS
      3. cropxHP97ac      Cropland (excl harv & past) - NASS
      4. cropHar97ac      Cropland Harvested - NASS
      5. cropPas97ac      Cropland Pastured Only - NASS
      6. pastTot97ac      Pastureland Total - NASS
      7. pastxCW97ac      Pastureland (excl crp & wood) - NASS
      8. woodTot97ac      Woodland Total - NASS
      9. woodxP97ac      Woodland (excl past) - NASS
      10. woodPas97ac      Woodland Pastured – NASS
  - f. Convert all values to hectares by calculating new variables (multiply acres by .404686):
    1. aglnxCPW97ha      Ag Land (excl crop & past & wood) - NASS
    2. cropTot97ha      Cropland Total - NASS
    3. cropxHP97ha      Cropland (excl harv & past) - NASS

4. cropHar97ha Cropland Harvested - NASS
  5. cropPas97ha Cropland Pastured Only - NASS
  6. pastTot97ha Pastureland Total - NASS
  7. pastxCW97ha Pastureland (excl crp & wood) - NASS
  8. woodTot97ha Woodland Total - NASS
  9. woodxP97ha Woodland (excl past) - NASS
  10. woodPas97ha Woodland Pastured – NASS
- g. Import spreadsheet to a new table in ArcGIS
    - i. Name the new table NASS#### (#### corresponding to the year, e.g., NASS2002)
    - ii. Note: if you get a “Failed to connect to database” error, download the Excel 2007 driver (necessary even if a more recent version of Excel is already installed). <http://www.gisarea.com/topic/3523-facing-error-in-arcgis-102/>
  - h. Convert all values in all fields from NULL to zeros using the following Python code in the Field Calculator (this is necessary because any calculation involving a NULL value results in a NULL value. This would be inappropriate in instances, for example, when a present day value is NULL but a historic value is positive; this should result in a positive value of abandoned land, but would instead appear as NULL and ultimately, zero)
    - i. Python Script:
 

```
def nullFunc(x):
    if x is None:
        return 0
    else:
        return x

nullFunc( !FIELD! )
```
3. Acquire any updated NLCD data and recalculate the Urban Conversion fractions
    - a. See NLCD instructions below, and an update to the procedure for 2016.....
  4. Acquire any necessary years of historical pasture data.
    - a. See CISER instructions above.....
  5. In a new table called “Results19502012” (make a copy of the ResultsTemplate table and rename the title and field names with the appropriate scenario years) calculate the following new fields by joining it to the other tables:
    - a. Max19502012 = Maximum occurring value of cropland area in the period between the historic limit and the present day. Make sure it is HECTARES!!
      - i. Join the historicUSGS table and the NASS#### tables to the Results table
      - ii. Python code: max([!field1!, !field2!, !field3!])
      - iii. Use the Crop#####ha fields in the historic table
      - iv. Use the cropTot##Ha in the NASS tables

- v. Do NOT include the 1997 field in the historic table; use the 1997 NASS instead.
- b.  $Aban19502012 = max19502012 - NASS2017:cropTot12ha$  (difference in the amount of total cropland area between historic maximum and present day). Use the following code to perform the subtraction, while also setting negative values to zero.

- i. Set NULL values to zero and any negative results to zero:

- 1. Python code:

```
def convertNullsAndZeros(max,current):
    if max is None:
        max = 0
    if current is None:
        current = 0
    diff = max - current
    if diff < 0:
        diff = 0
    return diff
```

```
convertNullsAndZeros(
!Results19782012.max19782012!,
!NASS2012.cropTot12ha!)
```

- c.  $toUrbn19502012 = Aban19502012 * UrbanConversion:urCh01to11$   
(Amount of the abandoned ag land that has transitioned to an urban use. Based on calculations using NLCD 2001 and 2011.)
- d.  $Pot19502012 = Aban19502012 - toUrbn19502012$  (Potential cropland after removing the land estimated to have transitioned to urban)
- e.  $histPasture19502012 =$  Value of pastureland (excluding cropland & woodland) in the earliest year of the period being investigated. (This is deliberately the amount in the earliest year of the period rather than the maximum that occurs in any intervening year.) In the NASS tables it is field “pastxCW##ha”. This is field “V218” in the AgCensus1978 table. CONVERT TO HECTARES! Convert NULLs to zero:

- i. If pulling from NASS table, use this Python code:

```
def convertNulls(hist):
    if hist is None:
        hist = 0
    return hist
```

```
convertNulls( !NASS1997.pastxCW97ha! )
```

- ii. If pulling from historic (CISER) Ag Census file, use this Python code:

```
def convertNulls(hist):
    if hist is None:
        hist = 0
```

```
hist = hist * .404686
return hist
```

```
convertNulls( !AgCensus1978.V218! )
```

- f. `toPasture19502012 = NASS2012.pastxCW12ha - histPasture19502012`  
(difference in the amount of total pastureland (excl C&W) between the present day and historic limit. This is assumed to be the amount of cropland that has transitioned to pastureland and therefore not available for use.) Also set negative values to zero.

- i. Set NULL values to zero and any negative results to zero:

1. Python code:

```
def convertNullsAndZeros(current,hist):
    if current is None:
        current = 0
    if hist is None:
        hist = 0
    diff = current - hist
    if diff < 0:
        diff = 0
    return diff
```

```
convertNullsAndZeros(
!NASS2012.pastxCW12ha!,
!Results19782012.histPasture19782012!)
```

- g. `useable19502012 = Pot19502012 – toPasture19502012` (Net amount of useable abandoned cropland after both urban and pasture conversions are removed.)

- i. Set negative values to zero.

1. Python code:

```
def convertNullsAndZeros(pot,pas):
    if pot is None:
        pot = 0
    if pas is None:
        pas = 0
    diff = pot - pas
    if diff < 0:
        diff = 0
    return diff
```

```
convertNullsAndZeros(
!Results19782012.pot19782012! ,
!Results19782012.toPasture19782012!)
```

- h. Create normalized versions of TACL and UACL by dividing by the max cropland amount:
  - i. Calculate new fields:
    1.  $TACL_{norm} = useable19502012 / Max19502012$
    2.  $UACL_{norm} = Aban19502012 / Max19502012$
  - ii.
    - i.  $sgPdN019502012 = SwitchgrassYield:SGYDN0 * useable19502012$
    - j.  $sgPdN119502012 = SwitchgrassYield:SGYDN1 * useable19502012$
    - k.  $sgPdN219502012 = SwitchgrassYield:SGYDN2 * useable19502012$
- l.  $abanPasture19502012 = histPasture19502012 - NASS2012:pastxCW12ha$   
 (Amount of permanent pasture that has been lost during the time frame being investigated. All negative values are set to zero. Positive values indicate Abandoned Permanent Pasture, and therefore a potential land area for the production of biofuel feedstocks. This value is separate from the Abandoned Cropland calculated above, but could be added to that net amount for a grand total of useable Abandoned Agricultural Land.)
  - i. Set NULL values to zero and any negative results to zero:
    1. Python code:
 

```
def convertNullsAndZeros(hist,current):
    if hist is None:
        hist = 0
    if current is None:
        current = 0
    diff = hist - current
    if diff < 0:
        diff = 0
    return diff

convertNullsAndZeros(!Results19782012.histPasture19782012!,
!NASS2012.pastxCW12ha!)
```
1.  $max18502012$  = The max occurring cropland value between current year and 1850. Use (join) the 1940-adjusted historic cropland table (HistoricCroplandUSGS1940Adjusted) to calculate the max occurring value. Make sure it is HECTARES!!
  - i. Join the Adjusted historic USGS table and the NASS#### tables to the Results table
  - ii. Python code:  $max([!field1!, !field2!, !field3!])$
  - iii. Use the Crop####ha fields in the historic table
  - iv. Use the cropTot##Ha in the NASS tables
  - v. Do NOT include the 1997 field in the historic table; use the 1997 NASS instead.

- m.  $\text{totalAban18502012} = \text{max18502012} - \text{NASS2012:cropTot12ha}$   
(difference in the amount of total cropland area between the adjusted historic maximum and present day). Also set negative values to zero.

- i. Set NULL values to zero and any negative results to zero:

- 1. Python code:

```
def convertNullsAndZeros(max,current):
    if max is None:
        max = 0
    if current is None:
        current = 0
    diff = max - current
    if diff < 0:
        diff = 0
    return diff
```

```
convertNullsAndZeros(
!Results19782012.max18502012!,
!NASS2012.cropTot12ha!)
```

- m.

- 1. In an Excel spreadsheet (ScenarioResultsTotals.xlsx), calculate the SUMs of all values and populate a row for each scenario run.

- i. Also calculate a weighted national average of the Urban Conversion fractions (pDev01to11), that uses the aban19782012 values as the weights:

- 1. =SUMPRODUCT(A2:A3,B2:B3)/SUM(B2:B3)

#### 2012 and 2016 NLCD UPDATE, URBAN CONVERSION ADJUSTMENT

1. DEFINITELY use the 2001 – 2011 numbers instead of the 1992 – 2001 numbers due to the increased accuracy of the NLCD data. The NLCD documentation paper (see literature) indicates that in particular the Cropland class improved its classification accuracy significantly between the two data periods.
2. Acquire 2001 and 2011 nlcd
  - a. We have determined that the combined NLCD categories of Cultivated Crops + Pasture/Hay are a better measure of Cropland as defined in the Ag Census
  - b. Therefore, we should develop an urban conversion fraction that treats both cropland and pasture/hay as a single class in the NLCD to adjust the Total Cropland numbers in the Ag Census.
3. To illustrate the match of the categories in NLCD with the Ag Census in both 2001(2002) and 2011(2012) (perform this using the regular NLCD products, not the change rasters):
  - a. Create the following RECLASSED rasters setting the corresponding values to 1 and all others to 0:
    - i. cCrops01 = 82 (in the 2001 NLCD)
    - ii. cCrops11 = 82 (in the 2011 NLCD)
    - iii. pastHay01 = 81 (in the 2001 NLCD)

- iv.  $\text{pastHay11} = 81$  (in the 2011 NLCD)
- b. Use the Zonal Statistics as Table tool to create a new table in the File Geodatabase that contains the SUM of the pixel values in the corresponding raster:
  - i.  $\text{znCCrp01}$
  - ii.  $\text{znCCrp11}$
  - iii.  $\text{znPsHy01}$
  - iv.  $\text{znPsHy11}$
- c. Create new fields in the Counties2001to2011 feature class that calculate the separate and combined Cultivated Crops and Pasture/Hay totals in 2001 and 2011:
  - i.  $\text{cCrops01}$
  - ii.  $\text{cCrops11}$
  - iii.  $\text{pastHay01}$
  - iv.  $\text{pastHay11}$
  - v.  $\text{crpPsHy01} = \text{cCrops01} + \text{pastHay01}$
  - vi.  $\text{crpPsHy11} = \text{cCrops11} + \text{pastHay11}$
- d. The above values are in units of pixels. Convert them to hectares by multiplying by 900 and multiplying by .0001 (the 900 converts each 30m pixel to meters, and the .0001 converts each square meter to hectares)
  - i.  $\text{crpPas01ha} = \text{crpPsHy01} * 900 * .0001$
  - ii.  $\text{crpPas11ha} = \text{crpPsHy11} * 900 * .0001$
- e. Compare the combined NLCD totals with the Cropland total in the Ag Census:
  - i. Perform a join on the Counties2001to2011 feature class with the NASS tables to access the Total Cropland numbers
    - 1.  $\text{cropTot02ha}$  in the NASS2002 table
    - 2.  $\text{cropTot12ha}$  in the NASS2012 table
  - ii. Create new fields to hold the difference between the NLCD and Census as a percentage of the Ag Census value
    - 1.  $\text{Cen02Nlcd01}$  (Use the following VB script to avoid dividing by zero)
 

```

dim theThing
if [cropTot02ha] <> 0 then
  theThing = ([cropTot02ha] - [crpPas01ha]) / [cropTot02ha]
else
  theThing = 0
end if
              
```
    - 2.  $\text{Cen02Nlcd11}$  (Use the following VB script to avoid dividing by zero)
 

```

dim theThing
if [cropTot12ha] <> 0 then
  theThing = ([cropTot12ha] - [crpPas11ha]) / [cropTot12ha]
else
              
```



theThing = 0

end if

3. Negative values indicate that the NLCD value is greater than the Ag Census value.

4. Acquire

nlcd\_2001\_to\_2011\_landcover\_fromto\_change\_index\_2011\_eeedition\_2014\_04\_09 raster

- a. Changes for the 2006-2016 analysis:

**There is no NLCD product that specifically shows change between 2006 and 2016, unlike the 2001 instructions above. Therefore, I need to use the 2006 and 2016 land cover datasets and calculate the changes manually.**

2006 and 2016 Landcover codes:

- CultivatedCrops or Pasture/Hay
  - 81,82
- Developed or Barren
  - 21,22,23,24,31

```
agToDev = Con(("nlcd_2006_land_cover_148_20210604.img" == 81) |
("nlcd_2006_land_cover_148_20210604.img" == 82)) &
(("nlcd_2016_land_cover_148_20210604.img" == 21) |
("nlcd_2016_land_cover_148_20210604.img" == 22) |
("nlcd_2016_land_cover_148_20210604.img" == 23) |
("nlcd_2016_land_cover_148_20210604.img" == 24) |
("nlcd_2016_land_cover_148_20210604.img" == 31)), 1, 0)
```

```
agToElse = Con(("nlcd_2006_land_cover_148_20210604.img" == 81) |
("nlcd_2006_land_cover_148_20210604.img" == 82)) &
(("nlcd_2016_land_cover_148_20210604.img" != 21) &
("nlcd_2016_land_cover_148_20210604.img" != 22) &
("nlcd_2016_land_cover_148_20210604.img" != 23) &
("nlcd_2016_land_cover_148_20210604.img" != 24) &
("nlcd_2016_land_cover_148_20210604.img" != 31) &
("nlcd_2016_land_cover_148_20210604.img" != 81) &
("nlcd_2016_land_cover_148_20210604.img" != 82)), 1, 0)
```

In the **Environments** settings:

- Set the Snap Raster to be the NLCD 2006 raster. This ensures that the pixels in the output raster align with those in the input rasters. For some reason, running a test without this setting resulted in an output that was shifted diagonally up and to the right.
- Processing Extent is set to the Intersection of Inputs

5. Create the following RECLASSED rasters setting the corresponding values to 1 and all others to 0:
  - a. `agToDev` = (CultivatedCrops and Pasture/Hay to Developed or Barren)
    - i. 225-229,242-246
  - b. `agToEls` = (CultivatedCrops and Pasture/Hay to all other categories except CultivatedCrops, Pasture/Hay, Developed and Barren)
    - i. 222-224,230-234,237-238,239-241,247-251,254-255
6. Use the Zonal Statistics as Table tool to create a new table in the File Geodatabase that contains the SUM of the pixel values in the corresponding raster:
  - a. `znAgToDev`
  - b. `znAgToEls`
7. Join the tables to the Counties feature class and use the Calculate Field tool to populate new fields in the attribute table for each of the joined tables:
  - a. `agToDev`
  - b. `agToEls`
8. Create a new field, `agToAll`, to contain the sum of `agToDev` and `agToElse`.
9. Create new field, `urCh01to11`, to contain the fraction of total ag land change between 2001 and 2011 that transitioned to a 'developed' class.
  - a. Use the following VB script to avoid dividing by zero:
 

```
dim theThing
if [agToAll] <> 0 then
theThing = [agToDev] / [agToAll]
else
theThing = 0
end if
```

### **Python version:**

Expression:  
`calc(!agToAll!,!agToDev!)`

Code Block:

```
def calc(all,dev):
    global theThing
    if (all != 0):
        theThing = dev / all
    else:
        theThing = 0

    return theThing
```

10. Create a new table in the core geodatabase with the updated UrbanConversion values (archive the old one to a separate geodatabase and rename UrbanConversion92\_01).
11. To compare our estimate of abandoned cropland with raw numbers from NLCD:
  - a. Create the following RECLASSED rasters setting the corresponding values to 1 and all others to 0:
    - i. cPasToGrsSh = 250,251,233,234 (Cultivated Crops and Pasture/Hay to Shrub/Scrub and Grassland)
  - b. Use the Zonal Statistics as Table tool to create a new table in the File Geodatabase that contains the SUM of the pixel values in the corresponding raster:
    - i. znCrPsToGrSh
  - c. Join the znCrPsToGrSh column to the Counties feature class and compare its sum to the sum of the PotentialCropland values calculated earlier (at some point I need to redo the PotentialCropland numbers using the updated urban conversion fractions that include both cropland and pasture/hay in NLCD). Run a Results scenario for the time period 2002 – 2012 for the best comparison.
  - d. After doing a back of the envelope overview in ComparisonOfNLCDGrasslandAndAbandonedAg.xlsx, the NLCD numbers don't agree with our estimates of abandoned cropland. I'm not too concerned with this, as we are not using NLCD for absolute areas, but rather the relative change in cropland during specific time periods.

### RESULTS Table Data Dictionary:

- Max19502012 - Maximum occurring value of cropland area in the period between the historic limit and the present day.
- **aban19502012** - Difference in the amount of total cropland area between historic maximum and present day (max19502012 – NASS2012:cropTot12ha). Negative values set to zero. **This is the raw TACL value.**
- toUrbn19502012 - Amount of the abandoned cropland that has transitioned to an urban use. (Aban19502012 \* UrbanConversion:pDev01to11). Based on calculations using NLCD 2001 and 2011.
- **pot19502012** - Potential abandoned cropland after removing the land estimated to have transitioned to urban (Aban19502012 – toUrbn19502012). **AACL.**
- histPasture19502012 - Amount of permanent pastureland (excluding cropland & woodland) in the earliest year of the period being investigated. (This is deliberately the amount in the earliest year of the period rather than the maximum that occurs in any intervening year.)
- toPasture19502012 - Difference in the amount of permanent pastureland (excluding cropland & woodland) between the present day and historic limit (NASS2012:pastxCW12ha - histPasture19502012). This is assumed to be the amount of abandoned cropland that has transitioned to pastureland and therefore not available for use. Negative values set to zero.

- **useable19502012** - Net amount of useable abandoned cropland after both urban and pasture conversions are removed ( $\text{Pot19502012} - \text{toPasture19502012}$ ). Negative values set to zero. **This is the raw UACL value.**
- **TACLn timer** - normalized version of TACL by dividing by the max cropland amount. Use this in the regression.
- **UACLn timer** - normalized version of UACL by dividing by the max cropland amount. Use this in the regression.
- **sgPdN019502012** - Switchgrass production totals based on a yield model with a nitrogen input of zero ( $\text{SwitchgrassYield:SGYDN0} * \text{useable19502012}$ ).
- **sgPdN119502012** - Switchgrass production totals based on a yield model with a nitrogen input of 100 kg/ha ( $\text{SwitchgrassYield:SGYDN1} * \text{useable19502012}$ ).
- **sgPdN219502012** - Switchgrass production totals based on a yield model with a nitrogen input of 200 kg/ha ( $\text{SwitchgrassYield:SGYDN2} * \text{useable19502012}$ ).
- **abanPasture19502012** - Amount of permanent pasture that has been lost during the time frame being investigated ( $\text{histPasture19502012} - \text{NASS2012:pastxCW12ha}$ ). Negative values set to zero. (Positive values indicate Abandoned Permanent Pasture, and therefore a potential land area for the production of biofuel feedstocks. This value is separate from the Abandoned Cropland calculated above, but could be added to that net amount for a grand total of useable Abandoned Agricultural Land.) I didn't proceed with this.

## Appendix B. Data Processing Procedures for Correlation Analysis

1. Download NED
  - a. <https://apps.nationalmap.gov/downloader/>
  - b. Use the instructions on this page (<https://apps.nationalmap.gov/uget-instructions/>) to bulk download tiles
  - c. Metadata:  
<https://www.sciencebase.gov/catalog/item/61e11197d34e8911d9ff0fa9>
  - d. Add all tiles to ArcGIS
  - e. Remove any tiles west of 101 degrees west. Either do this here or in the step below. In either case, this is done to reduce processing time, since the analysis will be confined to the east half of conus.
2. Constrain analysis to east of the 100<sup>th</sup> parallel.
  - a. Download the MLRA (LRR) data from USDA
  - b. Dissolve the MLRAs into the larger LRRs based on the LRR name of each polygon.
    - i. Allow multi-part polygons
  - c. Remove the NED tiles west of 101 degrees west.
    - i. Keep the one with 100 degrees west in its name as the farthest-west tile.
  - d. Mosaic the remaining tiles together into a new raster, called DEM, in the AbandonedCropland geodatabase.
    - i. 16-bit Unsigned
      1. This should truncate off all decimal values leaving just whole numbers. But it will allow for values up to 65,536 which is way more than needed. (8-bit was too low since it maxes out at 255). Losing the precision of the decimals shouldn't be a big deal. That's sub-meter detail that's probably way within the margin of error in the dataset.
      2. Trying to make the process run faster and not fail. Previous run went for over 48 hours and ultimately failed due to the table size maximum being exceeded; that run was specified for 32-bit Signed. My hope is that by reducing the bit depth and constraining the spatial extent to east of the 100<sup>th</sup> parallel will allow it to finish successfully.
    - ii. Use the Define Projection tool to add a vertical datum to the mosaic dataset's properties:
      1. NAVD88 height (m)
    - iii. Build pyramids using Bilinear technique
  - e. Use the Surface Parameters tool to generate a slope raster:
    - i. Input: DEM
    - ii. Output raster: Slope

- iii. Output slope measurement: Degree
  - f. Build pyramids using Bilinear technique
  - g. Use the Zonal Statistics as Table tool to convert slope values to the mean and standard deviation for each county
    - i. NOTE: Only the counties east of the 100<sup>th</sup> parallel will exist in the resulting table
- 3. Acquire all datasets according to the Variables20072017.xlsx spreadsheet
- 4. Extract each variable from NASS Quick Stats individually.
- 5. Save each table as a .xlsx. In Excel:
  - a. Create a new column that matches the FIPS\_1 field in the shapefile for use when joining.
    - i. FIPS\_1 combines the two-digit state code with the three-digit county code
    - ii. State code has no leading zero (therefore some counties are four digits and others five)
    - iii. Calculate new column by multiplying State by 1000 and adding the County
  - b. Delete the following columns:
    - i. Program, Period, Week Ending, Geo Level, Ag District, Ag District Code, Zip Code, Region, Watershed, Commodity, Domain, Domain Category and all “CV (%)” columns
  - c. Rename the Value column to match the desired name for the variable, e.g., LndVal12.
- 6. Export the counties feature class table to create a new table (Regression20072017) in the abandonedcropland.gdb to hold TACLnorm, UACLnorm, and all the regression independent variables.
- 7. Delete any extraneous columns from the new table, leaving TACLnorm, UACLnorm, etc.
- 8. In ArcGIS Pro, join the Results20072017 table and each of the variable tables (their sources are listed in Variables20072017.xlsx) one at a time to the Regression20072017 table.
- 9. Create a new field in the Regression20072017 table for each of the independent variables.
  - a. Open the Fields view and use Copy/Paste to create a new field in the Regression20072017 table.
- 10. Then go back to the regular table view and use Calculate field to copy the values into the new field.
- 11. Make copies of the Counties feature class and the Regression20072017 table, adding the name “exclude”
  - a. Counties\_exclude, Regression20072017\_exclude
- 12. Delete records from the feature class and table all the counties west of the 100<sup>th</sup> parallel. Delete those counties with an avSlope of null.
- 13. Overlay the LRRs\_multiPart feature class on the counties.

14. Use Spatial Join to create a new column, LRR, that contains the LRR\_Name value from the LRR\_multiPart layer:
  - a. Target: Counties\_exclude
  - b. Join Features: LRRs\_multiPart\_exclude
  - c. Output Feature Class: Counties\_exclude\_SpatialJoin
  - d. Join Operation: Join one to one
  - e. Keep all target features
  - f. Match Option: Have their center in
  - g. Field Map:
    - i. Output Field LRR = LRR\_Name from the LRR layer
15. Join the Regression20072017\_exclude table to the Counties\_exclude\_SpatialJoin feature class
16. Export the attribute table to Regression20072017\_excludeWithLRRs
17. Export the Counties\_exclude\_SpatialJoin feature class to a new layer called Counties\_excludeWithLRRs (without the regression attributes)
18. I plan to exclude any county with a TACLnorm of 1. These are places that have little cropland to begin with, and 100% of it was abandoned, whether to urban or something else. These are also all counties for which the 2017 value for total cropland is redacted to protect the identify of a farmer. So, the data makes it appear that 100% of cropland was abandoned, when in fact it is likely the no abandonment has occurred. These are the counties that have redacted 2017 total cropland values and will be excluded from the analysis:

6075	CALIFORNIA	6	SAN FRANCISCO
6003	CALIFORNIA	6	ALPINE
34017	NEW JERSEY	34	HUDSON
34039	NEW JERSEY	34	UNION
36081	NEW YORK	36	QUEENS
36085	NEW YORK	36	RICHMOND
48301	TEXAS	48	LOVING
48495	TEXAS	48	WINKLER
54045	WEST VIRGINIA	54	LOGAN
54059	WEST VIRGINIA	54	MINGO
55078	WISCONSIN	55	MENOMINEE
55079	WISCONSIN	55	MILWAUKEE
32029	NEVADA	32	STOREY
35028	NEW MEXICO	35	LOS ALAMOS
51013	VIRGINIA	51	ARLINGTON

19. Export the Counties\_excludeWithLRRs layer to a new feature class called Counties\_excludeFinal.
20. Join the Regression20072017\_excludeWithLRRs table, and select features in the Counties\_excludeFinal layer that have a TACLnorm = 1. Delete these features.
21. Be sure the Regression20072017 table is joined to the Counties\_excludeFinal feature class and export the feature class to a new feature class called Counties\_excludeFinal\_withVariables that includes all of the variables in the attribute table.
22. Export the attribute table to Regression20072017\_excludeFinal.xlsx.

- a. I made a second version of this that includes four new variables presenting some values as percents rather than absolutes. I saved the previous version as Regression20072017\_excludeFinal\_Old.xlsx.
- 23. Leave an intact version of the table
- 24. Make a copy and save it in the R folder
- 25. Delete extraneous columns
- 26. Add a column, LRR\_ID, to contain an integer id for each LRR name. This should simplify running subsets in R.



## Appendix C. gSSURGO Variable Descriptions

Descriptions come from the USDA-NRCS Soil Development Data Toolbox for ArcGIS downloaded from the following site: <https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database>.

### NCCPI

National Commodity Crop Productivity Index is a method of arraying the soils of the United States for non-irrigated commodity crop production based on their inherent soil properties. This version features a separate index for soybeans. In the past, soybeans and corn were considered together. The rating a soil is assigned is the highest one of four basic crop group indices, which are based on the climate where the crop is typically grown. Cooler climates are represented by winter wheat, moderate climates are represented by corn and soybeans, and warmer climates are represented by cotton. ([http://www.nrcs.usda.gov/Internet/FSE\\_DOCUMENTS/nrcs142p2\\_050734.pdf](http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs142p2_050734.pdf)) The interpretation is applicable to both heavily populated and sparsely populated areas. Ratings are for soils in their present condition. The present land use is not considered in the ratings.

Ratings are based on properties and qualities to the depth normally observed during soil mapping (approximately 6 feet). Soil, site, and climate properties that influence the growth of crops are major considerations. Soil productivity is influenced by many soil properties. An ideal soil will store adequate amounts of water to nurture the crop between rains. This soil will have a near-neutral pH, will store nutrients, and lack toxic materials. The soil will have no barriers, either physical or chemical, to root growth. Water and gas transmission through the soil will be sufficient to maintain both water and oxygen at sufficient levels in the root zone. The soil will not be saturated with water during the growing season to the point that root growth is inhibited. The soil will not be subject to excessive flooding or ponding during the growing season. Slope is an important consideration because it affects erosion by water, runoff, and the operation of equipment. The climate must provide adequate water and heat to allow the desired crop to mature. A soil that differs from the ideal in any of these features will have lower inherent productivity for a particular crop. The further a soil differs from ideality in any one or all of the factors that determine inherent productivity, the lower its inherent productivity will be.

The ratings are both verbal and numerical. Rating class terms indicate the estimated productivity which is determined by all of the soil, site, and climatic features that affect crop productivity. "High inherent productivity" indicates that the soil, site, and climate have features that are very favorable for crop production. High yields and low risk of crop failure can be expected if a high level of management is employed. "Moderately

high inherent productivity" indicates that the soil has features that are generally quite favorable for crop production. Good yields and moderately low risk of crop failure can be expected. "Moderate inherent productivity" indicates that the soil has features that are generally favorable for crop production. Good yields and moderate risk of crop failure can be expected. "Moderately low inherent productivity" indicates that the soil has features that are generally not favorable for crop production. Low yields and moderately high risk of crop failure can be expected. "Low inherent productivity" indicates that the soil has one or more features that are unfavorable for crop production. Low yields and high risk of crop failure can be expected.

Numerical ratings indicate the overall productivity of the soil. The ratings are shown in decimal fractions ranging from 1.00 to 0.01. They indicate gradations between the point at which the combination of soil, site, and climate features has the greatest positive impact on inherent productivity (1.00) and the point at which the soil features are very unfavorable (0.01).

The map unit components listed for each map unit in the accompanying Summary by Map Unit table in Web Soil Survey or the Aggregation Report in Soil Data Viewer are determined by the aggregation method chosen. An aggregated rating class is shown for each map unit. The components listed for each map unit are only those that have the same rating class as listed for the map unit. The percent composition of each component in a particular map unit is presented to help the user better understand the percentage of each map unit that has the rating presented.

Other components with different ratings may be present in each map unit. The ratings for all components, regardless of the map unit aggregated rating, can be viewed by generating the equivalent report from the Soil Reports tab in Web Soil Survey. Onsite investigation may be needed to validate these interpretations and to confirm the identity of the soil on a given site.

## **Drought**

Even in a year, having normal precipitation or slightly less than normal, some soils are prone to having drought stress occur in the plants growing on them. Several conditions can allow this to happen. Most influential may be a relative lack of effective precipitation, as is estimated by subtracting the mean annual precipitation from an estimate of the annual evapotranspiration. Soils west of the 100th meridian frequently fall into this situation, especially at low elevations. Also, a soil may have an inherently low ability to store water. This is typical of sandy or shallow soils or soils having a high content of rock fragments. In this case, even though there may be significant rainfall, the soil matrix does not retain sufficient water for crop growth.

Topographic and climatic characteristics can be present to mitigate a soil's droughty tendencies. Some soils exist on water-gathering portions of the landscape and can thus

support more plant growth than their similar neighbors because of run on. Some soils have a water table present within the rooting zone during the growing season to supply plant water needs. Finally, some soils exist in a climate where precipitation is much higher than evapotranspiration and the soil is nearly always moist. This can occur in cool climates at high elevations.

The ratings are both verbal and numerical. Rating class terms indicate the extent to which the soils are vulnerable to drought. Numerical ratings indicate the degree of vulnerability associated with each soil or site feature. The ratings are shown in decimal fractions ranging from 0.01 to 1.00. They indicate gradations between the point at which a soil feature imparts the greatest degree of vulnerability (1.00) and the point at which the soil feature helps to mitigate drought vulnerability (0.00).

Verbal ratings are defined as follows:

Severely drought vulnerable (rating index equals 1.0). — The soil and site properties present are such that the plants growing on the soil must be very drought tolerant even in years with normal amounts of rainfall. The soil may have very low water storage capacity (below 5 cm) or may be in an area of low annual precipitation or high annual temperature or both.

Drought vulnerable (rating index is greater than 0.67 but less than 1.0). — The soil and site properties are such that drought conditions generally occur every year. The soil may have low water storage capacity (5 to 15 cm) and the site may have low annual precipitation or high annual temperature or both.

Moderately drought vulnerable (rating index is greater than 0.33 but less than 0.67). — The soil and site properties are such that in an average year, some water stress may occur, but in a good year, plant available water is generally adequate. Water storage is in the range of 15 to 25 cm. Rainfall and estimated potential evapotranspiration are nearly equal.

Somewhat drought vulnerable (rating index is greater than 0 but less than 0.33). — These soils have greater than 25 cm of water storage and annual precipitation is generally adequate for plant growth. In dry years some water stress may occur.

Slightly drought vulnerable (rating index equals 0). — These soils are either in lowlying parts of the landscape where plant roots may exploit near-surface ground water or are in areas where precipitation is much higher than potential evapotranspiration. In an extremely dry year plants may be water stressed on these soils.

The map unit components listed for each map unit in the accompanying Summary by Map Unit table in Web Soil Survey or the Aggregation Report in Soil Data Viewer are determined by the aggregation method chosen. An aggregated rating class is shown for each map unit. The components listed for each map unit are only those that have the same rating class as listed for the map unit. The percent composition of each component in a particular map unit is provided to help the user better understand the percentage of each map unit that has the rating presented.

Other components with different ratings may be present in each map unit. The ratings for all components, regardless of the map unit aggregated rating, can be viewed by generating the equivalent report from the Soil Reports tab in Web Soil Survey or from the Soil Data Mart site. Onsite investigation may be needed to validate these interpretations and to confirm the identity of the soil on a given site.

## **Soil Organic Content**

Organic matter percent is the weight of decomposed plant, animal, and microbial residues exclusive of non-decomposed plant and animal residues. It is expressed as a percentage, by weight, of the soil material that is less than 2 mm in diameter.

### **Significance:**

Soil organic matter (SOM) influences the physical, chemical, and biological properties of soils far more than suggested by its relatively small proportion in most soils. The organic fraction influences plant growth through its influence on these soil properties. It encourages soil aggregation, especially macroaggregation, increases porosity, and lowers bulk density. Because the soil structure is improved, water infiltration rates increase. SOM has a high capacity to adsorb and exchange cations and is important to pesticide binding. It furnishes energy to microorganisms in the soil. As SOM is decomposed by soil microbes, it releases nitrogen, phosphorous, sulfur, and many micronutrients, which become available for plant growth. SOM is a heterogeneous, dynamic substance that varies in particle size, carbon content, decomposition rate, and turnover time. In general, the content of SOM is highest at the surface—where plant, animal, and microbial residue inputs are greatest—and decreases with depth.

Total organic carbon (TOC) is the carbon (C) stored in SOM. Total organic carbon is also referred to as soil organic carbon (SOC) in the scientific literature. Organic carbon enters the soil through the decomposition of plant and animal residues, root exudates, and living and dead microorganisms. Inorganic carbon is common in calcareous soils in the form of calcium and magnesium carbonates. In calcareous soils, the content of inorganic carbon can exceed TOC.

### **Factors Affecting Content of SOM and SOC:**

Inherent factors - Soil texture, parent material, drainage, climate, and time affect accumulation of SOM. Soils that are rich in clay have greater capacity to protect SOM from decomposition by stabilizing substances that bind to clay surfaces. The formation of soil aggregates—enabled by the presence of clay, aluminum and iron oxides, fungal hyphae, bacterial exudates (carbohydrates), and fine roots—protects SOM from microbial decomposition. Extractable aluminum and allophanes, which are present in volcanic soils, can react with SOM to form compounds that are stable and resist microbial decomposition. Warm temperatures increase decomposition rates of SOM. High mean

annual precipitation increases accumulation rates of SOM by stimulating the production of plant biomass.

Loss of SOM through erosion results in SOM variations along slope gradients. Areas of level topography tend to have much more SOM than areas with other slope classes. Both elevation and topographic gradients affect local climate, vegetation distribution, and soil properties. They also affect associated biogeochemical processes, including SOM dynamics. Analysis of factors affecting C in the conterminous United States indicates that the effects of land use, topography (elevation and slope), and mean annual precipitation on SOM are more obvious than the effects of mean annual temperature. However, when other variables are highly restricted, SOM content clearly declines with increasing temperature.

Dynamic factors - Dynamic gains and losses in SOM are due primarily to management decisions in combination with climate and microbial influences. Accumulation of SOM is controlled by the rate of C mineralization, the amount and stage of decomposition of plant residues, and the addition of organic amendments to soil.

Soil organic carbon comprises approximately 52 to 58% of the SOM and is the main source of energy for soil microorganisms. The C within plant residues, particulate organic matter, and soil microbial biomass is generally considered to be within the active pool of SOM. The emergent view of SOM focuses on microbial access to SOM and includes an emphasis on the need to manage C flows rather than discrete C pools. During decomposition of SOM, energy and nutrients are released and utilized by plant roots and soil biota. Recognizing that SOM is a continuum of decomposition products is a first step in designing management strategies for renewing SOM sources throughout the year.

Soil aggregates of various sizes and stabilities can act as sites at which SOM is physically protected from decomposition and C mineralization. Soil disturbance and aggregate destruction increase biodegradation of SOM. Aggregates are readily broken apart by tillage operations.

Crop residues incorporated into or left on the soil surface reduce erosion and the losses of SOM associated with sediment. In acidic soils, applications of lime increase plant productivity, microbial activity, organic matter decomposition, and CO<sub>2</sub> release.

The diversity of the soil microbial population affects SOM. For example, while soil bacteria and some fungi participate in SOM loss by mineralizing C compounds, other fungi, such as mycorrhizae, facilitate stabilization and physical protection by aggregating SOM with clay and minerals. SOM is better protected from degradation within aggregates than in free-form.

#### Relationship to Soil Function:

SOM is one of the most important soil constituents. It affects plant growth by improving aggregate stability, soil structure, water availability, and nutrient cycling. SOM fractions in the active pool, described above, are the main source of energy and nutrients for soil microorganisms, which mediate nutrient cycling in the soil.

Biochemically stable SOM participates in aggregate stability and in holding capacity for nutrients and water.

Microaggregates are formed by mineral interactions with iron and aluminum oxides and are generally considered an inherent soil characteristic. They are, however, impacted by current and past management. Fine roots, fungal hyphae, and organic carbon compounds, such as complex sugars (carbohydrates) and proteins (also referred to as glues), bind mineral particles and microaggregates together to form macroaggregates that are still porous enough to allow air, water, and plant roots to move through the soil.

An increase in SOM leads to greater biological diversity and activity in the soil, thus increasing biological control of plant diseases and pests.

#### Problems Associated with Low Organic Matter Levels:

Low levels of SOM result in energy-source shortages and thereby lowered levels of microbial biomass, activity, and nutrient mineralization. In noncalcareous soils, aggregate stability, infiltration, drainage, and airflow are also reduced. Scarcity of SOM results in less diversity in soil biota and a risk of disruption to the food chain equilibrium. This disruption can cause disturbance in the soil environment (e.g., increased plant pests and diseases and accumulation of toxic substances).

#### Improving SOM Levels:

An estimated  $4.4 \times 10^9$  tons of C have been lost from soils of the United States due to traditional farming practices. Most of this carbon was SOC. Nearly half of the SOM has been lost from many agricultural soils. Other farming practices, such as no-till and cover cropping (especially when used together), can stop losses of SOM and even lead to increases. Continuous application of manure and compost can increase SOM. Burning, harvesting, or otherwise removing plant residues decreases SOM.

#### Measurement:

SOM is measured in the laboratory by determining total carbon (TC) content using either dry or wet-dry combustion. Current analytical methods do not distinguish between decomposed and nondecomposed residues, so soil is first sieved to 2 mm to remove as much of the recognizable plant material as possible. If no carbonates are present, TC is considered to be the same as TOC (or SOC). For calcareous soils, soil inorganic carbon in the form carbonates must also be measured and then subtracted from the TC to determine TOC content. Results are given as the percent TOC in dry soil. To convert percent TOC to percent SOM, multiply the TOC percentage by 1.724. To convert percent SOM to percent TOC, divide the SOM percentage by 1.724. Note that this value continues to be debated by researchers with possible values ranging from 1.4 to 2.5 (Pribyl, 2010). A conversion factor of 2 has been suggested for this database but has not yet been adopted. Detailed procedures for measurement of SOM are outlined in 'Soil Survey Investigations Report No. 42, Kellogg Soil Survey Laboratory Methods Manual, Version 5.0,' (Soil Survey Staff, 2014).

Many soil testing laboratories use a 'loss on ignition' method to estimate soil organic matter. The estimate produced by this method must be correlated to analytical TOC measurements for each area to improve accuracy. The loss on ignition method can provide a good indication of the trend in SOM content within a field. It is important to note that temperature and timing used for the loss on ignition approach vary across labs and can influence results. Thus, comparisons should be made using only results from within a given lab.

Currently, no standard method exists to measure TOC in the field. Attempts have been made to develop charts that match color to TOC content, but the correlation is better within soil landscapes and only for limited soils. Near-infrared spectroscopy has been tested for measuring C directly in the field, but it is expensive and sensitive to moisture content.

Estimates:

Color and feel are soil characteristics that can be used to estimate SOM content. Color comparisons in areas of similar parent materials and textures can be correlated with laboratory data and thereby enable a soil scientist to make field estimates. In general, darker colors or black indicate the presence of higher amounts of organic matter. The contrast of color between the A horizon and subsurface horizons is also a good indicator. Sandy soils tend to look darker with a lower content of SOM. In general, lower numbers for hue, value, and chroma (in the Munsell soil color system) tend to be associated with darker soil colors that are attributed to higher content of SOM, soil moisture, or both.

For each soil layer, this attribute is actually recorded as three separate values in the database. A low value and a high value indicate the range of this attribute for the soil component. A 'representative' value indicates the expected value of this attribute for the component. For this soil property, only the representative value is used.

### **Available Water Storage**

Available water storage (AWS) is the total volume of water (in centimeters) that should be available to plants when the soil, inclusive of rock fragments, is at field capacity. It is commonly estimated as the amount of water held between field capacity and the wilting point, with corrections for salinity, rock fragments, and rooting depth. AWS is reported as a single value (in centimeters) of water for the specified depth of the soil. AWS is calculated as the available water capacity times the thickness of each soil horizon to a specified depth.

For each soil layer, available water capacity, used in the computation of AWS, is recorded as three separate values in the database. A low value and a high value indicate the range of this attribute for the soil component. A "representative" value indicates the expected value of this attribute for the component. For the derivation of AWS, only the representative value for available water capacity is used.

The available water storage for each map unit component is computed as described above and then aggregated to a single value for the map unit by the process described below.

A map unit typically consists of one or more "components." A component is either some type of soil or some nonsoil entity, e.g., rock outcrop. For the attribute being aggregated (e.g., available water storage), the first step of the aggregation process is to derive one attribute value for each of a map unit's components. From this set of component attributes, the next step of the process is to derive a single value that represents the map unit as a whole. Once a single value for each map unit is derived, a thematic map for the map units can be generated. Aggregation is needed because map units rather than components are delineated on the soil maps.

The composition of each component in a map unit is recorded as a percentage. A composition of 60 indicates that the component typically makes up approximately 60 percent of the map unit.

For the available water storage, when a weighted average of all component values is computed, percent composition is the weighting factor.

### **Flood Frequency**

Flooding is the temporary inundation of an area caused by overflowing streams, by runoff from adjacent slopes, or by tides. Water standing for short periods after rainfall or snowmelt is not considered flooding, and water standing in swamps and marshes is considered ponding rather than flooding.

Frequency is expressed as none, very rare, rare, occasional, frequent, and very frequent.

"None" means that flooding is not probable. The chance of flooding is nearly 0 percent in any year. Flooding occurs less than once in 500 years.

"Very rare" means that flooding is very unlikely but possible under extremely unusual weather conditions. The chance of flooding is less than 1 percent in any year.

"Rare" means that flooding is unlikely but possible under unusual weather conditions. The chance of flooding is 1 to 5 percent in any year.

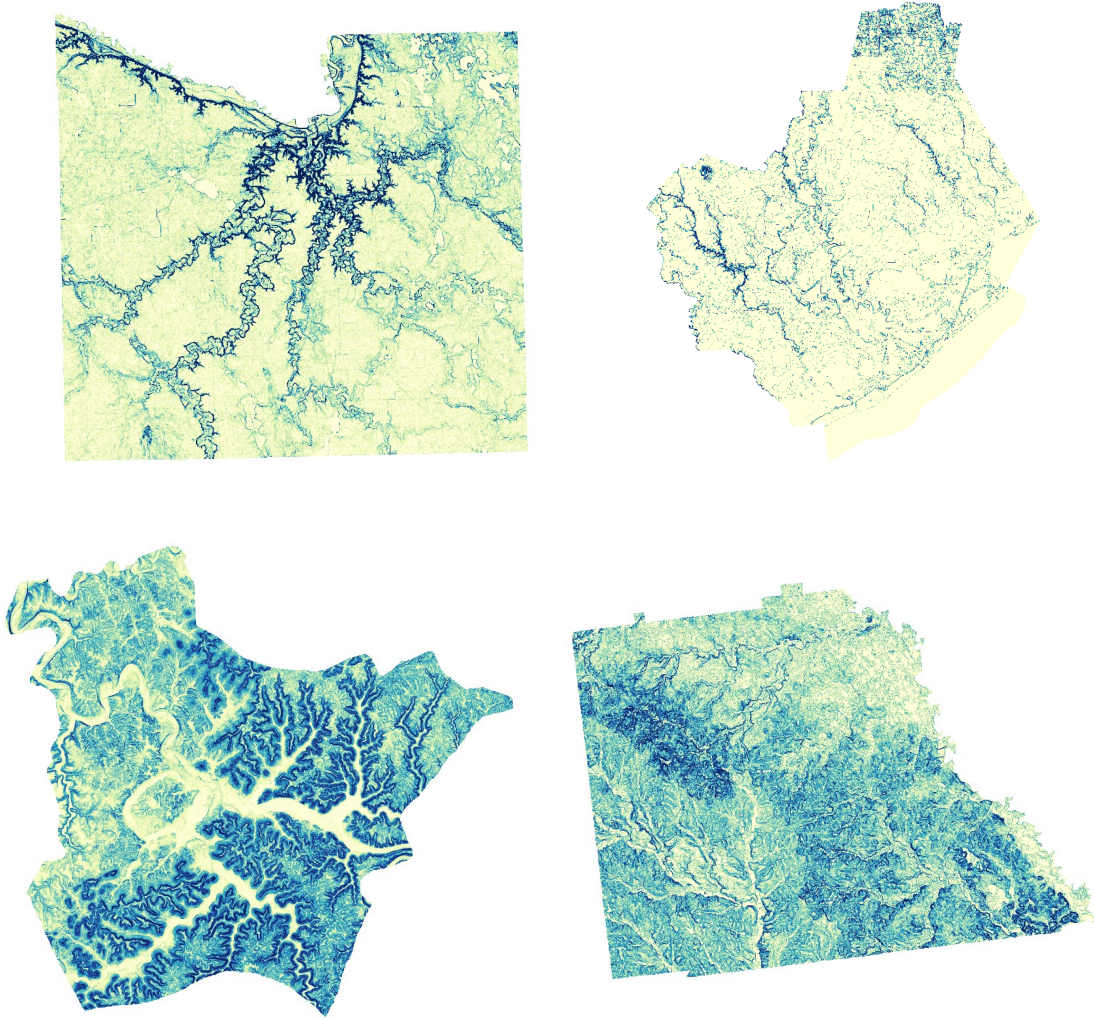
"Occasional" means that flooding occurs infrequently under normal weather conditions. The chance of flooding is 5 to 50 percent in any year.

"Frequent" means that flooding is likely to occur often under normal weather conditions. The chance of flooding is more than 50 percent in any year but is less than 50 percent in all months in any year.

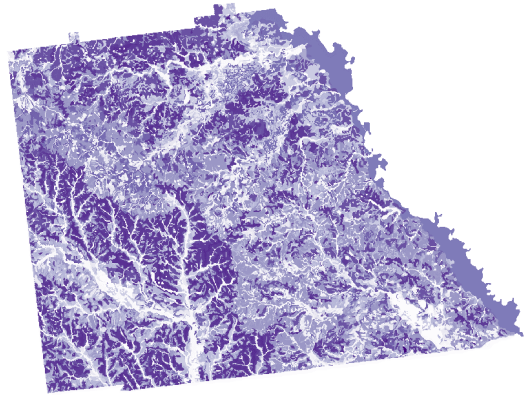
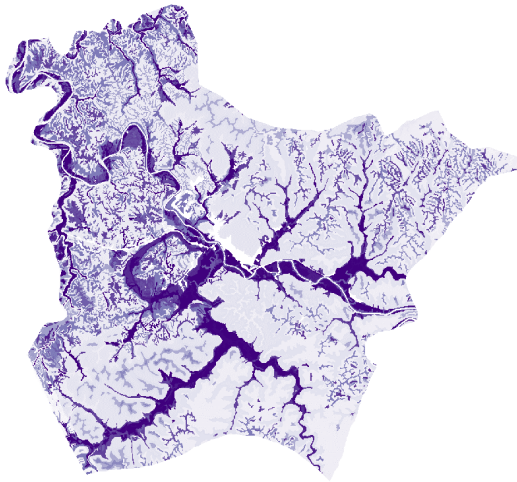
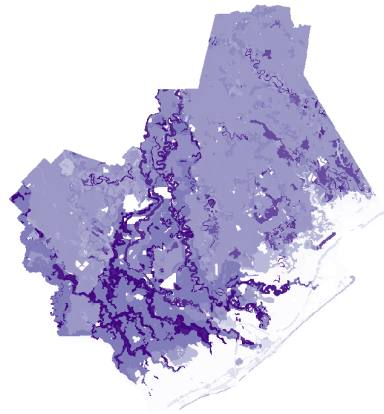
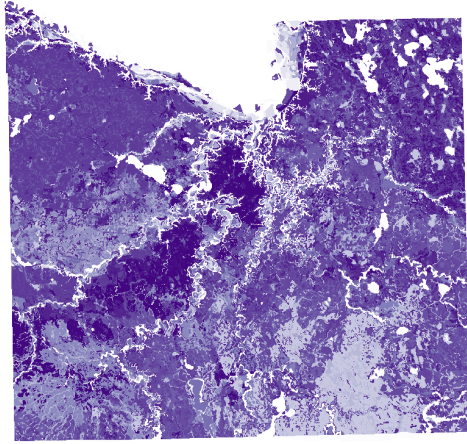
"Very frequent" means that flooding is likely to occur very often under normal weather conditions. The chance of flooding is more than 50 percent in all months of any year.



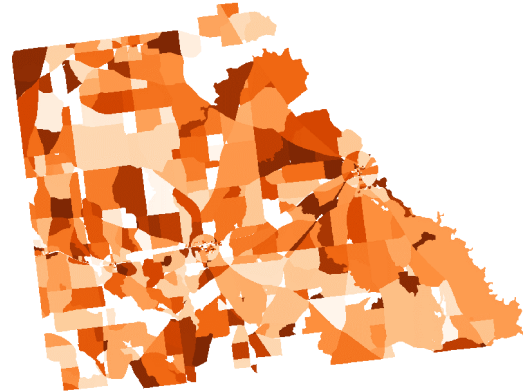
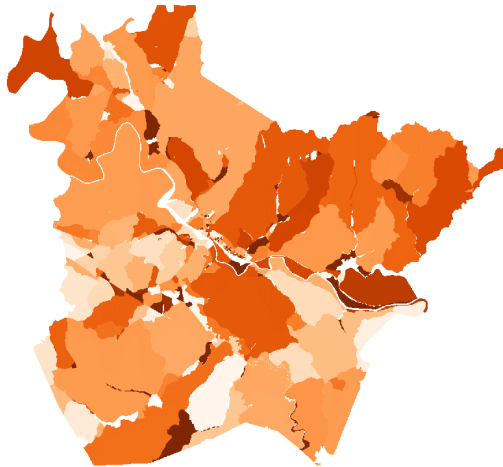
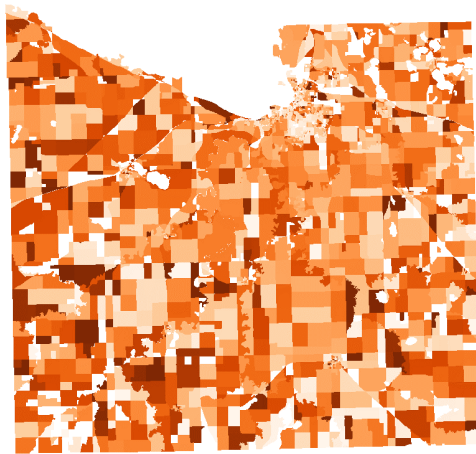
## Appendix D. Predictor Variable County Maps



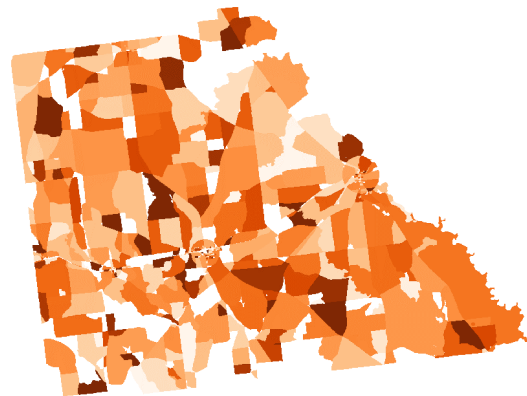
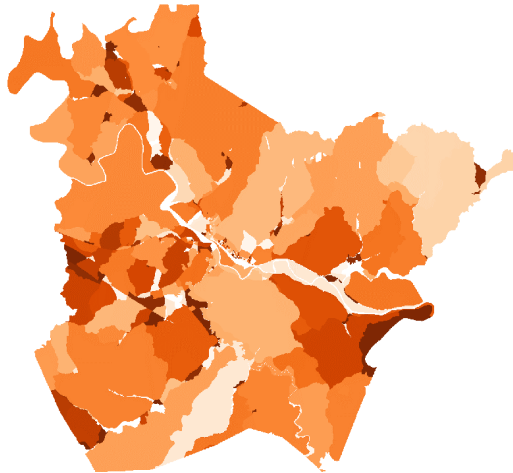
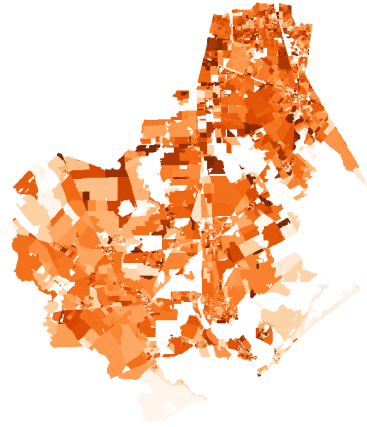
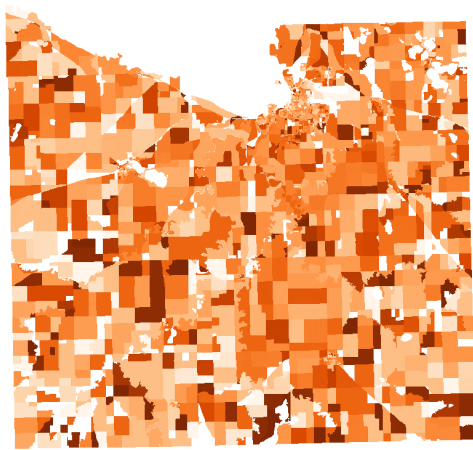
**Slope.** Darker colors indicate a greater slope. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).



**Crop Productivity (NCCPI).** Darker colors indicate greater productivity. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).

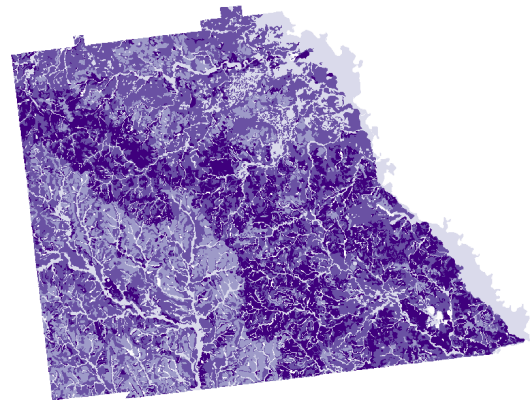
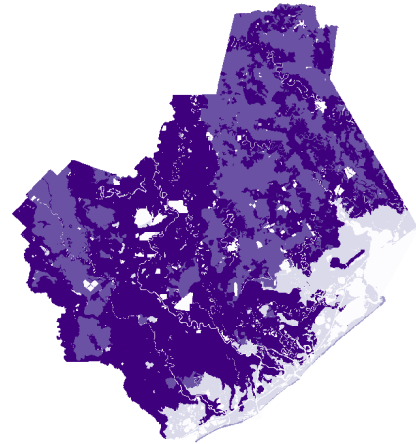
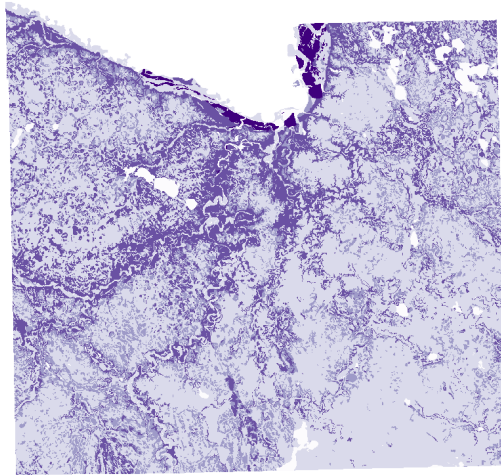


**Median Age.** Darker colors indicate a higher median age. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).

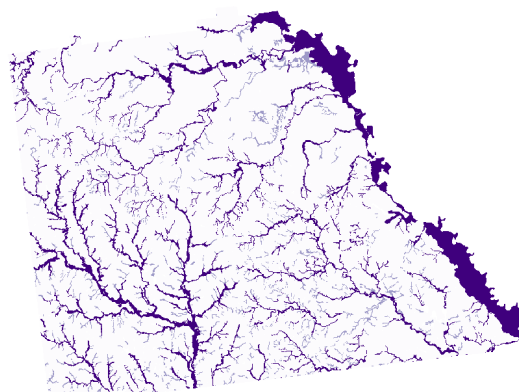
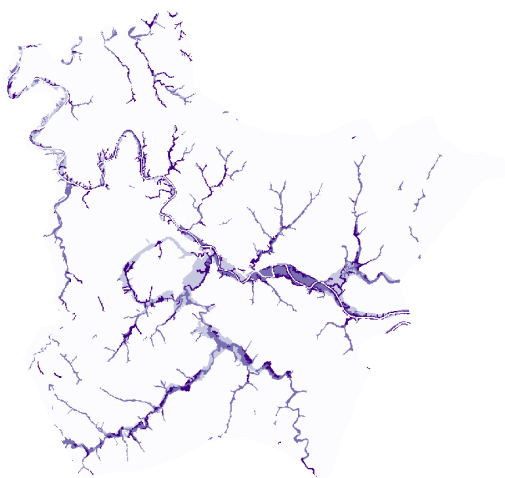
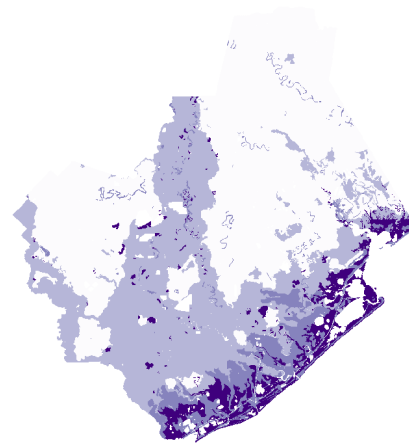
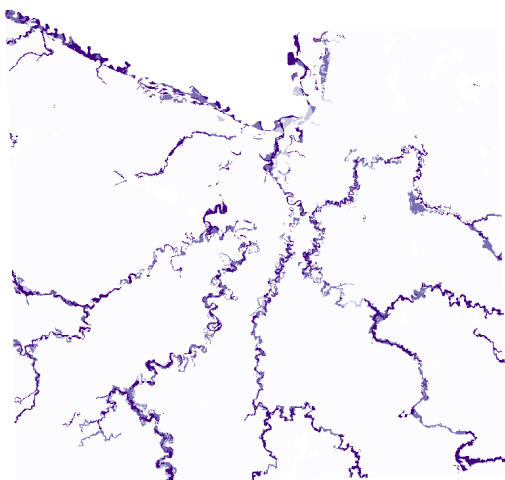


**Average Household Size.** Darker colors indicate larger household size. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).

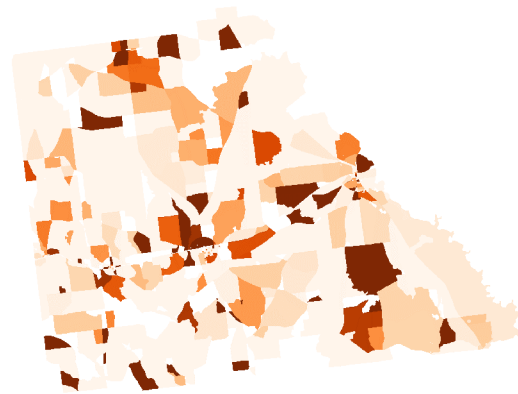
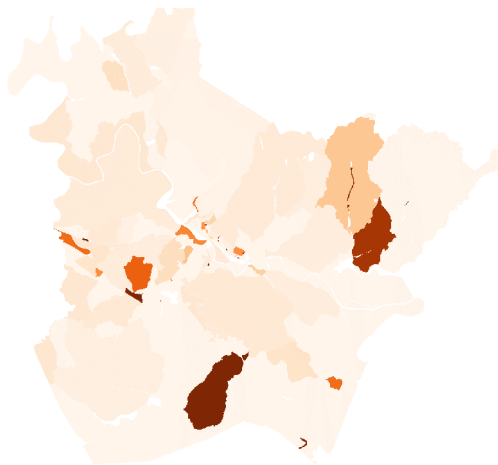
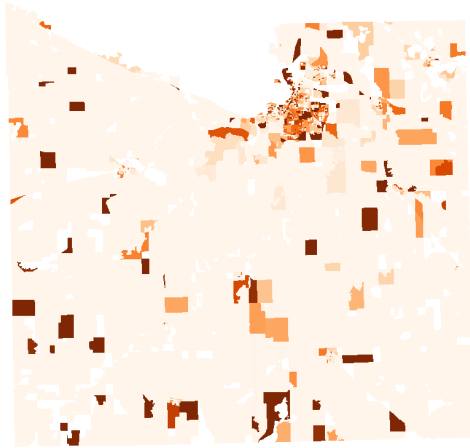




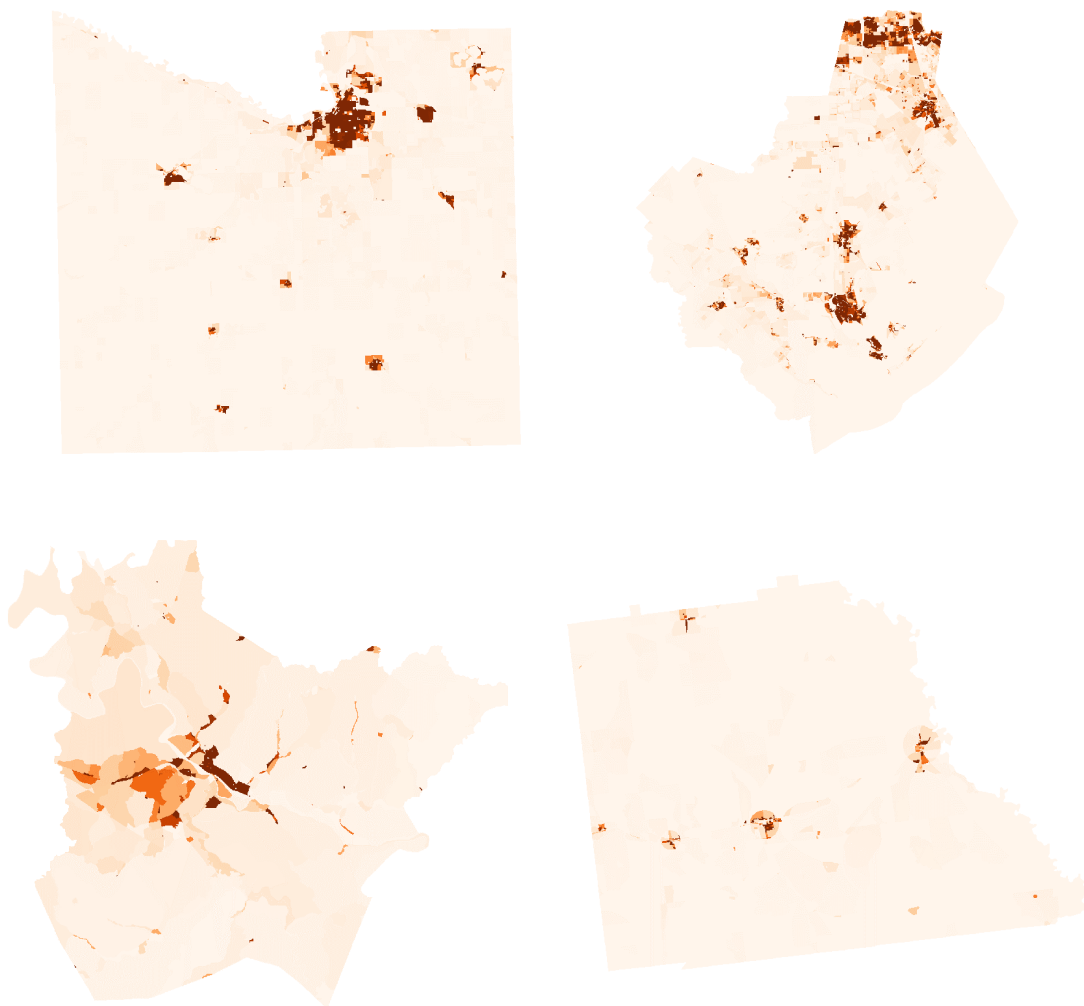
**Drought Vulnerability.** Darker colors indicate greater risk. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).



**Flood Frequency.** Darker colors indicate greater frequency. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).

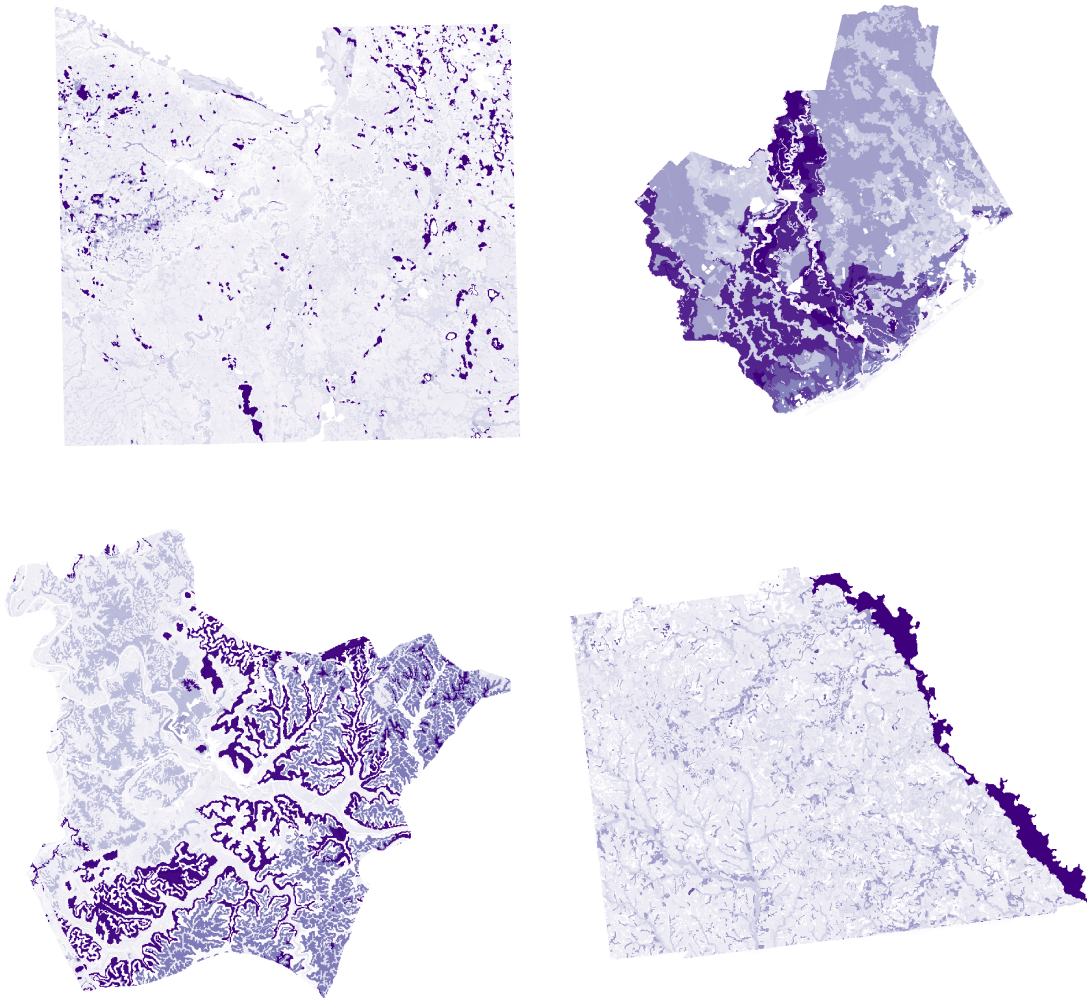


**Percent of Population Non-White.** Darker colors indicate a higher percentage. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).

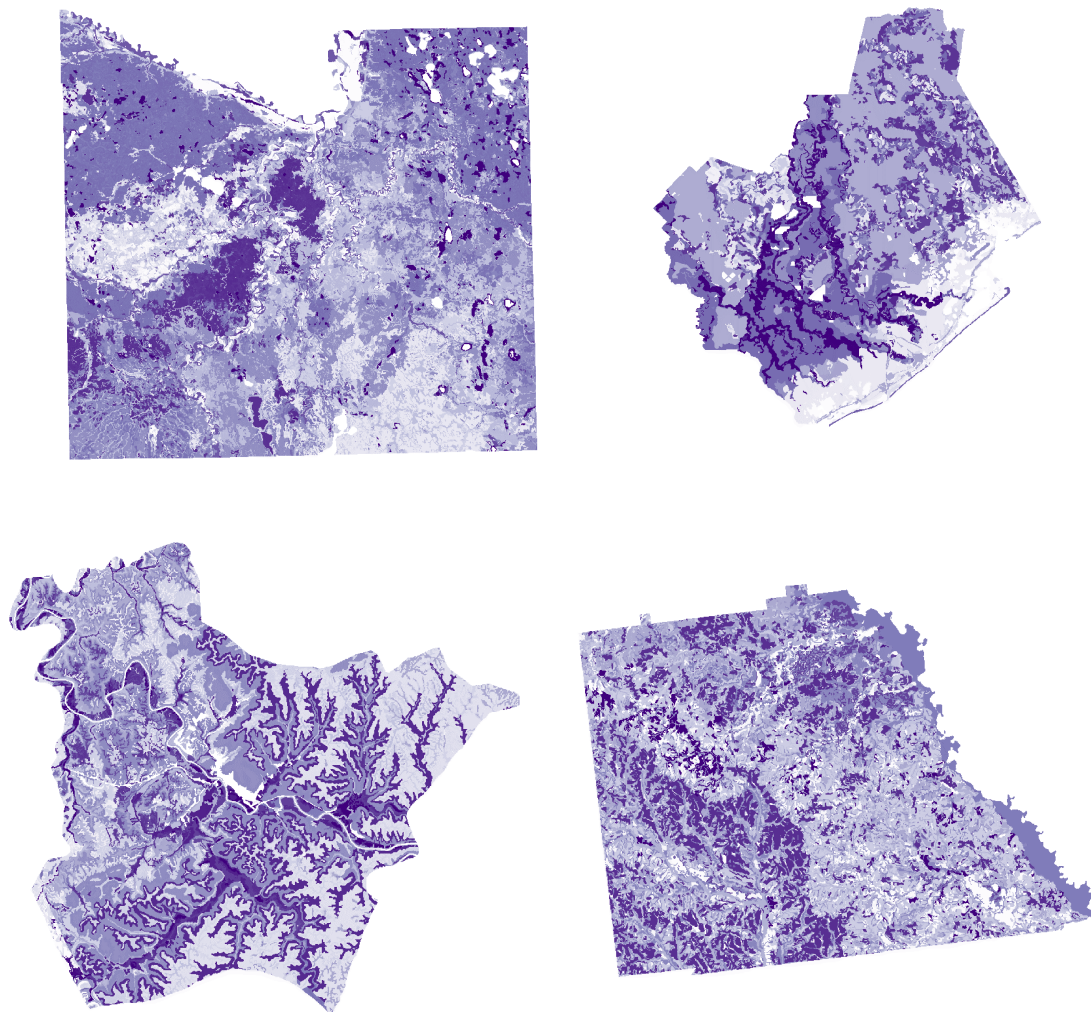


**Population Density.** Darker colors indicate a higher density. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).

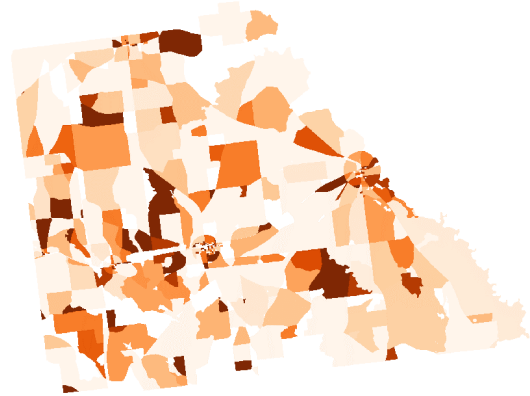
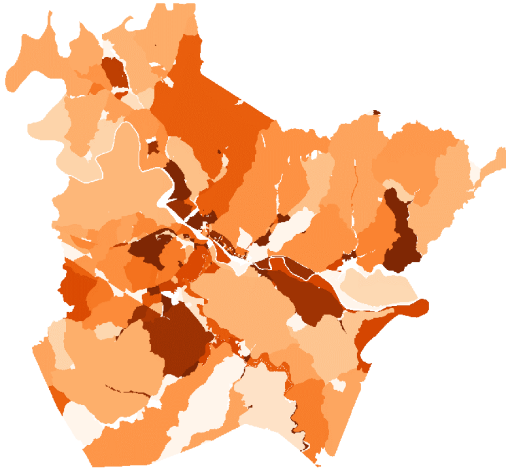
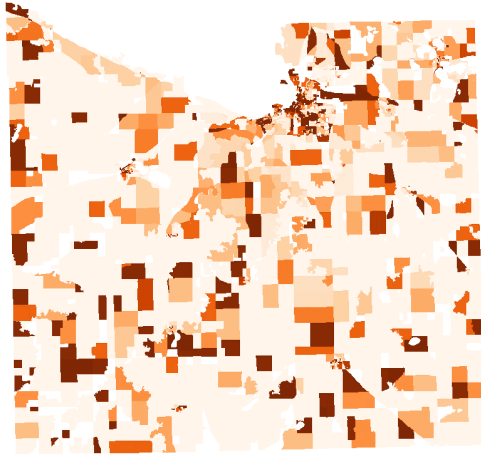




**Soil Organic Matter.** Darker colors indicate greater amounts. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).



**Soil Water Availability.** Darker colors indicate greater amounts. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).



**Percent of Households Renting.** Darker colors indicate a higher percentage. Upper row: Blue Earth County, MN (left), Brazoria County, TX (right). Lower row: Estill County, KY (left), Wilcox County, GA (right).

## Appendix E. Data Processing Procedures for Dyna-CLUE Analysis

1. In ArcGIS, select counties in each region that have a UACL greater than the median, a pctCrp12 greater than the median, and where the NLCD shows a reduction in the area of cropland over time. Stats are for the region only, not the entire study area.
  - a. This would represent a county with an average to above-average amount of cropland and where my model suggests a relatively high rate of abandonment to UACL.
2. Alternatively, find counties whose Ag Census change in Harvested Cropland between 2007 and 2017 matches the change in Cultivated Crops in NLCD between 2006 and 2016.
  - a. Create a county layer with the 2007 and 2017 Harvested Cropland numbers from Ag Census.
  - b. Reclassify the 2006 and 2017 NLCDs so that Cultivated Crops = 1 and all other classes = 0.
  - c. Use Zonal Statistics as Table to calculate how many Cultivated Crops pixels in the 2006 NLCD.
  - d. Use Zonal Statistics as Table to calculate how many Cultivated Crops pixels in the 2016 NLCD.
  - e. Add them as new fields in the county feature class.
  - f. For the Ag Census and NLCD numbers, calculate new fields showing the % change in cropland.
    - i. Fields:
      1.  $\text{AgCensusCrop0717} = ((\text{HarvCropland17} - \text{HarvCropland07}) / \text{HarvCropland07}) * 100$
      2.  $\text{NLCDCrop0616} = ((\text{NLCD CultCrop2016} - \text{NLCD CultCrop2006}) / \text{NLCD CultCrop2006}) * 100$
      3.  $\text{CensusNLCDDiff} = \text{AgCensusCrop0717} - \text{NLCD Crop0616}$
  - g. Select counties with a CensusNLCDDiff of 0 and a UACL and %cropland values as described above. These are counties where the Ag Census and NLCD agree how much cropland area changed over the ten year period.
    - i. Corn Belt:
      1.  $\text{UACL} > 0.0226634$  AND  $\text{pctCrp12} > 0.6824$  AND  $\text{NLCD Crop0616} \leq -1$
      - 2. Blue Earth, MN**
    - ii. Appalachia:
      1.  $\text{UACL} > 0.105265$  AND  $\text{pctCrp12} > 0.136854$  AND  $\text{NLCD Crop0616} \leq -1$
      - 2. Estill, KY (selected before these criteria)**
    - iii. Black Belt

1.  $UACL > 0.1426495$  AND  $pctCrp12 > 0.103829$  AND  $NLCDCrop0616 \leq -1$
- 2. Wilcox, GA**
- iv. Gulf Coast
  - 1. Brazoria, TX**

## Data Acquisition and Processing

Important that all raster layers have exactly the same pixel size and alignment.

1. Create ArcGIS Pro project for each of the four counties.
3. Geometry Shapefiles:
  - a. <https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2010&layergroup=Blocks>
  - b. Choose the state and county for 2010 and download the .zip file
  - c. Unzip the data and copy into the Blocks folder in the county spatial data folder.
  - d. Export the shapefile to a feature class in the county geodatabase.
  - e. Rename it to Blocks2010
2. NLCD
  - a. Add 2006 NLCD from the PhD\_Data folder.
  - b. Set map coordinate system to Albers Equal Area to match the 2006 NLCD (use the Layers list in the coordinate systems dialog and select the NLCD2006 layer).
  - c. Use the Clip Raster tool to clip the NLCD to the county boundary.
    - i. Check “Use input features for clipping geometry”
    - ii. Environments:
      1. Output Coordinate System: nlcd\_2006.....
      2. Snap Raster: nlcd\_2006\_land\_cover....
  - d. Use the Resample tool to adjust pixel size to 30x30
    - i. Output Raster Dataset: EstillNLCD2006
3. DEM (slope)
  - a. Add NED slope raster from PhD\_Data folder.
  - b. Use the Clip Raster tool to clip slope to actual extent of the county feature
    - i. Output Raster Dataset: Slope\_Clip
    - ii. Output Extent: county feature class
    - iii. Check “Use input features for clipping geometry”
    - iv. Environments:
      1. Output Coordinate System: NLCD2006
      2. Snap raster: NLCD2006
      3. Pyramids, Resampling Technique: Bilinear
  - c. Use the Resample tool to convert the slope raster to the same pixel size as the NLCD.

- i. Output Raster Dataset: EstillSlope
  - ii. Output cell size: NLCD2006
  - iii. Use the Bilinear option since data is continuous.
  - iv. Environments:
    - 1. Snap raster: NLCD2006
    - 2. Pyramids, Resampling Technique: Bilinear
- 4. GSSURGO
  - a. Download state versions of the GSSURGO dataset for MN, MS, GA, KY
    - i. <https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database>
    - ii. Followed link to the Box site
    - iii. Save this geodatabase in the county folder as gSSURGO\_<state>.gdb
  - b. Add the MapunitRaster\_10m... raster to ArcGIS Pro
  - c. Clip the MapunitRaster... to the county boundary
    - i. Use the Clip Raster tool to clip ssurgo to actual extent of county boundary
      - 1. Output Extent: County feature class
      - 2. Check “Use input features for clipping geometry”
      - 3. Environments:
        - a. Output Coordinate System: NLCD2006
        - b. Snap raster: NLCD2006
  - d. Use the Resample tool
    - i. MapunitRaster... is the input
    - ii. Output Raster Dataset: <county>gSSURGO
    - iii. Output cell size: same as NLCD2006
    - iv. Nearest Neighbor is the resampling technique
    - v. Environment settings:
      - 1. Output Coordinate System: Same as NLCD2006
      - 2. Snap Raster: NLCD2006
  - e. Copy the <county>gSSURGO raster from the county geodatabase to the gSSURGO\_<state>.gdb
    - i. This is necessary because the toolbox tool in ArcGIS Desktop below requires that the raster layer be in the gSSURGO geodatabase
  - f. Close ArcGIS Pro
- 5. gSSURGO Attributes
  - a. Download the **Soil Development Data Toolbox** from the following site:
  - b. <https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database>
  - c. Open ArcGIS Desktop
    - i. Save the MXD as <county>gSSURGOTables.mxd in the county folder.

- ii. Add the <county>gSSURGO raster
    - 1. must be added from the gSSURGO\_<state> geodatabase, not the county geodatabase.
- d. Add the toolbox to ArcGIS Desktop (Not Pro)
  - i. VALUE1 table in the geodatabase will be used by the toolbox tools:
    - 1. Refer to **<https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database.pdf>** for details of the attributes in the table.
    - 2. These attributes are GIS-ready variables from ssurgo that are already mapped to the map units. NCCPI and other variables are in there.
    - 3. From <https://www.nrcs.usda.gov/resources/data-and-reports/gridded-soil-survey-geographic-gssurgo-database>:
- f. Included with the gSSURGO database, but not a part of the standard SSURGO dataset is a table called Valu1. This table contains 57 pre-summarized or “ready to map” attributes derived from the official SSURGO database. These attribute data are pre-summarized to the map unit level using best-practice generalization methods intended to meet the needs of most users. The generalization methods include map unit component weighted averages and percent of the map unit meeting a given criteria. These themes were prepared to better meet the mapping needs of users of soil survey information and can be used with both SSURGO and gridded SSURGO (gSSURGO) datasets. Below is a partial list of the data found in the valu1 table.
  - i. Soil organic carbon - weighted average (g C/m<sup>2</sup>)
  - ii. Available water storage - weighted average (mm)
  - iii. National Commodity Crop Productivity Index (NCCPI) Version 3 - weighted average index for major components (Dobos, Sinclair, and Robotham, 2012)
  - iv. Root-zone depth of commodity crops - weighted average (cm) major components (Dobos et al., 2012)
  - v. Available water storage within the root-zone depth - weighted average (mm) major components
  - vi. Drought-vulnerable soil landscapes (The map unit is identified as either drought vulnerable or not drought vulnerable. Drought-vulnerable soil

- landscape map units have 152 millimeters (6 inches) or less root zone available water storage for major components.)
- vii. Potential wetland soil landscapes (PWSL Version 1) - percentage of the map unit that meets the criteria for a potential wetland soil landscape (see table metadata for detailed criteria)
- e. Open the Create Soil Map tool (under gSSURGO Mapping Toolset)
- i. Select the <county>gSSURGOWGS1984 layer and the variable of interest
    - 1. See list below
    - 2. I believe this just creates a layer (.lyr) file and a map layer in the mxd.
- f. Variables to generate:
- i. **NCCPI**
    - 1. Selections in the tool dialog window:
      - 1. Land Classifications – National Commodity Crop Productivity Index
      - 2. I assume this is the NCCPI\_all variable.
      - 2. See Appendix C for metadata from the layer in ArcGIS Desktop.
  - ii. **Drought Vulnerability (droughty)**
    - 1. Land Management – Drought Vulnerable Soils
    - 2. See Appendix C for metadata from the layer in ArcGIS Desktop.
  - iii. **Soil organic carbon stock estimate (SOC) in total soil profile**
    - 1. Selections in the tool dialog window:
      - 3. Soil Health Properties – Organic Matter
      - 4. Top Depth: 0
      - 5. Bottom Depth: 200
    - 2. See Appendix C for metadata from the layer in ArcGIS Desktop.
  - iv. **Available water storage estimate (AWS) in total soil profile**
    - 1. Selections in the tool dialog window:
      - a. Soil Physical Properties – Available Water Storage
      - b. Top Depth: 0
      - c. Bottom Depth: 200



3. See Appendix C for metadata from the layer in ArcGIS Desktop.
- v. **Flooding frequency class**
  1. Selections in the tool dialog window:
    - a. Water Features – Flooding Frequency Class
  4. See Appendix C for metadata from the layer in ArcGIS Desktop.
- g. Open the Convert Soil Map Layers to Raster tool (under gSSURGO Raster Toolset)
  - i. Select the maps created in the previous step and specify a location for the new raster dataset
    1. Output Workspace: County geodatabase (e.g., EstillKY.gdb)
    2. New rasters are named automatically by the tool.
  - h. Close ArcGIS Desktop
6. Socio-Economic Variables:
  - a. Census (Block-level)
    - i. Geometry Shapefiles (should have already been downloaded earlier):
      1. <https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2010&layergroup=Blocks>
      2. Choose the state and county for 2010 and download the .zip file
      3. Unzip the data and copy into the Blocks folder in the county spatial data folder.
      4. Export the shapefile to a feature class in the county geodatabase.
        - a. Rename it to Blocks2010
    - ii. Tables:
      1. <https://data.census.gov/advanced>
        - b. If the download popup appears in the lower right of the screen but gets stuck, click the little x icon and choose Resume Download.
      2. Filters:
        - c. Median Age
          - i. Geography: All Blocks within Estill County, Kentucky
          - ii. Surveys: Decennial Census, SF1
          - iii. Years: 2010

- iv. Topics: Populations and People, Age and Sex
  - v. Tab P13
  - vi. Variable: P013001
- d. Average Household Size
  - i. Geography: All Blocks within Estill County, Kentucky
  - ii. Surveys: Decennial Census, SF1
  - iii. Years: 2010
  - iv. Topics: Housing, Housing
  - v. Table H12
  - vi. Variable: H012001
- e. Population Density
  - i. Geography: All Blocks within Estill County, Kentucky
  - ii. Surveys: Decennial Census, SF1
  - iii. Years: 2010
  - iv. Topics: Populations and People, Populations and People
  - v. Tab P1
  - vi. Variable: PopDensity
- f. Percent of Population Non-White
  - i. Geography: All Blocks within Estill County, Kentucky
  - ii. Surveys: Decennial Census, SF1
  - iii. Years: 2010
  - iv. Topics: Populations and People, Populations and People
  - v. Tab P8
  - vi. Variable: pctPopNonWhite
- g. Percent of Households Renting
  - i. Geography: All Blocks within Estill County, Kentucky
  - ii. Surveys: Decennial Census, SF1
  - iii. Years: 2010
  - iv. Topics: Housing , Owner/Renter, Owner/Renter (householder) characteristics
  - v. Tab H16
  - vi. Variable: pctHouseholdsRenting
- iii. Data Processing:

- h. Click the “Download Table Data” hyperlink
- i. Check the box by the relevant table under the Tables tab
- j. Click download and save the 2010 data to the CensusTables folder in the county spatial data folder.
- k. Rename the file something like 2010P13MedianAge\_Blocks.csv and open in Excel
- l. Insert a new column to the right of the GEO\_ID column.
- m. Use the Convert Text to Columns tool under the Data tab to split the GEO\_ID column after the 9<sup>th</sup> character “1000000US” (Fixed width)
  - i. Specify both columns to be of type TEXT.
  - ii. (For some reason, opening the file in Excel will always try to treat the values as numbers, but in ArcGIS it should appear as text, which is necessary to join to the feature class.)
- n. Give the new column the header “GEOID10”.
- o. Add “ID” to the second row below GEOID10.
- p. In the second row, delete the descriptions of each of the P013... variables; this prevents ArcGIS from interpreting the column as Text. Leave a text description, like “ID”, in each of the ID column headings, so that ArcGIS treats those columns as text, which is necessary to join to the shapefile in ArcGIS.
- q. Close Excel.
- r. Using the ArcGIS Pro Catalog pane, import the table into the county geodatabase.
  - i. Rename it something like MedianAge2010\_Blocks
- s. Add the geodatabase table to the ArcGIS Pro project.
- t. Convert zeros to null (if necessary and appropriate):
  - i. In ArcGIS Pro, open the table and right-click the column (e.g., H012001) heading and click Calculate Field.

- ii. In the box right above the Code Block, enter `convertZeros(!H012001!)`, specifying the correct variable name.
- iii. In the Code Block enter:

```
def convertZeros(var):
    if (var == 0):
        return None
    else:
        return var
```

- u. Join the table to the block layer using the GEOID10 fields.
- v. Use the P013001 variable (Median Age, Both Sexes), for example.
- w. Create new field (if necessary and appropriate).
  - i. Average Household Size:
    1. Add a new copy of the Blocks2010 feature class and rename it to `AveHouseholdSize2010_Blocks`
    2. Join the table and proceed to the Feature to Raster step using the field `H012001`
  - ii. Median Age:
    1. Add a new copy of the Blocks2010 feature class and rename it to `MedianAge2010_Blocks`
    2. Join the table and proceed to the Feature to Raster step using the field `P013001`
  - iii. Population Density:
    1. Add a new copy of the Blocks2010 feature class and rename it to `PopulationDensity2010_Blocks`
    2. Before joining the table to the feature class, open attribute table and add a new fields, `AreaSqMiles` and `PopDensity` to the feature class.
    3. Use the Calculate Geometry option to populate the `AreaSqMiles` field:
      - a. Property: Area

- b. Area Unit: Square US Survey Miles
    - c. Coordinate System:  
countyNLCD2006
  4. Join the table to the feature class and use the Calculate Field tool to populate the PopDensity field:
    - a.  $P001001 / \text{Area}$
  - iv. pctPopNonWhite:
    1. Add a new copy of the Blocks2010 feature class and rename it to PctPopNonWhite2010\_Blocks
    2. Before joining the table to the feature class, open attribute table and add a new field, pctPopNonWhite to the feature class.
    3. Join the table to the feature class and use the Calculate Field tool to populate the pctPopNonWhite field:
      - a.  $(P008001 - P008003) / P008001$
      - b.  $(\text{total pop} - \text{white pop}) / \text{total pop}$
  - v. pctHouseholdsRenting:
    1. Add a new copy of the Blocks2010 feature class and rename it to pctHouseholdsRenting\_Blocks
    2. Before joining the table to the feature class, open attribute table and add a new field, pctHouseholdsRenting to the feature class.
    3. Join the table to the feature class and use the Calculate Field tool to populate the pctHouseholdsRenting field:
      - a.  $H016010 / H016001$
      - b.  $\frac{\text{Total households renting}}{\text{total households}}$
7. Convert vector census layers to raster
  - a. Use the Feature to Raster tool in ArcGIS Pro toolbox
  - b. Input features: block or block group feature class

- c. Field: attribute from the joined census table
  - d. Output raster: e.g., MedianAgeBlocks2010\_BlocksRaster (in county geodatabase)
    - i. The raster name must be different from the table name, thus why adding “raster” to the end.
  - e. Output cell size: countyNLCD2006
  - f. Environments:
    - i. Output Coordinate System: countyNLCD2006
    - ii. Cell Size: countyNLCD2006
    - iii. Snap Raster: countyNLCD2006
8. In ArcGIS Pro, use the Resample tool to ensure all independent variable layers precisely match and align (including soils, census, slope, etc.)
- a. Input Raster: each variable one at a time
  - b. Output Raster Dataset: something like PopulationDensity2010resample
  - c. Output Cell Size: countyNLCD2006
  - d. Resampling technique: Nearest
  - e. Environments:
    - i. Output Coordinate System: countyNLCD2006
    - ii. Processing Extent: countyNLCD2006
    - iii. Snap Raster: countyNLCD2006
9. Convert any <null> pixels to -9999
- a. Use the Con tool in ArcGIS Pro
  - b. Input raster: each ...\_Resample raster.
  - c. Where Value is null
  - d. Input true value: -9999
  - e. Input false value: ...\_Resample raster.
10. Convert Raster layers to ASCII files
- a. In ArcGIS Pro, use the Raster to ASCII tool
  - b. Input raster: Select each of the independent variable layers (...\_9999) one at a time
  - c. Output ASCII raster file: Save in the ASCII Rasters folder in the county folder with a name like ExtillPopNonWhite.txt.
    - i. Leave all other settings at their defaults
      - 1. Copy all the ASCII rasters into the CLUE folder for the county (e.g., ...\\PhD\\Downscaling\\CLUE\\EstillKY.
      - 2. Copy all the CLUE program files into the county folder too. Seems like the program needs everything to be in the same directory.

3. Copy and rename each of the ascii driving forces (location factors, i.e., independent variables) to sclgr\*.fil. Where \* indicates the numeric code for the variable (see below).

0. Slope
1. NCCPI
2. Median Age
3. Average Household Size
4. Drought Vulnerability
5. Flood Frequency
6. Percent Population Non-White
7. Population Density
8. Soil Organic Matter
9. Soil Water Storage
10. Percent Households Renting

- ii. These files are needed later when the CLUE model is run.
- d. Open the NLCD2006 raster in ArcGIS Pro
  - i. Use the Reclassify tool to recalculate each of the land cover types so their values match the 0-14 codes below.

0. 11. Water
1. 21. Developed, Open Space
2. 22. Developed, Low Intensity
3. 23. Developed, Medium Intensity
4. 24. Developed High Intensity
5. 31. Bare Rock/Sand/Clay
6. 41. Deciduous Forest
7. 42. Evergreen Forest
8. 43. Mixed Forest
9. 52. Shrub/Scrub
10. 71. Grasslands/Herbaceous
11. 81. Pasture/Hay
12. 82. Cultivated Crops
13. 90. Woody Wetlands
14. 95. Emergent Herbaceous Wetlands

**ALSO:** Convert any <null> values to -9999. Just like for the independent variable rasters above.

- ii. Output to a raster called cov\_all.
- iii. Export the cov\_all raster as an ascii version named cov\_all.0 to the county CLUE folder.

11. Use the File Convert tool (convert.exe) provided by CLUE to convert ascii files into a single tabular file in which each row is a pixel and each column contains the land cover type and each of the independent variables.

a. Parameters:

i. I can't check the "Exclude No Data Values" box because the manual indicates that all files must have "exactly the same number of NODATA values at the same geographical locations." Some of my layers have values everywhere, and others have some no data pixels (block-level data with no people, for example).

ii. Version 1:

1. 100% of all observations in final sample

2. 0 number of cells distance between sampling

3. Uncheck Exclude No Data values

4. Uncheck Balanced sample (I'm not sure exactly what this is).

5. Estill County results:

a. Good.

6. Blue Earth results:

a. Will not converge on a solution so coefficients are poor.

iii. List all the ascii text rasters in the Edit File List.

1. Copy this list into a text editor and then copy/paste from there.

cov\_all.0  
sc1gr0.fil  
sc1gr1.fil  
sc1gr2.fil  
sc1gr3.fil  
sc1gr4.fil  
sc1gr5.fil  
sc1gr6.fil  
sc1gr7.fil  
sc1gr8.fil  
sc1gr9.fil  
sc1gr10.fil

b. Result is a file, stat.txt.

c. Make a copy of stat.txt with the Version name from above. (Each new run will overwrite the stat.txt file.)



## Logistic Regression

12. Copy the stat.txt file to the county folder under  
PhD/Downscaling/R/LogisticRegressions...
13. Create a separate Markdown document for each county
14. Process a logistic regression and ROC test for each land cover type in the NLCD
15. Use the option(scipen=999) setting to prevent the use of scientific notation in the coefficients. Handy for when copying into CLUE.
16. Filter the records to only include ones that do not include a -9999 value in any column.
  - a. Don't do this. Even though it would produce a better regression, since all the -9999 values would be removed, and even though it would make the variables not correlated with each other, this causes CLUE to fail for some reason. CLUE only works when using regression coefficients from a regression that includes all rows.
17. Generate a correlation matrix and bubble plot.
  - a. Filter out the -9999 values first. Otherwise each variable is very highly correlated with each other.
18. The diagonal line through the middle of the ROC plot indicates a model that does no better than a random prediction; that represents an AUC score of .5, which means that half of the plot area is under the line. A perfect predictive model would have an AUC score of 1, and the plot would be as close to the upper left corner as possible. So, the goal is to have an AUC score close to 1 and the curve to be as close to the upper left corner as possible.
19. Here are the codes in the NLCD:

0. 11. Water
12. Perennial Ice Snow
1. 21. Developed, Open Space
2. 22. Developed, Low Intensity
3. 23. Developed, Medium Intensity
4. 24. Developed High Intensity
5. 31. Bare Rock/Sand/Clay
6. 41. Deciduous Forest
7. 42. Evergreen Forest
8. 43. Mixed Forest
9. 52. Shrub/Scrub
10. 71. Grasslands/Herbaceous
11. 81. Pasture/Hay
12. 82. Cultivated Crops
13. 90. Woody Wetlands
14. 95. Emergent Herbaceous Wetlands

- a. I believe all occur except for Perennial Ice Snow
20. Open the Raster Attribute Table in ArcGIS to see each of the land types that occur in the county NLCD
21. Copy and paste the table here.... (second column is the cell count for the land type)

Estill, KY: (For Estill, the first column is not land cover type, it's ObjectID. Refer to the text description for land class.)

1	4929	70	107	159	255	Open Water
2	25382	222	197	197	255	Developed, Open Space
3	15213	217	146	130	255	Developed, Low Intensity
4	4748	235	0	0	255	Developed, Medium Intensity
5	998	171	0	0	255	Developed, High Intensity
6	1051	179	172	159	255	Barren Land
7	462182		104	171	95	255 Deciduous Forest
8	3359	28	95	44	255	Evergreen Forest
9	83383	181	197	143	255	Mixed Forest
10	2211	204	184	121	255	Shrub/Scrub
11	10066	223	223	194	255	Herbaceous
12	118417		220	217	57	255 Hay/Pasture
13	6813	171	108	40	255	Cultivated Crops
14	976	184	217	235	255	Woody Wetlands
15	222	108	159	184	255	Emergent Herbaceous Wetlands

Blue Earth, MN

0	53107
1	81822
2	41409
3	26025
4	9938
5	7618
6	87645
7	115
8	1238
9	215
10	21892
11	35710
12	1680528
13	81742
14	74004

Brazoria, TX

0	47084
1	64590
2	47641
3	17221
4	7699
5	2465
6	20755
7	20849
8	30669
9	35939
10	43007
11	381181
12	433991
13	141960
14	174100

Wilcox, GA

0	11494
1	34103
2	14537
3	1875
4	398
5	746
6	13935
7	285329
8	39979
9	20389
10	55062
11	12162
12	339954
13	261785
14	8141

22. From the county CLUE folder, run clues.exe.

## CLUE Modeling

### 23. Regression Results

- a. Under Edit Input, choose Regression Results.
- b. Better yet, edit the file directly in Text Pad to facilitate copy paste from the R regression results.
- c. Refer to CLUE\_manual.pdf for details on the file structure
- d. Edits the *alloc1.reg* file in the county CLUE folder.
- e. Use the following numbering for the land types:
  0. Open Water
  1. Developed, Open Space
  2. Developed, Low Intensity
  3. Developed, Medium Intensity
  4. Developed High Intensity
  5. Bare Rock/Sand/Clay
  6. Deciduous Forest
  7. Evergreen Forest
  8. Mixed Forest
  9. Shrub/Scrub
  10. Grasslands/Herbaceous
  11. Pasture/Hay
  12. Cultivated Crops
  13. Woody Wetlands
  14. Emergent Herbaceous Wetlands
- f. Use the following numbering for the driving factors:
  0. Slope
  1. NCCPI
  2. Median Age
  3. Average Household Size
  4. Drought Vulnerability
  5. Flood Frequency
  6. Percent Population Non-White
  7. Population Density
  8. Soil Organic Matter
  9. Soil Water Storage
  10. Percent Households Renting
- g. Maybe paste the regression results into Excel, use Text to Columns tool to separate by TAB and Space then change the cell properties to show the coefficients as decimals instead of scientific notation. Add a column next

to the coefficients numbered 1-9 and copy/paste both columns into the text files to speed things up.

- i. Actually, I used the options(scipen = 999) function in each .rmd to force output to not use scientific notation.
  - ii. Still paste into Excel to add a second column with the 0 – 10 numbers.
- h. I excluded Land Cover Type 6 (Deciduous Forest) and 12 (Cultivated Crops) from the BlueEarth regression result because its coefficients were many orders of magnitude too big. Some sort of error.

## **24. Main Parameters**

- a. Refer to DynaCLUE\_Help\_contents.pdf for details on the file structure.
  - i. Parameters (line number, description | my setting):
    - 1 Number of land use types Integer
      - 15
    - 2 Number of regions Integer
      - 1
    - 3 Max. number of independent variables in a regression equation Integer
      - 11
    - 4 Total number of driving factors Integer
      - 11
    - 5 Number of rows Integer
      - Blue Earth: 1548
      - Estill: 1103
      - Wilcox: 1115
      - Brazoria: 3084
    - 6 Number of columns Integer
      - Blue Earth: 1640
      - Estill: 1191
      - Wilcox: 1475
      - Brazoria: 2653 (region2: 1219)
    - 7 Cell area Float (area of each pixel, in hectares)
      - .09
    - 8 xll coordinate Float
      - Blue Earth: 129585
      - Estill: 1032675
      - Wilcox: 1160295
      - Brazoria: 12225 (region2: 1219)
    - 9 yll coordinate Float
      - Blue Earth: 2318484.7677146

- Estill: 1678783.7553716
  - Wilcox: 1051479.9728759
  - Brazoria: 632625
- 10 Number coding of the land use types Integers
  - 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
- 11 Codes for conversion elasticities Float. Provide a number from 0 (easy conversion) to 1 (irreversible change) for each of the land types in the list above.
  - Scenario 1:
    - 1 0.25 0.25 0.25 0.25 0.9 0.75 0.75 0.75 0.25 0.1 0.1 0.1 0.9 0.9
      - Open Water
      - Developed, Open Space
      - Developed, Low Intensity
      - Developed, Medium Intensity
      - Developed High Intensity
      - Bare Rock/Sand/Clay
      - Deciduous Forest
      - Evergreen Forest
      - Mixed Forest
      - Shrub/Scrub
      - Grasslands/Herbaceous
      - Pasture/Hay
      - Cultivated Crops
      - Woody Wetlands
      - Emergent Herbaceous Wetlands
- 12 Iteration variables Float
  - Attempting a Scenario 4 in the hopes that results will be successful and meaningful.
  - 0 1 2
    - The first number (1) means that the amount of pixels allocated is measured as a percentage of the demanded amount.
    - The second number (1) means the **average** deviation between demanded changes and actually allocated changes
    - The third number (10) means the **maximum** deviation between demanded changes and actually allocated changes.
  - This parameter required trial and error to narrow in on an optimal set of values.

- 0 1 2 resulted in a solution.
- 13 Start and end year of simulation Integers
  - 2006 2016
- 14 Number and coding of explanatory factors that change every year Integers
  - 0
- 15 Output/input file choice 1, 0, -2 or 2
  - 1
  - CLUE sometimes throws an error here. Seems to be related to whether the input grids have the correct headers. As of the writing of this sentence, my grids require the 1 setting.
  - Double check this setting if CLUE throws errors about not being able to read any of the input grids of the independent variables.
- 16 Region specific regression choice 0, 1 or 2
  - 0
- 17 Initialization of land use history 0, 1 or 2
  - 1 5
    - The 1 indicates that a random number will be generated for each pixel to indicate the number of years prior to year zero the pixel has been in the current land use type.
    - The 5 is the maximum number of years the number generator can choose.
- 18 Neighborhood calculation choice 0, 1 or 2
  - 0
- 19 Location specific preference addition Integers
  - 0
- 20 Optional iteration parameter Float
  - 0.05 (default)

b. Edits the *main.1* file in the county CLUE folder.

c. Edit in Text Pad might be easier than the CLUE interface.

## 25. Conversion Matrix

- a. These values can be pasted into the Change Matrix menu of the CLUE interface.
  - i. Easier to paste the table below into TextPad first, and then copy/paste from there.

- b. Table of all land types: rows indicate a pixel's starting land type and columns indicate a future land type. 1 = conversion allowed between the land types, 0 = conversion is not allowed between the land types.
- c. 105 means that the pixel must remain in the initial land type for a minimum of 5 years before being allowed to convert to the future land type
- d. -105 means that the pixel must convert from its initial type within 5 years.

	Open Water	Dev. Open Space	Dev. Low Intensity	Dev. Medium Intensity	Dev. High Intensity	Bare Rock	Deciduous Forest	Evergreen Forest	Mixed Forest	Shrub/ Scrub	Grasslands	Pasture/ Hay	Cultivated Crops	Woody Wetlands	Emergent Herbaceous Wetlands
Open Water	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dev. Open Space	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Dev. Low Intensity	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Dev. Medium Intensity	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Dev. High Intensity	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Bare Rock	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Deciduous Forest	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Evergreen Forest	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Mixed Forest	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Shrub/Scrub	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Grasslands	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Pasture/Hay	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Cultivated Crops	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
Woody Wetlands	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Emergent Herb. Wetlands	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1



## **26. Area Restrictions**

- a. Create an ascii raster that indicates the area (pixels) that the model should use in its run. In my case, it will simply be the extent of the county NLCD raster.
- b. In ArcGIS Pro, use the Reclassify tool to convert all land cover types to the value 0, leaving the -9999 pixels as-is.
- c. Export the new raster to an ascii file, called region1.fil, and copy it to the county CLUE folder.
  - i. Do not copy the xml or prj files

## **27. Demand Scenario**

- a. Create a table in Excel in which each column represents one land type and each row represents a year in the model run (e.g., 2006 – 2016).
- b. Each value indicates the area of each land type in hectares.
- c. Use the same order and numbering for each land type as above.
- d. Refer to the raster attribute table above to see the pixel count for each land type in the raster.
  - i. Convert the pixel counts to hectares and enter the values into the first row of the table.
    1. Each pixel is 30m x 30m, which is 900 square meters.
    2. Which equals 0.09 hectares (Divide by 10,000 to get hectares).
    3. Multiply pixel count by 0.09 to calculate the total hectares of each land type.

### **b. Test Scenario**

- i. Only model the change from Cropland to grassland. Leave development unchanged.
  1. Cropland reduces by the UACL value
  2. Grassland increases by the UACL value
- ii. Changes in main config file:
  1. Set all conversion elasticities to 1 except for cropland and grassland which are 0
  2. Increase the deviation settings until the model runs.
    - a. Estill is at: 0 2 5
  3. Delete all the regression information except for cropland and grassland
- iii. Conversion matrix only allows changes from Cropland to Grassland. No other change trajectories are allowed.
- iv. This scenario reflects the notion that I can't model and account for the processes driving changes in all land types. For example, in the Wilcox, GA region, large patches of forest convert to grassland

between 2006 and 2016 in the NLCD. These changes are likely due to commercial forestry and the harvesting of pine trees. In light of my inability to account for all such processes and because my interest is solely in the change from cropland to grassland, I will constrain my land change drivers to the exchange of land between those two land types, keeping the areas of all other land types constant.

**c. Final Scenario**

- i. Same as test scenario, only changing pixels from cropland to grassland.
- ii. Begin with the 2006 NLCD and project change through 2056.
  1. Use the same rate of UACL expansion, but extrapolate across 50 years instead of just 10.
    - a. Since the UACL decimal calculated in chapter 2 is a percentage of land that converts over 10 years, divide it by 10 to derive the percent change per year. Use the per-year value to multiply the previous year's land type area to derive the annual change. For each year in the model, be sure to multiply the UACL per-year value by the previous year's land area. In this way, the reduction in cropland becomes less and less over time.
  2. Starting from 2006 instead of starting at 2016. The reason for this is because (1) my value of UACL is based on change between 2006 and 2016, and therefore its starting date is 2006, and (2) the NLCD has poor accuracy (approximately 20%) when modeling pixels that change from cropland to another land type. Given this poor accuracy of change and the disagreement between my UACL values, which are derived from the Census of Agriculture, starting at 2016 is reasonable. Furthermore, NLCD and the Census of Agriculture do not agree in terms of counties' net change in cropland. In some cases, one will indicate an increase in cropland while the other indicates a decrease over the same time period. Reconciling these differences does not have an obvious solution. Given the challenges in interpreting cropland from satellite imagery and the reported inaccuracies of the NLCD, the Census of Agriculture is likely a more reliable source of information about the area of land in cropland production

(Baxter/Calvert citation). Consequently, starting a model run from 2016 may not add any additional information than starting from 2006.

## **28. Region Files:**

- a. A region file must be selected when running CLUE, even if it is simply the entire extent.
- b. Region1.fil
  - i. Entire county
- c. Region2.fil
  - i. A small rectangular area just for demo purposes to test the model..
  - ii. For Brazoria, region2 is a 1218x1218 area that is necessary because the entire county (region1) is too big for CLUE to run.

## **29. Demand Scenario**

## **30. Run CLUE Model**

- a. Results are saved as cov\_all.\*
  - i. The \* indicates the year after the start of the simulation
- b. Copy all of the cov\_all.\* result rasters to a scenario folder under the CLUEResults folder under the county's Spatial Data folder.
- c. Add .asc to the end of each file name to inform ArcGIS that the files are ASCII rasters.
  - i. Use the following code in a PowerShell window:

```
$suffix = ".asc"
Get-ChildItem -Path *.* -File | ForEach-Object {
    $currentFile = $_
    $newName = $_.Name + $suffix
    Rename-Item -path $_ -NewName $newName
    Write-Host "Renamed file $currentFile to $newName"
}
```

## **31. View Results in ArcGIS Pro**

- a. Add the cov\_0 thru cov\_50 ascii rasters to Pro
- b. Import the symbology from the CLUEResults\NLCDReclass.clr colormap file to match the NLCD color scheme.

## **32. Errors**

- a. If CLUE fails saying that there's an error with the sclgr#.fil files, change the parameters in line 12 or main.1 to increase the allowable deviation.

## Calculate Abandoned Cropland

1. Use Raster Calculator to identify pixels that changed from cropland in year 0 to grassland in each year after (change the cov\_all.2.asc for each raster and change the output accordingly):

- a. Use the Model Builder model to run this as a batch for all 50 rasters.

$$\text{Con}(\text{Con}(\text{"cov\_all.0.asc"}==12,1,0) + \text{Con}(\text{"cov\_all.2.asc"}==10,1,0)==2,1,0)$$

- b. Result values:

- i. 1 = UACL
- ii. 0 = Cropland changing to another land type and not usable, or land that converted to grassland from a non-cropland type.
- iii. 0 = Land that was not cropland to begin with.

- c. Save output raster as WilcoxUACL## in the county geodatabase

## Landscape Metrics

1. Export the cov\_## rasters from Pro... (Use tool in Model Builder)
  - i. FragStats recommends using GeoTIFFs.
  - b. Save TIFF files in a Fragstats folder in the county SpatialData folder.
2. Open Fragstats
  - a. Add the tifs and save as a project like "Wilcox."
  - b. Use the .fbt files to batch load all 50.
3. All Class-level metrics (quoted definitions from fragstats online documentation. (<https://www.fragstats.org/index.php/documentation>)
  - a. Average patch area (AREA\_MN)
    - i. Mean patch size. Fragstats calculates the area of each patch in the class, sums them, and divides by the total number of patches in the class. (hectares)
    - ii. Larger patches are better
  - b. Largest patch index (LPI)
    - i. Percent of the entire landscape comprised by the largest patch
    - ii. "LPI approaches 0 when the largest patch of the corresponding patch type is increasingly small. LPI = 100 when the entire landscape consists of a single patch of the corresponding patch type; that is, when the largest patch comprises 100% of the landscape."
    - iii. Higher LPI is better
  - c. Edge density (ED)

- i. Sum of the lengths of all patches of the class type divided by total landscape area. I.e., are there more, complexly shaped patches. Similar to PD except it includes a measure of how complex or irregular the patch shape is.
  - ii. “ED equals the sum of the lengths (m) of all edge segments involving the corresponding patch type, divided by the total landscape area (m<sup>2</sup>), multiplied by 10,000 (to convert to hectares).”
  - iii. Keep the default setting to not include edges along the raster boundary
  - iv. Lower ED is better
- d. Percentage of Landscape (PLAND)
  - i. “PLAND equals the sum of the areas (m<sup>2</sup>) of all patches of the corresponding patch type, divided by total landscape area (m<sup>2</sup>), multiplied by 100 (to convert to a percentage); in other words, PLAND equals the percentage the landscape comprised of the corresponding patch type. Note, total landscape area (A) includes any internal background present.”
  - ii. Higher is better
- e. Mean perimeter-area ratio (PARA\_MN)
  - i. “Perimeter-area ratio is a simple measure of shape complexity, but without standardization to a simple Euclidean shape (e.g., square). A problem with this metric as a shape index is that it varies with the size of the patch. For example, holding shape constant, an increase in patch size will cause a decrease in the perimeter-area ratio.”
  - ii. Ratio of patch perimeter length over patch area
  - iii. Lower is better
- f. Connectance index (CONNECT)
  - i. The percent of all possible patch pairings that are within a certain distance of another patch of the same class. I.e., I specify a threshold distance (e.g., 100m) and Fragstats determines how many pairs of patches are within that distance of each other.
  - ii. “Connectance is defined on the number of functional joinings between patches of the corresponding patch type, where each pair of patches is either connected or not based on a user-specified distance criterion. Connectance is reported as a percentage of the maximum possible connectance given the number of patches.”
  - iii. Set the threshold to 100. (I assume the units are meters.)
  - iv. Higher is better

- g. Patch density (PD)
  - i. Number of patches of a certain class divided by the total area of the landscape. Basically provides an area-normalized version of the total number of patches.
  - ii. “PD equals the number of patches of the corresponding patch type divided by total landscape area (m<sup>2</sup>), multiplied by 10,000 and 100 (to convert to 100 hectares).”
- h. Aggregation index (AI)
  - i. For all pixels of a certain class, this calculates how many pixels are adjacent to another pixel of the same class divided by the maximum possible number of such adjacencies (i.e., add up all the possible pairs of class pixels that would exist if the landscape had one large patch).
  - ii. “AI equals the number of like adjacencies involving the corresponding class, divided by the maximum possible number of like adjacencies involving the corresponding class, which is achieved when the class is maximally clumped into a single, compact patch; multiplied by 100 (to convert to a percentage).”
  - iii. Higher is better
- 4. Save the output to WilcoxScenarioX.class
- 5. Import each county .class file into a separate sheet in Excel
  - a. Save the Excel file in the R folder.
- 6. Filter the Type column to only show the cls\_1 records. (UACL)
- 7. Plot each metric on a line chart.

## Appendix F. Dyna-CLUE Demand Inputs

Demand input for Blue Earth County, MN (hectares).

Year	0. Open Water	1. Developed, Open Space	2. Developed, Low Intensity	3. Developed, Medium Intensity	4. Developed High Intensity	5. Bare Rock/Sand/Clay	6. Deciduous Forest	7. Evergreen Forest	8. Mixed Forest	9. Shrub/Scrub	10. Grasslands/Herbaceous	11. Pasture/Hay	12. Cultivated Crops	13. Woody Wetlands	14. Emergent Herbaceous Wetlands	TOTAL
0	4780	7364	3727	2342	894	686	7888	10	111	19	1970	3214	151248	7357	6660	<b>198271</b>
1	4780	7364	3727	2342	894	686	7888	10	111	19	2471	3214	150747	7357	6660	<b>198271</b>
2	4780	7364	3727	2342	894	686	7888	10	111	19	2970	3214	150248	7357	6660	<b>198271</b>
3	4780	7364	3727	2342	894	686	7888	10	111	19	3467	3214	149750	7357	6660	<b>198271</b>
4	4780	7364	3727	2342	894	686	7888	10	111	19	3963	3214	149255	7357	6660	<b>198271</b>
5	4780	7364	3727	2342	894	686	7888	10	111	19	4457	3214	148761	7357	6660	<b>198271</b>
6	4780	7364	3727	2342	894	686	7888	10	111	19	4950	3214	148268	7357	6660	<b>198271</b>
7	4780	7364	3727	2342	894	686	7888	10	111	19	5441	3214	147777	7357	6660	<b>198271</b>
8	4780	7364	3727	2342	894	686	7888	10	111	19	5930	3214	147288	7357	6660	<b>198271</b>
9	4780	7364	3727	2342	894	686	7888	10	111	19	6417	3214	146800	7357	6660	<b>198271</b>
10	4780	7364	3727	2342	894	686	7888	10	111	19	6903	3214	146314	7357	6660	<b>198271</b>
11	4780	7364	3727	2342	894	686	7888	10	111	19	7388	3214	145830	7357	6660	<b>198271</b>
12	4780	7364	3727	2342	894	686	7888	10	111	19	7871	3214	145347	7357	6660	<b>198271</b>

13	4780	7364	3727	2342	894	686	7888	10	111	19	8352	3214	144866	7357	6660	<b>198271</b>
14	4780	7364	3727	2342	894	686	7888	10	111	19	8831	3214	144387	7357	6660	<b>198271</b>
15	4780	7364	3727	2342	894	686	7888	10	111	19	9309	3214	143909	7357	6660	<b>198271</b>
16	4780	7364	3727	2342	894	686	7888	10	111	19	9786	3214	143432	7357	6660	<b>198271</b>
17	4780	7364	3727	2342	894	686	7888	10	111	19	10261	3214	142957	7357	6660	<b>198271</b>
18	4780	7364	3727	2342	894	686	7888	10	111	19	10734	3214	142484	7357	6660	<b>198271</b>
19	4780	7364	3727	2342	894	686	7888	10	111	19	11205	3214	142012	7357	6660	<b>198271</b>
20	4780	7364	3727	2342	894	686	7888	10	111	19	11676	3214	141542	7357	6660	<b>198271</b>
21	4780	7364	3727	2342	894	686	7888	10	111	19	12144	3214	141074	7357	6660	<b>198271</b>
22	4780	7364	3727	2342	894	686	7888	10	111	19	12611	3214	140607	7357	6660	<b>198271</b>
23	4780	7364	3727	2342	894	686	7888	10	111	19	13077	3214	140141	7357	6660	<b>198271</b>
24	4780	7364	3727	2342	894	686	7888	10	111	19	13541	3214	139677	7357	6660	<b>198271</b>
25	4780	7364	3727	2342	894	686	7888	10	111	19	14003	3214	139215	7357	6660	<b>198271</b>
26	4780	7364	3727	2342	894	686	7888	10	111	19	14464	3214	138754	7357	6660	<b>198271</b>
27	4780	7364	3727	2342	894	686	7888	10	111	19	14923	3214	138295	7357	6660	<b>198271</b>
28	4780	7364	3727	2342	894	686	7888	10	111	19	15381	3214	137837	7357	6660	<b>198271</b>
29	4780	7364	3727	2342	894	686	7888	10	111	19	15837	3214	137380	7357	6660	<b>198271</b>
30	4780	7364	3727	2342	894	686	7888	10	111	19	16292	3214	136926	7357	6660	<b>198271</b>
31	4780	7364	3727	2342	894	686	7888	10	111	19	16745	3214	136472	7357	6660	<b>198271</b>
32	4780	7364	3727	2342	894	686	7888	10	111	19	17197	3214	136021	7357	6660	<b>198271</b>
33	4780	7364	3727	2342	894	686	7888	10	111	19	17648	3214	135570	7357	6660	<b>198271</b>
34	4780	7364	3727	2342	894	686	7888	10	111	19	18096	3214	135121	7357	6660	<b>198271</b>
35	4780	7364	3727	2342	894	686	7888	10	111	19	18544	3214	134674	7357	6660	<b>198271</b>
36	4780	7364	3727	2342	894	686	7888	10	111	19	18990	3214	134228	7357	6660	<b>198271</b>
37	4780	7364	3727	2342	894	686	7888	10	111	19	19434	3214	133784	7357	6660	<b>198271</b>
38	4780	7364	3727	2342	894	686	7888	10	111	19	19877	3214	133341	7357	6660	<b>198271</b>
39	4780	7364	3727	2342	894	686	7888	10	111	19	20318	3214	132900	7357	6660	<b>198271</b>
40	4780	7364	3727	2342	894	686	7888	10	111	19	20758	3214	132460	7357	6660	<b>198271</b>



41	4780	7364	3727	2342	894	686	7888	10	111	19	21197	3214	132021	7357	6660	<b>198271</b>
42	4780	7364	3727	2342	894	686	7888	10	111	19	21634	3214	131584	7357	6660	<b>198271</b>
43	4780	7364	3727	2342	894	686	7888	10	111	19	22069	3214	131148	7357	6660	<b>198271</b>
44	4780	7364	3727	2342	894	686	7888	10	111	19	22503	3214	130714	7357	6660	<b>198271</b>
45	4780	7364	3727	2342	894	686	7888	10	111	19	22936	3214	130282	7357	6660	<b>198271</b>
46	4780	7364	3727	2342	894	686	7888	10	111	19	23368	3214	129850	7357	6660	<b>198271</b>
47	4780	7364	3727	2342	894	686	7888	10	111	19	23797	3214	129420	7357	6660	<b>198271</b>
48	4780	7364	3727	2342	894	686	7888	10	111	19	24226	3214	128992	7357	6660	<b>198271</b>
49	4780	7364	3727	2342	894	686	7888	10	111	19	24653	3214	128565	7357	6660	<b>198271</b>
50	4780	7364	3727	2342	894	686	7888	10	111	19	25078	3214	128139	7357	6660	<b>198271</b>

Demand Input for Brazoria County, TX (hectares).

Year	0. Open Water	1. Developed, Open Space	2. Developed, Low Intensity	3. Developed, Medium Intensity	4. Developed High Intensity	5. Bare Rock/Sand/Clay	6. Deciduous Forest	7. Evergreen Forest	8. Mixed Forest	9. Shrub/Scrub	10. Grasslands/Herbaceous	11. Pasture/Hay	12. Cultivated Crops	13. Woody Wetlands	14. Emergent Herbaceous Wetlands	TOTAL
0	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	10337	82519	58508	55920	63856	<b>413866</b>
1	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	11173	82519	57673	55920	63856	<b>413866</b>
2	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	11996	82519	56849	55920	63856	<b>413866</b>
3	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	12807	82519	56038	55920	63856	<b>413866</b>
4	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	13607	82519	55238	55920	63856	<b>413866</b>
5	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	14396	82519	54449	55920	63856	<b>413866</b>
6	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	15173	82519	53672	55920	63856	<b>413866</b>
7	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	15939	82519	52906	55920	63856	<b>413866</b>
8	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	16695	82519	52151	55920	63856	<b>413866</b>
9	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	17439	82519	51406	55920	63856	<b>413866</b>
10	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	18173	82519	50672	55920	63856	<b>413866</b>
11	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	18896	82519	49949	55920	63856	<b>413866</b>
12	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	19609	82519	49236	55920	63856	<b>413866</b>
13	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	20312	82519	48533	55920	63856	<b>413866</b>
14	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	21005	82519	47840	55920	63856	<b>413866</b>
15	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	21688	82519	47157	55920	63856	<b>413866</b>
16	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	22361	82519	46484	55920	63856	<b>413866</b>
17	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	23025	82519	45821	55920	63856	<b>413866</b>
18	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	23679	82519	45166	55920	63856	<b>413866</b>

19	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	24324	82519	44522	55920	63856	<b>413866</b>
20	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	24959	82519	43886	55920	63856	<b>413866</b>
21	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	25586	82519	43260	55920	63856	<b>413866</b>
22	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	26203	82519	42642	55920	63856	<b>413866</b>
23	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	26812	82519	42033	55920	63856	<b>413866</b>
24	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	27412	82519	41433	55920	63856	<b>413866</b>
25	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	28003	82519	40842	55920	63856	<b>413866</b>
26	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	28586	82519	40259	55920	63856	<b>413866</b>
27	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	29161	82519	39684	55920	63856	<b>413866</b>
28	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	29728	82519	39118	55920	63856	<b>413866</b>
29	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	30286	82519	38559	55920	63856	<b>413866</b>
30	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	30837	82519	38009	55920	63856	<b>413866</b>
31	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	31379	82519	37466	55920	63856	<b>413866</b>
32	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	31914	82519	36931	55920	63856	<b>413866</b>
33	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	32441	82519	36404	55920	63856	<b>413866</b>
34	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	32961	82519	35884	55920	63856	<b>413866</b>
35	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	33473	82519	35372	55920	63856	<b>413866</b>
36	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	33978	82519	34867	55920	63856	<b>413866</b>
37	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	34476	82519	34369	55920	63856	<b>413866</b>
38	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	34966	82519	33879	55920	63856	<b>413866</b>
39	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	35450	82519	33395	55920	63856	<b>413866</b>
40	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	35927	82519	32918	55920	63856	<b>413866</b>
41	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	36397	82519	32449	55920	63856	<b>413866</b>
42	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	36860	82519	31985	55920	63856	<b>413866</b>
43	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	37317	82519	31529	55920	63856	<b>413866</b>
44	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	37767	82519	31079	55920	63856	<b>413866</b>
45	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	38210	82519	30635	55920	63856	<b>413866</b>
46	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	38648	82519	30198	55920	63856	<b>413866</b>

47	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	39079	82519	29767	55920	63856	<b>413866</b>
48	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	39504	82519	29342	55920	63856	<b>413866</b>
49	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	39922	82519	28923	55920	63856	<b>413866</b>
50	56477	18369	14870	7889	3809	1963	9732	8921	10847	9848	40335	82519	28510	55920	63856	<b>413866</b>

Demand input for Estill County, KY (hectares).

Year	0. Open Water	1. Developed, Open Space	2. Developed, Low Intensity	3. Developed, Medium Intensity	4. Developed High Intensity	5. Bare Rock/Sand/Clay	6. Deciduous Forest	7. Evergreen Forest	8. Mixed Forest	9. Shrub/Scrub	10. Grasslands/Herbaceous	11. Pasture/Hay	12. Cultivated Crops	13. Woody Wetlands	14. Emergent Herbaceous Wetlands	TOTAL
0	444	2284	1369	427	90	95	41596	302	7504	199	906	10658	613	88	20	<b>66576</b>
1	444	2284	1369	427	90	95	41596	302	7504	199	926	10658	593	88	20	<b>66576</b>
2	444	2284	1369	427	90	95	41596	302	7504	199	946	10658	573	88	20	<b>66576</b>
3	444	2284	1369	427	90	95	41596	302	7504	199	965	10658	554	88	20	<b>66576</b>
4	444	2284	1369	427	90	95	41596	302	7504	199	983	10658	536	88	20	<b>66576</b>
5	444	2284	1369	427	90	95	41596	302	7504	199	1001	10658	518	88	20	<b>66576</b>
6	444	2284	1369	427	90	95	41596	302	7504	199	1018	10658	501	88	20	<b>66576</b>
7	444	2284	1369	427	90	95	41596	302	7504	199	1035	10658	484	88	20	<b>66576</b>
8	444	2284	1369	427	90	95	41596	302	7504	199	1051	10658	468	88	20	<b>66576</b>
9	444	2284	1369	427	90	95	41596	302	7504	199	1066	10658	453	88	20	<b>66576</b>
10	444	2284	1369	427	90	95	41596	302	7504	199	1081	10658	438	88	20	<b>66576</b>
11	444	2284	1369	427	90	95	41596	302	7504	199	1096	10658	423	88	20	<b>66576</b>
12	444	2284	1369	427	90	95	41596	302	7504	199	1110	10658	409	88	20	<b>66576</b>
13	444	2284	1369	427	90	95	41596	302	7504	199	1123	10658	396	88	20	<b>66576</b>
14	444	2284	1369	427	90	95	41596	302	7504	199	1137	10658	383	88	20	<b>66576</b>
15	444	2284	1369	427	90	95	41596	302	7504	199	1149	10658	370	88	20	<b>66576</b>
16	444	2284	1369	427	90	95	41596	302	7504	199	1162	10658	358	88	20	<b>66576</b>
17	444	2284	1369	427	90	95	41596	302	7504	199	1173	10658	346	88	20	<b>66576</b>
18	444	2284	1369	427	90	95	41596	302	7504	199	1185	10658	334	88	20	<b>66576</b>

19	444	2284	1369	427	90	95	41596	302	7504	199	1196	10658	323	88	20	<b>66576</b>
20	444	2284	1369	427	90	95	41596	302	7504	199	1207	10658	313	88	20	<b>66576</b>
21	444	2284	1369	427	90	95	41596	302	7504	199	1217	10658	302	88	20	<b>66576</b>
22	444	2284	1369	427	90	95	41596	302	7504	199	1227	10658	292	88	20	<b>66576</b>
23	444	2284	1369	427	90	95	41596	302	7504	199	1237	10658	282	88	20	<b>66576</b>
24	444	2284	1369	427	90	95	41596	302	7504	199	1246	10658	273	88	20	<b>66576</b>
25	444	2284	1369	427	90	95	41596	302	7504	199	1255	10658	264	88	20	<b>66576</b>
26	444	2284	1369	427	90	95	41596	302	7504	199	1264	10658	255	88	20	<b>66576</b>
27	444	2284	1369	427	90	95	41596	302	7504	199	1272	10658	247	88	20	<b>66576</b>
28	444	2284	1369	427	90	95	41596	302	7504	199	1280	10658	239	88	20	<b>66576</b>
29	444	2284	1369	427	90	95	41596	302	7504	199	1288	10658	231	88	20	<b>66576</b>
30	444	2284	1369	427	90	95	41596	302	7504	199	1296	10658	223	88	20	<b>66576</b>
31	444	2284	1369	427	90	95	41596	302	7504	199	1303	10658	216	88	20	<b>66576</b>
32	444	2284	1369	427	90	95	41596	302	7504	199	1311	10658	209	88	20	<b>66576</b>
33	444	2284	1369	427	90	95	41596	302	7504	199	1317	10658	202	88	20	<b>66576</b>
34	444	2284	1369	427	90	95	41596	302	7504	199	1324	10658	195	88	20	<b>66576</b>
35	444	2284	1369	427	90	95	41596	302	7504	199	1331	10658	189	88	20	<b>66576</b>
36	444	2284	1369	427	90	95	41596	302	7504	199	1337	10658	182	88	20	<b>66576</b>
37	444	2284	1369	427	90	95	41596	302	7504	199	1343	10658	176	88	20	<b>66576</b>
38	444	2284	1369	427	90	95	41596	302	7504	199	1349	10658	170	88	20	<b>66576</b>
39	444	2284	1369	427	90	95	41596	302	7504	199	1354	10658	165	88	20	<b>66576</b>
40	444	2284	1369	427	90	95	41596	302	7504	199	1360	10658	159	88	20	<b>66576</b>
41	444	2284	1369	427	90	95	41596	302	7504	199	1365	10658	154	88	20	<b>66576</b>
42	444	2284	1369	427	90	95	41596	302	7504	199	1370	10658	149	88	20	<b>66576</b>
43	444	2284	1369	427	90	95	41596	302	7504	199	1375	10658	144	88	20	<b>66576</b>
44	444	2284	1369	427	90	95	41596	302	7504	199	1380	10658	139	88	20	<b>66576</b>
45	444	2284	1369	427	90	95	41596	302	7504	199	1385	10658	135	88	20	<b>66576</b>
46	444	2284	1369	427	90	95	41596	302	7504	199	1389	10658	130	88	20	<b>66576</b>

47	444	2284	1369	427	90	95	41596	302	7504	199	1393	10658	126	88	20	<b>66576</b>
48	444	2284	1369	427	90	95	41596	302	7504	199	1397	10658	122	88	20	<b>66576</b>
49	444	2284	1369	427	90	95	41596	302	7504	199	1402	10658	118	88	20	<b>66576</b>
50	444	2284	1369	427	90	95	41596	302	7504	199	1405	10658	114	88	20	<b>66576</b>

Demand input for Wilcox County, GA (hectares).

Year	0. Open Water	1. Developed, Open Space	2. Developed, Low Intensity	3. Developed, Medium Intensity	4. Developed High Intensity	5. Bare Rock/Sand/Clay	6. Deciduous Forest	7. Evergreen Forest	8. Mixed Forest	9. Shrub/Scrub	10. Grasslands/Herbaceous	11. Pasture/Hay	12. Cultivated Crops	13. Woody Wetlands	14. Emergent Herbaceous Wetlands	TOTAL
0	1034	3069	1308	169	36	67	1254	25680	3598	1835	4956	1095	30596	23561	733	<b>98990</b>
1	1034	3069	1308	169	36	67	1254	25680	3598	1835	5767	1095	29784	23561	733	<b>98990</b>
2	1034	3069	1308	169	36	67	1254	25680	3598	1835	6557	1095	28994	23561	733	<b>98990</b>
3	1034	3069	1308	169	36	67	1254	25680	3598	1835	7326	1095	28226	23561	733	<b>98990</b>
4	1034	3069	1308	169	36	67	1254	25680	3598	1835	8074	1095	27477	23561	733	<b>98990</b>
5	1034	3069	1308	169	36	67	1254	25680	3598	1835	8803	1095	26748	23561	733	<b>98990</b>
6	1034	3069	1308	169	36	67	1254	25680	3598	1835	9513	1095	26039	23561	733	<b>98990</b>
7	1034	3069	1308	169	36	67	1254	25680	3598	1835	10203	1095	25348	23561	733	<b>98990</b>
8	1034	3069	1308	169	36	67	1254	25680	3598	1835	10875	1095	24676	23561	733	<b>98990</b>
9	1034	3069	1308	169	36	67	1254	25680	3598	1835	11530	1095	24022	23561	733	<b>98990</b>
10	1034	3069	1308	169	36	67	1254	25680	3598	1835	12167	1095	23384	23561	733	<b>98990</b>
11	1034	3069	1308	169	36	67	1254	25680	3598	1835	12787	1095	22764	23561	733	<b>98990</b>
12	1034	3069	1308	169	36	67	1254	25680	3598	1835	13391	1095	22161	23561	733	<b>98990</b>
13	1034	3069	1308	169	36	67	1254	25680	3598	1835	13979	1095	21573	23561	733	<b>98990</b>
14	1034	3069	1308	169	36	67	1254	25680	3598	1835	14551	1095	21001	23561	733	<b>98990</b>
15	1034	3069	1308	169	36	67	1254	25680	3598	1835	15108	1095	20444	23561	733	<b>98990</b>
16	1034	3069	1308	169	36	67	1254	25680	3598	1835	15650	1095	19902	23561	733	<b>98990</b>
17	1034	3069	1308	169	36	67	1254	25680	3598	1835	16178	1095	19374	23561	733	<b>98990</b>
18	1034	3069	1308	169	36	67	1254	25680	3598	1835	16692	1095	18860	23561	733	<b>98990</b>



19	1034	3069	1308	169	36	67	1254	25680	3598	1835	17192	1095	18360	23561	733	<b>98990</b>
20	1034	3069	1308	169	36	67	1254	25680	3598	1835	17679	1095	17873	23561	733	<b>98990</b>
21	1034	3069	1308	169	36	67	1254	25680	3598	1835	18153	1095	17399	23561	733	<b>98990</b>
22	1034	3069	1308	169	36	67	1254	25680	3598	1835	18614	1095	16937	23561	733	<b>98990</b>
23	1034	3069	1308	169	36	67	1254	25680	3598	1835	19063	1095	16488	23561	733	<b>98990</b>
24	1034	3069	1308	169	36	67	1254	25680	3598	1835	19501	1095	16051	23561	733	<b>98990</b>
25	1034	3069	1308	169	36	67	1254	25680	3598	1835	19926	1095	15625	23561	733	<b>98990</b>
26	1034	3069	1308	169	36	67	1254	25680	3598	1835	20341	1095	15211	23561	733	<b>98990</b>
27	1034	3069	1308	169	36	67	1254	25680	3598	1835	20744	1095	14807	23561	733	<b>98990</b>
28	1034	3069	1308	169	36	67	1254	25680	3598	1835	21137	1095	14415	23561	733	<b>98990</b>
29	1034	3069	1308	169	36	67	1254	25680	3598	1835	21519	1095	14032	23561	733	<b>98990</b>
30	1034	3069	1308	169	36	67	1254	25680	3598	1835	21891	1095	13660	23561	733	<b>98990</b>
31	1034	3069	1308	169	36	67	1254	25680	3598	1835	22254	1095	13298	23561	733	<b>98990</b>
32	1034	3069	1308	169	36	67	1254	25680	3598	1835	22606	1095	12945	23561	733	<b>98990</b>
33	1034	3069	1308	169	36	67	1254	25680	3598	1835	22950	1095	12602	23561	733	<b>98990</b>
34	1034	3069	1308	169	36	67	1254	25680	3598	1835	23284	1095	12268	23561	733	<b>98990</b>
35	1034	3069	1308	169	36	67	1254	25680	3598	1835	23609	1095	11942	23561	733	<b>98990</b>
36	1034	3069	1308	169	36	67	1254	25680	3598	1835	23926	1095	11626	23561	733	<b>98990</b>
37	1034	3069	1308	169	36	67	1254	25680	3598	1835	24234	1095	11317	23561	733	<b>98990</b>
38	1034	3069	1308	169	36	67	1254	25680	3598	1835	24534	1095	11017	23561	733	<b>98990</b>
39	1034	3069	1308	169	36	67	1254	25680	3598	1835	24827	1095	10725	23561	733	<b>98990</b>
40	1034	3069	1308	169	36	67	1254	25680	3598	1835	25111	1095	10440	23561	733	<b>98990</b>
41	1034	3069	1308	169	36	67	1254	25680	3598	1835	25388	1095	10164	23561	733	<b>98990</b>
42	1034	3069	1308	169	36	67	1254	25680	3598	1835	25657	1095	9894	23561	733	<b>98990</b>
43	1034	3069	1308	169	36	67	1254	25680	3598	1835	25920	1095	9632	23561	733	<b>98990</b>
44	1034	3069	1308	169	36	67	1254	25680	3598	1835	26175	1095	9376	23561	733	<b>98990</b>
45	1034	3069	1308	169	36	67	1254	25680	3598	1835	26424	1095	9128	23561	733	<b>98990</b>
46	1034	3069	1308	169	36	67	1254	25680	3598	1835	26666	1095	8885	23561	733	<b>98990</b>

47	1034	3069	1308	169	36	67	1254	25680	3598	1835	26902	1095	8650	23561	733	<b>98990</b>
48	1034	3069	1308	169	36	67	1254	25680	3598	1835	27131	1095	8420	23561	733	<b>98990</b>
49	1034	3069	1308	169	36	67	1254	25680	3598	1835	27354	1095	8197	23561	733	<b>98990</b>
50	1034	3069	1308	169	36	67	1254	25680	3598	1835	27572	1095	7980	23561	733	<b>98990</b>

## Appendix G. Logistic Regression Results

The variable names below refer to the following predictors:

sc1gr0.fil – Slope  
 sc1gr1.fil – NCCPI  
 sc1gr2.fil – Median Age  
 sc1gr3.fil - Average Household Size  
 sc1gr4.fil - Drought Vulnerability  
 sc1gr5.fil - Flood Frequency  
 sc1gr6.fil - Percent Population Non-White  
 sc1gr7.fil - Population Density  
 sc1gr8.fil - Soil Organic Matter  
 sc1gr9.fil - Soil Water Storage  
 sc1gr10.fil - Percent Households Renting

### Blue Earth County, MN:

#### 0. Water

No regression performed for this land type.

#### 1. Developed, Open Space

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-3.256779157	0.028996528	-112.316	< 0.0000000000000002	***
sc1fr0.fil	-0.000394075	0.000008445	-46.662	< 0.0000000000000002	***
sc1fr1.fil	0.000059812	0.000008159	7.331	0.0000000000000228	***
sc1fr2.fil	-0.002338602	0.000336734	-6.945	0.0000000000003786	***
sc1fr3.fil	-0.002686513	0.005517679	-0.487	0.626	
sc1fr4.fil	0.000566594	0.000022143	25.588	< 0.0000000000000002	***
sc1fr5.fil	0.000482864	0.000010676	45.230	< 0.0000000000000002	***
sc1fr6.fil	0.002222472	0.000338880	6.558	0.0000000000054431	***
sc1fr7.fil	0.000141571	0.000002897	48.869	< 0.0000000000000002	***
sc1fr8.fil	-0.002645225	0.000470489	-5.622	0.000000018844988	***
sc1fr9.fil	0.002419779	0.000469259	5.157	0.000000251484689	***
sc1fr10.fil	0.002775297	0.005518606	0.503	0.615	

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 2. Developed, Low Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-3.360675028	0.039867767	-84.296	< 0.0000000000000002	***
sc1fr0.fil	-0.000315760	0.000014586	-21.648	< 0.0000000000000002	***
sc1fr1.fil	-0.000042619	0.000007146	-5.964	0.000000000246	***
sc1fr2.fil	-0.007841124	0.000478695	-16.380	< 0.0000000000000002	***
sc1fr3.fil	-0.070581076	0.007633723	-9.246	< 0.0000000000000002	***
sc1fr4.fil	0.000070159	0.000025368	2.766	0.00568	**
sc1fr5.fil	0.000534341	0.000017431	30.655	< 0.0000000000000002	***
sc1fr6.fil	0.007268944	0.000482147	15.076	< 0.0000000000000002	***
sc1fr7.fil	0.000380491	0.000003296	115.427	< 0.0000000000000002	***
sc1fr8.fil	0.008290015	0.000644907	12.855	< 0.0000000000000002	***
sc1fr9.fil	-0.008397008	0.000643247	-13.054	< 0.0000000000000002	***
sc1fr10.fil	0.071146765	0.007634689	9.319	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 3. Developed, Medium Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-2.658670319	0.049632858	-53.567	< 0.0000000000000002	***
sc1fr0.fil	0.000007761	0.000045887	0.169	0.866	
sc1fr1.fil	0.000004534	0.000011626	0.390	0.697	
sc1fr2.fil	-0.022462412	0.000647111	-34.712	< 0.0000000000000002	***
sc1fr3.fil	-0.269929144	0.009785590	-27.584	< 0.0000000000000002	***
sc1fr4.fil	-0.000222456	0.000041117	-5.410	0.0000000629	***
sc1fr5.fil	0.000535171	0.000015235	35.129	< 0.0000000000000002	***
sc1fr6.fil	0.021477994	0.000651161	32.984	< 0.0000000000000002	***
sc1fr7.fil	0.000611059	0.000003872	157.803	< 0.0000000000000002	***
sc1fr8.fil	0.021596508	0.000804394	26.848	< 0.0000000000000002	***
sc1fr9.fil	-0.021759886	0.000802325	-27.121	< 0.0000000000000002	***
sc1fr10.fil	0.270951375	0.009787460	27.684	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 4. Developed High Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.676683664	0.067107254	-10.084	< 0.0000000000000002	***
sc1fr0.fil	0.000599717	0.000138893	4.318	0.0000158	***
sc1fr1.fil	0.000094559	0.000027435	3.447	0.000567	***
sc1fr2.fil	-0.051280607	0.001089522	-47.067	< 0.0000000000000002	***
sc1fr3.fil	-0.906581862	0.015630699	-58.000	< 0.0000000000000002	***
sc1fr4.fil	-0.000240362	0.000049955	-4.812	0.0000015	***
sc1fr5.fil	0.000596815	0.000018091	32.989	< 0.0000000000000002	***
sc1fr6.fil	0.051220338	0.001094392	46.803	< 0.0000000000000002	***
sc1fr7.fil	0.000255103	0.000003843	66.377	< 0.0000000000000002	***
sc1fr8.fil	0.043941512	0.001137154	38.642	< 0.0000000000000002	***
sc1fr9.fil	-0.044198108	0.001134294	-38.965	< 0.0000000000000002	***
sc1fr10.fil	0.906852512	0.015632887	58.009	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 5. Bare Rock/Sand/Clay

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	0.01724571	0.08611459	0.200	0.8413
sc1fr0.fil	0.00075695	0.00006704	11.291	< 0.0000000000000002 ***
sc1fr1.fil	0.19692066	0.00868562	22.672	< 0.0000000000000002 ***
sc1fr2.fil	-0.02451550	0.00107808	-22.740	< 0.0000000000000002 ***
sc1fr3.fil	-0.25225485	0.01730839	-14.574	< 0.0000000000000002 ***
sc1fr4.fil	-0.00020561	0.00003206	-6.413	0.000000000143 ***
sc1fr5.fil	0.00012354	0.00002110	5.855	0.000000004757 ***
sc1fr6.fil	0.02472751	0.00108429	22.805	< 0.0000000000000002 ***
sc1fr7.fil	-0.00003136	0.00001281	-2.448	0.0144 *
sc1fr8.fil	-0.04570227	0.00854227	-5.350	0.000000087891 ***
sc1fr9.fil	-0.15085841	0.00133542	-112.967	< 0.0000000000000002 ***
sc1fr10.fil	0.25220974	0.01731176	14.569	< 0.0000000000000002 ***

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 Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 6. Deciduous Forest

Coefficients:

	Estimate	Std. Error	z value
Pr(> z )			
(Intercept)	-2526294905911744.00	367599.06	-6872419351
<0.0000000000000002 ***			
sc1fr0.fil	318753765154.27	174.06	1831280146
<0.0000000000000002 ***			
sc1fr1.fil	-33637917910.57	79.58	-422671162
<0.0000000000000002 ***			
sc1fr2.fil	3268617267120.84	4232.53	772260420
<0.0000000000000002 ***			
sc1fr3.fil	36056538984064.20	70165.53	513878226
<0.0000000000000002 ***			
sc1fr4.fil	-300956982526.39	170.79	-1762151738
<0.0000000000000002 ***			
sc1fr5.fil	120613222753.10	92.55	1303158046
<0.0000000000000002 ***			
sc1fr6.fil	-3336279537352.65	4258.27	-783481623
<0.0000000000000002 ***			
sc1fr7.fil	62088777586.84	65.89	942346942
<0.0000000000000002 ***			
sc1fr8.fil	-2623208194752.98	5971.31	-439302151
<0.0000000000000002 ***			
sc1fr9.fil	2655719654901.33	5955.73	445909972
<0.0000000000000002 ***			
sc1fr10.fil	-35990398462675.13	70181.82	-512816519
<0.0000000000000002 ***			

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 Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 7. Evergreen Forest

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-7.09637148	0.66068263	-10.741	< 0.0000000000000002 ***
sc1fr0.fil	0.06272577	0.01402277	4.473	0.00000770806633 ***
sc1fr1.fil	-0.00018149	0.00007231	-2.510	0.01208 *
sc1fr2.fil	-0.00672603	0.00840590	-0.800	0.42362
sc1fr3.fil	-0.41896276	0.14507194	-2.888	0.00388 **

sc1fr4.fil	0.00027078	0.00187615	0.144	0.88524
sc1fr5.fil	-0.00019584	0.00049496	-0.396	0.69234
sc1fr6.fil	0.00611884	0.01370810	0.446	0.65533
sc1fr7.fil	-0.00001279	0.00013671	-0.094	0.92548
sc1fr8.fil	0.06788040	0.00947445	7.165	0.00000000000078 ***
sc1fr9.fil	-0.06731528	0.00945918	-7.116	0.00000000000111 ***
sc1fr10.fil	0.41967994	0.14534646	2.887	0.00388 **

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 8. Mixed Forest

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-8.14047129	0.24207189	-33.628	<0.0000000000000002 ***
sc1fr0.fil	0.12493602	0.00262755	47.548	<0.0000000000000002 ***
sc1fr1.fil	-0.00022681	0.00001808	-12.548	<0.0000000000000002 ***
sc1fr2.fil	-0.00193325	0.00278186	-0.695	0.4871
sc1fr3.fil	0.02885959	0.04517685	0.639	0.5229
sc1fr4.fil	0.00004516	0.00040262	0.112	0.9107
sc1fr5.fil	-0.00019708	0.00030235	-0.652	0.5145
sc1fr6.fil	0.00135054	0.00367423	0.368	0.7132
sc1fr7.fil	0.00001057	0.00004019	0.263	0.7926
sc1fr8.fil	-0.00621754	0.00403357	-1.541	0.1232
sc1fr9.fil	0.00675277	0.00401874	1.680	0.0929 .
sc1fr10.fil	-0.02823990	0.04523094	-0.624	0.5324

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 9. Shrub/Scrub

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-8.45507334	0.61467208	-13.755	< 0.0000000000000002 ***
sc1fr0.fil	0.10206619	0.00706155	14.454	< 0.0000000000000002 ***
sc1fr1.fil	-0.00026250	0.00003899	-6.733	0.00000000000167 ***
sc1fr2.fil	0.00801925	0.00711230	1.128	0.259523
sc1fr3.fil	0.13973624	0.12281417	1.138	0.255210
sc1fr4.fil	0.00022881	0.00119417	0.192	0.848054
sc1fr5.fil	-0.00020396	0.00033490	-0.609	0.542509
sc1fr6.fil	-1.40061192	0.36985914	-3.787	0.000153 ***
sc1fr7.fil	0.00003723	0.00004561	0.816	0.414353
sc1fr8.fil	0.08406368	0.00652732	12.879	< 0.0000000000000002 ***
sc1fr9.fil	-0.08341487	0.00651723	-12.799	< 0.0000000000000002 ***
sc1fr10.fil	1.25281392	0.31632548	3.961	0.0000747862097 ***

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 10. Grasslands/Herbaceous

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-4.56986995	0.05567681	-82.079	<0.0000000000000002 ***
sc1fr0.fil	0.07425715	0.00097385	76.251	<0.0000000000000002 ***
sc1fr1.fil	0.00003608	0.00001451	2.486	0.0129 *
sc1fr2.fil	0.00660623	0.00065003	10.163	<0.0000000000000002 ***
sc1fr3.fil	0.12092006	0.01072827	11.271	<0.0000000000000002 ***
sc1fr4.fil	0.00011899	0.00012483	0.953	0.3405

sc1fr5.fil	0.00018740	0.00001484	12.624	<0.0000000000000002	***
sc1fr6.fil	-0.00715148	0.00082870	-8.630	<0.0000000000000002	***
sc1fr7.fil	-0.00001253	0.00001134	-1.105	0.2692	
sc1fr8.fil	0.03038777	0.00082968	36.626	<0.0000000000000002	***
sc1fr9.fil	-0.03040991	0.00082758	-36.746	<0.0000000000000002	***
sc1fr10.fil	-0.12039343	0.01073927	-11.211	<0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 11. Pasture/Hay

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-5.206352060	0.049954406	-104.222	< 0.0000000000000002	***
sc1fr0.fil	0.034960724	0.001086652	32.173	< 0.0000000000000002	***
sc1fr1.fil	-0.000052135	0.000007273	-7.168	0.0000000000000761	***
sc1fr2.fil	0.013870224	0.000551915	25.131	< 0.0000000000000002	***
sc1fr3.fil	0.298563586	0.009268638	32.212	< 0.0000000000000002	***
sc1fr4.fil	-0.000170945	0.000023255	-7.351	0.0000000000000197	***
sc1fr5.fil	0.000135933	0.000012343	11.013	< 0.0000000000000002	***
sc1fr6.fil	-0.185963352	0.032953555	-5.643	0.000000016692262	***
sc1fr7.fil	0.000020592	0.000007364	2.796	0.00517	**
sc1fr8.fil	0.013633471	0.000678199	20.102	< 0.0000000000000002	***
sc1fr9.fil	-0.013555586	0.000676447	-20.039	< 0.0000000000000002	***
sc1fr10.fil	-0.126602202	0.029724802	-4.259	0.000020521155093	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 12. Cultivated Crops

These results are excluded due to irregular coefficient values.

Coefficients:

	Estimate	Std. Error	z value
Pr(> z )			
(Intercept)	-519161464109799.44	367599.06	-1412303561
<0.0000000000000002	***		
sc1fr0.fil	990815951367.61	174.06	5692361248
<0.0000000000000002	***		
sc1fr1.fil	152256933907.50	79.58	1913156911
<0.0000000000000002	***		
sc1fr2.fil	20095919511800.47	4232.53	4747965873
<0.0000000000000002	***		
sc1fr3.fil	-201195968937731.28	70165.53	-2867447359
<0.0000000000000002	***		
sc1fr4.fil	230943583908.88	170.79	1352211982
<0.0000000000000002	***		
sc1fr5.fil	111210282686.37	92.55	1201564566
<0.0000000000000002	***		
sc1fr6.fil	-20356538136981.38	4258.27	-4780466794
<0.0000000000000002	***		
sc1fr7.fil	-922767583543.57	65.89	-14005223553
<0.0000000000000002	***		
sc1fr8.fil	-31255585838032.94	5971.31	-5234295212
<0.0000000000000002	***		
sc1fr9.fil	31318327685698.42	5955.73	5258519886
<0.0000000000000002	***		
sc1fr10.fil	201232405305735.72	70181.82	2867300893
<0.0000000000000002	***		

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### 13. Woody Wetlands

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-2.925657756	0.029185972	-100.242	< 0.0000000000000002	***
sc1fr0.fil	0.042127138	0.000724820	58.121	< 0.0000000000000002	***
sc1fr1.fil	-0.000022285	0.000005531	-4.029	0.00005598521851250	***
sc1fr2.fil	-0.003309646	0.000340501	-9.720	< 0.0000000000000002	***
sc1fr3.fil	-0.089179639	0.005673429	-15.719	< 0.0000000000000002	***
sc1fr4.fil	0.000163972	0.000021182	7.741	0.000000000000000986	***
sc1fr5.fil	-0.000118168	0.000016690	-7.080	0.000000000000143872	***
sc1fr6.fil	0.002665413	0.000567819	4.694	0.00000267755596843	***
sc1fr7.fil	-0.000342889	0.000012542	-27.340	< 0.0000000000000002	***
sc1fr8.fil	0.003601375	0.000464258	7.757	0.000000000000000868	***
sc1fr9.fil	-0.003375220	0.000462996	-7.290	0.000000000000031007	***
sc1fr10.fil	0.089806145	0.005687331	15.791	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### 14. Emergent Herbaceous Wetlands

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.125968775	0.030134193	-4.180	0.0000291	***
sc1fr0.fil	0.000626411	0.000043371	14.443	< 0.0000000000000002	***
sc1fr1.fil	-0.000232802	0.000002915	-79.859	< 0.0000000000000002	***
sc1fr2.fil	-0.009168997	0.000373358	-24.558	< 0.0000000000000002	***
sc1fr3.fil	-0.185033350	0.006188270	-29.901	< 0.0000000000000002	***
sc1fr4.fil	0.000330854	0.000036827	8.984	< 0.0000000000000002	***
sc1fr5.fil	-0.000331521	0.000026324	-12.594	< 0.0000000000000002	***
sc1fr6.fil	0.008925134	0.000389399	22.920	< 0.0000000000000002	***
sc1fr7.fil	-0.000199631	0.000009815	-20.340	< 0.0000000000000002	***
sc1fr8.fil	0.102828732	0.000451514	227.742	< 0.0000000000000002	***
sc1fr9.fil	-0.102078477	0.000450569	-226.555	< 0.0000000000000002	***
sc1fr10.fil	0.185318084	0.006190450	29.936	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1



## Brazoria County, TX:

### 0. Water

No regression performed for this land type.

### 1. Developed, Open Space

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-3.617999011	0.024717913	-146.372	< 0.0000000000000002	***
sclgr0.fil	-0.000057115	0.000015622	-3.656	0.000256	***
sclgr1.fil	0.000055831	0.000014462	3.861	0.000113	***
sclgr2.fil	-0.014475239	0.000325940	-44.411	< 0.0000000000000002	***
sclgr3.fil	0.061268213	0.004656096	13.159	< 0.0000000000000002	***
sclgr4.fil	0.000387412	0.000015100	25.657	< 0.0000000000000002	***
sclgr5.fil	-0.211430060	0.002506101	-84.366	< 0.0000000000000002	***
sclgr6.fil	0.014064729	0.000329256	42.717	< 0.0000000000000002	***
sclgr7.fil	0.000177801	0.000001506	118.074	< 0.0000000000000002	***
sclgr8.fil	0.158385741	0.002350678	67.379	< 0.0000000000000002	***
sclgr9.fil	0.053056479	0.000381589	139.041	< 0.0000000000000002	***
sclgr10.fil	-0.060736001	0.004656677	-13.043	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### 2. Developed, Low Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-3.346678675	0.027672976	-120.937	< 0.0000000000000002	***
sclgr0.fil	-0.000045859	0.000024994	-1.835	0.06653	.
sclgr1.fil	0.000027681	0.000008108	3.414	0.00064	***
sclgr2.fil	-0.011880469	0.000378585	-31.381	< 0.0000000000000002	***
sclgr3.fil	0.057195974	0.005309416	10.773	< 0.0000000000000002	***
sclgr4.fil	0.000410103	0.000021102	19.434	< 0.0000000000000002	***
sclgr5.fil	-0.112840156	0.002384289	-47.327	< 0.0000000000000002	***
sclgr6.fil	0.010768761	0.000382453	28.157	< 0.0000000000000002	***
sclgr7.fil	0.000427886	0.000001542	277.560	< 0.0000000000000002	***
sclgr8.fil	0.094698208	0.002321908	40.785	< 0.0000000000000002	***
sclgr9.fil	0.018288768	0.000378087	48.372	< 0.0000000000000002	***
sclgr10.fil	-0.056024209	0.005310251	-10.550	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### 3. Developed, Medium Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-4.259168337	0.040202710	-105.942	< 0.0000000000000002	***
sclgr0.fil	-0.000088314	0.000035073	-2.518	0.01180	*
sclgr1.fil	0.000022599	0.000007553	2.992	0.00277	**
sclgr2.fil	-0.003856804	0.000567152	-6.800	0.0000000000104	***
sclgr3.fil	0.016144627	0.007719678	2.091	0.03650	*
sclgr4.fil	0.000425638	0.000026568	16.020	< 0.0000000000000002	***
sclgr5.fil	-0.040169061	0.002985495	-13.455	< 0.0000000000000002	***
sclgr6.fil	0.001678870	0.000572305	2.934	0.00335	**
sclgr7.fil	0.000665385	0.000001940	342.907	< 0.0000000000000002	***
sclgr8.fil	0.041874673	0.003006506	13.928	< 0.0000000000000002	***
sclgr9.fil	-0.001534778	0.000505756	-3.035	0.00241	**
sclgr10.fil	-0.013998258	0.007721143	-1.813	0.06984	.

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signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### 4. Developed High Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-1.43633011	0.05597228	-25.661	< 0.0000000000000002	***
sclgr0.fil	0.00010250	0.00012215	0.839	0.40140	
sclgr1.fil	0.00028155	0.00001640	17.167	< 0.0000000000000002	***
sclgr2.fil	-0.05570801	0.00083624	-66.618	< 0.0000000000000002	***
sclgr3.fil	-0.64677104	0.01082221	-59.763	< 0.0000000000000002	***
sclgr4.fil	0.01771378	0.00615562	2.878	0.00401	**
sclgr5.fil	0.13984415	0.00378896	36.908	< 0.0000000000000002	***
sclgr6.fil	0.05495248	0.00084384	65.122	< 0.0000000000000002	***
sclgr7.fil	0.00029598	0.00000261	113.422	< 0.0000000000000002	***
sclgr8.fil	-0.13867655	0.00372101	-37.269	< 0.0000000000000002	***
sclgr9.fil	-0.00122249	0.00067084	-1.822	0.06841	.
sclgr10.fil	0.64779396	0.01082346	59.851	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### 5. Bare Rock/Sand/Clay

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-5.025630208	0.115429994	-43.538	< 0.0000000000000002	***
sclgr0.fil	0.000835340	0.000046476	17.974	< 0.0000000000000002	***
sclgr1.fil	-0.000098204	0.000003035	-32.355	< 0.0000000000000002	***
sclgr2.fil	-0.015264867	0.001559023	-9.791	< 0.0000000000000002	***
sclgr3.fil	-0.500740654	0.023808180	-21.032	< 0.0000000000000002	***
sclgr4.fil	0.000204530	0.000003658	55.919	< 0.0000000000000002	***
sclgr5.fil	0.517618076	0.004964138	104.271	< 0.0000000000000002	***
sclgr6.fil	0.015355858	0.001571579	9.771	< 0.0000000000000002	***
sclgr7.fil	-0.000099068	0.000018815	-5.265	0.0000001399534	***
sclgr8.fil	-0.523587326	0.005244362	-99.838	< 0.0000000000000002	***
sclgr9.fil	0.005847474	0.000873038	6.698	0.0000000000212	***
sclgr10.fil	0.500763243	0.023811537	21.030	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### 6. Deciduous Forest

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-5.167259863	0.035029016	-147.514	< 0.0000000000000002	***
sclgr0.fil	0.000268938	0.000040030	6.718	0.00000000000184	***
sclgr1.fil	0.000408228	0.000085820	4.757	0.0000019670049	***
sclgr2.fil	0.011527737	0.000446073	25.843	< 0.0000000000000002	***
sclgr3.fil	-0.250469915	0.006866255	-36.478	< 0.0000000000000002	***
sclgr4.fil	0.000521139	0.000038235	13.630	< 0.0000000000000002	***
sclgr5.fil	-0.174663817	0.003034499	-57.559	< 0.0000000000000002	***
sclgr6.fil	-0.011596836	0.000450136	-25.763	< 0.0000000000000002	***
sclgr7.fil	-0.000268447	0.000006617	-40.570	< 0.0000000000000002	***
sclgr8.fil	0.096709042	0.002825085	34.232	< 0.0000000000000002	***
sclgr9.fil	0.077553081	0.000498482	155.578	< 0.0000000000000002	***
sclgr10.fil	0.250600033	0.006866999	36.493	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 7. Evergreen Forest

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-5.45297354	0.03690773	-147.746	< 0.0000000000000002	***
sclgr0.fil	0.00071961	0.00008289	8.681	< 0.0000000000000002	***
sclgr1.fil	0.00034488	0.00006974	4.945	0.0000007607149374	***
sclgr2.fil	0.00747074	0.00046875	15.938	< 0.0000000000000002	***
sclgr3.fil	-0.00677815	0.00714829	-0.948	0.343	
sclgr4.fil	0.00054609	0.00007246	7.536	0.0000000000000483	***
sclgr5.fil	-0.16733602	0.00325194	-51.457	< 0.0000000000000002	***
sclgr6.fil	-0.00798080	0.00053691	-14.864	< 0.0000000000000002	***
sclgr7.fil	-0.00063855	0.00001149	-55.555	< 0.0000000000000002	***
sclgr8.fil	0.09421213	0.00301955	31.201	< 0.0000000000000002	***
sclgr9.fil	0.07291666	0.00052832	138.015	< 0.0000000000000002	***
sclgr10.fil	0.00733928	0.00715241	1.026	0.305	

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 8. Mixed Forest

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-4.82077250	0.03297424	-146.198	< 0.0000000000000002	***
sclgr0.fil	0.00064450	0.00005442	11.842	< 0.0000000000000002	***
sclgr1.fil	0.00068732	0.00034452	1.995	0.046	*
sclgr2.fil	0.00446128	0.00042225	10.565	< 0.0000000000000002	***
sclgr3.fil	0.03046253	0.00636473	4.786	0.00000170	***
sclgr4.fil	0.00072563	0.00005388	13.468	< 0.0000000000000002	***
sclgr5.fil	-0.16810673	0.00299074	-56.209	< 0.0000000000000002	***
sclgr6.fil	-0.00433938	0.00042589	-10.189	< 0.0000000000000002	***
sclgr7.fil	-0.00076867	0.00001180	-65.165	< 0.0000000000000002	***
sclgr8.fil	0.10769800	0.00280797	38.354	< 0.0000000000000002	***
sclgr9.fil	0.05977237	0.00047468	125.922	< 0.0000000000000002	***
sclgr10.fil	-0.03050055	0.00636543	-4.792	0.00000165	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 9. Shrub/Scrub

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-2.388792377	0.034484499	-69.271	< 0.0000000000000002	***
sclgr0.fil	0.000499911	0.000062995	7.936	0.00000000000000209	***
sclgr1.fil	0.403863437	0.004540566	88.946	< 0.0000000000000002	***
sclgr2.fil	-0.014809326	0.000451484	-32.801	< 0.0000000000000002	***
sclgr3.fil	-0.090997274	0.006562826	-13.866	< 0.0000000000000002	***
sclgr4.fil	0.000712745	0.000065241	10.925	< 0.0000000000000002	***
sclgr5.fil	-0.334069644	0.003429870	-97.400	< 0.0000000000000002	***
sclgr6.fil	0.014906533	0.000455691	32.712	< 0.0000000000000002	***
sclgr7.fil	-0.000607084	0.000009964	-60.927	< 0.0000000000000002	***
sclgr8.fil	-0.091842633	0.004642265	-19.784	< 0.0000000000000002	***
sclgr9.fil	0.022308561	0.000479135	46.560	< 0.0000000000000002	***
sclgr10.fil	0.091048516	0.006563557	13.872	< 0.0000000000000002	***

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 10. Grasslands/Herbaceous

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-3.685601450	0.037021485	-99.553	< 0.0000000000000002	***
sclgr0.fil	0.000205312	0.000044876	4.575	0.00000476	***
sclgr1.fil	0.000133591	0.000010400	12.845	< 0.0000000000000002	***
sclgr2.fil	-0.012218397	0.000503649	-24.260	< 0.0000000000000002	***
sclgr3.fil	0.079955070	0.007266779	11.003	< 0.0000000000000002	***
sclgr4.fil	0.000589940	0.000038773	15.215	< 0.0000000000000002	***
sclgr5.fil	-0.051967705	0.002308052	-22.516	< 0.0000000000000002	***
sclgr6.fil	0.012384517	0.000507784	24.389	< 0.0000000000000002	***
sclgr7.fil	-0.000049254	0.000003716	-13.255	< 0.0000000000000002	***
sclgr8.fil	0.036260502	0.002309935	15.698	< 0.0000000000000002	***
sclgr9.fil	0.015728254	0.000395394	39.779	< 0.0000000000000002	***
sclgr10.fil	-0.080129865	0.007267613	-11.026	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 11. Pasture/Hay

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-1.797216946	0.014576072	-123.299	< 0.0000000000000002	***
sclgr0.fil	0.000683670	0.000019205	35.599	< 0.0000000000000002	***
sclgr1.fil	0.315545212	0.001654217	190.752	< 0.0000000000000002	***
sclgr2.fil	-0.000433511	0.000187993	-2.306	0.021111	*
sclgr3.fil	0.175494096	0.002783419	63.050	< 0.0000000000000002	***
sclgr4.fil	0.000682154	0.000018546	36.782	< 0.0000000000000002	***
sclgr5.fil	-0.379358197	0.001362177	-278.494	< 0.0000000000000002	***
sclgr6.fil	0.000627941	0.000189611	3.312	0.000927	***
sclgr7.fil	-0.000794460	0.000004158	-191.066	< 0.0000000000000002	***
sclgr8.fil	0.020600739	0.001740970	11.833	< 0.0000000000000002	***
sclgr9.fil	0.043415672	0.000198826	218.360	< 0.0000000000000002	***
sclgr10.fil	-0.175640974	0.002783721	-63.096	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 12. Cultivated Crops

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.49344300	0.01933597	-25.52	< 0.0000000000000002	***
sclgr0.fil	0.00082938	0.00001777	46.66	< 0.0000000000000002	***
sclgr1.fil	0.61903251	0.00214388	288.74	< 0.0000000000000002	***
sclgr2.fil	-0.02951197	0.00027244	-108.33	< 0.0000000000000002	***
sclgr3.fil	0.05023970	0.00363935	13.80	< 0.0000000000000002	***
sclgr4.fil	0.00183095	0.00001907	96.03	< 0.0000000000000002	***
sclgr5.fil	-1.12439155	0.00241482	-465.62	< 0.0000000000000002	***
sclgr6.fil	-0.43977710	0.00675599	-65.09	< 0.0000000000000002	***
sclgr7.fil	-0.00199082	0.00001164	-170.97	< 0.0000000000000002	***
sclgr8.fil	0.46767761	0.00268505	174.18	< 0.0000000000000002	***
sclgr9.fil	0.03797181	0.00026952	140.89	< 0.0000000000000002	***
sclgr10.fil	0.41907612	0.00691064	60.64	< 0.0000000000000002	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### 13. Woody Wetlands

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-3.236982606	0.016457373	-196.69	<0.0000000000000002	***
sclgr0.fil	0.000846851	0.000017796	47.59	<0.0000000000000002	***
sclgr1.fil	0.000333628	0.000021368	15.61	<0.0000000000000002	***
sclgr2.fil	0.018704800	0.000214830	87.07	<0.0000000000000002	***
sclgr3.fil	0.104628258	0.003204295	32.65	<0.0000000000000002	***
sclgr4.fil	0.001149328	0.000016748	68.63	<0.0000000000000002	***
sclgr5.fil	-0.205109362	0.001316612	-155.79	<0.0000000000000002	***
sclgr6.fil	-0.018880561	0.000216938	-87.03	<0.0000000000000002	***
sclgr7.fil	-0.001298171	0.000008212	-158.08	<0.0000000000000002	***
sclgr8.fil	0.167925194	0.001271993	132.02	<0.0000000000000002	***
sclgr9.fil	0.036917457	0.000208471	177.09	<0.0000000000000002	***
sclgr10.fil	-0.104475969	0.003204639	-32.60	<0.0000000000000002	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### 14. Emergent Herbaceous Wetlands

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	1.218457127	0.023701105	51.41	<0.0000000000000002	***
sclgr0.fil	0.001324538	0.000044999	29.43	<0.0000000000000002	***
sclgr1.fil	0.000370810	0.000002178	170.22	<0.0000000000000002	***
sclgr2.fil	0.012296896	0.000321278	38.27	<0.0000000000000002	***
sclgr3.fil	-0.553737564	0.004904711	-112.90	<0.0000000000000002	***
sclgr4.fil	0.001733954	0.000024369	71.16	<0.0000000000000002	***
sclgr5.fil	0.779323696	0.001303688	597.78	<0.0000000000000002	***
sclgr6.fil	-0.012758027	0.000332495	-38.37	<0.0000000000000002	***
sclgr7.fil	-0.001733338	0.000018425	-94.07	<0.0000000000000002	***
sclgr8.fil	-0.648306555	0.001294791	-500.70	<0.0000000000000002	***
sclgr9.fil	-0.131059209	0.000231922	-565.10	<0.0000000000000002	***
sclgr10.fil	0.554219028	0.004905599	112.98	<0.0000000000000002	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## Estill County, KY:

(Variable names are different for this county but refer to the same predictors)

### 0. Water

No regression performed for this land type.

### 1. Developed, Open Space

Coefficients:

	Estimate	Std. Error	z value	
Pr(> z )				
(Intercept)	-2.434749049	0.095551894	-25.481	<
0.0000000000000002 ***				
estillslope.txt	-0.000092952	0.000025638	-3.626	
0.000288 ***				
estillnccpi.txt	0.526977641	0.008453075	62.342	<
0.0000000000000002 ***				
estillmedianage.txt	0.004383308	0.001182001	3.708	
0.000209 ***				
estillavehouseholdsize.txt	-0.011024636	0.023634139	-0.466	
0.640879				
estilldroughtvulnerability.txt	0.056239012	0.011247432	5.000	
0.000000573 ***				
estillfloodfrequency.txt	0.000573168	0.000057445	9.978	<
0.0000000000000002 ***				
estillpctpopnonwhite.txt	-0.131044443	0.046912691	-2.793	
0.005216 **				
estillpopulationdensity.txt	0.000098040	0.000004471	21.929	<
0.0000000000000002 ***				
estillsoilorganicmatter.txt	-0.481143779	0.008022165	-59.977	<
0.0000000000000002 ***				
estillwaterstorage.txt	-0.045807582	0.001190827	-38.467	<
0.0000000000000002 ***				
estillpcthouseholdsrenting.txt	0.137628088	0.045733760	3.009	
0.002618 **				
---				
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

### 2. Developed, Low Intensity

Coefficients:

	Estimate	Std. Error	z value	
Pr(> z )				
(Intercept)	-3.44342380	0.12058794	-28.555	<
0.0000000000000002 ***				
estillslope.txt	-0.00011973	0.00003335	-3.590	
0.00033 ***				
estillnccpi.txt	1.02151641	0.01644672	62.111	<
0.0000000000000002 ***				
estillmedianage.txt	0.00317501	0.00151670	2.093	
0.03632 *				
estillavehouseholdsize.txt	0.21343561	0.02755643	7.745	
0.00000000000000953 ***				
estilldroughtvulnerability.txt	0.00063337	0.00011804	5.366	
0.00000008058198350 ***				
estillfloodfrequency.txt	0.00059096	0.00004354	13.572	<
0.0000000000000002 ***				

```

estillpctpopnonwhite.txt      -0.87438106  0.06206155 -14.089 <
0.0000000000000002 ***
estillpopulationdensity.txt    0.00013973  0.00000621  22.502 <
0.0000000000000002 ***
estillsoilorganicmatter.txt    -0.98637339  0.01590485 -62.017 <
0.0000000000000002 ***
estillwaterstorage.txt        -0.03528231  0.00117246 -30.093 <
0.0000000000000002 ***
estillpcthouseholdsrenting.txt 0.65767122  0.05456267  12.054 <
0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

### 3. Developed, Medium Intensity

```

Coefficients:
                                Estimate Std. Error z value
Pr(>|z|)
(Intercept)                    -3.86621851  0.19145063 -20.194 <
0.0000000000000002 ***
estillslope.txt                -0.00010108  0.00008209  -1.231
0.218
estillnccpi.txt                0.92744527  0.03400891  27.271 <
0.0000000000000002 ***
estillmedianage.txt           -0.01923988  0.00234071  -8.220 <
0.0000000000000002 ***
estillavehouseholdsize.txt     -0.34713683  0.04279477  -8.112
0.000000000000000499 ***
estilldroughtvulnerability.txt 0.50483320  0.03297740  15.308 <
0.0000000000000002 ***
estillfloodfrequency.txt       0.00046025  0.00002340  19.671 <
0.0000000000000002 ***
estillpctpopnonwhite.txt       0.01902482  0.00235090   8.093
0.000000000000000584 ***
estillpopulationdensity.txt     0.00021063  0.00001050  20.062 <
0.0000000000000002 ***
estillsoilorganicmatter.txt    -0.86235364  0.03268775 -26.382 <
0.0000000000000002 ***
estillwaterstorage.txt        -0.06516443  0.00318884 -20.435 <
0.0000000000000002 ***
estillpcthouseholdsrenting.txt 0.34743916  0.04280311   8.117
0.000000000000000477 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

### 4. Developed High Intensity

```

Coefficients:
                                Estimate Std. Error z value
Pr(>|z|)
(Intercept)                    -7.65975185  0.53998967 -14.185 <
0.0000000000000002 ***
estillslope.txt                -0.00007576  0.00023977  -0.316
0.752024
estillnccpi.txt                0.57758092  0.13687875   4.220
0.00002446779252311 ***
estillmedianage.txt           -0.01908053  0.00503457  -3.790
0.000151 ***
estillavehouseholdsize.txt     -1.07167888  0.08600340 -12.461 <
0.0000000000000002 ***

```

```

estilldroughtvulnerability.txt 0.94495538 0.10456748 9.037 <
0.0000000000000002 ***
estillfloodfrequency.txt 0.00077627 0.00010002 7.761
0.00000000000000839 ***
estillpctpopnonwhite.txt 0.01923543 0.00505300 3.807
0.000141 ***
estillpopulationdensity.txt 0.00007317 0.00001694 4.319
0.00001570459219360 ***
estillsoilorganicmatter.txt -0.51503868 0.13074740 -3.939
0.00008175764508403 ***
estillwaterstorage.txt -0.06274148 0.01342526 -4.673
0.00000296267648199 ***
estillpcthouseholdsrenting.txt 1.07160057 0.08601868 12.458 <
0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

## 5. Bare Rock/Sand/Clay

```

Coefficients:
Estimate Std. Error z value
Pr(>|z|)
(Intercept) -10.73788290 0.61933853 -17.338 <
0.0000000000000002 ***
estillslope.txt 0.03013326 0.00429977 7.008
0.0000000000002416 ***
estillnccpi.txt 0.21881455 0.03780927 5.787
0.000000007151631 ***
estillmedianage.txt 0.02938275 0.00597316 4.919
0.000000869288281 ***
estillavehouseholdsize.txt -0.67509466 0.13984678 -4.827
0.000001383353915 ***
estilldroughtvulnerability.txt 1.83968172 0.04565350 40.297 <
0.0000000000000002 ***
estillfloodfrequency.txt 0.00002563 0.00001680 1.525
0.12728
estillpctpopnonwhite.txt -0.70186639 0.27237095 -2.577
0.00997 **
estillpopulationdensity.txt 0.00004486 0.00001780 2.520
0.01173 *
estillsoilorganicmatter.txt -0.04880786 0.03728419 -1.309
0.19051
estillwaterstorage.txt -0.16955543 0.00712122 -23.810 <
0.0000000000000002 ***
estillpcthouseholdsrenting.txt 1.34761298 0.18159777 7.421
0.0000000000000116 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

## 6. Deciduous Forest

```

Coefficients:
Estimate Std. Error z value
Pr(>|z|)
(Intercept) -0.008561509 0.037045768 -0.231
0.817
estillslope.txt 0.000533078 0.000048704 10.945 <
0.0000000000000002 ***
estillnccpi.txt -0.749887467 0.003294872 -227.592 <
0.0000000000000002 ***

```



estillmedianage.txt	0.003981848	0.000488014	8.159
0.0000000000000000337 ***			
estillavehouseholdsize.txt	-0.194745551	0.009533749	-20.427 <
0.000000000000000002 ***			
estilldroughtvulnerability.txt	0.000355500	0.000050019	7.107
0.0000000000001183880 ***			
estillfloodfrequency.txt	-0.000219309	0.000005411	-40.529 <
0.000000000000000002 ***			
estillpctpopnonwhite.txt	-0.003940829	0.000512588	-7.688
0.0000000000000014933 ***			
estillpopulationdensity.txt	0.000014947	0.000001888	7.919
0.0000000000000002396 ***			
estillsoilorganicmatter.txt	0.738035074	0.003131385	235.690 <
0.000000000000000002 ***			
estillwaterstorage.txt	0.012115604	0.000334449	36.226 <
0.000000000000000002 ***			
estillpcthouseholdsrenting.txt	0.194792728	0.009536972	20.425 <
0.000000000000000002 ***			

---  
 Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 7. Evergreen Forest

Coefficients:

	Estimate	Std. Error	z value
Pr(> z )			
(Intercept)	-2.977486053	0.244664918	-12.170 <
0.000000000000000002 ***			
estillslope.txt	0.000002234	0.000070605	0.032
0.975			
estillnccpi.txt	0.5811111365	0.023283040	24.959 <
0.000000000000000002 ***			
estillmedianage.txt	-0.046053324	0.003712543	-12.405 <
0.000000000000000002 ***			
estillavehouseholdsize.txt	0.271649713	0.050775479	5.350
0.0000000879456067 ***			
estilldroughtvulnerability.txt	0.000683268	0.000131754	5.186
0.0000002149355635 ***			
estillfloodfrequency.txt	0.000013959	0.000062611	0.223
0.824			
estillpctpopnonwhite.txt	-1.211558086	0.119429686	-10.145 <
0.000000000000000002 ***			
estillpopulationdensity.txt	-0.000178347	0.000017290	-10.315 <
0.000000000000000002 ***			
estillsoilorganicmatter.txt	-0.526762019	0.022358497	-23.560 <
0.000000000000000002 ***			
estillwaterstorage.txt	-0.054027002	0.002323015	-23.257 <
0.000000000000000002 ***			
estillpcthouseholdsrenting.txt	0.986141843	0.127828867	7.715
0.00000000000000121 ***			

---  
 Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 8. Mixed Forest

Coefficients:

	Estimate	Std. Error	z value	
Pr(> z )				
(Intercept)	-2.068305743	0.056201820	-36.801	<
0.0000000000000002 ***				
estillslope.txt	0.000100488	0.000028532	3.522	
0.000428 ***				
estillnccpi.txt	0.184219458	0.003989637	46.174	<
0.0000000000000002 ***				
estillmedianage.txt	-0.014752404	0.000758974	-19.437	<
0.0000000000000002 ***				
estillavehouseholdsize.txt	0.407887953	0.013478118	30.263	<
0.0000000000000002 ***				
estilldroughtvulnerability.txt	0.000856289	0.000048886	17.516	<
0.0000000000000002 ***				
estillfloodfrequency.txt	-0.000111114	0.000007719	-14.394	<
0.0000000000000002 ***				
estillpctpopnonwhite.txt	-0.947659533	0.027824214	-34.059	<
0.0000000000000002 ***				
estillpopulationdensity.txt	-0.000127401	0.000003383	-37.664	<
0.0000000000000002 ***				
estillsoilorganicmatter.txt	-0.167750255	0.003778677	-44.394	<
0.0000000000000002 ***				
estillwaterstorage.txt	-0.016286893	0.000481503	-33.825	<
0.0000000000000002 ***				
estillpcthouseholdsrenting.txt	0.554554424	0.027940927	19.847	<
0.0000000000000002 ***				
---				
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

## 9. Shrub/Scrub

Coefficients:

	Estimate	Std. Error	z value	
Pr(> z )				
(Intercept)	-5.25573997	0.32203653	-16.320	<
0.0000000000000002 ***				
estillslope.txt	0.00013772	0.00023494	0.586	
0.557755				
estillnccpi.txt	-0.06447943	0.02057228	-3.134	
0.001723 **				
estillmedianage.txt	-0.00862354	0.00426800	-2.021	
0.043330 *				
estillavehouseholdsize.txt	0.04140289	0.08167276	0.507	
0.612199				
estilldroughtvulnerability.txt	0.00059005	0.00025575	2.307	
0.021048 *				
estillfloodfrequency.txt	-0.00017425	0.00004742	-3.674	
0.000239 ***				
estillpctpopnonwhite.txt	-0.64117548	0.15098963	-4.246	
0.00002171 ***				
estillpopulationdensity.txt	0.00001051	0.00001712	0.614	
0.539374				
estillsoilorganicmatter.txt	0.09051971	0.01941848	4.662	
0.00000314 ***				
estillwaterstorage.txt	-0.02582925	0.00293197	-8.810	<
0.0000000000000002 ***				
estillpcthouseholdsrenting.txt	0.60842081	0.15825058	3.845	
0.000121 ***				
---				

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 10. Grasslands/Herbaceous

Coefficients:

	Estimate	Std. Error	z value	
Pr(> z )				
(Intercept)	-3.038660247	0.154612550	-19.653	<
0.00000000000000002 ***				
estillslope.txt	-0.000006406	0.000047609	-0.135	
0.892970				
estillnccpi.txt	0.027363350	0.010166648	2.691	
0.007114 **				
estillmedianage.txt	-0.027716062	0.002129363	-13.016	<
0.00000000000000002 ***				
estillavehouseholdsize.txt	0.158728677	0.035206379	4.509	
0.00000653 ***				
estilldroughtvulnerability.txt	0.057056751	0.017318565	3.295	
0.000986 ***				
estillfloodfrequency.txt	-0.000130685	0.000012414	-10.527	<
0.00000000000000002 ***				
estillpctpopnonwhite.txt	-1.314562296	0.070572051	-18.627	<
0.00000000000000002 ***				
estillpopulationdensity.txt	-0.000030139	0.000006712	-4.490	
0.00000712 ***				
estillsoilorganicmatter.txt	0.024622877	0.009450619	2.605	
0.009176 **				
estillwaterstorage.txt	-0.051835780	0.002111083	-24.554	<
0.00000000000000002 ***				
estillpcthouseholdsrenting.txt	1.183598252	0.073197079	16.170	<
0.00000000000000002 ***				

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 11. Pasture/Hay

Coefficients:

	Estimate	Std. Error	z value	
Pr(> z )				
(Intercept)	-2.480376210	0.054669775	-45.370	
<0.00000000000000002 ***				
estillslope.txt	-0.000184878	0.000016270	-11.363	
<0.00000000000000002 ***				
estillnccpi.txt	1.264811067	0.006987165	181.019	
<0.00000000000000002 ***				
estillmedianage.txt	0.006679141	0.000687496	9.715	
<0.00000000000000002 ***				
estillavehouseholdsize.txt	0.485719227	0.012733487	38.145	
<0.00000000000000002 ***				
estilldroughtvulnerability.txt	0.001073819	0.000048465	22.157	
<0.00000000000000002 ***				
estillfloodfrequency.txt	0.000209494	0.000006408	32.692	
<0.00000000000000002 ***				
estillpctpopnonwhite.txt	-1.253125931	0.028299954	-44.280	
<0.00000000000000002 ***				
estillpopulationdensity.txt	-0.000028640	0.000002133	-13.425	
<0.00000000000000002 ***				
estillsoilorganicmatter.txt	-1.259807082	0.006782334	-185.748	
<0.00000000000000002 ***				

```

estillwaterstorage.txt      -0.004952071  0.000431981  -11.464
<0.0000000000000002 ***
estillpcthouseholdsrenting.txt  0.760523624  0.025595716   29.713
<0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

## 12. Cultivated Crops

Coefficients:

	Estimate	Std. Error	z value	
Pr(> z )				
(Intercept)	-9.042263556	0.224659964	-40.249	<
0.0000000000000002 ***				
estillslope.txt	-0.000145166	0.000047770	-3.039	
0.00237 **				
estillnccpi.txt	3.867625689	0.065251144	59.273	<
0.0000000000000002 ***				
estillmedianage.txt	0.041487537	0.002091718	19.834	<
0.0000000000000002 ***				
estillavehouseholdsize.txt	-0.631952972	0.039941179	-15.822	<
0.0000000000000002 ***				
estilldroughtvulnerability.txt	1.072855987	0.042776665	25.080	<
0.0000000000000002 ***				
estillfloodfrequency.txt	0.000018081	0.000051647	0.350	
0.72627				
estillpctpopnonwhite.txt	-2.046336093	0.078733348	-25.991	<
0.0000000000000002 ***				
estillpopulationdensity.txt	0.000051289	0.000007049	7.276	
0.0000000000000344 ***				
estillsoilorganicmatter.txt	-3.871412488	0.063851185	-60.632	<
0.0000000000000002 ***				
estillwaterstorage.txt	0.004343826	0.002706517	1.605	
0.10850				
estillpcthouseholdsrenting.txt	2.636668158	0.062744899	42.022	<
0.0000000000000002 ***				
---				
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

## 13. Woody Wetlands

Coefficients:

	Estimate	Std. Error	z value	
Pr(> z )				
(Intercept)	-16.94447253	0.50757309	-33.383	<
0.0000000000000002 ***				
estillslope.txt	-0.00012615	0.00011819	-1.067	
0.285819				
estillnccpi.txt	0.56963945	0.07047228	8.083	
0.000000000000000631 ***				
estillmedianage.txt	0.13411448	0.00451709	29.690	<
0.0000000000000002 ***				
estillavehouseholdsize.txt	0.30597683	0.10038271	3.048	
0.002303 **				
estilldroughtvulnerability.txt	0.62479216	0.08464597	7.381	
0.0000000000000156822 ***				
estillfloodfrequency.txt	0.00014595	0.00008300	1.758	
0.078683 .				
estillpctpopnonwhite.txt	-0.78759144	0.20605263	-3.822	
0.000132 ***				

```

estillpopulationdensity.txt      0.00022918    0.00002087   10.979 <
0.00000000000000002 ***
estillsoilorganicmatter.txt     -0.62242893    0.06723767   -9.257 <
0.00000000000000002 ***
estillwaterstorage.txt          0.05298920    0.00573595    9.238 <
0.00000000000000002 ***
estillpcthouseholdsrenting.txt  0.34662180    0.16554417    2.094
0.036275 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

#### 14. Emergent Herbaceous Wetlands

```

Coefficients:
Pr(>|z|)
(Intercept)                -23.93906655    1.24927966  -19.162 <
0.00000000000000002 ***
estillslope.txt            -0.00006113    0.00022738   -0.269
0.7880
estillnccpi.txt            1.23908304    0.25196430    4.918
0.000000875701646 ***
estillmedianage.txt         0.07758789    0.01070605    7.247
0.0000000000000426 ***
estillavehouseholdsize.txt  0.07885413    0.20222983    0.390
0.6966
estilldroughtvulnerability.txt 2.49235241    0.17647224   14.123 <
0.00000000000000002 ***
estillfloodfrequency.txt   -0.00053391    0.00048115   -1.110
0.2671
estillpctpopnonwhite.txt   -2.07213447    0.37483130   -5.528
0.000000032357195 ***
estillpopulationdensity.txt  0.00008025    0.00002986    2.687
0.0072 **
estillsoilorganicmatter.txt -1.32586722    0.24419008   -5.430
0.000000056463943 ***
estillwaterstorage.txt      0.08758826    0.01514819    5.782
0.000000007377724 ***
estillpcthouseholdsrenting.txt 1.91518724    0.31247246    6.129
0.000000000883557 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

## Wilcox County, GA:

### 0. Water

No regression performed for this land type.

### 1. Developed, Open Space

n/a

### 2. Developed, Low Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-4.145863108	0.078443049	-52.852	< 0.0000000000000002	***
sc1fr0.fil	-0.000103498	0.000035779	-2.893	0.00382	**
sc1fr1.fil	1.955140565	0.055449497	35.260	< 0.0000000000000002	***
sc1fr2.fil	-0.004739603	0.000839629	-5.645	0.00000001653	***
sc1fr3.fil	-0.093360777	0.016192517	-5.766	0.00000000813	***
sc1fr4.fil	0.000501852	0.000043181	11.622	< 0.0000000000000002	***
sc1fr5.fil	-0.160713585	0.013358085	-12.031	< 0.0000000000000002	***
sc1fr6.fil	0.005015901	0.000847225	5.920	0.00000000321	***
sc1fr7.fil	0.000045730	0.000002961	15.447	< 0.0000000000000002	***
sc1fr8.fil	-1.798221547	0.060715540	-29.617	< 0.0000000000000002	***
sc1fr9.fil	0.003906420	0.002075539	1.882	0.05982	.
sc1fr10.fil	0.093126061	0.016194282	5.751	0.00000000890	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### 3. Developed, Medium Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-4.59304635	0.21518975	-21.344	< 0.0000000000000002	***
sc1fr0.fil	0.00029833	0.00060488	0.493	0.6219	
sc1fr1.fil	1.40391778	0.14080652	9.971	< 0.0000000000000002	***
sc1fr2.fil	-0.02773845	0.00236947	-11.707	< 0.0000000000000002	***
sc1fr3.fil	-0.54482661	0.04736103	-11.504	< 0.0000000000000002	***
sc1fr4.fil	0.33314772	0.04262321	7.816	0.00000000000000545	***
sc1fr5.fil	-0.38945753	0.04213601	-9.243	< 0.0000000000000002	***
sc1fr6.fil	0.02823380	0.00238828	11.822	< 0.0000000000000002	***
sc1fr7.fil	0.00003316	0.00000448	7.403	0.00000000000013346	***
sc1fr8.fil	-0.99633582	0.15405789	-6.467	0.0000000009978132	***
sc1fr9.fil	-0.01791339	0.00828436	-2.162	0.0306	*
sc1fr10.fil	0.54453694	0.04736678	11.496	< 0.0000000000000002	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### 4. Developed High Intensity

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-3.91226030	0.46810555	-8.358	< 0.0000000000000002	***
sc1fr0.fil	0.00022934	0.00088865	0.258	0.7963	
sc1fr1.fil	0.96190021	0.29467854	3.264	0.0011	**
sc1fr2.fil	-0.06895444	0.00553015	-12.469	< 0.0000000000000002	***
sc1fr3.fil	-1.23442808	0.10829840	-11.398	< 0.0000000000000002	***

sc1fr4.fil	0.57599466	0.08700347	6.620	0.0000000000358	***
sc1fr5.fil	-0.62830151	0.10234160	-6.139	0.0000000008291	***
sc1fr6.fil	-0.35758821	0.19017299	-1.880	0.0601	.
sc1fr7.fil	0.00003315	0.00001078	3.076	0.0021	**
sc1fr8.fil	-0.32647243	0.32766719	-0.996	0.3191	
sc1fr9.fil	-0.00684071	0.01779464	-0.384	0.7007	
sc1fr10.fil	1.66145707	0.17765331	9.352	< 0.0000000000000002	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 5. Bare Rock/Sand/Clay

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	3.3646720	0.3460254	9.724	< 0.0000000000000002	***
sc1fr0.fil	0.2488422	0.0198026	12.566	< 0.0000000000000002	***
sc1fr1.fil	2.3394512	0.3215338	7.276	0.000000000000344	***
sc1fr2.fil	-0.0454547	0.0036222	-12.549	< 0.0000000000000002	***
sc1fr3.fil	-0.8495358	0.0742613	-11.440	< 0.0000000000000002	***
sc1fr4.fil	0.0006644	0.0012165	0.546	0.584943	
sc1fr5.fil	0.1473293	0.0646870	2.278	0.022752	*
sc1fr6.fil	-0.4545600	0.1264823	-3.594	0.000326	***
sc1fr7.fil	-0.0001402	0.0001650	-0.850	0.395498	
sc1fr8.fil	-1.9876504	0.3346644	-5.939	0.000000002863568	***
sc1fr9.fil	-0.4987047	0.0184560	-27.021	< 0.0000000000000002	***
sc1fr10.fil	1.3500281	0.1318849	10.236	< 0.0000000000000002	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 6. Deciduous Forest

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-4.247639322	0.081410163	-52.176	< 0.0000000000000002	***
sc1fr0.fil	0.000180289	0.000135602	1.330	0.183667	
sc1fr1.fil	0.555513289	0.041885803	13.263	< 0.0000000000000002	***
sc1fr2.fil	0.015925812	0.000874118	18.219	< 0.0000000000000002	***
sc1fr3.fil	0.319422865	0.016618940	19.220	< 0.0000000000000002	***
sc1fr4.fil	0.000595083	0.000167391	3.555	0.000378	***
sc1fr5.fil	-0.222043745	0.011119061	-19.970	< 0.0000000000000002	***
sc1fr6.fil	-0.230580009	0.031622680	-7.292	0.000000000000306	***
sc1fr7.fil	-0.000002941	0.000012993	-0.226	0.820903	
sc1fr8.fil	-0.259969984	0.046926636	-5.540	0.000000030260345	***
sc1fr9.fil	-0.073234937	0.002202283	-33.254	< 0.0000000000000002	***
sc1fr10.fil	-0.104912584	0.031398835	-3.341	0.000834	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 7. Evergreen Forest

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	0.33011369	0.02126221	15.526	< 0.0000000000000002	***
sc1fr0.fil	0.00092707	0.00002703	34.302	< 0.0000000000000002	***
sc1fr1.fil	0.49762802	0.01019560	48.808	< 0.0000000000000002	***
sc1fr2.fil	-0.00117042	0.00023405	-5.001	0.000000571	***
sc1fr3.fil	0.20293563	0.00447381	45.361	< 0.0000000000000002	***
sc1fr4.fil	0.00086900	0.00002750	31.603	< 0.0000000000000002	***

sc1fr5.fil	-0.30538671	0.00273702	-111.576	<	0.00000000000000002	***
sc1fr6.fil	-0.16313240	0.00814457	-20.030	<	0.00000000000000002	***
sc1fr7.fil	-0.00099408	0.00002795	-35.568	<	0.00000000000000002	***
sc1fr8.fil	-0.11417476	0.01158931	-9.852	<	0.00000000000000002	***
sc1fr9.fil	-0.07772254	0.00054902	-141.566	<	0.00000000000000002	***
sc1fr10.fil	-0.03867205	0.00806412	-4.796		0.000001622	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 8. Mixed Forest

Coefficients:

	Estimate	Std. Error	z value		Pr(> z )	
(Intercept)	-2.59680805	0.04870747	-53.314	<	0.00000000000000002	***
sc1fr0.fil	0.00044316	0.00014038	3.157		0.00159	**
sc1fr1.fil	0.68636777	0.02602972	26.369	<	0.00000000000000002	***
sc1fr2.fil	0.00739647	0.00052740	14.024	<	0.00000000000000002	***
sc1fr3.fil	0.15348442	0.01014143	15.134	<	0.00000000000000002	***
sc1fr4.fil	0.00024105	0.00013851	1.740		0.08181	.
sc1fr5.fil	-0.23416143	0.00686257	-34.122	<	0.00000000000000002	***
sc1fr6.fil	-0.31992366	0.01898727	-16.849	<	0.00000000000000002	***
sc1fr7.fil	-0.00001113	0.00001166	-0.955		0.33969	
sc1fr8.fil	-0.38894122	0.02908754	-13.371	<	0.00000000000000002	***
sc1fr9.fil	-0.06302411	0.00130484	-48.300	<	0.00000000000000002	***
sc1fr10.fil	0.15897153	0.01875869	8.475	<	0.00000000000000002	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 9. Shrub/Scrub

Coefficients:

	Estimate	Std. Error	z value		Pr(> z )	
(Intercept)	-2.42393193	0.07125555	-34.017	<	0.00000000000000002	***
sc1fr0.fil	0.00033512	0.00008359	4.009		0.000060928	***
sc1fr1.fil	0.30952414	0.03488558	8.873	<	0.00000000000000002	***
sc1fr2.fil	0.00375213	0.00077344	4.851		0.000001227	***
sc1fr3.fil	-0.19702529	0.01579037	-12.478	<	0.00000000000000002	***
sc1fr4.fil	0.00061517	0.00011024	5.580		0.000000024	***
sc1fr5.fil	-0.44340010	0.01257007	-35.274	<	0.00000000000000002	***
sc1fr6.fil	-0.04609223	0.02794997	-1.649		0.0991	.
sc1fr7.fil	-0.00027327	0.00003264	-8.371	<	0.00000000000000002	***
sc1fr8.fil	0.18619290	0.04088114	4.554		0.000005251	***
sc1fr9.fil	-0.05192604	0.00178026	-29.168	<	0.00000000000000002	***
sc1fr10.fil	0.23932540	0.02786291	8.589	<	0.00000000000000002	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## 10. Grasslands/Herbaceous

Coefficients:

	Estimate	Std. Error	z value		Pr(> z )	
(Intercept)	-0.25979803	0.04213538	-6.166		0.0000000007013063	***
sc1fr0.fil	0.00023877	0.00004805	4.969		0.0000006734346253	***
sc1fr1.fil	0.57688901	0.02238572	25.770	<	0.00000000000000002	***
sc1fr2.fil	-0.00672901	0.00046117	-14.591	<	0.00000000000000002	***
sc1fr3.fil	-0.23156113	0.00922449	-25.103	<	0.00000000000000002	***
sc1fr4.fil	0.00080039	0.00006468	12.375	<	0.00000000000000002	***
sc1fr5.fil	-0.32347602	0.00662376	-48.836	<	0.00000000000000002	***



```

sc1fr6.fil -0.11367842 0.01644225 -6.914 0.0000000000047184 ***
sc1fr7.fil -0.00019556 0.00002540 -7.700 0.0000000000000136 ***
sc1fr8.fil -0.16673873 0.02522793 -6.609 0.00000000000386166 ***
sc1fr9.fil -0.08642403 0.00115419 -74.878 < 0.0000000000000002 ***
sc1fr10.fil 0.35202519 0.01631954 21.571 < 0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

### 11. Pasture/Hay

Coefficients:

```

              Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.325964647 0.087387787 -38.060 < 0.0000000000000002 ***
sc1fr0.fil   0.108091572 0.005656390 19.110 < 0.0000000000000002 ***
sc1fr1.fil   0.822689001 0.053291774 15.437 < 0.0000000000000002 ***
sc1fr2.fil  -0.001464188 0.000932716 -1.570 0.116
sc1fr3.fil   0.019232867 0.017988811 1.069 0.285
sc1fr4.fil   0.000075627 0.000099705 0.759 0.448
sc1fr5.fil  -0.420562583 0.018259801 -23.032 < 0.0000000000000002 ***
sc1fr6.fil  -0.050947034 0.032520151 -1.567 0.117
sc1fr7.fil   0.000005561 0.000007419 0.749 0.454
sc1fr8.fil  -0.345936055 0.059509376 -5.813 0.00000000613 ***
sc1fr9.fil  -0.056033024 0.002413873 -23.213 < 0.0000000000000002 ***
sc1fr10.fil  0.033191537 0.032397756 1.025 0.306
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

### 12. Cultivated Crops

Coefficients:

```

              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.72370138 0.02107219 -34.344 < 0.0000000000000002 ***
sc1fr0.fil   0.00054161 0.00003040 17.816 < 0.0000000000000002 ***
sc1fr1.fil   4.17216413 0.01666080 250.418 < 0.0000000000000002 ***
sc1fr2.fil  -0.00384707 0.00022496 -17.101 < 0.0000000000000002 ***
sc1fr3.fil  -0.14269622 0.00433062 -32.951 < 0.0000000000000002 ***
sc1fr4.fil   0.00061373 0.00002993 20.502 < 0.0000000000000002 ***
sc1fr5.fil  -0.17328894 0.00378031 -45.840 < 0.0000000000000002 ***
sc1fr6.fil   0.00401117 0.00022902 17.514 < 0.0000000000000002 ***
sc1fr7.fil  -0.00043965 0.00001938 -22.688 < 0.0000000000000002 ***
sc1fr8.fil  -3.99670745 0.01803058 -221.663 < 0.0000000000000002 ***
sc1fr9.fil  -0.00206544 0.00057647 -3.583 0.00034 ***
sc1fr10.fil  0.14261751 0.00433107 32.929 < 0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

### 13. Woody Wetlands

Coefficients:

```

              Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.40518845 0.02728365 -161.459 < 0.0000000000000002 ***
sc1fr0.fil   0.00061090 0.00001950 31.323 < 0.0000000000000002 ***
sc1fr1.fil  -4.42714313 0.01840819 -240.499 < 0.0000000000000002 ***
sc1fr2.fil   0.01024955 0.00028247 36.285 < 0.0000000000000002 ***
sc1fr3.fil   0.03244734 0.00553052 5.867 0.0000000044385226 ***
sc1fr4.fil   0.00018193 0.00002278 7.986 0.0000000000000014 ***
sc1fr5.fil   0.31552016 0.00214356 147.195 < 0.0000000000000002 ***
sc1fr6.fil  -0.01068448 0.00035616 -29.999 < 0.0000000000000002 ***

```

```

sc1fr7.fil -0.00008782 0.00001814 -4.840 0.0000012998239590 ***
sc1fr8.fil 3.98503312 0.01925215 206.992 < 0.0000000000000002 ***
sc1fr9.fil 0.12631404 0.00076966 164.116 < 0.0000000000000002 ***
sc1fr10.fil -0.03207796 0.00553385 -5.797 0.0000000067642523 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

#### 14. Emergent Herbaceous Wetlands

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-5.040072359	0.125731183	-40.086	< 0.0000000000000002	***
sc1fr0.fil	0.000582592	0.000121071	4.812	0.00000149	***
sc1fr1.fil	-0.939938396	0.022812270	-41.203	< 0.0000000000000002	***
sc1fr2.fil	-0.001592248	0.001308859	-1.217	0.22379	
sc1fr3.fil	-0.332861008	0.027041056	-12.309	< 0.0000000000000002	***
sc1fr4.fil	0.000324411	0.000112277	2.889	0.00386	**
sc1fr5.fil	0.142923232	0.007882383	18.132	< 0.0000000000000002	***
sc1fr6.fil	-0.090947250	0.047338826	-1.921	0.05471	.
sc1fr7.fil	-0.000000399	0.000018177	-0.022	0.98249	
sc1fr8.fil	0.771137741	0.028357742	27.193	< 0.0000000000000002	***
sc1fr9.fil	0.025588237	0.003043771	8.407	< 0.0000000000000002	***
sc1fr10.fil	0.425457266	0.046656279	9.119	< 0.0000000000000002	***

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## VITA

# Ryan E. Baxter

### EDUCATION

Doctor of Philosophy, Geography, The Pennsylvania State University (2024)

Dissertation Title: *Multi-Scalar Drivers and Patterns of Abandoned Cropland in the United States: Implications for Renewable Energy*

Master of Science, Geography, The Pennsylvania State University (1999)

Bachelor of Arts, Environmental Sciences and Geography, Northwestern University (1997)

### APPOINTMENTS

Associate Teaching Professor, Department of Geography, Penn State (2018 – present)

Assistant Research Professor, John A. Dutton e-Education Institute, Penn State (2011 – 2018)

Senior Research Assistant, Institutes of Energy & the Environment, Penn State (2007 – 2011)

Research Assistant, Institutes of Energy & the Environment, Penn State (2000 – 2007)

### TEACHING

*Cloud & Server GIS*, Geog 865 (Co-Author) (online)

*Geospatial System Analysis and Design*, Geog 583 (online)

*Environmental Applications of GIS*, Geog 487 (online)

*Nature of Geographic Information*, Geog 482 (online)

*Geographic Information Systems*, Geog 363 (resident)

*Introduction to Geographic Information Science*, Geog 260 (resident)

*Mapping Our Changing World*, Geog 160 Web (online)

*Mapping Our Changing World*, Geog 160 (previously Geog 121) (resident)

### SELECTED PUBLICATIONS

Baxter, R.E., Calvert, K.E. (2017). Estimating Available Abandoned Cropland in the United States: Possibilities for Energy Crop Production. *Annals of the American Association of Geographers*, 107(5): 1162-1178.

Feyereisen, G.W., Camargo, G.G.T., Baxter, R.E., Baker, J., Richard, T.L. (2013). Cellulosic Biofuel Potential of a Winter Rye Double Crop across the U.S. Corn-Soybean Belt. *Agronomy Journal*, 105(3): 631 – 642.

Baxter, R.E., Feyereisen, G.W., Yu, Y., Richard, T.L. (2011). Winter crop and residue biomass potential in China. *Biofuels*, 2(5): 503 – 513.

### SELECTED GRANTS

*Pennsylvania Spatial Data Access (PASDA)*, *The Official Geospatial Data Clearinghouse for the Commonwealth of Pennsylvania* (2000 – present), Co-Principal Investigator (since 2020), Governor's Office of Administration, Office for Information Technology.

*Cooperating Technical Partners (CTP) Community Outreach and Mitigation Strategies: Pennsylvania Flood Risk Mapping Application* (2019 – present), Co-Principal Investigator, Federal Emergency Management Agency.