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AGRICULTURAL BEST MANAGEMENT PRACTICE ADOPTION DECISIONS AND SPATIAL DEPENDENCE IN SOUTHEASTERN PENNSYLVANIA FARMS AND WATERSHEDS

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ABSTRACT

The objective of this study is to determine factors influencing the Best Management Practice (BMP) adoption decisions of farmers within 17 counties in Southeastern Pennsylvania. Specifically, the land-based characteristics of adoption are analyzed along with the spatial distribution of BMP adoption. In an attempt to discover patterns in adoption at varying scales, both farm and watershed-level models are utilized. BMP adoption across farms and watersheds is analyzed utilizing count models. Spatial lag, spatial error, and a general spatial model are utilized to determine whether contagion plays a role in BMP adoption decisions at the farm-level. Study results indicate that farm acreage and the presence of a stream are significant contributors to BMP adoption. However, the efficiency of policy targeting could be improved through greater emphasis on adoptions near impaired streams and in higher priority watersheds. Despite the presence of spatially correlated errors, results indicate that contagion plays a significant role in BMP adoption. It is hypothesized that neighbor interactions and social networking play a role in creating this spatial dependence.

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CHAPTER 1: BACKGROUND

1.1 Objectives

The objective of this thesis is to explain factors influencing the Best Management Practice (BMP) adoption decisions of farmers within 17 counties in Southeastern Pennsylvania. Specifically, the objectives of this thesis are to:

- Determine land-based characteristics influencing the frequency of BMP adoption across farms
- Determine land-based characteristics influencing the frequency of BMP adoption across watersheds
- Determine whether space, and specifically distance between farms, effects BMP adoption decisions utilizing spatial error and spatial lag models.
- Use these models to analyze whether NRCS programs are efficiently targeting impaired areas with their programming

1.2 BMP Adoption and Significance

BMP adoption is of vital importance to the conservation of our nations' watersheds, soils, and habitats. A wide variety of programs, utilizing a combination of local, state, federal, and private funds, have been implemented to promote BMP adoption. These programs facilitate interactions between farmers and all levels of government as well as non-profit and private organizations. The primary vehicle for the promotion of BMP adoption on farms is government sponsored programs implemented through the Farm Bill. As a result, understanding the BMP adoption process is of critical importance to policymakers.

Implementation of BMPs through voluntary programs, such as the Chesapeake Bay Watershed Initiative (CBWI), has been the primary method adopted by government agencies to combat pollution of land and water resources due to agricultural activities. Agricultural BMPs have been found to effectively reduce pollution from agricultural runoff. By definition, these practices are economically benign. In other words, they result in profits equal to or greater than profit levels would have been had the BMP not been adopted (Feather and Amacher, 1994). As a result, the adoption of these practices by farmers should be commonplace as they should not hurt profit margins while they carry significant benefits, albeit not directly captured by the farmer in the case of environmental benefits. Magnifying this expectation is the relatively lengthy history of federal and state programs aimed at encouraging farmers to adopt conservation based practices. (Gillespie et al., 2007).

Historically, there has been an emphasis on the adoption of BMPs, both in research and in practice. The past several decades have seen a host of new programs implemented by the federal government in attempts to reduce the negative effects of nutrient runoff, soil erosion, and groundwater pollution. According to Ervin and Ervin, interest swelled in the 1970s with increases in agricultural production and increased risks for erosion as agricultural practices and land use changed (1982). However, many of the already active soil conservation programs in the 1970s and 1980s were found to be relatively ineffective. These programs included the USDA's Conservation Operations and Great Plains Conservation Programs and the Agricultural Conservation Program (Ervin and Ervin, 1982).

Since 1985, there has been an increased focus on implementing conservation programs, particularly within the Farm Bill. Generally, these programs focus on conserving soil, reducing runoff, and restoring water resources (Gillespie and Paudel, 2005). That focus has expanded to include programs targeting wildlife habitat, farm and ranch lands, grasslands, and impaired watersheds. The resources devoted to such programs have also expanded, with funding increasing by $9 billion over the following decade, or 80%, in the 2002 Farm Bill (Redlin et al., 2007). As before, they are largely voluntary and promote participation through education and by offering technical assistance and/or cost-sharing (Bosch et al., 1995). These programs are implemented by USDA's Natural Resources Conservation Service (NRCS). Examples include the Environmental Quality Incentives Program (EQIP) and Agricultural Management Assistance (USDA NRCS "Pennsylvania NRCS Programs", 2010). Given the significant resources devoted to these programs, they are expected to result in higher levels of adoption of conservation practices as well as improvements in soil and water resources.

However, the literature shows that adoption of BMPs has been relatively limited despite these incentives (Gillespie et al., 2007). Napier et al. point out that this is certainly not due to a lack of progress in the development of conservation technologies. These technologies exist, but many farmers have been unwilling to utilize them (2000). Thus, the resources expended for such policies requires more research that can serve to guide policy makers as to what factors consistently influence adoption behavior. In attempts to support effective policy, there has already been a wealth of research over the past several decades examining the effects of these programs and, more generally, what factors lead farmers to adopt BMPs. The literature focuses largely on the characteristics of those who adopt BMPs. If the characteristics of farmers, farms, and communities that tend to adopt such practices are understood, this should facilitate policy design that results in both the most efficient use of resources as well as an increase in the adoption of

BMPs. A full summary of the adoption literature, along with articles that address the shortcomings listed below, can be found in the next sections.

1.3 Gaps in the adoption literature

A major contribution of this study to the literature is explicitly modeling the spatial distribution of the BMP adoption decision with spatial lag, spatial errors, and a general spatial model. There is a lack of explicit spatial analysis in the BMP adoption literature. However, since agricultural production and conservation practice decisions are influenced in part by environmental characteristics such as soil characteristics and the location of water resources, the spatial nature of these environmental characteristics necessitates spatial analysis (Caswell, 1989). Effective analysis of the spatial factors related to BMP adoption can serve to inform policy in a variety of ways. For instance, does BMP adoption tend to be relatively fragmented (or dispersed) or does it cluster? If BMP adoption clusters, this implies that policy promoting increased interactions among adopters and their non-adopting neighbors could be effective. On the other hand, if they tend to be relatively dispersed, perhaps spatial factors limit the adoption of BMPs.

The literature also tends to represent adoption as a dichotomous choice. A fundamental flaw in this type of approach is that it ignores the issue of scale. Scale, in turn, carries implications for the effect of BMPs on water quality. For example, a farmer altering their tilling practices to benefit soil quality and prevent erosion can improve water quality in nearby streams. However, this effect could be amplified if these tilling practices are paired with a comprehensive nutrient management program and increased planting of riparian buffers along stream banks. When considering issues of scale, new questions emerge. Once a farmer decides to adopt a BMP, do they tend to adopt individual practices or multiple practices? If farmers do indeed tend to adopt multiple practices, why and in what combinations? In turn, do these combinations focus on one area (structural practices, riparian-based, etc...) or is adoption more holistic? Answering all of these questions goes beyond the scope of this research, but they are certainly areas that future research can and should address.

This study employs various models to explain the scale of BMP adoption on farms in 17 counties in Southeastern Pennsylvania. In contrast to much of the adoption literature, this study utilizes the number of BMPs adopted as the dependent variable. This was necessary because studies utilizing adoption as a dichotomous choice employed survey data that included socioeconomic, land-based, and farm characteristics for adopters and non-adopters alike. The data utilized for this study were spatial in nature and lacked identifying information for individuals and their farms. However, the spatial character of the data facilitated the analysis of new questions.

Initially, non-spatial regressions analyzing factors determining the extent of BMP adoption within the study area were run. Since the dependent variable was composed of count data, a Poisson model was estimated via maximum likelihood. A common problem with the Poisson model is its inflexibility, derived from the restrictive assumption that the mean and variance of its parameter, λ, are equal. In the case of this study, the count of BMPs adopted exhibited over-dispersion, implying that the Poisson model is inappropriate. Thus, a negative binomial model was also estimated via maximum likelihood. The results from this regression were then compared with ordinary least squares (OLS) results. Use of OLS is generally inappropriate for count data as the range of potential values is restricted and the assumption of normality is often invalid. However, if OLS and negative binomial estimation results are similar, estimation of continuous spatial models should yield useful results. A similar model was estimated at the watershed-level to attempt to explain patterns of BMP adoption at a larger scale.

1.4 BMP Adoption Literature

1.4.1 Introduction

Economic theory of BMP adoption relies on utility maximization “subject to prices, policies, personal characteristics, and natural resource assets” (Caswell et al., 2001, pg. 5). There are many personal characteristics that influence a farmer's adoption decision. These include a farmer's perception of environmental quality and the consequences of their farming practices on environmental quality, access to information, and socioeconomic characteristics, to name a few. For example, several studies examine the impacts of environmental awareness or concern on adoption behavior (Alonge and Martin, 1995; Feather and Amacher, 1994; Habron, 2004). However, since environmental benefits accrue to the public while economic profits accrue only to the farmer, the financial implications of BMP adoption decisions may largely influence the adoption decision. The diversity of potential determinants of the adoption decision paired with a host of methodological choices has resulted in a diffuse literature. Indeed, there are a wide variety of methodologies and theoretical bases within the literature. Lockeretz contends that these issues along with a lack of recognition of uncertainty in what we know and theoretical errors has lead to a segmented literature that fails to adequately explain conservation practice adoption (Lockeretz, 1990). Without adequate information on explanatory variables that consistently influence adoption patterns among farmers, policy may remain ineffective (Napier et al., 2000).

Government programs tend to focus on encouraging adoption through voluntary means. Such policies generally include elements of education, technical assistance, and cost-sharing or subsidies. Adhering to the theoretical perspective that producers weight adoption decisions based on their profitability, a 2006 US Government Accountability Office (GAO) report cited lack of adequate cost-sharing funds as the main reason for non adoption. Policy recommendations included increased funding, more technical assistance, and less cumbersome administrative requirements (US GAO, 2006). However, the literature is far from conclusive. Though most adoption studies include financial data of some kind, including debt ratios, income, or cost-sharing measures, their significance varies. In a 2002 study, Napier and Bridges examined the success of such programs in an Ohio watershed. Participants had been exposed to a wide variety of local, state, and federal programs. A nearby watershed not exposed to such programs was used as a control. Adoption rates were defined by a composite index made up of 18 different practices. Though only using descriptive statistical techniques, the authors found no discernible differences in adoption rates between the two watersheds. This throws into the question the primary policy approach utilized by governments to encourage conservation practice adoption (Napier and Bridges, 2002).

A more recent study of Kansas farmers by Smith et al. also throws current policy into question. Sharp discrepancies emerged between cost-sharing program awareness and adoption. Significant majorities were aware of conservation programs such as the Conservation Reserve Program (CRP) (97%) and Environmental Quality Incentive Program (EQIP) (80.5%), but fewer farmers participated in these programs (45% and 31% respectively). Smith et al. concluded that such discrepancies imply that "the participation gap is likely due to factors other than financial considerations" (Smith et al., 2007, pg. 100). Results also indicated that producers believe that BMPs are effective and that environmental resources are worth protecting, though there was no consensus that water resources were currently polluted. They attribute low adoption rates partially to this gap between perceived levels of water quality impairment and actual impairment levels. With 76% of Kansas streams deemed impaired, this gap is quite large. They also cite extensive government oversight and administrative requirements as limiting adoption (Smith et al., 2007).

In order to provide an indication of the current state of the adoption literature, Prokopy et al. utilized a vote-count methodology to elicit patterns in the BMP adoption literature as a whole (Prokopy et al., 2008). The analysis focused on trends in the significance of variables in studies focusing on BMP adoption in the U.S. Studies have utilized a variety of methods to analyze adoption decisions of one or more BMPs. Logit and probit models were the most common, though others such as linear regression were used. A wide variety of explanatory variables were used as independent variables, grouped generally by the authors into categories of capacity, attitudes, awareness and farm characteristics.

Capacity includes variables relating to human capital, networking, financial characteristics, types of farm operations and labor. Of particular interest to this study are variables related to social networks, including farmers' relationships with other farmers, government agencies and businesses. The presence or absence of such networks can influence the spatial distribution of BMP adoption as well as its scale. Attitude variables relate to farmer perceptions of the environment and water quality, profitability of practices, risk, and whether the farm would stay in the family. The awareness category was based not on perceptions and beliefs, but on knowledge and information of the potential impacts of farming practices, the environment and programs available to farmers. Finally, farm characteristics variables include the type of farm as well as physical characteristics relating to land relationships and soil (Prokopy et al., 2008).

Results from the vote count indicated that most variables were insignificant the majority of the time. Similar to the conclusions of Lockeretz (1990), this indicates a high degree of uncertainty and a lack of understanding of BMP adoption decisions. The authors looked at significance alone in assessing patterns in the literature. In general, farm size, education, income, access to information, labor availability, environmental attitudes, risk attitudes, profitability attitudes, awareness, access to social networks, soil slope and soil quality had positive significant relationships with BMP adoption. Age, farms other than grain, and, surprisingly, proximity to streams were found to negatively influence BMP adoption. However, these variables were often insignificant and, in some cases, found to exhibit more positive than negative relationships in slightly more studies and vice versa. Some variables, such as proximity to streams, were only included in a few studies, making any definitive conclusions difficult (Prokopy et al., 2008). Results indicating the general significance of social network and information based variables imply the potential for clustering in adoption behavior. However, any results indicating clusters or hotspots in this study can not be directly attributed to such factors since social network and information variables were not available. Nevertheless, the results of Prokopy et al. imply that clustering in BMP adoption may result as information spreads through social networks.

1.4.2 Spatial Analysis in the adoption literature

Much of the adoption literature utilizes data from the Area Studies Survey (US GAO, 2006), a joint project of the USDA, NASS, and NRCS with input from USGS and EPA. The intent of the project was to connect natural resource and land characteristics to production and conservation practice adoption decisions. The study design recognized that if production and adoption decisions within the survey are effected by land-based characteristics, the spatial distribution of adoption becomes important. Furthermore, the diffusion of adoption technologies may take on a spatial component as new technologies become more commonplace. While the adoption literature makes wide use of natural resource and land characteristic variables, the focus remains largely on the individual farmer and little research has examined the spatial pattern of adoption decisions across these individuals. Research focusing on this spatial pattern is necessary and can serve to guide policy (Lockeretz, 1990).

Though there is a lack of explicit spatial analysis in the BMP adoption literature, it has been applied in many other areas. Spatial modeling is useful for examining epidemics related to the spread of diseases and pests or invasive species. Migration flows have also been modeled spatially. Of more relevance is the use of spatial modeling within the technology adoption literature. For instance, Scherngell and Barber examined the influence of proximity in research and development collaborations (2008). Sarmiento and Wilson modeled the spatial dependence in adoption decisions surrounding the use of shuttle train grain elevators on farms (2005). Case explored how opinions on technology adoption vary across space amongst Indonesian farmers, finding evidence of a large spatial lag structure (2002).

Spatial patterns in the BMP adoption decision may emerge for a variety of reasons. Physical characteristics of the land vary across space. If adoption is tied to such characteristics, spatial patterns will emerge. Of more interest is the effect of contagion or spread of adoption behavior due to community and social network factors. Factors that have been explored in the literature include participation in community organizations and living in areas that have organized to protect water quality. For instance, Ervin and Ervin included a variable noting whether participants lived in a watershed that had organized to coordinate conservation activities among residents, though analysis found this variable to be insignificant in explaining adoption decisions. More generally, spatial clustering due to “contagion” or an “infection” deals with the spread of information (Ervin and Ervin, 1982).

Feather and Amacher hypothesized that adoption rates may increase if more resources are utilized to inform farmers of the financial and environmental benefits of conservation practices. At the core of this argument is the need to both “decrease uncertainty” and alter existing perceptions of farmers (Feather and Amacher, 1994, pg.

166). They make the assumption that since BMPs are by definition at least as profitable as existing practices, then non-adopters must simply be unaware of the potential economic and environmental benefits associated with BMPs. They model the adoption decision for each BMP individually as a utility maximization problem estimated with a probit model while including parameters for existing knowledge and perceptions. A second stage linear model is estimated for the intensity of adoption. Results indicate that profit-oriented perceptions have a larger effect on adoption rates than environmental perceptions. While they do not explicitly include spatial elements in their study focusing on the role of information and economic and environmental perceptions in BMP adoption, they include commentary on the spread of information in the farming community. Their study looks at adoption rates across areas exposed to Federal BMP Demonstration Projects, with results indicating that such projects have effects beyond their boundaries. This implies a need to focus on the spatial dimension of BMP adoption and to include spatial interaction in adoption models (Feather and Amacher, 1994).

Habron takes this analysis a step further by focusing on spatial flows of information. He notes that most adoption based studies focus on individuals while ignoring information flows between these individuals. While other studies include perception and awareness indicators, these variables do not effectively capture the spread of information across space. Both “a desire for more information regarding the survey” and “a tendency to tell other landowners about conservation decisions” emerged as significant variables (2004, pg. 114). These results lend support to the notion that information flows and networks may influence adoption. Since these flows are inherently spatial in nature, research analyzing the spatial distribution of BMP adoption is necessary (Habron, 2004).

Community ties can facilitate the spread of information among farmers and organizations promoting the adoption of BMPs. In their study of how the distribution of farm family resources relates to the adoption of no-plow tillage, Belknap and Saupe found that engagement with community institutions was a significant factor (1988). Korshing et al. found similar results in a study of Iowa farmers. They also found that early adopters of technologies tended to have greater organizational participation rates. If early adopters tend to encourage adoption through other social networks, this could influence BMP adoption on a spatial scale (Korshing et al., 1983). Bultena and Hoiberg found that farmers were less likely to adopt conservation tillage if they perceived little community acceptance for the practice. To the extent that community organizations may increase the level of acceptance for adopting conservation tillage, this result conforms to those of Korshing et al. and Belknap and Saupe (Bultena and Hoibert, 1983). If community organizations are a vehicle for spreading information and increasing community acceptance of conservation practices, this implies a need for explicit spatial analysis of BMP adoption. Areas with more of these organizations and/or more active organizations may result in spatially clustered adoption patterns. Though data concerning social networks and engagement with community organizations is unavailable for this study, it is informative in that it implies the need for spatially focused research.

However, it is important to temper the role of the spread of information with the notion that farmers ultimately may tend to adopt only those practices that are compatible with their farms, and may be informed of such practices regardless of the presence of information networks. In a study of the factors affecting the awareness and adoption of precision agriculture, a relatively new technology, Daberkow and McBride found that those whose interests were served by adopting precision agriculture were already aware of it despite survey data indicated that large percentages (~70%) were unaware of this technology at the time of the study (Daberkow and McBride, 2003).

Similarly, Alonge and Martin analyzed the adoption of sustainable agricultural practices such as reduced fertilizer and herbicide use. In accordance with Feather and Amacher (1994), the purpose of the study was to relate perceptions of the profitability of sustainable agricultural practices and environmental attitudes to practice adoption. Citing Lovejoy & Napier (1986), they contend that environmental damages may not be enough to sway farmers to utilize conservation based approaches. Economic concerns may hold greater influence, as was found by Feather and Amacher. The resulting regression analysis supported these findings. Those farmers that viewed the set of 9 practices surveyed as most compatible with their current operation were more likely to adopt (Alonge and Martin, 1995).

1.4.3 Count models and the adoption literature

Just as it is important to recognize the potential for interplay across individuals and their environment to influence the spatial distribution of BMP adoption, it is important to discuss the merits of analyzing BMPs individually as opposed to analysis across BMPs. This study utilizes the latter methodology, analyzing the number of BMPs adopted as the dependent variable utilizing a count model. In general, the BMP adoption literature tends to treat BMP adoption on a practice-by-practice basis. In other words, BMP practice adoption decisions are assumed to be made independently of one another. Studies focusing on the adoption of only one type of BMP make this assumption implicitly. For example, Bosch et al. focused on voluntary versus mandatory adoption of nitrogen testing in Nebraska (1995), Gould et al. looked at how perceptions of soil erosion influence adoption of conservation tillage (1989), Belknap and Saupe explored factors influencing the adoption of no-plow tillage in 8 counties in Wisconsin (1988) and Korsching et al. analyzed the adoption of minimum tillage practices through time (1983). Several studies have evaluated the intensity of application of individual practices (Ervin and Ervin, 1982; Gould et al., 1989; Feather and Amacher, 1994), but this approach neglects the effect of scale across practices. Other studies examine the adoption of multiple types of conservation practices, but treat them individually rather than jointly. Gillespie et al. analyzed the characteristics of non-adopters of 16 different BMPs appropriate to the beef cattle industry, but ran a separate model for each practice (2007). Non-adopters may tend to reject adoption of all practices jointly for particular reasons. If so, this study would not capture these effects.

An examination of the number of BMPs adopted within each farm in the study area (excluding non-adopting farms) rejects this practice-by-practice approach as most adopting farms have adopted multiple practices. BMP adopting farms averaged 3.1 practices adopted per farm across the study area with a maximum of near twenty unique practices adopted on multiple farms, implying that NRCS BMP adoption programs may focus more on a holistic conservation plan as opposed to the piecemeal adoption of individual BMPs (NRCS Conservation Contract, 2010). If NRCS conservation plans do indeed tend to treat conservation practice adoption holistically, then models assessing the factors influencing the adoption of individual BMPs are inappropriate and will lead to incorrect inferences.

Park and Lohr provide justification for treating BMP adoption decisions jointly (2004). They explored the adoption decisions of organic farmers making pest management decisions to control diseases, insects, and weeds. They argue that adoption must be treated as a system since there is an interplay between practices when adopted together versus individually. Joint adoption can lead to increased management efficiency, and thus “it is the total technology package that maximizes the farmer's utility” (pg. 469). Furthermore, adopters of individual practices may simply be experimenting with practices and thus are not true adopters. Holistic practice adoption is particularly relevant for organic farmers, who must have deep knowledge of a wide variety of practices to successfully control disease, insects, and weeds.

Featherstone and Goodwin examined the scale of investment by utilizing total conservation expenditures as a dependent variable. They examined farmers' conservation expenditures by treating BMP adoption and other conservation expenditures as long-term investments that compete with other potential investments for limited capital and credit. Simultaneous equations were estimated using a tobit model to examine both the investment decision (with a binary dependent variable) and the amount of conservation expenditure. Among other conclusions, the study found that larger, corporate owned farms tend to invest more in conservation. However, dollar value conservation expenditures do not necessarily translate to level of BMP adoption as costs vary across BMPs. Furthermore, conservation expenditures will be influenced by the level of government cost-sharing, a variable included by the authors but unavailable in the dataset utilized in this study (Featherstone and Goodwin,1993).

Napier et al. explicitly recognize the shortcomings of the literature in determining what factors influence adoption, citing treatment of BMPs individually as a possible reason. In regards to the relatively diffuse results of prior adoption studies, the article points out that “it is quite possible that use of single item indicators of conservation adoption behavior...may have introduced so much measurement error that theoretical models developed for testing may have not been appropriately evaluated” (Napier et al., 2000, pg. 123). To overcome these shortcomings, they created a composite “index” of adoption developed from a survey pertaining to multiple conservation practices. Responses for adoption of each practice were weighted by the frequency of use and the environmental impacts of the practice as determined by the authors. A composite index is one way of incorporating scale into the analysis, but is rather subjective as the authors determined the practices to be included on the survey and the weights used. Results varied between states, with little consistency emerging (Napier et al., 2000). Wu and Babcock began from a similar premise, namely that certain types of BMPs can go together. They assumed that farmers often make BMP adoption decisions jointly. In making this assumption Wu and Babcock are explicitly accounting for the fact that multiple practices adoptions will have varying effects on erosion and water quality as compared to the adoption of these practices individually. Employing a polychotomouschoice decision model, they explored farmers' decisions to adopt various tillage, crop rotation, and soil testing practices as well as the economic and environmental effects of different combinations of adoptions. The model allows the flexibility to determine the effects of these combinations as well as individual adoptions while controlling for self-selection bias (i.e. those that benefit most from a practice are most likely to adopt). They include the standard socioeconomic and farm-based variables in their analysis. Results indicate that adoption of any combination of the three practices in question (conservation tillage, crop rotation, soil testing) decreases soil erosion and nitrogen application rates as compared to non-adopters (Wu and Babcock, 1998).

In a similar study, Fuglie analyzed both the adoption of conservation tillage as well as its effects on pesticide use. Though conservation tillage practices reduce erosion, these benefits may be countered if pesticide and herbicide use increases as a result. A multinomial logit model was employed to assess the adoption of conservation tillage, the results of which were utilized to determine the effects of adoption on yield and quantity of inputs. Results indicated that those farmers receiving technical assistance or cost-sharing were more likely to adopt some type of conservation tillage as are farmers with greater erosion problems. Though this may appear obvious, it provides evidence that programs of the type NRCS offers have been effective. Going beyond this analysis to explain how NRCS has influenced adoption spatially will add to our understanding of their programs. Results were mixed as to the effects of conservation tillage adoption on the use of chemical inputs. However, it is important to note that since conservation tillage may influence chemical input use, it is useful to pair the implementation of various tillage practices with nutrient management plans (Fuglie, 1999).

Ervin and Ervin argue that researchers must go beyond explaining the reasons why farmers adopt conservation practices by analyzing the resultant effects on conservation. After all, the goal of encouraging farmers to adopt BMPs is to yield improvements in soil and water quality as well as wildlife habitat. They conceptualize the adoption decision as a three stage process including recognition of an erosion problem, the decision to adopt, and the effort or intensity of adoption in a study of Missouri farmers. Equations were estimated utilizing both the number of practices adopted and the effort expended in adopting each practice as dependent variables. The analysis is particularly useful in that it allows comparison between the two indicators to see if significant explanatory variable differences emerge. Effort was defined as the difference between estimated erosion rates with and without the conservation practices adopted. In doing so, Ervin and Ervin connect scale of adoption with estimated impacts on soil conservation and water resources. However, results indicated few differences between equations for number of practices adopted and effort (Ervin and Ervin, 1982).

Though much of the BMP adoption literature used some variation of logit, probit, or tobit analysis, some studies have utilized count methodologies. Both the Poisson and negative binomial distributions have been utilized to model count data (see chapter 2 for further discussion). The Poisson distribution is a special case of the negative binomial distribution where the variance is equal to the mean. If the variance is found to exceed the mean, the data exhibits over-dispersion while under-dispersion results from a variance that is smaller than the mean. Park and Lohr (2004) utilized a negative binomial count model to analyze BMP adoption among organic farmers. Similarly, Rahelizatovo and Gillespie model over-dispersed BMP adoption data from Louisiana dairy farmers utilizing a negative binomial count model (2004).

However, care should be taken in analyzing the scale of BMP adoption across practices. Using the number of BMPs adopted as the dependent variable implies that all BMPs could be feasibly adopted. Thus, there are no constraints to adopting all BMPs and the adoption of one BMP does not nullify the adoption of any other on a practical basis (Rahelizatovo and Gillespie, 2004). Additionally, it may be inappropriate to analyze BMP adoption decisions jointly if the determinants for BMP adoption vary across practices. Utilizing the number of BMPs adopted as the dependent variable, as is done in this study, will hide these differences if this is the case.

For example, in a study of the factors influencing the adoption of conservation practices in three Oregon watersheds, Habron ran separate logit equations for multiple individual practices while including the other practices as explanatory variables. Different sets of significant explanatory variables emerged for each equation, a result that may discourage estimation of equations when the dependent variable includes multiple practices (Habron, 2004). Offering a different critique, Khanna points out that studies assuming that practices are adopted jointly or independently may both suffer from theoretical errors if practices are actually adopted sequentially (2001). Khanna analyzed the sequential adoption decision of soil testing and variable rate technology utilizing a bivariate probit analysis.

However, this study aims to explain adoption decisions of farmers amongst many

BMPs along with the spatial distribution of these decisions. In cases where adopters have many choices, count models are useful (Rahelizatovo and Gillespie, 2004). Individual analysis would have been far too cumbersome. Furthermore, it is appropriate to model the scale of BMP adoption if the factors that lead to spatial concentrations of adoption is of interest as spatial factors may influence the scale of adoption. For instance, it is useful to know what land characteristics might lead a farmer to increase their frequency of adoption. Examples include presence of a stream and various soil characteristics. Rahelizatovo and Gillespie included such measures, finding greater numbers of BMP adoption among producers with a stream or river running through their property (2004). For these reasons, a count model was deemed appropriate for this study.

1.4.4 Future directions for research

In general, prior research has addressed one of two directions for analysis. Many studies made the attempt to connect conservation practices with environmental consequences at various scales (farm, watershed, regional, etc.) while others addressed the factors facilitating adoption decisions. I discussed primarily the latter, while the environmental consequences of conservation practices involves physical models beyond the scope of this study. Wu et al. attempted to connect the practice adoption with environmental consequences by predicting adoption and land use decisions at the micro-level and using environmental simulation models to predict the resulting environmental effects (2004). Such methodologies represent important steps for BMP adoption research, this study included. While it is useful and necessary to explain the factors influencing the scale of BMP adoption in Southeastern PA, it is also necessary to connect these decision making processes with environmental quality indicators. After all, improvement of water quality, less erosion, and reduced nutrient loadings are goals for policymakers. Connecting practice adoption to environmental results gives policymakers more tools to ensure that these end goals are reached by the most efficient means possible.

Wu et al. analyzed the impacts of farm-level decision making on macro-level environmental quality in the upper Mississippi River Basin. The model was applied to the application of incentive payments to encourage adoption of conservation tillage and crop rotation. Cropping and tillage acreage were estimated utilizing micro-level multinomial logit models including cost, profit, and yield variables along with physical characteristics including land, soil, and climatic conditions. Acreages were estimated for a baseline scenario along with the incentive payments. The associated impacts of these cropping and conservation practice decisions on nutrient runoff and erosion were estimated using environmental simulation functions. Results showed that while payments increase the application of crop rotation and conservation tillage, the associated impacts on environmental quality indicators are small. While potentially useful to policymakers, these results ignore the potential of factors other than land and profit-oriented variables to influence adoption decisions. Such effects include other spatially explicit criteria such as access to information from neighbors and community organizations as well as other socioeconomic and farmer characteristics (Wu et al., 2004).

As previously stated, the adoption literature is a diverse body of work lacking cohesion and clear recommendations for policymakers. Incorporating explicit spatial analysis addresses one major gap in this literature. The study also recognizes the potential interplay across practices by utilizing the total count of BMPs adopted as the dependent variable. Future studies should connect adoption with environmental consequences, as Wu et al. point out (2004). However, it is challenging to incorporate all of these elements into one study. In the end, the most useful conclusion to be reached from the BMP adoption literature may be that the adoption decisions are complex and are influenced by a multitude of factors.

1.5 Overview of Study

The aim of this study is to contribute to the larger BMP adoption literature by focusing on the spatial distribution and adoption decisions of farmers within a 17 county region in Southeastern Pennsylvania. The study analyzes the adoption decisions at both the farm and watershed scales based on farm, land, and soil characteristics. A major goal of the farm-based analysis is to look for the presence of contagion in the adoption decisions of farmers. Contagion might occur for a variety of reasons, and is of interest due to its implications for future conservation programming efforts. Various spatial models are run, including a spatial errors, spatial lag, and general spatial model. OLS estimation results are compared to count model estimation results, as count models are more appropriate to the study at hand but do not allow the incorporation of spatial elements. The watershed analysis aids in the detection of adoption patterns at a larger scale through the estimation of Poisson and negative binomial count models. Chapter 2 details the study area, methods, models, and data sources. Chapter 3 discusses the estimation results. Finally, Chapter 4 summarizes and discusses these results along with pointing to potential directions for future research.

Chapter 2: Methodology

2.1 Study Area

The Chesapeake Bay, our nations largest estuary, is a vital ecosystem providing habitat for thousands of species. The waters within the Chesapeake Bay are classified as "degraded," due in large part to runoff of nitrogen, phosphorus, and sediment from agriculture. These pollutants contribute to rising oxygen levels in the bay resulting in algae blooms, fish kills and general degradation of ecosystem health (Chesapeake Bay Program, 2007). Loadings of nitrogen, phosphorus, and sediment were approximately 240 million pounds, 11.3 million pounds and 2 million tons in 2009, respectively. Agriculture accounted for 38% of nitrogen loadings, 44% of phosphorus loadings, and 60% of sediment loadings (Chesapeake Bay Program "Pollutants", 2009). To combat water quality damage due to each of these pollutants, the Chesapeake Bay Program has established goals to be reached by 2010. However, as of 2009 only 52% of the agricultural nitrogen goal, 50% of the agricultural phosphorus goal, and 50% of the agricultural sediment goal had been achieved (Chesapeake Bay Program "Agricultural Pollution Controls", 2009).

Clearly, there is a need for research addressing ways to improve water quality within the waters of Pennsylvania and the larger Chesapeake Bay region as well as programs that effectively and efficiently utilize this research to promote conservation (Chesapeake Bay Program, 2007). Due to the significance of non-point source pollution from agricultural sources within Pennsylvania and the Chesapeake Bay Watershed, implementing conservation practices on farms must be a major focus of these activities.

Penn State University, along with local governments, non-profit groups, and volunteers, has been a major partner in undertaking research aimed at increasing conservation activities in Pennsylvania watersheds contained by the Chesapeake Bay Watershed. Much of this research has focused on the Conewago Watershed, an impaired watershed in Dauphin, Lancaster, and Lebanon Counties.

The study area covers 17 counties in Southeastern Pennsylvania. These counties are Adams, Berks, Chester, Cumberland, Dauphin, Franklin, Huntingdon, Juniata, Lancaster, Lebanon, Mifflin, Northumberland, Perry, Schuylkill, Snyder, Union, and York (Figure 1). These counties were selected due to their location within the Chesapeake Bay Watershed. A portion of Chester, Berks, and Schuylkill, the majority of Lancaster and Lebanon, and all of the remaining counties lie within the Chesapeake Bay Watershed. Data from counties only partially within the Chesapeake Bay Watershed were included to ensure that the watershed analysis included the entirety of watersheds that lie partially within the boundaries of these counties.

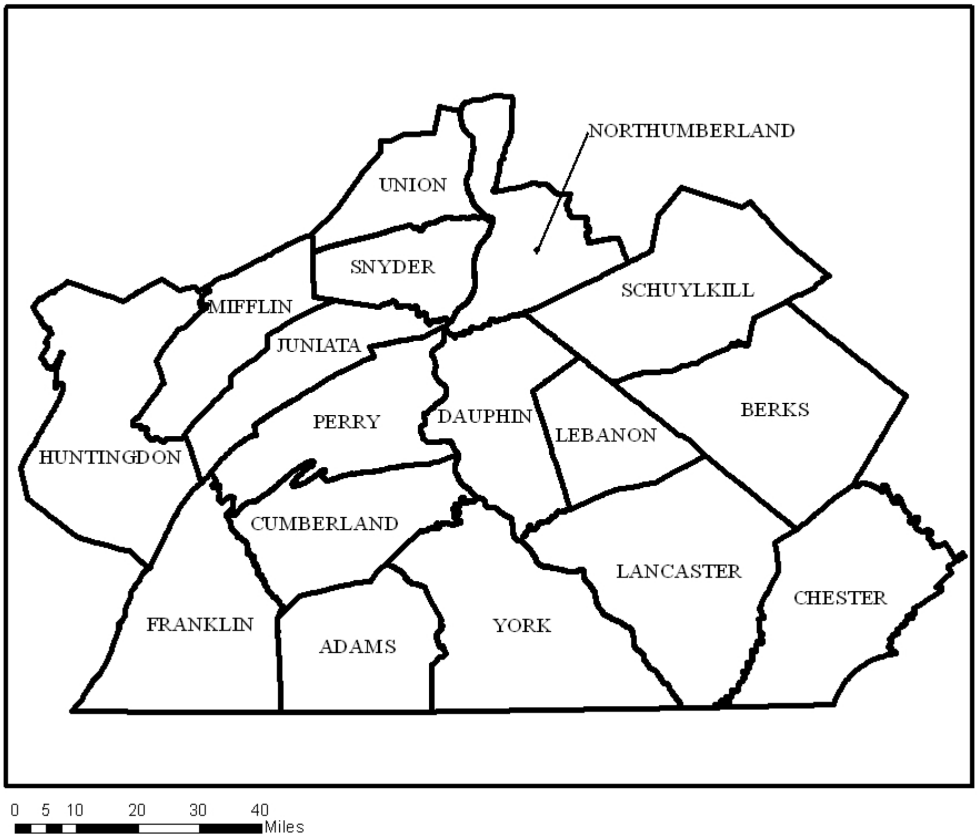

Figure 1: Counties in the study area. The study area included BMP adoption data from 17 counties in Southeastern Pennsylvania.

The watershed scale analysis is necessitated by adoption programming that focuses on priority watersheds. The Chesapeake Bay Watershed Initiative (CBWI) is one program focused on Chesapeake Bay watersheds. The CBWI is a federally funded initiative of the Natural Resources Conservation Service (NRCS). The study area for this study contains many watersheds that are deemed to be medium or high priority watersheds by the CBWI, including the Conewago Watershed (2008) (Figure 2). The 2008 Farm Bill created the CBWI and in so doing gave NRCS authority for increased technical assistance and cost-sharing practices aimed at reducing pollution within the Chesapeake Bay. The CBWI designates priority watersheds each year, with more weight given to farmers located within these priority watersheds. The CBWI focuses on implementation of conservation practices controlling erosion and sediment and decreasing nutrient loss (USDA, 2009). The efficiency of NRCS programming can be analyzed by including priority watershed designation as an independent variable.

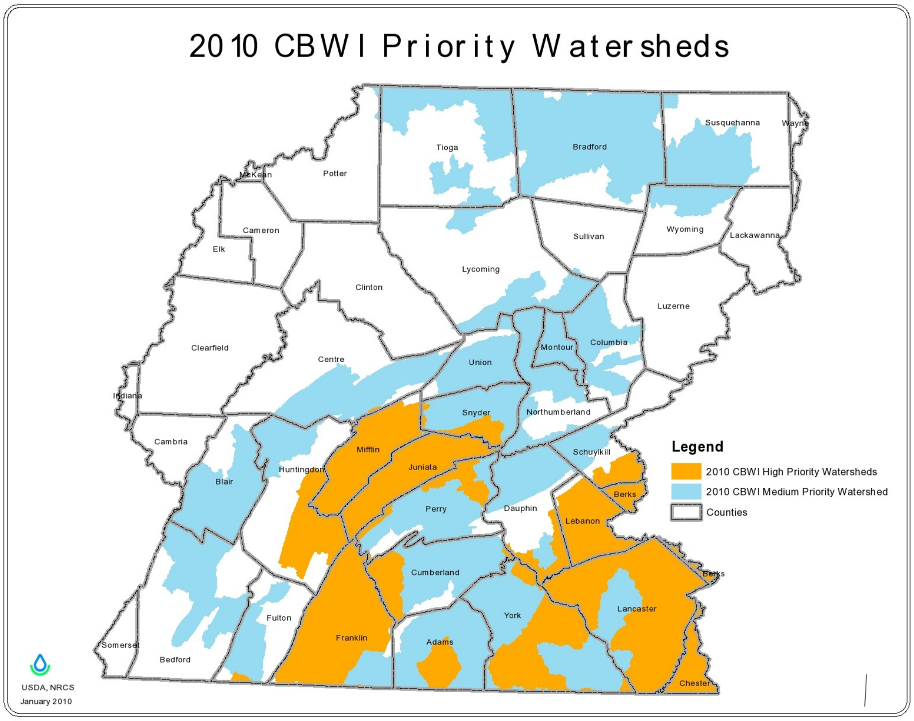

Figure 2: 2010 CBWI Medium and High Priority Watersheds in the study area within the larger Chesapeake Bay Watershed in PA (USDA NRCS "Chesapeake", 2010).

As an example, it is useful to detail a representative watershed within the study area. As mentioned, the Conewago Watershed has been one focus of research at Penn State and has been recognized as a high priority watershed by the CBWI. The watershed covers 53.2 square miles in Dauphin, Lancaster, and Lebanon counties in southeastern Pennsylvania. Beginning in Lebanon County, the Conewago Creek flows southwest through primarily forested and agricultural land until it empties into the Susquehanna River, the largest tributary for the Chesapeake Bay. The Conewago Watershed was assessed by biologists in 1994 and 1997. As a result of high sediment runoff and increased nutrient loadings, much of the watershed has been designated as impaired. Impaired means that the stream "is too polluted to sustain the kind of fish and other aquatic life that it could sustain if it were a healthy stream" (TCCCA).

Land use within the watershed is primarily agricultural, with 53% of its area utilized for that purpose. As a result, any policy aimed at improving the water quality within the watershed must address the role that agricultural runoff plays in impairing the watershed. Runoff of chemicals such as phosphorous and nitrogen from nearby agricultural fields not only threaten aquatic life and biodiversity within the watershed, but all waters downstream as well. However, non-point pollution sources such as agricultural runoff are difficult to monitor. As a result, voluntary adoption of BMPs can be a valuable tool to reduce agricultural runoff within the Conewago and other watersheds.

2.2 BMP Adoption and Scales of Analysis

Data were obtained from the NRCS office in Harrisburg, Pennsylvania. The data included all available digitized data on conservation contracts implemented for NRCS programs in 17 counties in Southeastern Pennsylvania. Farmers within Pennsylvania are eligible for technical assistance or cost-sharing through a variety of programs. NRCS is responsible for implementing these programs. Programs adopted within the study area include Agricultural Management Assistance (AMA), Chesapeake Bay Watershed Initiative (CBWI), Conservation Reserve Program (CRP), Conservation Security Program (CSP), General Conservation Technical Assistance (CTA-GENRL), Conservation Technical Assistance – Grazing Lands Conservation (CTA-GLC), Environmental Quality Incentives Program (EQIP), Farm and Ranch Land Protection Program (FRPP), Grasslands Reserve Program (GRP), Watershed Operations (WF-08), Wildlife Habitat Incentives Program (WHIP), and Wetlands Reserve Program (WRP). The most commonly utilized programs within the study area are EQIP and CRP, along with general technical assistance (CTA-GENRL). Farmers taking advantage of educational opportunities and technical assistance are generally not obligated to fulfill requirements within a conservation plan. However, if they receive cost-sharing, they are obligated to uphold the terms of a soil conservation plan (Fuglie, 1999). Farmers wishing for help in implementing BMPs contact NRCS. NRCS then proposes appropriate practices and programs based on information provided by the farmer and a field visit. A contract is then negotiated and a soil conservation plan signed if the farmer is receiving funds through any NRCS programs (Hasemeier 2010).

The adoption process can create patterns at varying scales. As a result, the analysis is carried out at two scales – for farms in the study area as well as watersheds that fall within the area relevant to the CBWI (all watersheds in the Chesapeake Bay

Watershed). Farm scale models allow the analysis of the relevance of spatial land-based variables to the number of BMPs adopted. Variables include soil characteristics and proximity to streams. Watershed scale models allow the analysis of the relevance of designation as a medium or high priority watershed to the number of BMPs adopted. In turn, this provides a useful indication of whether NRCS programs are effectively targeting watersheds with the greatest need for conservation projects. Section 2.3 details the farm-level model, variables, and data while section 2.4 deals with the watershed scale analysis.

2.3 Farm-Level Analysis

As detailed in the previous chapter, the BMP adoption literature has utilized a wide variety of methodological approaches. The most common statistical models employed have been logit, probit, and multinomial logit. However, such models are inappropriate for this analysis as these models are utilized for qualitative dependent variables. Thus, the studies utilizing logit and probit analysis were analyzing the adoption decision as a dichotomous “yes or no” choice (Kennedy 2003). The dependent variable of choice in this study is the number of unique BMPs adopted. What qualifies as a unique BMP is detailed in section 2.3.3

Since the number of unique BMPs adopted for farms in the study area is count data, the dependent variable is not continuous as the values that the dependent variable can take on are limited. The farm-level analysis is further complicated by the fact that there are a large number of zero observations in the data set. In other words, there are many farms that have not adopted any BMPs at all. The study area included a total of

41,492 farms, 4,819 of which had adopted BMPs through NRCS programs, or approximately 11.6%. This leaves 36,673 farms not adopting any BMPs at all, or approximately 88.4%.

Variables included in the model were limited to land-based characteristics associated with the farms in question. These were the only data available for non-adopters of BMPs as they were not included in the conservation contract dataset obtained from NRCS. Variables were extracted for all farms with the aid of geographic information system software ArcGIS 9.3.1 and the 2010 Farm Service Agency (FSA) Common Land Unit (CLU) dataset (ESRI, 2009). The variables utilized for the farm-level count and spatial models are listed in table 1 on the next page.

Table 1: Farm Model Variables	
Dependent Variable: Farm BMP Count	
Independent Variables	**Description**
Acres	Farm Acreage
Stream	Presence of a stream intersecting the farm
Impaired Stream	Presence of an impaired stream intersecting the farm
Medium Priority WS	Farm location in a CBWI medium priority WS
High Priority WS	Farm location in a CBWI high priority WS
AWA LCC	Area Weighted Average for Land Capability Class
AWA Slope	Area Weighted Average for soil slope
AWA TFactor	Area Weighted Average for soil T factor
Crop Farm	Primary land use dummy variable
Livestock	Primary land use dummy variable
Fruits/Vegetables	Primary land use dummy variable
County dummy variables	County farm centroid is located in
Adams	
Berks	
Chester	
Cumberland	
Dauphin	
Franklin	
Huntingdon	
Juniata	
Lebanon	
Mifflin	
Northumberland	
Perry	
Schuylkill	
Snyder	
Union	
York	

Acres represents the total farm acreage. Accounting for the size of the farm is important since larger farms may have more opportunities for BMP adoption. Stream and Impaired Stream are dummies that account for stream presence and whether that stream is impaired. Medium Priority WS and High Priority Watershed are dummies included representing whether or not a farm lies within a medium or high priority watershed as designated by the CBWI. The next three variables are area-weighted averages of soil characteristics, with AWA LCC accounting for the land capability class, AWA Slope accounting for slope, and AWA TFactor accounting for the soil T factor. Crop farm, Livestock, and Fruits/Vegetables account for the primary land use of the farm. The next several dummy variables account for the county that the farm (farm centroid for overlapping farms) falls within, excluding Lancaster County to avoid multicollinearity. Including county dummy variables allows analysis of differences in adoption across counties by accounting for county soil conservation districts. The last three dummy variables account for the majority land use of the farm as primarily for crops, livestock, or fruits and vegetables.

2.3.1 Development of Count Models

The intended analysis for this thesis is complicated by two factors. First, as stated above, the dependent variable is composed of count data with a significant number of zero observations. Linear regression is generally deemed inappropriate for count data for a number of reasons. First, count data are composed of a set of non-negative discrete values, and thus are not continuous. Furthermore, as Cameron and Trivedi point out, data are often “skewed to the left and intrinsically heteroskedastic with variance increasing with the mean" (1999, pg. 2). The data in question follow this pattern (Figure 3). The 36,673 non-adopting farms have been eliminated for ease of viewing.

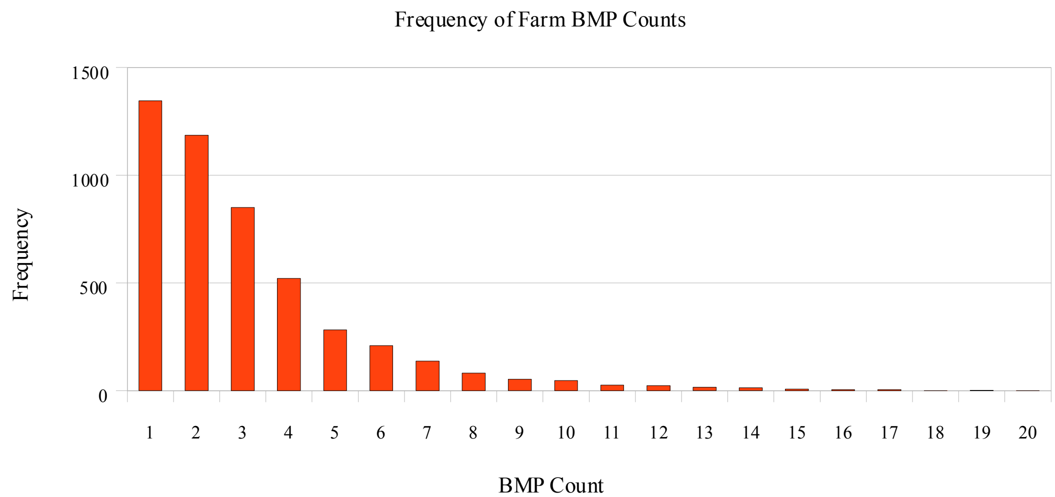

Figure 3: Frequency distribution of the number of farms with particular BMP counts (excluding 36,673 non-adopting farms)

Thus, a model must be adopted that is suitable for data of this nature. The most commonly utilized model for count data is the Poisson model:

$$pr = e^{-\lambda}\lambda^{y}/y!$$

The value of the distribution accounts for the probability of y events occurring with explanatory variables being modeled by the parameter λ. Specifically, it is assumed that λ = exp(Xβ) such that:

$$pr = e^{-X\beta}X\beta^{y}/y!$$

λ is set equal to an exponential function of Xβ so that only non-negative values are possible (Kennedy, 2003). Poisson models are estimated via maximum likelihood. If non-zero observations are unavailable, then a truncated version of the model must be estimated. Including information from non-adopting farms allows us to avoid the estimation of a truncated model, despite the fact that the high percentage of zero observations will likely distort results.

Though a common starting point for count data, the Poisson model is often inappropriate due to its restrictive assumption that sample mean equals the sample variance. In practice, this is often not the case as count data are frequently characterized by over-dispersion. In other words, the sample variance is often larger than the sample mean. Utilizing the Poisson model in such cases results in a smaller estimated variance than is exhibited in the actual data. Therefore, the Poisson model must be generalized to include a stochastic term that will allow the estimated variance to increase beyond that of the estimated sample mean. This is accomplished by introducing an error term, ε, by setting λ = exp(Xβ + ε). If a gamma distribution is assumed for ε, this results in a negative binomial distribution with mean λ and variance $\lambda + \alpha^{-1}\lambda^2$ (Kennedy, 2003).

For the study in question, a Poisson model was first estimated. Upon estimation of the Poisson model, it was determined that the dependent variable exhibited over-dispersion sufficient to warrant estimation of the negative binomial model. The variance of the BMP adoption count (1.7) is nearly 5 times that of the mean number of BMPs adopted (0.36). Thus, the same structure was then estimated via a negative binomial model. Estimation was performed utilizing the Generalized Linear Model (GLM) function in the open source statistical analysis program R (R, 2010). The results of the negative binomial model were compared to results from the estimation of an identical model via OLS. These two models were similar enough such that the estimation of a standard continuous spatial model was warranted, despite the incorrect assumption of continuity inherent in the spatial model.

2.3.2 Development of Spatial Models

The Poisson and negative binomial models were estimated without integrating spatial components into the analysis. Due to the complex nature of integrating spatial econometric methods into models for count data, such studies are largely nonexistent in the literature. Any available methods would necessitate Bayesian statistical methods. These methods are beyond the scope of this study.

However, a major goal of the analysis is to determine if the frequency of BMP adoption is spatially related across observations. Namely, the influence of observations on nearby observations is of interest. Clustering behavior, in turn, implies that there is a contagion or infection effect going on in BMP adoption. Due to an inability to integrate spatial econometric models with the negative binomial count model for reasons previously listed, an alternative spatial econometric approach was adopted. An identical farm-based model was estimated via ordinary least squares (OLS) under the (incorrect) assumption that the dependent variable is continuous. The similarity of the OLS and negative binomial results warranted the estimation of continuous spatial weights models. The spatial weights models were estimated with the knowledge that the assumption of a continuous dependent variable was incorrect. In this way, estimation of a count data model with a spatial component is avoided.

Spatial econometrics is representative of a broad category of models that explicitly account for the influence of location across observations. Inclusion of space is often necessitated for one of two reasons. Spatial heterogeneity results when parameters or functional forms differ across space. Such analysis requires identification of the source of the variation and the selection of an appropriate classification of data according to that variation. For instance, in an analysis of housing prices, functional forms may differ between low and high priced houses (LeSage, 1999). Spatial autocorrelation results from an interdependence across space between observations. In other words, a pattern exists between the location of observations and their values (Muller, 1995). Autocorrelation can result from measurement error or because space does, in fact, influence the values of observations. Spatial autocorrelation can result from measurement error if the variable of interest can vary at a different scale than the data is collected. On the other hand, space may truly be an important determinant of data values. For instance, if observations of similar values tend to cluster across space, this is indicative of neighbor effects. For the analysis at hand, such patterns may result from the diffusion of information due to existing social networks between farmers.

Three spatial models were run for the farm-level analysis, each utilized to test for different types of spatial dependence. A spatial errors model (SEM) tests for spatial dependence in the residuals while a spatial autoregressive, or spatial lag, model tests for spatial dependence in the dependent variable. A general spatial model, incorporating both a spatial lag and a spatial errors process, was also run. Confirmation of spatial dependence has a different interpretation depending on the model run. If the data are generated by a spatial errors process, then this implies that there are omitted spatially dependent variables that influence neighboring observations. On the other hand, if the data are generated by a spatial lag process, then this implies a contagion effect in the dependent variable. If values for the dependent variable are higher than average for an observation, then neighboring observations will also tend to have higher than average values for the dependent variable. A generalized spatial model is useful as it allows us to analyze how large the spatial lag is in the presence of spatial correlated errors.

Each model utilizes a spatial weights matrix, W, to test for spatial dependence. W is n x n, where n is the number of observations and can either be a contiguity or distance matrix. Entries in a contiguity matrix are given a value of one if the two observations are contiguous to one another whereas entries in a distance matrix are calculated according to the distance between two observations. For the study in question, a distance matrix was utilized. Typically, entries reflect inverse distance and rows are normalized. Inverse distances are utilized so that the distance matrix places higher emphasis on observations that are closer to one another. Given the size of the dataset at hand (41,492 farms), this task was computationally difficult even for software designed to handle large datasets. With the aid of Penn State's high powered computing center, a spatial weights matrix was calculated with normalized inverse distances between points.

Finally, a distance threshold was selected according to the estimated scale of the spatial dependence for the question at hand. The distance threshold can vary because different spatial processes can occur at varying scales. For example, a model testing for spatial dependence in house values in a city would use a very different distance threshold than a model testing for spatial dependence of an invasive species affecting an entire state. Recall that the main goal is determining if spatial dependence exists in the frequency of BMPs adopted due to neighborhood or infection effects. Such effects might result from existing social and community-based networks, and operate on a limited spatial scale. Though the scale of such networks certainly varies, a threshold of 10 miles was selected for this study because it was assumed that social networks operate at this scale. Any pair of observations further than 10 miles apart was given a value of zero in the spatial weights matrix. Many farms in the study area were spread out, including disconnected fields and tracts. For the ease of calculation, all distances were calculated between the centroids of farms.

With the distance matrix calculated, the spatial lag, spatial errors, and generalized spatial model were ready for estimation. Each of these models was estimated with the aid of the spatial econometrics toolbox for Matlab software created by James LeSage (2010; Mathworks, 2009). Furthermore, Lagrange multiplier (LM) and robust LM statistics were calculated for the spatial lag and spatial errors models. These statistics help in determining whether a spatial errors or spatial lag process best describe the data.

2.3.2.1 Spatial Lag Model

A spatial lag model incorporates y as an independent variable to capture spatial variation in y across data observations where W is the spatial weights matrix, ρ is the spatial parameter to be estimated, $X\beta$ is the standard matrix of explanatory variables with coefficients to be estimated, and ε is a disturbance term.

$$y = \rho Wy + X\beta + \varepsilon$$

W is incorporated with the dependent variable y such that Wy represents the average impact of neighboring observations on the observation in question. The model is estimated via maximum likelihood as a traditional least squares approach leads to biased coefficient estimates (LeSage, 1999).

2.3.2.2 Spatial Errors Model

A spatial errors model incorporates the spatial weights matrix with the residuals to measure the existence of spatially dependent omitted variables. The model and error term, μ, is structured as follows, where λ is the spatial parameter to be estimated, W is a spatial weights matrix, ε is a disturbance term, and $X\beta$ is the standard matrix of explanatory variables with coefficients to be estimated.

$$y = X\beta + \mu,$$

$$\mu = \lambda W\mu + \varepsilon$$

W is incorporated with the residuals such that $W\mu$ represents the average impact of neighboring observations on the error term of the observation in question. Once again, the model is estimated via maximum likelihood as a traditional least squares approach leads to biased coefficient estimates (LeSage, 1999).

2.3.2.3 General Spatial Model

The general spatial model incorporates both a spatial lag and spatial errors component. As a result, both ρ and λ are estimated. The model is structured as follows.

$$y = \rho Wy + X\beta + \mu$$

$$\mu = \lambda W\mu + \varepsilon$$

As above, ρ and λ are spatial parameters to be estimated, μ is the spatial errors structure, W is a spatial weights matrix, ε is a disturbance term, and $X\beta$ is the standard matrix of explanatory variables with coefficients to be estimated (LeSage, 1999).

2.3.3 Description of Variable Data and Data Management

Data were collected from a variety of governmental agencies. Since the data were spatial in nature, the data were collected primarily in the form of ArcGIS shapefiles. These layers were processed and managed utilizing ArcGIS 9.3.1 and all spatial variables were extracted with this program (ESRI, 2009). Information on the frequency of BMP adoption was obtained from the NRCS conservation contract data, obtained through the cooperation of the NRCS office in Harrisburg, Pennsylvania and a Freedom of Information Act request.

Due to the structure and sheer size of the dataset, it required significant management. Each point in the dataset represented the adoption of a BMP, with each point spatially referenced to a tract in one of the 17 counties in the study area. There were a total of 47,915 points, or adoptions. Several points were eliminated due to lack of spatial referencing or tract number. A total of 46,662 adoptions within 5,515 tracts in 17 counties remained.

There were a total of 109 different BMPs in all in the dataset as determined by NRCS. See the appendix, table 11, for a complete list of BMPs in the entire data set. In an effort to simplify the analysis and reduce the number of variables, 66 of the practices were eliminated due to either low frequencies of adoption or lack of a clear water quality focus. See the appendix, table 12, for a complete list of eliminated practices as well as the reason for elimination. Though 66 practices were eliminated, the remaining 43 practices included the vast majority of points (~93%). See the appendix, table 13, for a complete list of included practices.

The BMPs in the NRCS Conservation Contract data layer were organized into tracts. However, tracts were deemed an inappropriate unit of analysis as the many farmers owned multiple tracts. Additionally, the Conservation Contract layer contained no information on non-adopting farms. Without information from non-adopters, a truncated model would have to be estimated. The Farm Service Agency (FSA) Common Land Unit (CLU) layer enabled consolidation of tracts into farms and the identification of non-adopting farms. Data were obtained through contact with NRCS and an FOIA request. The CLU polygon layer was managed in ArcGIS 9.3.1, with each polygon representing a Common Land Unit. As defined by the FSA, a CLU is “the smallest unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner and a common producer association” (FSA, 2010). In turn, each CLU was tied to a farm. CLU boundaries were consolidated into farms.

There were a total of 41,527 farms in the 17 county study area. However, 35 farms were found to lie completely outside of the study area as a result of discrepancies between the county a farm resides in and the administrative county for the farm. Thus, these 35 farms were in the study area administratively, but not geographically. Since the analysis was tied geographically to the 17 counties in the study area, these farms were eliminated from the dataset. 41,492 farms remained. The farm boundaries enabled each BMP adoption point to be tied to a farm.

A certain amount of measurement error was expected. First, 655 points that did not fall within the new farm boundaries were eliminated from the dataset, leaving 42,698 points in total. Since these points represented a small percentage (~1.5%) of the total and were not concentrated in any one county, the elimination of these points was considered acceptable. Second, tract numbers in the BMP Conservation Contract layer did not match up with tract numbers in the farm polygon layer for 4,059 observations. In the interest of preserving as much data as possible, it was assumed that these points were correctly spatially referenced, and thus they were assigned to farms based on their location.

Having matched BMPs with farms, the next task was to determine which of the remaining 42,698 BMP adoptions should be counted as events for the analysis. The unique number of BMPs adopted is of interest. Within the 43 remaining BMPs there were many instances of multiple adoptions of the same practice on the same farm. These do not represent unique adoptions. Multiple adoptions of the same practice could represent first time failures that needed to be implemented again. These multiple adoptions were eliminated utilizing Microsoft Excel. Once accomplished, 14,956 unique adoptions spread across 41,492 farms remained. However, as mentioned, only 4,819 of these farms had adopted BMPs, with 36,673 farms adopting zero BMPs. The dependent variable is the unique count of BMP practices adopted on each farm.

Independent variables were extracted utilizing ArcGIS 9.3.1. They were chosen based on land-based characteristics thought to influence the adoption of BMPs. Variables included presence of streams, location in a priority watershed, soil characteristics, land use characteristics, and county.

Farm acreage was included in each model. Larger farms have more opportunities for BMP adoption as well as potentially more resources to invest in these practices. Thus, it is expected that an increase in the size of the farm should lead to an increase in the BMP count, all else equal.

Dummy variables were included to indicate both the presence of a stream and if that stream was impaired. Stream presence was based on whether a stream passed through any portion of the farm using stream data available from the U.S. Geological Survey National Hydrography Data (NHD) for 2010. Stream impairment data were obtained through the PA Department of Environmental Protection (DEP) list of non-attaining streams for Pennsylvania. This layer is downloadable from PASDA (Pennsylvania Spatial Data Access). Since the presence of a stream makes more BMPs applicable and increases the likelihood that pollutants will impair water quality, it was hypothesized that stream presence should increase BMP adoption. Likewise, if conservation efforts are targeted efficiently, the presence of an impaired stream should increase BMP adoption as well.

Two watershed dummy variables were included to indicate whether the watershed containing the farm had been designated as a medium or high priority watershed by the NRCS Chesapeake Bay Watershed Initiative (CBWI). Spatial data layers for medium and high priority watersheds were obtained through the NRCS office in Harrisburg, PA, with all watersheds designated at the HUC 12 scale (NRCS, 2010). Data for all HUC 12 watersheds in the study area was obtained through the NRCS Geospatial Data Gateway. For the purposes of this study, the spatial reference utilized to determine farm location was the centroid of the farm. Location within a medium or high priority watershed was hypothesized to increase the frequency of BMP adoption, with location within a high priority watershed yielding a larger increase.

Physical soil characteristics play a major role in erosion potential and non-point source pollution. Thus, such characteristics are likely to influence BMP adoption. Soil variables were extracted utilizing SSURGO soil data downloaded from the NRCS Soil Data Mart (NRCS Soil Data Mart, 2010). Clearly, soil characteristics will vary across farms. Soil characteristics were aggregated into a single number by calculating an area weighted average across all map units intersecting the farm in question.

Variables were included for soil land capability class, slope, and T factor. Land capability class is a way of categorizing soils based on their ability to retain their productivity over a long period of time (USDA NRCS "NHHD", 2010). Higher quality soils are less likely to need structural BMPs to prevent erosion, but it is important to note that these soils could still benefit from other types of BMPs like conservation tillage practices. Higher quality soils (soils with a lower capability class) were hypothesized to lead to fewer BMP adoptions. Since steeply sloped soils are at greater risk for erosion, it is thought that the greater the slope, the more BMPs will be adopted. The soil T factor, or loss tolerance factor, is an indicator of the "maximum amount of erosion at which the quality of a soil as a medium for plant growth can be maintained." T factor is measured in tons per acre (USDA NRCS "NHHD", 2010). Since a higher loss tolerance factor indicates a higher soil tolerance for erosion, it is hypothesized that higher T factors should result in a lower frequency of BMP adoption.

A dummy variable was included for each county, with a value of one being assigned to the respective county dummy variable if the centroid of the farm fell within that county. PA Department of Transportation county boundaries were obtained through PASDA. Lancaster County was omitted to avoid multicollinearity between the variables. Lancaster was chosen due to it being the county with the highest frequency of adoption of all counties. Including county dummy variables captures variation in the frequency of adoption due to administrative boundaries, such as the influence of county-based soil conservation districts. Differences might also reflect land characteristics such as the amount of farmland in each county.

Finally, a dummy variable was included to account for the primary activity of each farm in the study as either crop, livestock, or fruit/vegetable. As this information was not indicated in the conservation contract dataset (for adopting farms) or the CLU dataset (for non-adopting farms), alternative means of determining the primary land use were necessary. The National Agricultural Statistics Service (NASS) Cropland Data Layer is the most detailed account of acreage and land use. Due to the large number of agricultural product categories contained in the data, commodities were grouped into the three major land use categories above with the aid of Becker's report on the NASS layer (2007). Farms were assigned to one of these categories based on the dominant agricultural use for the farm. In the absence of this information from the farmers themselves, use of the NASS dataset is the best method available. According to the NASS data, some farms did not have acreage in any of the three farm land use categories. The NASS data layer includes other land uses such as woodlands or forested land, wetlands, and developed land. While having zero acreage in row crops, pastureland, or for growing fruits and vegetables can be partially attributed to error in the data set, it is also possible that many farms are composed of unfarmed land. Such farms were assigned a value of 0 for each of the three dummy variables.

2.4 Watershed-Level Analysis

A similar analysis was also carried out at the watershed scale. Changing the scale of the analysis allows the exploration of different relationships. For instance, the CBWI, a new NRCS program, places precedence on targeting medium and high priority watersheds, offering funding for “core conservation practices” that reduce sediment and nutrient loss from fields (USDA NRCS “Chesapeake”, 2010). Analyzing the frequency of BMP adoption across watersheds can tell us if such programs are effective in targeting priority watersheds. Since incentive payments are involved, a watershed model can give us an idea of how efficiently funds are being utilized to promote conservation. Ideally, funds are targeted to the watersheds that benefits most from conservation practice implementation.

Since only watersheds within the Chesapeake Bay watershed can receive CBWI designation as priority watersheds, the analysis was limited to HUC 12 watersheds falling completely within watersheds that drain into the Chesapeake. Several watersheds in Chester, Berks, and Lebanon Counties were eliminated as much of these counties lie in the Delaware River watershed which is not a part of the Chesapeake Bay Watershed. In all, there were 211 watersheds falling within the study area. Farms were assigned to watersheds based on farm centroid location.

2.4.1 Development of Count Models

Though the dependent variable for the watershed model remains the frequency of BMP adoption, the change in scale alters the nature of the count data. The watershed data contain fewer observations with a greater variance and fewer, though still some, zero observations. As a result, a negative binomial count model was the appropriate model. Despite there being fewer zero observations, this data still falls victim to the same pitfalls as the farm model insofar as estimation via OLS is inappropriate. The Poisson model was also deemed inappropriate as the dependent variable exhibits clear over-dispersion with a variance (~2127) more than 41 times its mean (~51). See figure 4 on the next page for the frequency distribution of the dependent variable.

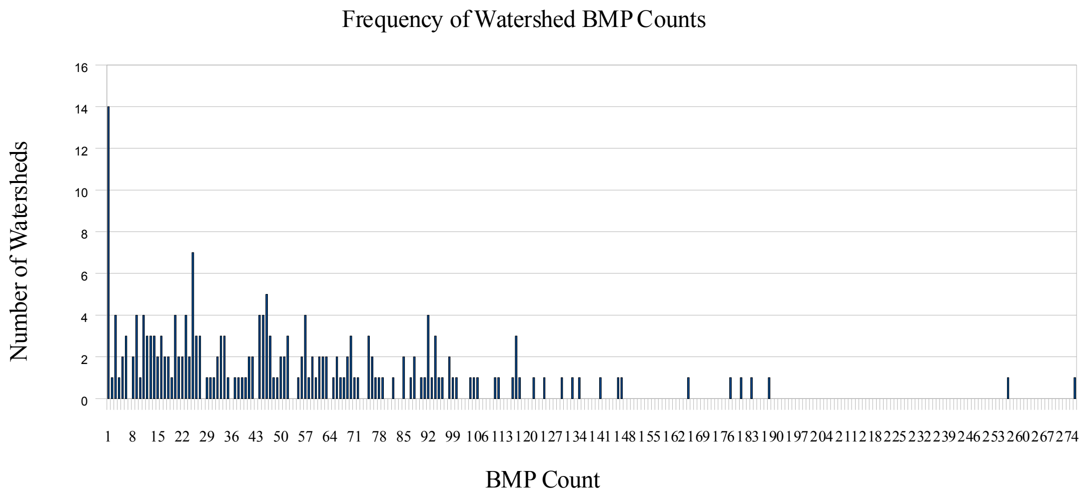

Figure 4: The frequency distribution of the number of watersheds with particular BMP counts

Similar to the farm-level analysis, variables included in the model were limited to land-based characteristics associated with the farms in question. These were the only data available for non-adopters of BMPs as they were not included in the conservation contract dataset obtained from NRCS. Variables were extracted for all watersheds with the aid of ArcGIS 9.3.1. The variables utilized for the watershed model are in table 2 on the next page.

Table 2: Watershed Model Variables	
Dependent Variable: Watershed BMP Count (HUC 12 Watersheds)	
Independent Variables	**Description**
Watershed Farm Acreage	Total farm acreage in the watershed
Medium Priority Watershed	CBWI designation as a medium priority watershed
High Priority Watershed	CBWI designation as a high priority watershed
Watershed Crop Acres	Cropland acreage in the watershed
Watershed Pasture Acres	Pastureland acreage in the watershed
Watershed Fruit/Veg Acres	Fruit/Vegetable crop acreage in the watershed
County dummy variables	County farm centroid is located in
Adams	
Berks	
Chester	
Cumberland	
Dauphin	
Franklin	
Huntingdon	
Juniata	
Lebanon	
Mifflin	
Northumberland	
Perry	
Schuylkill	
Snyder	
Union	
York	

Many of the variables in the watershed model are similar to those in the farm model. Watershed Farm Acreage accounts for varying opportunities for BMP adoption within watersheds. Including county dummies once again accounts for differing impacts of county-level governments and soil conservation districts on BMP adoption. Crop Acres, Pastureland Acres, and Fruit/Vegetable Acres variables were included to account for varying land uses within watersheds. The main variables of interest are Medium Priority Watershed and High Priority Watershed. If NRCS program funds are being used efficiently, priority watersheds should have a higher frequency of adoption.

Both Poisson and negative binomial models were estimated for the watershed model. A spatial model was not estimated as the spatial interactions of interest should not operate at the watershed scale. The spread of information due to social networks should only occur at the farm-level scale. The much smaller dataset, composed of 211 observations, allowed the estimation of the watershed models with Stata (StataCorp, 2009).

2.4.2 Watershed Data

Extraction of watershed variables was an easy task as the already managed and cleaned farm-level dataset simply had to be consolidated at the watershed scale. Farms were assigned to the appropriate watershed based on the location of their centroid. Once this was accomplished, data were analyzed to calculate farm and land use (crop, livestock/grazing, fruits/vegetables) acreages. The medium and high priority watershed variables were easily calculated utilizing the NRCS CBWI priority watersheds datasets. Finally, watersheds were assigned to counties based on their spatial centers. Data sources for these layers have already been cited in the description of the farm model variables (see section 2.3.3).

Chapter 3: Results from Model Estimation

3.1 Results from Farm-Level Regressions

The farm-based analysis involved six different regressions. Initial non-spatial models were estimated via OLS and Poisson count regression. Since the dependent variable exhibited over-dispersion, a negative binomial count model was also estimated. Spatial error, spatial lag, and general spatial models were also estimated. The full results for each of these models can be found in tables 3-8 in this chapter.

3.1.1 Poisson and Negative Binomial Count Models

Nearly every independent variable in the Poisson model is statistically significant at the 1% level (see table 3 at end of section). Only three of the county variables (Snyder, Union, and York) and soil T Factor are not significant. However, this is likely the result of over-dispersion in the model. Since the Poisson model forces the equality of the mean and variance of the number of occurrences, this can lead to incorrect statistical inference when over-dispersion exists (Kennedy, 2003). In cases where a Poisson model is estimated despite over-dispersion, coefficient estimates remain consistent, but variance estimates will be biased (Kennedy, 2003). Estimation results for the Poisson and negative binomial count models bear this out. The coefficient estimates for the two models are similar. However, standard error estimates are much smaller for the Poisson model, often by a factor of 2 or more. As a result, the number of significant variables, as well as the level of significance, decreased for the negative binomial model.

Since the negative binomial distribution more accurately represents the data, it is unnecessary to further discuss estimation results from the Poisson model. Estimation of the negative binomial count model was performed with R, an open source statistical analysis program (see table 4 at end of section). The likelihood ratio chi-square statistic is significant at the 1% level, indicating the overall significance of the model. When interpreting coefficients for the negative binomial model, a one unit increase in the independent variable leads to an increase in the log count by the amount of the coefficient.

As expected, the coefficient for farm acreage is positive and is significant at the 1% level. Thus, a one unit increase in farm acreage leads to a 0.00645 increase in the log count of BMPs adopted. Furthermore, the presence of a stream increases the log count of BMP adoption by 0.294631. Since the presence of a stream increases the number of applicable BMPs that can be adopted, this result is expected. Surprisingly, results indicate that designation as an impaired stream does not necessarily increase the log count of BMP adoption. Though the coefficient for presence of an impaired stream is positive, it is not statistically significant. The overall quality of streams and rivers within a watershed was hypothesized to influence farm BMP adoption, with location in a watershed designated by NRCS as a medium or high priority watershed serving as a metric for overall watershed health. As expected, coefficients for farms located in watersheds designated as medium or high priority are positive, but only that for high priority watersheds is significant.

Results for soil characteristic variables were mixed for the negative binomial model. All else equal, it was hypothesized that a lower area weighted average for land capability class (LCC) (higher quality soils) and a higher T Factor decreases log BMP count because farmers with higher quality (lower LCC) and more erosion resistant soils (higher T Factor) have less of an incentive to adopt BMPs. As expected, the coefficient for T Factor is negative, but the coefficient for land capability class is negative and significant. Furthermore, the coefficient for T Factor is not significant. Finally, it was also hypothesized that an increase in the area weighted average of soil slope increases the log count of BMP adoption. Surprisingly, the coefficient for slope is negative, though it is very small and not statistically significant.

Coefficients for farm land use categories are larger than other coefficients, positive, and statistically significant at the 1% level. Many of the farms in the study area did not fall into any of these categories and were thus assigned a value of 0 for each of these dummy variables. If it is assumed that these farms with no acreage in row crops, pastureland, or fruits and vegetable crops are unfarmed, then the results imply that actively farmed land greatly increases the likelihood of adopting BMPs. While not an important conclusion, it is interesting to note the relative size of the coefficients. The coefficient for farms that are primarily composed of fruit and vegetable crops (~2.24) is approximately twice that for farms focused primarily on row crops (~1.26) or livestock (~1.24). Fruit and vegetable farmers may be more likely to adopt BMPs, or these farmers may be targeted at greater levels by organizations promoting conservation practice adoption.

Estimation results for county dummy variables were much more mixed. Since a dummy for Lancaster County was excluded from the model, all other county dummy coefficients must be interpreted relative to Lancaster. Coefficients for Adams, Franklin, Perry, Snyder, and York counties were all statistically significant in the negative direction, implying that the log BMP count for each of these counties is less than that for Lancaster by the amount of the coefficient. Conversely, coefficients for Chester, Juniata, Lebanon, Mifflin, Northumberland, and Schuylkill counties were all statistically significant in the positive direction. These results may be due to less (more) active soil conservation district employees in these counties in addition to other omitted differences across counties including available farmland and soil quality.

Table 3: Farm Analysis Poisson Count Model Estimation Coefficients and Statistical Significance

N = 41,492
Dependent Variable = Farm BMP Count

Log-Likelihood = -40,431
Likelihood Ratio Test Chi-Square: 4688.1***

Variable	Coefficient	Standard Error	z-value	z-probability
Intercept	-2.976000	0.118800	-25.047	0.000000***
Acres	0.001156	0.000020	57.703	0.000000***
Stream	0.581900	0.020040	29.035	0.000000***
Impaired Stream	0.078150	0.025670	3.044	0.002340***
Medium Priority WS	0.152900	0.033630	4.546	0.000005***
High Priority WS	0.179100	0.030140	5.941	0.000000***
Land Capability Class	-0.182800	0.018740	-9.752	0.000000***
Slope	0.011580	0.002823	4.101	0.000041***
T Factor	0.016490	0.013970	1.181	0.237780
Crop Farm	1.612000	0.081680	19.738	0.000000***
Livestock	1.465000	0.085450	17.142	0.000000***
Fruits/Vegetables	2.463000	0.153800	16.015	0.000000***
Adams	-0.148800	0.050280	-2.959	0.003080***
Berks	0.223400	0.046160	4.840	0.000001***
Chester	0.590700	0.039090	15.109	0.000000***
Cumberland	0.125300	0.045200	2.772	0.005570***
Dauphin	-0.120300	0.054990	-2.188	0.028690**
Franklin	-0.079700	0.041800	-1.906	0.056590*
Huntingdon	0.363400	0.053380	6.808	0.000000***
Juniata	0.450100	0.046890	9.599	0.000000***
Lebanon	0.364800	0.041290	8.834	0.000000***
Mifflin	0.616900	0.051480	11.985	0.000000***
Northumberland	0.465000	0.046670	9.963	0.000000***
Perry	-0.190300	0.065250	-2.916	0.003540***
Schuylkill	0.356100	0.046880	7.595	0.000000***
Snyder	-0.034890	0.060140	-0.580	0.561840
Union	-0.084810	0.070420	-1.204	0.228470
York	-0.029190	0.037890	-0.770	0.441080

Significance: ***(.01), **(.05), *(.1)

Table 4: Farm Analysis Negative Binomial Count Model Estimation Coefficients and Statistical Significance				
N = 41,492 Dependent Variable = Farm BMP Count			Log-Likelihood = -23998.09 Likelihood Ratio Test Chi-Square: 1201.1***	
Variable	**Coefficient**	**Standard Error**	**z-value**	**z-probability**
Intercept	-2.776861	0.231673	-11.986	0.000000***
Acres	0.006450	0.000189	34.184	0.000000***
Stream	0.294631	0.046519	6.334	0.000000***
Impaired Stream	0.083877	0.068772	1.220	0.222598
Medium Priority WS	0.112065	0.082644	1.356	0.175100
High Priority WS	0.206476	0.075741	2.726	0.006409***
Land Capability Class	-0.110940	0.041825	-2.652	0.007990***
Slope	-0.003686	0.006506	-0.567	0.571019
T Factor	-0.014402	0.032851	-0.438	0.661093
Crop Farm	1.263594	0.111777	11.305	0.000000***
Livestock	1.236311	0.124831	9.904	0.000000***
Fruits/Vegetables	2.235471	0.428853	5.213	0.000000***
Adams	-0.363124	0.114735	-3.165	0.001551***
Berks	0.112197	0.109550	1.024	0.305761
Chester	0.426730	0.103027	4.142	0.000034***
Cumberland	-0.153795	0.105575	-1.457	0.145187
Dauphin	-0.202310	0.126091	-1.604	0.108610
Franklin	-0.473984	0.097266	-4.873	0.000001***
Huntingdon	0.138823	0.134965	1.029	0.303674
Juniata	0.215660	0.120086	1.796	0.072514*
Lebanon	0.223284	0.101848	2.192	0.028356**
Mifflin	0.379009	0.141647	2.676	0.007456***
Northumberland	0.399584	0.116269	3.437	0.000589***
Perry	-0.585003	0.145807	-4.012	0.000060***
Schuylkill	0.210154	0.116010	1.812	0.070062*
Snyder	-0.236998	0.135877	-1.744	0.081122*
Union	-0.127206	0.156506	-0.813	0.416342
York	-0.141207	0.085204	-1.657	0.097464*
Significance: ***(.01), **(.05), *(.1)				

3.1.2 Comparing Negative Binomial and OLS Results

In the absence of a model integrating a spatial component into a count model, a model identical to the negative binomial model was estimated via OLS. See table 5 at the end of the section for full results. Comparison of the two model estimations reveal similarities in both coefficients and statistical significance, despite OLS estimates of count data being biased, inefficient and inconsistent. These similarities warrant the estimation of continuous spatial weights models.

The signs of all independent variable coefficients are identical in each model except for the intercept term and soil slope. In the case of soil slope, the coefficient for the negative binomial regression (-0.003686) and the OLS regression (0.000131) are very close to zero and not statistically significant. Again with the exception of the soil slope, all coefficients are larger in the direction of their sign in the negative binomial count model as opposed to OLS coefficients. Thus, negative coefficient estimates are larger in the negative direction while positive coefficient estimates are larger in the positive direction for the negative binomial model. However, it is difficult to gain useful inferences when comparing the size of coefficients between count model estimation and OLS estimates. OLS coefficients imply a direct change in the dependent variable due to a one unit increase in the independent variable while count model estimates imply an increase in the log count due to a one unit increase in the independent variable.

Comparison of the statistical significance of coefficients between these two models yields more differences, but overall statistical significance is consistent between model estimates. Only one more variable is statistically significant in the OLS estimation

(19) than in the negative binomial estimation (20). Only soil slope, T Factor, and six of the county independent variable coefficients are not statistically significant at the 5% level, with the majority of coefficients significant at the 1% level while presence of an impaired stream, location in a medium priority watershed, slope, T Factor, and five county independent variable coefficients are insignificant in the negative binomial estimation. As in the negative binomial model, farm acres, the presence of a stream, and location in a high priority watershed are significant at the 1% level in the OLS estimation. However, both the presence of an impaired stream and location in a medium priority watershed are significant in the OLS estimation but insignificant in the negative binomial estimation. Estimation results are similar across soil characteristic independent variables. For both models, only land capability class is significant, with both estimates significant at the 1% level in the negative direction. Furthermore, all three land use variables are significant at the 1% level for both models. The largest differences in significance for the two models occur among the county location dummy variables. Cumberland, Dauphin, Huntingdon, and Union county variables are insignificant in both models. However, both Snyder and York are statistically significant in the negative binomial regression, albeit at the 10% level, while these variables are insignificant in the OLS estimation. On the other hand, Berks is significant in the OLS estimation, but is not significant in the negative binomial estimation.

The similarities in estimation results between the OLS and negative binomial estimations imply that results from the estimation of a conventional spatial weights model will be useful, despite the incorrect assumption of continuity in the dependent variable.

Since the results of the negative binomial estimation are comparable to OLS estimation, by extension estimation results from a spatial weights model can be expected to imitate those from a more appropriate count model incorporating spatial weights. The estimation of these spatial models and their usefulness for determining spatial dependence in both the dependent variable and the error term is commonplace (LeSage, 1999).

Table 5: Farm Analysis Ordinary Least Squares Estimation Coefficients and Statistical Significance			
N = 41,492 Dependent Variable = Farm BMP Count		R-squared: .0407 Rbar-squared: .0400 Sigma squared: 1.6339	
Variable	**Coefficient**	**t-statistic**	**t-probability**
Intercept	0.059707	0.863782	0.387712
Acres	0.002200	32.930549	0.000000***
Stream	0.098935	6.719726	0.000000***
Impaired Stream	0.050998	2.250029	0.024452**
Medium Priority WS	0.073125	2.760091	0.005781***
High Priority WS	0.083249	3.405597	0.000661***
Land Capability Class	-0.049899	-3.920377	0.000089***
Slope	0.000131	0.065538	0.947746
T Factor	-0.007057	-0.685337	0.493135
Crop Farm	0.179575	6.565089	0.000000***
Livestock	0.168487	5.187492	0.000000***
Fruits/Vegetables	0.532064	3.664284	0.000248***
Adams	-0.086800	-2.419857	0.015531**
Berks	0.071963	2.058812	0.039518**
Chester	0.219549	6.528828	0.000000***
Cumberland	-0.006196	-0.185849	0.852564
Dauphin	-0.052981	-1.330981	0.183203
Franklin	-0.093071	-3.046530	0.002316***
Huntingdon	0.032811	0.745792	0.455797
Juniata	0.124320	3.209052	0.001333***
Lebanon	0.105850	3.228406	0.001246***
Mifflin	0.205368	4.367675	0.000013***
Northumberland	0.144667	3.839366	0.000124***
Perry	-0.126502	-2.836713	0.004560***
Schuylkill	0.109032	2.930271	0.003389***
Snyder	-0.036036	-0.852127	0.394149
Union	-0.064231	-1.292080	0.196337
York	-0.026342	-0.982711	0.325756
Significance: ***(.01), **(.05), *(.1)			

3.1.3 Spatial Model Results

Three spatial weights models were estimated, each designed to test for different types of spatial dependence. The first, a spatial errors model (SEM), incorporates a spatial weights matrix into the error term of the model while the second, a spatial lag structure, investigates spatial dependence by including a spatially weighted dependent variable along with the other independent variables in estimation. The third is a generalized model incorporating both a spatial lag and a spatial errors structure. In each case, the spatial weight was a sparse distance matrix. Values in the matrix were normalized inverse distances between each farm, with a threshold of 10 miles between farms. Spatial error models, when structured correctly, estimate the average influence of neighboring farms on the error term of the farm in question (LeSage, 1999). Spatial dependence in the residuals, then, implies that the model omits variables that exhibit spatial dependence. Similarly, a spatial lag model is designed to test the average influence of neighboring observations on the value of y, or BMP count. Spatial lag estimation results are of more policy relevance to the study at hand, as spatial dependence in the number of BMPs adopted by farmers implies that BMP adoption may exhibit attributes of an epidemic or infestation. These, in turn, can be caused as knowledge of BMPs spreads through neighboring farmers talking and through other socially based networks.

Results from the spatial errors model can be found in table 6 at the end of the section. Though the r bar squared is relatively low at 0.0536, this is not necessarily surprising due to the large number of zeroes in the dataset and the incorrect assumption of continuity of the dependent variable. Excluding county variables, the set of significant independent variables in the SEM model is identical to that of the negative binomial model. All significant variables are significant in the expected direction.

Both farm acreage and the presence of a stream are statistically significant at the 1% level in the positive direction. The presence of an impaired stream and location in a medium priority watershed remain insignificant, though both coefficients are positive as expected. However, as in the negative binomial model, designation as a high priority watershed is statistically significant in the positive direction at the 10% level. As for soil variables, land capability class is the lone significant variable, but once again in the unexpected direction. Once again, slope has an unexpectedly negative coefficient, though it is highly insignificant. Variables for row crop based farms, livestock farms, and fruit and vegetable farmers are significant at the 1% level in the positive direction. The coefficient for fruit and vegetable based farms is more than three times that of the other two, indicating a stronger positive relationship between fruit and vegetable farmers and BMP adoption. Only five of the county based variables are significant: Chester, Dauphin, Franklin, Perry, and York.

The variable of interest in determining spatial dependence in the residuals is λ. Recall that in the SEM model the error term, μ, is structured such that $\mu = \lambda W\mu + \varepsilon$. As reported in table 6, λ is highly statistically significant beyond the 1% level with a large coefficient of 0.912. Strong spatial dependence in the error terms of this model implies that there are omitted variables that exhibit spatial dependence. There are a number of variables that were not available for inclusion in this study due to a lack of data that serve as potential candidates. Socioeconomic data such as farmer income or participation in community organizations are common variables included in other studies that were not available for this study. These variables could exhibit spatial dependence. An LM test affirms the evidence that spatial correlation exists in the residuals, with an LM statistic (943.1752) that is significant well beyond the 1% level.

Results from the spatial lag model can be found in table 7 at the end of the section. An inspection of estimation results shows that outside of the county dummy variables, coefficients between the SEM and spatial lag models are very similar in both size and significance, as they were between the SEM and negative binomial regressions. As in the SEM model, farm acreage, presence of a stream, location in a high priority watershed, soil land capability class, and all farm land use variables are significant. Only land capability class is not significant in the expected direction. Presence of an impaired stream, location in a medium priority watershed, soil slope and soil T Factor remain insignificant. However, as mentioned, the county dummy variable coefficients and their significance vary widely between the SEM and spatial lag models. Seven county dummy variables are significant: Berks, Chester, Franklin, Huntingdon, Lebanon, Perry, and Schuylkill. Chester, Franklin, and Perry county dummies are significant in both spatial models, with Chester significant in the positive direction and Franklin and Perry significant in the negative direction. In addition to the significance of county coefficients varying between the spatial models, the signs of these coefficients vary as well. The variable of interest for spatial dependence in the dependent variable, ρ, is significant beyond the 1 percent level, with a coefficient of 0.846. An LM test affirms the existence of spatial correlation in the dependent variable with an LM statistic (777.4605) that is significant beyond the 1% level.

Only the county level dummy variables vary significantly based on the type of spatial dependence being tested. Additionally, the number of significant county dummy variables decreased upon inclusion of a spatial element. Eleven of the county dummy variables were significant in the negative binomial regression while 10 were significant in the OLS regression. Only 5 and 7 were significant in the SEM and spatial lag regressions, respectively. Without a spatial element explicitly incorporated into the model, the county dummy variables may have been capturing some of the spatial dependence that existed in BMP counts, albeit at a larger scale. Thus it makes sense that inclusion of a spatial weights matrix results in fewer significant county dummy variables. Recall that the spatial weight matrix in the SEM and spatial lag model defines neighbors as those farms located within 10 miles of each other, thus capturing spatial dependence at a small scale. Spatial dependence may exist at a larger scale (captured by the county dummy variables) and at a small scale (captured by the spatial weights matrix).

The spatial dependence coefficients were significant in both the SEM and spatial lag models. LM tests for spatial dependence affirmed the presence of spatial correlation in both models. However, it is not necessarily the case that spatial dependence exists in both the residuals and the dependent variable. If in reality spatial dependence exists in the residuals but a spatial lag model is run, it is likely that the results will indicate the presence of spatial dependence in the dependent variable. Likewise, if spatial dependence exists in the dependent variable but a SEM model is run, it is likely that results will indicate the presence of spatial dependence in the residuals. However, there is no straightforward way to test the true type of spatial dependence generated by the data. Robust LM tests can aid in discerning which spatial model does a better job of describing the data. They do so by testing for one type of spatial dependence when the other type of spatial dependence is also present. Therefore, a spatial lag robust LM statistic tests for spatial dependence in the dependent variable with the presence of spatial dependence in the residuals and vice versa.

Robust LM tests indicate that both types of spatial dependence exist in the farm BMP count data. The robust LM statistic for the SEM model remains quite large at 170.2307. While still significant, the robust LM statistic for the spatial lag model is much smaller at 4.516. The results seem to imply that a spatial errors structure more appropriately describes the data. However, with the knowledge that there are inevitably key omitted variables, it is not surprising that the robust LM statistic for the SEM model remains large. The focal point, then, is that even in the presence of known omitted variables, a spatial lag process still exists. This implies that there is a contagion effect with BMP adoption across farms in the study area.

While the robust LM statistic tell us that a spatial lag is present, it does not reflect magnitude. A general spatial model allows us to see how large the spatial lag is while spatially correlated errors are also present because the general spatial model includes both spatial structures. Results for this model can be found in table 8 at the end of the section. Coefficient size and significance for the general model are relatively similar to the other spatial models outside of the county variables. There are a few differences, however. The presence of an impaired stream takes on an unexpectedly negative coefficient in the general model, but it is highly insignificant as it was in the other spatial models. Location in a high priority watershed is not significant in the general model as it was in the other spatial models, but it is positive. Finally, T Factor is significant in the negative direction, while it was insignificant in the other spatial models. Acres, the presence of a stream, land capability class, and the land use variables are all significant as they were in the other spatial models. Additionally, county variable coefficients and their significance vary quite a bit in the general model as compared to the other spatial models. County variables likely capture some spatial dependence, and thus their parameter estimates vary when the spatial structure of analysis is altered.

The parameters of interest are the spatial weights parameters, λ and ρ. As before, ρ is the spatial lag parameter and λ is the spatially correlated errors parameter. As mentioned previously, the general model allows us to see how large the spatial lag component is while spatial errors are present. As expected, both λ and ρ are highly significant. The coefficient for ρ is ~1.49 while that for λ is ~0.31. Thus, despite the presence of spatial errors, the results indicate a large spatial lag in the dependent variable. Contagion plays a significant role in the adoption of BMPs, a result that is discussed in more depth in the chapter 4.

Table 6: Farm Analysis Spatial Error Model (SEM) Estimation Coefficients			
N = 41,492 Dependent Variable = Farm BMP Count R-squared: .0542 Rbar-squared: .0536		Sigma squared: 1.6097 Log-Likelihood = -54435.531 LM test statistic: 943.1752*** Robust LM test statistic: 170.2307***	
Variable	**Coefficient**	**Asymptotic t-stat**	**z-probability**
Intercept	0.239029	1.978294	0.047896**
Acres	0.002218	33.198564	0.000000***
Stream	0.108472	7.153729	0.000000***
Impaired Stream	0.015342	0.602284	0.546985
Medium Priority WS	0.061920	1.478465	0.139283
High Priority WS	0.074437	1.918361	0.055065*
Land Capability Class	-0.062097	-4.662529	0.000003***
Slope	-0.001352	-0.632584	0.527005
T Factor	-0.020879	-1.627715	0.103585
Crop Farm	0.154533	5.661619	0.000000***
Livestock	0.157989	4.885747	0.000001***
Fruits/Vegetables	0.549291	3.684027	0.000230***
Adams	-0.132009	-1.086711	0.277164
Berks	0.003841	0.044893	0.964193
Chester	0.581036	7.009752	0.000000***
Cumberland	-0.101112	-0.808048	0.419063
Dauphin	-0.218809	-2.290443	0.021996**
Franklin	-0.294506	-2.003108	0.045166**
Huntingdon	-0.255419	-1.482492	0.138209
Juniata	-0.147169	-1.078391	0.280859
Lebanon	0.095919	1.139556	0.254471
Mifflin	-0.074533	-0.438599	0.660952
Northumberland	-0.058143	-0.485558	0.627281
Perry	-0.394786	-3.086993	0.002022***
Schuylkill	0.088164	0.784211	0.432916
Snyder	-0.192270	-1.444128	0.148703
Union	-0.126753	-0.872758	0.382795
York	-0.189122	-2.162027	0.030616**
Lambda	0.912000	49.484339	0.000000***
Significance: ***(.01), **(.05), *(.1)			

Table 7: Farm Analysis Spatial Lag Model Estimation Coefficients and Statistical Significance

N = 41,492 Dependent Variable = Farm BMP Count R-squared: .0308 Rbar-squared: .0301		Sigma squared: 1.6134 Log-Likelihood = -54469.602 LM test statistic: 777.4605*** Robust LM test statistic: 4.516**	
Variable	**Coefficient**	**Asymptotic t-stat**	**z-probability**
Intercept	-0.138354	-2.004018	0.045068**
Acres	0.002186	32.927125	0.000000***
Stream	0.103140	7.049191	0.000000***
Impaired Stream	0.015013	0.665522	0.505716
Medium Priority WS	0.041811	1.586727	0.112574
High Priority WS	0.045484	1.869680	0.061528*
Land Capability Class	-0.053021	-4.191810	0.000028***
Slope	-0.000654	-0.329631	0.741679
T Factor	-0.015337	-1.498372	0.134037
Crop Farm	0.167347	6.155903	0.000000***
Livestock	0.165969	5.142214	0.000000***
Fruits/Vegetables	0.518085	3.590516	0.000330***
Adams	-0.048976	-1.373105	0.169720
Berks	0.061030	1.757028	0.078913*
Chester	0.113701	3.381782	0.000720***
Cumberland	0.015885	0.479401	0.631654
Dauphin	-0.064589	-1.632820	0.102507
Franklin	-0.078037	-2.570234	0.010163**
Huntingdon	-0.080892	-1.842642	0.065381*
Juniata	0.046086	1.194138	0.232424
Lebanon	0.068799	2.109969	0.034861**
Mifflin	0.027521	0.583821	0.559341
Northumberland	0.044175	1.174632	0.240142
Perry	-0.106610	-2.405518	0.016150**
Schuylkill	0.067899	1.834983	0.066508*
Snyder	-0.018550	-0.441384	0.658935
Union	-0.029331	-0.593581	0.552792
York	0.006655	0.249608	0.802891
Rho	0.845975	28.499901	0.000000***
Significance: ***(.01), **(.05), *(.1)			

Table 8: Farm Analysis General Spatial Model Estimation Coefficients and Statistical Significance			
N = 41,492 Dependent Variable = Farm BMP Count Sigma squared: 1.6079		R-squared: .0553 Rbar-squared: .0547 Log-Likelihood = -54442.66	
Variable	**Coefficient**	**Asymptotic t-stat**	**z-probability**
Intercept	-0.304744	-3.955283	0.000076***
Acres	0.002188	32.891814	0.000000***
Stream	0.106340	7.182010	0.000000***
Impaired Stream	-0.004503	-0.190126	0.849210
Medium Priority WS	0.035718	1.174970	0.240007
High Priority WS	0.031044	1.102170	0.270388
Land Capability Class	-0.057297	-4.447535	0.000009***
Slope	-0.001204	-0.590979	0.554535
T Factor	-0.021944	-1.983100	0.047356**
Crop Farm	0.154929	5.692659	0.000000***
Livestock	0.162504	5.036163	0.000000***
Fruits/Vegetables	0.520421	3.566329	0.000362***
Adams	-0.012410	-0.271623	0.785912
Berks	0.060674	1.442329	0.149210
Chester	0.083040	1.863345	0.062414*
Cumberland	0.042382	0.980875	0.326654
Dauphin	-0.072162	-1.483351	0.137981
Franklin	-0.066480	-1.634198	0.102217
Huntingdon	-0.157052	-2.736457	0.006210***
Juniata	-0.002324	-0.047123	0.962415
Lebanon	0.058384	1.402587	0.160740
Mifflin	-0.082585	-1.314386	0.188716
Northumberland	-0.018803	-0.395806	0.692248
Perry	-0.105141	-1.927414	0.053928*
Schuylkill	0.058391	1.234682	0.216949
Snyder	-0.005984	-0.115544	0.908014
Union	-0.002795	-0.045747	0.963512
York	0.028892	0.836309	0.402981
Rho	1.493055	20.063051	0.000000***
Lambda	0.307000	5.587990	0.000000***
Significance: ***(.01), **(.05), *(.1)			

3.2 Results from Watershed-Level Regressions

Data for the watershed scale regressions included all watersheds within the 17 county study area contained within the Chesapeake Bay Watershed. These watersheds were selected because of their inclusion in the CBWI (see section 1.3), an NRCS program promoting conservation practice adoption and identifying medium and high priority watersheds. The watershed data differ significantly from the farm-level data in that there are very few zero observations. In other words, nearly every watershed of the 211 included in the analysis had at least one BMP adopting farm. Fourteen of the 211 watersheds included had a BMP count of 0. Having a large percentage of zero observations was inevitable for the farm-level analysis since inclusion of information on non-adopters was necessary to avoid a truncated data set and there were many non-adopting farms. However, having a large percentage of zero observations can also skew results. Thus, since the watershed-level data does not suffer from this flaw, the watershed-level analysis potentially provides a better picture of the influence of variables such as the impact of designation as a medium or high priority watershed on the number of BMPs adopted.

Results from the Poisson estimation can be found in table 9 at the end of the section. As with the farm-level analysis, nearly all variables are significant at the 1% level. Indeed, only the dummy variable for Mifflin County is not significant. However, this is likely because of over-dispersion in the data, which leads to biased standard error estimates. The Poisson and negative binomial estimation results reflect this, with the Poisson model having smaller standard error estimates for all coefficients. Over-dispersion is indicated by a dependent variable with a mean of ~51.5 and a variance of ~2126.9. A goodness of fit chi-square statistic presents more evidence for the existence of over-dispersion. The null hypothesis that the Poisson model is a good fit for the data is rejected by the chi-square statistic of 2572.062.

Results from the negative binomial estimation can be found in table 10 at the end of the section. The coefficient for farm acreage in the watershed is significant in the positive direction. Since watersheds with more farm acreage have more land available for BMP adoption, this result is expected. Designation as a medium or high priority watershed is also significant in the positive direction at the 1% level. Interestingly enough, there appears to be little distinction between medium and high priority watersheds as designation as a watershed of either type has a nearly identical impact on the log BMP count in the watershed. Designation as a medium priority watershed leads to a ~0.857 increase in log BMP count while designation as a high priority watershed leads to a ~0.845 increase in log BMP count.

Acreage in row crops and pastureland are both positive and statistically significant, though pastureland is only significant at the 10% level. Acreage in fruit or vegetable crops, though positive, is not statistically significant. Recall that farms that were primarily composed of fruit and vegetable crops had the largest impact on BMP count at the farm-level. Fruit and vegetable acreage may not be significant in the watershed scale analysis because its acreage is too small to lead to significant increases in the BMP count at this larger scale. Indeed, according to the NASS data used to estimate acreages, total crop acreage is 707,231.448, pastureland acreage is 70,543.518, and fruit and vegetable crop acreage is 3,699.480.

Six county dummy variables are significant, all in the negative direction: Adams, Cumberland, Dauphin, Franklin, Perry, and York. Of the insignificant variables, only dummies for Chester and Northumberland counties are positive. Since Lancaster County was the eliminated dummy variable, this implies that location in a Lancaster County watershed tends to lead to increases in log BMP Count. Lancaster County may be a focal point for conservation organizations. These differences may also result from more available farmland in Lancaster County or better soil quality.

Table 9: Watershed Analysis Poisson Count Model Estimation Coefficients and Statistical Significance

N = 211
Dependent Variable = Watershed BMP Count
Pseudo R-squared = .6052
Log-Likelihood = -1824.0934
Likelihood Ratio Test Chi-Square: 5591.89***
Chi-Square Goodness-of-fit statistic: 2572.062***

Variable	**Coefficient**	**Standard Error**	**z-value**	**z-probability**
Intercept	2.6050330	0.0642812	40.530	0.000***
Watershed Farm Acreage	0.0000499	0.0000034	14.590	0.000***
Medium Priority Watershed	0.4712728	0.0532571	8.850	0.000***
High Priority Watershed	0.5689035	0.0558421	10.190	0.000***
Watershed Crop Acres	0.0001042	0.0000077	13.450	0.000***
Watershed Pasture Acres	0.0001274	0.0000393	3.240	0.001***
Watershed Fruit/Veg Acres	0.0005154	0.0001302	3.960	0.000***
Adams	-0.7572707	0.0670459	-11.290	0.000***
Berks	-0.3120677	0.0967609	-3.230	0.001***
Chester	0.1876655	0.0598926	3.130	0.002***
Cumberland	-0.5219549	0.0564763	-9.240	0.000***
Dauphin	-0.2809533	0.0551371	-5.100	0.000***
Franklin	-0.7878739	0.0515319	-15.290	0.000***
Huntingdon	-0.2709395	0.0601251	-4.510	0.000***
Juniata	-0.1087798	0.0538638	-2.020	0.043**
Lebanon	-0.1755947	0.0497289	-3.530	0.000***
Mifflin	-0.0483592	0.0556843	-0.870	0.385
Northumberland	0.2379249	0.0682619	3.490	0.000***
Perry	-0.7852232	0.0663315	-11.840	0.000***
Schuylkill	0.2771098	0.0563388	4.920	0.000***
Snyder	-0.3055108	0.0638204	-4.790	0.000***
Union	-0.5024818	0.0836078	-6.010	0.000***
York	-0.1738253	0.0405103	-4.290	0.000***

Significance: ***(.01), **(.05), *(.1)

Table 10: Watershed Analysis Negative Binomial Count Model Estimation Coefficients and Statistical Significance				
N = 211 Dependent Variable = Watershed BMP Count Pseudo R-squared = .0998 Log-Likelihood = -940.30577 Likelihood Ratio Test Chi-Square: 208.59***				
Variable	**Coefficient**	**Standard Error**	**z-value**	**z-probability**
Intercept	2.0921610	0.2539295	8.240	0.000***
Watershed Farm Acreage	0.0000564	0.0000204	2.770	0.006***
Medium Priority Watershed	0.8568550	0.1951579	4.390	0.000***
High Priority Watershed	0.8447520	0.2065331	4.090	0.000***
Watershed Crop Acres	0.0001304	0.0000463	2.820	0.005***
Watershed Pasture Acres	0.0003818	0.0002273	1.680	0.093*
Watershed Fruit/Veg Acres	0.0005928	0.0005240	1.130	0.258
Adams	-0.9676874	0.2776965	-3.480	0.000***
Berks	-0.1422684	0.4550785	-0.310	0.755
Chester	0.4654785	0.3718478	1.250	0.211
Cumberland	-0.7320991	0.2469253	-2.960	0.003***
Dauphin	-0.4127229	0.2349691	-1.760	0.079*
Franklin	-0.7427009	0.2319829	-3.200	0.001***
Huntingdon	-0.0610897	0.2599047	-0.240	0.814
Juniata	-0.1368352	0.2640013	-0.520	0.604
Lebanon	-0.0520347	0.2663158	-0.200	0.845
Mifflin	-0.1801752	0.2714498	-0.660	0.507
Northumberland	0.2793979	0.3398199	0.820	0.411
Perry	-0.9983611	0.2425062	-4.120	0.000***
Schuylkill	-0.1587422	0.2942751	-0.540	0.590
Snyder	-0.4350498	0.2868525	-1.520	0.129
Union	-0.4988310	0.3488327	-1.430	0.153
York	-0.3489104	0.1854263	-1.880	0.060*
Significance: ***(.01), **(.05), *(.1)				

Chapter 4: Summary and Conclusions

Over the past several decades there has been growing concern over the water quality of our nations' streams, rivers, and estuaries. The Chesapeake Bay, the largest estuary in the United States, has received much of this attention. The Chesapeake and the watersheds leading into it provide vital and complex ecosystems that are home to an abundance of flora and fauna. At the same time, watersheds are placed under ever-increasing stress due to population increases and industrial and agricultural activities. Agriculture is a major contributor of degradation to our waterways, particularly in concentrations of nitrogen, phosphorous, and sediment. As a result, any attempt to improve the quality of these waterways must include efforts to reduce runoff and erosion in the agricultural sector. There have been increasing efforts by governmental and non-governmental organizations alike to promote the implementation of conservation practices and BMPs on farms. Services include information on BMPs, technical assistance, subsidies, and cost-sharing.

The study at hand analyzed the implementation of BMPs in 17 counties in Southeastern Pennsylvania. Counties were chosen based on their location within the Chesapeake Bay Watershed, though portions of several of the eastern-most counties do not fall within this watershed (Berks, Chester, Lancaster, Lebanon, and Schuylkill). The literature includes many studies analyzing the determinants of BMP adoption decisions. The study at hand differs from these studies in a number of ways. Most studies in the literature analyze BMP adoption as a yes or no decision, while this study analyzes the scale of BMP adoption by employing count models to analyze the determinants of the number of BMPs adopted. Though adoption decisions are generally made at the farm-level, it is also useful to view BMP adoption patterns at larger scales. Since BMP adoption aims to improve water quality, small watersheds are a useful scale to analyze adoption patterns. Thus, this study included count model regressions for watersheds at the HUC-12 scale, using the count of BMPs as the dependent variable. Such regressions can yield insight into how conservation efforts have been targeted historically and what improvements can be made in future efforts to promote BMP adoption. Finally, this study explicitly analyzes the influences of spatial processes on BMP adoption. Though a few studies implicitly account for the role of space in adoption decisions, this study does so through spatial lag and spatial errors modeling. These results reveal information on whether contagion may be a factor in BMP adoption and can inform the targeting and efficiency of future conservation practice policies.

The primary limiting factor was data availability. There was no socioeconomic or farmer information available for farmers within the study area. Thus, variables such as income, farmer perceptions of conservation practices and water quality, or level of interaction with governmental organizations promoting BMP adoption were unavailable. Information on non-adopting farmers was even more limited, with only farm location and size available. Thus, included variables were limited to location based variables such as soil characteristics or the presence of a stream. Another limiting factor was the lack of a model integrating a spatial weights matrix with count models. Such models are basically nonexistent in the literature and require methodologies beyond the scope of this study. Thus, spatial models were estimated with the incorrect assumption that the dependent variable was continuous, though OLS and count model results were first compared to ensure that estimation results were similar enough to justify this assumption. Within the farm analysis, there were a large majority of zero observations. There was little that could be done to rectify this problem aside from keeping this shortcoming in mind. Finally, spatial models did not include a temporal element. Practices in the study had been adopted between 2005 and 2010. If contagion effects are indeed occurring, it would be interesting to analyze how BMP adoptions spread over time in future studies.

Limitations aside, the study at hand does provide many useful insights. Noteworthy is the fact that 36,673 farms in the study area, or approximately 88.4%, have not adopted any conservation practices through NRCS programs. However, conservation efforts could have been made through alternative outlets. Furthermore, this study covered a limited number of years. Many of these farms may have adopted in years not available for this study. However, with such a large percentage of non-adopters it is likely that there are opportunities for expansion of NRCS programming in the study area, most of which lies in the high priority Chesapeake Bay Watershed.

Farm acreage was highly significant in all models, an expected result since larger farms likely have more opportunities for BMP adoption. However, farmers with more land may also have more financial capital at their disposal to invest in conservation expenditures. Furthermore, they may have more labor available, leaving the farmer more time to learn about applicable BMPs and work with government agencies. Perhaps there are other characteristics unique to large farmers such as level of risk aversion or attitudes towards conservation practices that lead to increased BMP adoption. Future studies could discern between these effects by utilizing BMP count per acre as the dependent variable, thus accounting for the impact of larger farms having more land available for BMP adoption. Other potential characteristics of larger farms that may lead to increased BMP adoption, such as farm income or amount of hired labor, could then be included as independent variables.

The farm-level analysis carries implications for effective targeting based on land use. Each of the regressions found that farms that were primarily composed of fruit and vegetable crops lead to the largest increases in BMP count. Such farmers may be more prone to seek NRCS assistance in implementing conservation practices, or conservation organizations may have focused their efforts on such farmers. If fruit and vegetable farmers are more likely to seek out NRCS assistance, they will likely continue to do so.

County dummy variable results were mixed, as expected. In general, results from county dummies capture differences across counties in soil conservation and water quality efforts. Variations across county dummy variables also capture differences across counties in available farm land as well as the relative quality of that farmland. The number of counties was too limited to allow for an explicit analysis of BMP adoption at this scale.

Soil variables were insignificant across all models. Soil land capability class was significant in all models, but in the opposite direction as hypothesized. A positive sign was hypothesized for the coefficient for land capability class, as farms with higher soil quality (lower land capability class) have less incentive to adopt. However, it was negative in all estimated models. Farmers with higher quality soils may be more vested in maintaining this soil quality, and thus may be more likely to adopt BMPs.

Stream results imply that NRCS could improve their efficiency amongst farms already adopting BMPs. With a limited amount of funding for conservation programs, it remains vital that these limited resources are utilized such that the greatest benefits are achieved for water quality. Funds should be targeted to the highest priority areas. More BMPs become applicable with the presence of a stream on a farm. Furthermore, the presence of an impaired stream implies a greater need for conservation practices. In the study at hand, the presence of a stream variable captures the effect of there being more applicable BMPs, while the impaired status variable captures targeting in higher need streams. Both are expected to be positive and significant. However, results from this study showed that while the presence of a stream regardless of status implied a higher BMP count, the presence of an impaired stream did not. Having a stream running through a farm presents clear opportunities for conservation practice adoption, but efficiently utilized funds could also place greater priority on approving applications and implementing practices near impaired streams.

The CBWI targets impaired waters at a larger scale by designating medium and high priority watersheds and placing emphasis on applications coming from these watersheds. However, farm-based results imply that farms within medium priority watersheds are not targeted, as the coefficient for this variable is insignificant in the negative binomial and spatial regressions, though presence in a high priority watershed is significant in all regressions. The coefficient for medium priority watersheds do approach significance in all regressions, with all estimated probabilities below 20%. This result conflicts with the watershed analysis, as both watershed variables are significant. However, the nearly identical coefficients for medium and high priority watershed dummies imply that medium and high priority watersheds are targeted equally. Thus, the farm scale analysis implies a failure to target medium priority watersheds, while the watershed scale analysis implies a failure to prioritize high priority watersheds over medium priority watersheds. Clearly, analysis at different scales can lead to varied results. However, the important point is that both results imply that there are potential improvements in the efficiency for the targeting of NRCS programs.

A major objective of this analysis was to examine whether the adoption of BMPs exhibited spatial dependence. Results from the estimation of spatial models indicate the presence of both a spatial lag and spatially correlated residuals. Robust LM tests confirm the presence of both, and show that a spatial lag exists even in the presence of spatially correlated errors. The presence of spatially correlated errors is not particularly surprising as there were many potentially spatially correlated omitted variables. The most obvious among these are farm income and other land use characteristics. Results from a general spatial model indicate that the spatial lag effect is quite large. The spatial lag parameter is also quite a bit larger in the general spatial model (~1.49) as compared to the spatial lag model (~0.85). Since both a spatial errors and a spatial lag structure exist for the data, results from the general spatial model are probably more accurate.

The existence of a spatial lag implies that there is a contagion effect in BMP adoption. Considering the relative paucity of studies in the BMP adoption literature including spatial elements, this result is very important. Recall that the structure of the spatial weights matrix included only those observations located within a 10 mile radius of each farm. Thus, the spatial lag captures spatial dependence in the dependent variable only at this scale. Social networks and neighbor interaction effects may play an important role in creating spatial dependence at this scale. As farmers in an area begin adopting BMPs, interactions between neighboring farmers may facilitate future adoptions through the spread of information. These interactions spread information through both increased knowledge of potential BMPs and the governmental programs available to facilitate their adoption. If the farmers have similar land and soil characteristics or operate the same type of farm, this effect could be magnified. Spatial dependence might also result from the successful outreach of employees of organizations that operate at this scale. Such organizations might include soil conservation districts or localized watershed conservation organizations such as the Tri-County Conewago Creek Association, located in Lancaster County, PA.

The exact source of contagion cannot be determined with this analysis. However, the existence of contagion should be encouraging to policymakers as it implies that BMP adoption may spread naturally through existing social and community networks. In other words, the spread of information on conservation practices can successfully increase BMP adoption. Programming should focus on increasing interactions within the farming community and between policymakers and farmers. Possible options for policymakers include highlighting example farms in communities that have successfully implemented BMPs, increasing their presence at community gatherings, or planning localized meetings. These efforts can effectively highlight why conservation is necessary, the potential benefits to the environment and the farmer, as well as technical assistance and cost-sharing availability.

Two major conclusions from this study center around potential targeting improvements for NRCS funds and the existence of contagion in the adoption of BMPs. In general, farmers approach NRCS when they are interested in creating a conservation plan. Applications are evaluated objectively and funds are not concentrated in any one area. One can see the value in this approach, as it avoids the perception of bias in NRCS decision-making. More recently, programs such as the CBWI have place greater priority on applications from medium and high priority watersheds. Such steps should be encouraged. Targeting funds to the highest need waters will yield the greatest environmental benefit. If impaired and degraded waters are not targeted, these vital ecosystems will likely remain degraded. This is particularly important given the limited stream of funding available to NRCS.

In a limited resource world, contagion implies that getting adoption started in any one area can have spillover effects for the immediate community. Placed within a targeting context, important questions emerge. Spillover effects are good if they occur in a desirable location, but could also carry negative consequences. For instance, if a farmer in a high priority watershed adopts several BMPs and proceeds to encourage neighboring farmers to adopt as well, significant improvements for already impaired waters could result. However, these spillovers could also occur away from degraded and impaired waters. Improvements in water quality would still occur, but funds would be used more efficiently elsewhere.

There are two issues. First, can NRCS begin to target high priority waters more than they have in the past? If so, can the contagion effects found by this study be harnessed such that adoption begins to cluster in these high priority areas? The results from this study are encouraging. Results imply that medium and high priority watersheds along with impaired streams have not been targeted as much as they could have been. However, improved targeting combined with programming facilitating the spread of information and increased interactions between farmers carries the potential for significant improvements in water quality. Policy should focus on targeting high priority areas where adoption is already occurring as well as on encouraging adoption and fostering spillover effects in high priority areas where adoption has not occurred.

Future studies should continue to examine the source and scale of contagion effects as well as what other variables may be spatially correlated. If the source of contagion can be determined, programs can be tailored towards encouraging this type of process where there has been little BMP adoption and in high need areas. For instance, if spatial dependence exists primarily due to neighboring farmers interacting with one another, programs can be designed to facilitate such interactions. Regardless of the source of contagion, the large spatial lag evident in this study implies the need for future studies to include explicit spatial analysis in BMP adoption research. If the importance of space and farm proximity is ignored, a diminished understanding of the factors influencing the BMP adoption decision will result. Additionally, it would be useful to include other variables common throughout the BMP adoption literature that were unavailable in the current study. These variables include socioeconomic variables as well as variables accounting for awareness and attitudes towards conservation practices.

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Appendix: Tables

Table 11: NRCS Best Management Practices in Study Area	
Access Control	Nutrient Management
Access Road	Obstruction Removal
Agrichemical Mixing Facility	Open Channel
Anaerobic Digestor, Controlled Temperature	Pasture and Hay Planting
Animal Mortality Facility	Pest Management
Animal Trails and Walkways	Pipeline
Atmospheric Resource Quality Management	Pond
Barnyard Runoff Management	Pond Sealing or Lining, Flexible Membrane
Brush Management	Prescribed Grazing
Channel Stabilization	Pumping Plant
Closure of Waste Impoundment	Residue and Tillage Management, Mulch Till
Composting Facility	Residue and Tillage Management, No-Till/Strip Till/ Direct Seed
Comprehensive Nutrient Management Plan	Residue and Tillage Management, Ridge Till
Comprehensive Nutrient Management Plan - Applied	Residue Management, Mulch Till
Comprehensive Nutrient Management Plan - Written	Residue Management, No-Till/Strip Till
Conservation Completion Incentive, First year	Residue Management, Ridge Till
Conservation Cover	Residue Management, Seasonal
Conservation Crop Rotation	Restoration and Management of Rare and Declining Habitats
Constructed Wetland	Rinsate Management
Contour Buffer Strips	Riparian Forest Buffer
Contour Farming	Riparian Herbaceous Cover
Contour Orchard and Other Fruit Area	Roof Runoff Structure
Cover Crop	Runoff Management System
Critical Area Planting	Sediment Basin
Cross Slope Farming	Shallow Water Development and Management
Deep Tillage	Sinkhole and Sinkhole Area Treatment
Diversion	Solid/Liquid Waste Separation Facility
Early Successional Habitat Development/Management	Spring Development

Table 11 cont.	
Enhancement – Air Resource Management	Stream Crossing
Enhancement – Energy Management	Stream Habitat Improvement and Management
Enhancement – Grazing Management	Streambank and Shoreline Protection
Enhancement – Habitat Management	Stripcropping
Enhancement – Nutrient Management	Stripcropping, field
Enhancement – Pest Management	Structure for Water Control
Enhancement – Soil Management	Subsurface Drain
Enhancement – Water Management	TA (technical assistance) Design
Feed Management	Terrace
Fence	Tree/Shrub Establishment
Field Border	Tree/Shrub Pruning
Filter Strip	Underground Outlet
Fish Passage	Upland Wildlife Habitat Management
Forage Harvest Management	Vegetated Treatment Area
Forest Stand Improvement	Waste Storage Facility
Grade Stabilization Structure	Waste Transfer
Grassed Waterway	Waste Treatment Lagoon
Heavy Use Area Protection	Waste Utilization
Hedgerow Planting	Water and Sediment Control Basin
Irrigation System, Microirrigation	Water Well
Irrigation System, Sprinkler	Watering Facility
Irrigation Water Conveyance, Pipeline, Aluminum Tubing	Well Decommissioning
Irrigation Water Conveyance, Pipeline, High-Pressure, Underground, Plastic	Wetland Enhancement
Irrigation Water Conveyance, Pipeline, Low-Pressure, Underground, Plastic	Wetland Restoration
Irrigation Water Management	Wetland Wildlife Habitat Management
Lined Waterway or Outlet	Windbreak/Shelterbelt Establishment
Mulching	

Table 12: Eliminated Best Management Practices

BMP	**Reason for Elimination**
Access Road	Lack of Water Quality Focus
Agrichemical Mixing Facility	Low Frequency of Adoption
Anaerobic Digestor, Controlled Temperature	Low Frequency of Adoption
Animal Mortality Facility	Low Frequency of Adoption/Lack of Water Quality Focus
Atmospheric Resource Quality Management	Low Frequency of Adoption/Lack of Water Quality Focus
Barnyard Runoff Management	Low Frequency of Adoption
Brush Management	Lack of Water Quality Focus
Channel Stabilization	Low Frequency of Adoption
Closure of Waste Impoundment	Low Frequency of Adoption
Composting Facility	Low Frequency of Adoption
Comprehensive Nutrient Management Plan - Applied	Low Frequency of Adoption
Comprehensive Nutrient Management Plan - Written	Low Frequency of Adoption
Conservation Completion Incentive, First year	Low Frequency of Adoption
Constructed Wetland	Low Frequency of Adoption
Contour Orchard and Other Fruit Area	Low Frequency of Adoption/Lack of Water Quality Focus
Cross Slope Farming	Low Frequency of Adoption
Early Successional Habitat Development/Management	Low Frequency of Adoption
Enhancement – Air Resource Management	Low Frequency of Adoption
Enhancement – Energy Management	Low Frequency of Adoption
Enhancement – Grazing Management	Low Frequency of Adoption
Enhancement – Habitat Management	Low Frequency of Adoption
Enhancement – Nutrient Management	Low Frequency of Adoption
Enhancement – Pest Management	Low Frequency of Adoption
Enhancement – Soil Management	Low Frequency of Adoption
Enhancement – Water Management	Low Frequency of Adoption
Feed Management	Low Frequency of Adoption
Fish Passage	Low Frequency of Adoption/Lack of Water Quality Focus

Table 12 cont.

Forage Harvest Management	Lack of Water Quality Focus
Forest Stand Improvement	Lack of Water Quality Focus
Grade Stabilization Structure	Low Frequency of Adoption
Hedgerow Planting	Low Frequency of Adoption
Irrigation System, Microirrigation	Lack of Water Quality Focus
Irrigation System, Sprinkler	Lack of Water Quality Focus
Irrigation Water Conveyance, Pipeline, Aluminum Tubing	Lack of Water Quality Focus
Irrigation Water Conveyance, Pipeline, High-Pressure, Underground, Plastic	Lack of Water Quality Focus
Irrigation Water Conveyance, Pipeline, Low-Pressure, Underground, Plastic	Lack of Water Quality Focus
Irrigation Water Management	Lack of Water Quality Focus
Mulching	Low Frequency of Adoption/Lack of Water Quality Focus
Obstruction Removal	Low Frequency of Adoption/Lack of Water Quality Focus
Open Channel	Low Frequency of Adoption
Pasture and Hay Planting	Lack of Water Quality Focus
Pond	Low Frequency of Adoption
Pond Sealing or Lining, Flexible Membrane	Low Frequency of Adoption
Residue and Tillage Management, Ridge Till	Low Frequency of Adoption
Residue Management, Ridge Till	Low Frequency of Adoption
Restoration and Management of Rare and Declining Habitats	Low Frequency of Adoption
Rinsate Management	Low Frequency of Adoption
Runoff Management System	Low Frequency of Adoption
Sediment Basin	Low Frequency of Adoption
Shallow Water Development and Management	Low Frequency of Adoption
Sinkhole and Sinkhole Area Treatment	Low Frequency of Adoption
Solid/Liquid Waste Separation Facility	Low Frequency of Adoption
Spring Development	Low Frequency of Adoption
Stream Habitat Improvement and Management	Low Frequency of Adoption
Stripcropping, field	Low Frequency of Adoption
TA (technical assistance) Design	Low Frequency of Adoption

Table 12 cont.	
Tree/Shrub Establishment	Lack of Water Quality Focus
Tree/Shrub Pruning	Low Frequency of Adoption
Vegetated Treatement Area	Low Frequency of Adoption
Waste Treatment Lagoon	Low Frequency of Adoption
Waste Utilization	Low Frequency of Adoption/Lack of Water Quality Focus
Water and Sediment Control Basin	Low Frequency of Adoption
Water Well	Low Frequency of Adoption/Lack of Water Quality Focus
Watering Facility	Lack of Water Quality Focus
Well Decommissioning	Low Frequency of Adoption/Lack of Water Quality Focus
Windbreak/Shelterbelt Establishment	Low Frequency of Adoption

Table 13: Included Best Management Practices	
Access Control	Residue and Tillage Management, Mulch Till
Animal Trails and Walkways	Residue and Tillage Management, No-Till/Strip Till/Direct Seed
Comprehensive Nutrient Management Plan	Residue Management, Mulch Till
Conservation Cover	Residue Management, No-Till/Strip Till
Conservation Crop Rotation	Residue Management, Seasonal
Contour Buffer Strips	Riparian Forest Buffer
Contour Farming	Riparian Herbaceous Cover
Cover Crop	Roof Runoff Structure
Critical Area Planting	Stream Crossing
Deep Tillage	Streambank and Shoreline Protection
Diversion	Stripcropping
Fence	Structure for Water Control
Field Border	Subsurface Drain
Filter Strip	Terrace
Grassed Waterway	Underground Outlet
Heavy Use Area Protection	Upland Wildlife Habitat Management
Lined Waterway or Outlet	Waste Storage Facility
Nutrient Management	Waste Transfer
Pest Management	Wetland Enhancement
Pipeline	Wetland Restoration
Prescribed Grazing	Wetland Wildlife Habitat Management
Pumping Plant	