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GREENHOUSE GAS EMISSIONS FROM AGROECOSYSTEMS: SIMULATING MANAGEMENT EFFECTS ON DAIRY FARM EMISSIONS

A Dissertation in

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by

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Abstract

How does agriculture contribute to greenhouse gas emissions and what farm management scenarios decrease net emissions from agroecosystems? The reduction of greenhouse gas emissions is becoming more important world-wide. Although farmland can serve as a sink for carbon, agriculture is also an important source of emissions. As a sector, agriculture is reported to be the greatest contributor of nitrous oxide and the third greatest contributor of methane. As a result, various studies have attempted to answer the motivating questions.

Despite the effort spent in answering these questions, most approaches have focused on one specific greenhouse gas, have used empirical relationships to quantify emissions, or have neglected important aspects an agricultural system. This research extended these approaches in order to answer the motivating questions by quantifying total net GHG emissions and developing a computer module to predict emissions using primarily mechanistic relationships. This module was incorporated into the Integrated Farm System Model (IFSM), which was then used to analyze reduction strategies in the context of a whole-farm system.

First, typical ranges of greenhouse gas emissions were identified from sources (i.e., animal housing facilities, croplands, and manure storages) on dairy farms. The typical emission values were used to identify the major sources of greenhouse gases from dairy farms in order to guide the model development. A computer model was then created to predict greenhouse gas emissions from sources on a dairy farm. Process-based relationships were utilized for all of the major sources, and as many of the minor sources as was justified. The refined version of IFSM was evaluated for both prediction accuracy and sensitivity, and was determined to adequately predict whole-farm emissions of greenhouse gases.

IFSM was then used to predict greenhouse gas emissions and net return from management scenarios in five categories: manure handling strategies, tillage systems, growth hormones, dietary forage concentration, and confined versus grazing production systems. The scenarios that emitted the least amount of greenhouse gases were: covered manure storages with surface application, no-till, using rBST growth hormone, high

forage:grain ratio with additional forage produced on-farm, and winter confinement with summer pasture. Emissions of greenhouse gases need to be analyzed in the context of productivity (e.g., milk production) as well as profitability because farmers are unlikely to implement reduction practices that reduce their profit. Based on this analysis, the practices that resulted in the least greenhouse gas emissions were not always the most profitable, although a full economic analysis was out of the scope of this dissertation. All of these analyses were performed assuming no legislation regulating greenhouse gas emissions; future regulations restricting emissions would change the analysis by affecting the profitability of the scenarios.

This research has identified management scenarios that result in environmental benefits and, in some cases, increased profitability. However, social factors and resistance to new practice will also influence whether the identified scenarios will actually be implemented. As a result, the identified scenarios must also be considered in the context of society and farm traditions.

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Chapter 1

Introduction and Objectives

1.1 Introduction

Like many environmental issues, global climate change is a fiercely debated topic with political and economic implications. Despite the debate, it is an incontrovertible fact that atmospheric greenhouse gas (GHG) concentrations have increased throughout the 20th century (IPCC, 2007). Concern about the increased emission and retention of these gases in the atmosphere has been growing internationally and, as a result, scientists and policymakers have focused on both quantifying and reducing anthropogenic emissions of GHGs world-wide.

Arguably, the most well-known initiative attempting to reduce GHG emissions is the Kyoto Protocol. The U.S. did not ratify the Kyoto Protocol, but several initiatives in the U.S. indicate that the American people are following international trends and becoming increasingly concerned about GHG emissions. One of the most ambitious initiatives at the state level aimed at curbing GHG emissions is California Assembly Bill 32 (AB 32). AB 32 commits California to reducing GHG emissions to 1990 levels by the year 2020, a reduction of approximately 25% compared to emissions in 2006 (CARB, 2007). Although the U.S. government has not yet passed federal legislation to regulate GHG emissions, an important Supreme Court case may change the current status quo. In April 2007, the Supreme Court ruled that GHGs were air pollutants that must be regulated by the EPA (Commonwealth of Massachusetts vs. U.S.E.P.A., Docket No. 05-1120). This landmark case may precipitate either national regulation under existing statutes or new legislation.

With this growing concern, scientists have focused their attention on the various sources of GHGs. Agriculture is believed to contribute 6% of total GHG emissions in the U.S. (EPA, 2005). Although this contribution represents only a small percent of carbon dioxide (CO_2) emissions, agriculture is the largest emitter of nitrous oxide (N_2O) and the third largest emitter of methane (CH_4), accounting for 75% and 29% of their respective national total emissions (EIA, 2006). In addition, the FAO reported in 2006 (FAO, 2006) that agriculture contributed more GHG in CO_2 equivalents (CO_2e) than the transportation sector. Reducing agricultural GHG emissions will thus contribute to the overall reduction of atmospheric concentrations. Agriculture may also reduce the concentration of CO_2 in the atmosphere by creating a short-term sink for carbon (C) in soil. Potential sequestration rates have been suggested ranging from 5% to 15% of total U.S. GHG emissions (Bruce et al., 1999; Lal, 2004). However, the actual rate of C sequestration, and thus net GHG emissions, on agricultural lands is highly dependent on the management strategies implemented on a farm.

Research thus needs to focus on quantifying and reducing all GHGs, while accounting for the factors impacting emissions. The various factors affecting emissions interact with each other as well as with the climate, hydrology, soil, and other components, making it difficult to predict their overall impact on emissions. Even when impacts are known, mitigation techniques are unlikely to be implemented if the practices decrease the profitability of farms. As a result, all individual factors and their interactions must be analyzed to identify cost-effective management practices that minimize emissions from farms. Arguably, no field study could feasibly record all of these factors while measuring GHG emissions. In addition, few data are available on farm-level emissions of net GHG emissions (Sedorovich et al., 2007).

Instead of using measurement techniques, a robust method of analyzing the impact of these factors is to use computer simulation to evaluate proposed reduction strategies in the context of a whole-farm system. The Agricultural Research Service (ARS) of the United States Department of Agriculture (USDA) has developed a model that is capable of simulating a whole-farm production system (Rotz et al., 2007). The current version of the Integrated Farm System Model (IFSM) simulates crop growth, herd performance, and nutrient flows through a farm, allowing the model to be used to analyze the effects of various cropping, feeding, manure handling, and other strategies. In addition, IFSM models the various transformations of nitrogen and phosphorus throughout the production system, providing results that reflect long-term losses of these nutrients expected from farms (Rotz et al., 2007). This model provides a tool for evaluating the performance, economics, and environmental impact of management on farm production systems.

Previous research has utilized IFSM to evaluate many different farm practices and whole farm production systems. For example, Rotz et al. (2001) examined the trend on Pennsylvania dairy farms of producing and feeding soybeans. Except in specific cases, such as the utilization of high corn silage rations and inefficient use of supplemental proteins, there was little impact on either farm profit or the environment when soybeans were added to cropping systems on these farms. Rotz (2004) demonstrated the potential of whole-farm management to decrease total N loss, noting that decreases in N loss in one area of the farm can be offset by increases in another area. As these and other studies (Rotz et al., 1999b; Rotz et al., 2002a, b) illustrate, IFSM is useful for analyzing how changes in management practices affect the whole-farm as a system, including effects on nutrient loss and farm profitability. However, previous versions of IFSM have not included the capability of simulating and predicting GHG emissions.

Existing methods of predicting GHG emissions from farm sources use empirical relationships or emission factors, are overly complex and require calibration, do not look at the whole farm system, or they were developed specifically for use in Europe. For example, IPCC's Tier I methodology to calculate CH_4 emissions due to enteric fermentation use default emission factors based on the number of cows. Changes in farm management (e.g., animal diet) do not impact CH_4 emissions using this default factor. As a result, a need exists for a process-based model capable of simulating GHG emissions at the farm scale. Integration of this model with IFSM will provide a tool for determining whole-farm GHG emissions and evaluating the effects of management on these emissions.

1.2 Research Objectives

The overall goal of this research was to develop a tool for evaluating whole-farm emissions of GHGs from dairy farms and to explore how management scenarios impact emissions. The research objectives were:

1. Determine typical ranges of GHG emissions from all sources on dairy farms and thus identify the major contributors to emissions;
2. Develop a module that simulates CO_2, CH_4, and N_2O emissions from dairy farms primarily using process-based relationships;

3. Evaluate model predictions from each source as well as from the whole farm to ensure that the model is capable of predicting GHG emissions; and
4. Compare GHG emissions as influenced by management scenarios on a representative Pennsylvania dairy farm (e.g., tillage practices, animal diets, manure handling methods, and production systems using crops with confinement feeding or grass with rotational grazing).

1.3 Document Organization

Documentation of this work is organized in seven chapters. Chapter 2 focuses on objective 1, where relevant literature is reviewed to identify and quantify important sources of GHG emission from dairy farms. Chapters 3 through 5 describe the process-based relationships and provide an evaluation of the model components, encompassing objectives 2 and 3. Chapter 6 focuses on objective 4 by evaluating the effects of management scenarios on GHG emissions and farm profitability,. Finally, Chapter 7 provides overall conclusions from this research.

Chapter 2

Greenhouse Gas Emissions From Dairy Farms[1]

***Abstract*.** The reduction of greenhouse gas emissions is becoming more important world-wide. As a sector, agriculture is reported to be the greatest contributor of nitrous oxide and the third greatest contributor of methane in the U.S. In order to design and implement reduction strategies, the main sources of emissions on a farm must be identified. Potential sources on dairy farms include soil, growing crops, feed storage, animals, and manure in animal housing facilities, during storage, and following field application. An extensive literature review was conducted to determine the major processes contributing to greenhouse gas emissions from dairy farms and to quantify typical emission levels. The main emission sources were identified as housing for both carbon dioxide (animal respiration) and methane (enteric fermentation), and cropland for nitrous oxide. Using the typical levels, emissions were estimated for a representative dairy farm. In carbon dioxide equivalents, croplands emitted -626 Mg CO_2e, manure storage emitted 384 Mg CO_2e, and housing facilities emitted 859 Mg CO_2e, for annual emissions of 617 Mg CO_2e. When field-applied manure was accounted for, the farm had an additional emission of 616 Mg CO_2e for a total of 1233 Mg CO_2e. This review and farm analysis will help direct modeling efforts by determining the important physical processes that drive emissions of carbon dioxide, methane, and nitrous oxide in dairy production. The review also expands the knowledge base of researchers, farm planners, and policymakers as they work to develop and maintain sustainable farming systems.

2.1 Introduction

Molecules of a greenhouse gas (GHG) trap heat in the lower atmosphere, which raises the surface temperature of the earth. Without this natural effect, the average temperature on the earth would be approximately -19°C rather than the observed 14°C (IPCC, 2001). Although the most important GHG is water vapor, direct anthropogenic impacts on water vapor have been thought to be negligible and are thus generally ignored. The other important GHGs are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), ozone (O_3), and several engineered gases (e.g., hydrofluorocarbons, perflurocarbons) (IPCC, 2001). Anthropogenic emissions have increased atmospheric concentrations of GHGs throughout the 20th century, and this is thought to have contributed to an increase in the surface temperature of the earth above the 14°C observed due to the natural effect (IPCC, 2001). As a result, policymakers and

[1] A version of this paper was presented at the 2007 ASABE National Meeting: Sedorovich, D.M, C.A. Rotz, and T.L. Richard. 2007. Greenhouse gas emissions from dairy farms. ASABE Paper No. 074096. St. Joseph, Mich.: ASABE.

researchers have focused on both quantifying and reducing anthropogenic GHG emissions.

Reduction of GHG emissions has become an important global concern. Although the U.S. government has not yet passed federal legislation to address emissions, certain regional initiatives show that the reduction of GHG emissions is a key issue even within the U.S. In 2003, the Chicago Climate Exchange (CCX) became the first voluntary program in the U.S. designed to reduce atmospheric CO_2 concentrations by trading emission credits. The CCX aims to reduce emissions to 6% below a baseline (i.e., average of emissions from 1998 to 2001) by 2010 (CCX, 2007). The Regional Greenhouse Gas Initiative (RGGI) is an agreement among seven states in the Northeast (i.e., Connecticut, Delaware, Maine, New Hampshire, New York, New Jersey, and Vermont) to reduce GHG emissions. Initially, the RGGI is focused on reducing CO_2 emissions from power plants; eventually, the program plans to include other gases and sources (RGGI, 2007).

The most ambitious program to-date in the U.S. was recently passed by California's legislature and signed into law in September 2006. Assembly Bill 32 (AB 32) aims to reduce California's GHG emissions to 1990 levels by 2020, a reduction of approximately 25% compared to current emissions. Under AB 32, the California Air Resources Board (CARB) is required to develop regulations and market-based mechanisms to reach this goal. For the first three years of the program, emission sources only need to report CO_2 emissions; afterwards, all six GHGs will be reported. Also, mandatory caps on emissions will be enacted for significant sources in 2012 (CARB, 2007). Since its passage last fall, AB 32 has been the focus of attention from other governors as well as international leaders.

On April 2, 2007, the U.S. Supreme Court determined that greenhouse gases are pollutants that must be regulated by the EPA (Commonwealth of Massachusetts vs. U.S.E.P.A., Docket No. 05-1120). This decision is likely to precipitate movement on the national level for either regulation under existing statues or new legislation to reduce emissions. The same week, the results of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) documented that the effects of climate change are already being felt and are causing negative impacts in many regions of the globe (IPCC, 2007). Assuming the current trend continues, concern over GHG emissions will continue to increase. Policy makers and scientists are thus investigating methods of reducing emissions and mitigating the current atmospheric concentrations of GHGs.

Research has shown that atmospheric concentrations of CO_2 can be reduced by sequestering carbon in soil (Bruce et al., 1999; Lal, 2004b). This suggests that agricultural lands may be used to help reduce atmospheric GHG concentrations. However, agriculture is also a source of GHGs. Because farms emit multiple GHGs, reduction strategies must focus on reducing net GHG emissions. To develop effective GHG reduction strategies, scientists must determine typical ranges of agricultural emissions in order to focus on the largest sources from farms.

The objective of this paper was to determine typical emissions from U.S. and Canadian farms and to quantify GHG emissions from a hypothetical, representative dairy farm in the U.S. Typical emissions were determined through an extensive review of previously published data that quantified emissions from soil, crop, and animal sources on farms. From these data, factors affecting emissions were determined. An evaluation of the importance of these data to future experimental and modeling studies is provided, along with a discussion of the implications to researchers, farm planners, and policy makers.

2.2 GHG Emissions from Agriculture

On-farm GHG emissions primarily occur from cropland and animal facilities. Emissions discussed in the following sections are first reported as the total mass of a specific gas (e.g., 1 kg CH_4, 1 kg N_2O). Using a conversion called the global warming potential (GWP), emissions are also converted to CO_2 equivalents (CO_2e). GWPs are used as a relative index to standardize emissions of GHGs for comparing how efficiently each gas traps heat in the atmosphere. GWPs are calculated by the IPCC as a function of two values: the radiative efficiency, or heat-absorbing capacity, of each GHG as compared to CO_2 and the decay rate of each gas, or how long a given mass remains in the atmosphere until it completely decays (IPCC, 2001). The GWP for CH_4 is 23 kg CO_2/kg CH_4, and the GWP for N_2O is 296 kg CO_2/kg N_2O (EIA, 2004). Because emissions are standardized to CO_2 emissions, the GWP of CO_2 is 1. Using these GWPs, 0.5 kg of CH_4

is expressed as 11.5 kg CO_2e and 0.5 kg of N_2O is expressed as 148 kg CO_2e. Thus, CH_4 emissions have more potential impact on global climate change than CO_2, and N_2O has considerably more potential impact than the other two gases.

2.3 Cropland Emissions

2.3.1 Carbon Dioxide

Farmland can be a source or sink of GHGs, with the contribution dependent upon the specific gas and the type of cropland. Typically, over the course of a full year, most agroecosystems assimilate carbon in the form of CO_2, as shown by an average net emission of -8,345 kg CO_2 ha^{-1} yr^{-1} (Table 2-1). This flux is equivalent to net ecosystem production (NEP; NEP = photosynthesis – plant respiration – soil respiration). By our definition, a negative value for NEP represents a flux into the system. This indicates that the plants capture more CO_2 through photosynthesis than they give off through respiration. Crops producing high amounts of biomass (e.g., corn and soybeans) tend to have a greater carbon input into the system compared to crops producing less biomass (e.g., grass without added fertilization). This greater input is caused by greater crop growth where more carbon is fixed in plant dry matter. Annual grain crops (e.g., corn, soybeans, and wheat) also have less carbon output at harvest when only the grain is removed and the rest of the crop biomass remains in the field. Crops with high amounts of biomass production and small amounts of biomass harvest and respiration will sequester, or assimilate, a greater amount of carbon in the soil. With more carbon and other organic matter (SOM) in the soil, microbial respiration in the soil may lead to greater emission of CO_2, offsetting a portion of this potential sequestration of carbon (Bruce et al., 1999; Post et al., 2004).

The averages that we present in this paper as compiled from published data generally agree with previously published trends (Table 2-1). Average net fluxes into corn and wheat crops are greater than that for soybeans, agreeing with observations by Franzluebbers et al. (1995) and Verma et al. (2005). Perennial forage crops are typically expected to sequester more carbon than annual grain crops, which is shown by the greater negative flux for alfalfa and grass as compared to soybean. In addition, little difference has been observed between emissions from alfalfa and from grass (Skinner, personal communication, 16 April 2007).

Table 2-1. Typical CO_2 emission ranges for croplands (kg CO_2 ha^{-1} yr^{-1}). The first data row (in italics) shows the statistics for all cropland, with subsequent rows specific to a given type of crop.

Crops	Number of data	Minimum (kg $CO_2 ha^{-1}$)	Maximum (kg CO_2 ha^{-1})	Average (kg CO_2 ha^{-1})	References[a]
All cropland	*55*	*-23,247*	*1,100*	*-8,345*	--
Grass	28	-14,600	-230	-6,396	a, c, e, g, h, i, l, m
Alfalfa	4	-12,870	-1,283	-6,343	k
Corn	10	-23,247	-10,633	-17,745	f, g, o
Soybeans	6	-5,133	1,100	-1,794	d, n
Wheat	7	-15,748	-4,220	-9,469	d
Bare soil[b]	10	2	522,000	276,000	b, j

[a] References: a. Flanagan et al. (2002); b. Flessa and Beese (2000); c. Frank and Dugas (2001); d. Franzluebbers et al. (1995); e. Gilmanov et al. (2003); f. Ginting et al. (2003); g. Kucharik et al. (2001); h. Lee et al. (2007); i. Owensby et al. (2006); j. Reicosky (1997); k. Skinner (personal communication, 16 March 2007); l. Sims and Bradford (2001); m. Suyker and Verma (2001); n. Suyker et al. (2005); o. Verma et al. (2005)

[b] Emissions from bare soil are due to soil respiration and manure application. Emissions on the low end of the range are primarily due to soil respiration; high emissions result from bare soil with manure application. Farms including a fallow period in crop rotations would likely observe emissions on the lower range.

Reported data tend to show a wide range in CO_2 emissions from croplands. Emissions from the same crop can vary due to different types of current management practices, different climates, and the management practices used over prior years for a given field. Perennial crops that have been established for a long time typically reach steady state where less carbon is assimilated compared to newly established perennial crops (Bruce et al., 1999). Additionally, crops produced using a no-tillage system sequester more carbon than crops using conservation or conventional tillage practices (Bruce et al., 1999; Six et al., 2000). No-till also effects emissions because of the amount of crop residue sequestered into the soil. Data from corn fields have shown that crops under no-till emitted less CO_2 (i.e., sequestered more carbon or had a greater negative emission) as compared to corn under conservation till (Grant et al., 2007). This results because tilling disrupts macroaggregates and favors decomposition of SOM in the soil. The data for cropland emissions shown in table 2-1 were drawn from published studies that utilized combinations of previous crop history, tillage practices, fertilization strategies, etc. The variety in management of the published data explains the great range in net flux within each crop.

Similarly, crops with a history of field applied manure sequester less carbon as compared to fields without manure applications. This greater rate results because fields with depleted carbon levels have a greater potential for sequestration (i.e., lower loss through soil respiration) as compared to well-managed fields with high C levels (Bruce et al., 1999). Many of the studies measuring CO_2 emissions shown in Table 2-1 did not provide information on field applications of manure during or prior to the study period; for those that did provide this information, no manure was applied. Since the majority of these studies were not associated with animal production, one can assume that this data does not reflect the influence of a long-term history of manure application. When applying these data to dairy farms, emissions resulting from field-applied manure must be considered.

The studies we used to obtain emissions data did not account for removal of biomass. Thus, the net flux reported here is different from the net carbon balance for the field. A carbon balance would include carbon flow into the crop system from manure or other organic material applied to the land and carbon leaving the system in the crop removed. In general, the long term soil carbon level will be in balance, i.e. the carbon inputs will equal carbon outputs. When transitioning to a given crop rotation or grass pasture, soil carbon level will increase or decrease over a period of years until an equilibrium in carbon flow is attained (Bruce et al., 1999; Fang and Moncrieff, 1999). In short-term studies and during transitions of cropping and grazing systems, gains and losses of soil carbon will occur.

2.3.2 Methane

Over a long period of time, agricultural lands typically are small sinks for CH_4, as shown by an average net emission over different crops of -1.5 kg CH_4 ha^{-1} yr^{-1} (Table 2-2). Soils can emit CH_4 in two ways. First, decomposition of organic matter by microorganisms in poorly aerated soils (e.g., rice paddies, wetlands) can emit CH_4 rather than CO_2. Throughout the year, sections of agricultural fields can be saturated with water, creating anaerobic microsites. This may cause minimal amounts of CH_4 to be emitted. However, over an entire year, agricultural soils typically are well-aerated and CH_4 is oxidized by soil microorganisms. In other words, agricultural soils are small sinks of CH_4.

Table 2-2. Typical CH_4 emission ranges for croplands (kg CH_4 ha^{-1} yr^{-1}). The first data row (in italics) shows the statistics for all cropland, with subsequent rows specific to a given type of crop.

Crops	Number of data	Minimum (kg CH_4 $ha^{-1}yr^{-1}$)	Maximum (kg CH_4 $ha^{-1}yr^{-1}$)	Average (kg CH_4 $ha^{-1}yr^{-1}$)	References[a]
All crop land	*17*	*-3.0*	*-0.4*	*-1.5*	--
Grass	3	-3.0	-0.5	-1.4	b, d, f
Alfalfa	1	-2.6	-2.6	-2.6	e
Corn	6	-2.2	-0.4	-1.5	c, d, e, f
Wheat	1	-1.9	-1.9	-1.9	d, e
Mixed[b]	6	-2.2	-1.1	-1.4	f
Bare soil	2	-0.1	0.0	0.0	a

[a] References: a. Flessa and Beese (2000); b. Flessa et al. (2002); c. Gregorich et al. (2005); d. Kaye et al. (2004); e. Kaye et al. (2005); f. Mosier et al. (2005)

[b] Mixed crop consists of a combination of the following: corn, soybeans, wheat, and/or fallow.

Soil and manure organic carbon sources have been considered as the sole source of CH_4 production from croplands. Without regular manure applications, microbial activity would likely decrease to levels found in non-cultivated soils. Subsequent CH_4 emissions would also decrease, eventually reverting to a sink under aerobic conditions. In other words, the effect of the manure application eventually disappears, and emissions return to typical background levels caused by organic matter decay. However, recent research suggests a second method of CH_4 emissions. Keppler and Röckmann (2007) indicate that the plants themselves may emit CH_4, although the mechanism is not currently known. Keppler and Röckmann (2007) measured emissions from live plants that were several orders of magnitude greater than that from dried plant residue, which emit CH_4 on the order of one billionth of a gram per hour. This implies that, considering soil and crop sources, croplands may provide a net emission of CH_4 under certain circumstances. However, our review shows that, integrated over an entire year, farmlands are small sinks for CH_4 (Table 2-2).

2.3.3 Nitrous Oxide

Unlike CH_4 emissions from cropland, data show strong support that farmland is a source of N_2O. A review of reported data gave an average net emission of 7.4 kg N_2O ha^{-1} yr^{-1} (Table 2-3). The small negative emission (i.e., N_2O sink) shown as the minimum for grassland has two explanations. First, and most importantly, the observed emission was reported to be below the detection limit of the measurement method used (Wagner-

Table 2-3. Typical N_2O emission ranges for croplands (kg N_2O ha^{-1} yr^{-1}). The first data row (in italics) shows the statistics for all cropland, with subsequent rows specific to a given type of crop.

Crops	Number of data	Minimum (kg N_2O $ha^{-1}yr^{-1}$)	Maximum (kg N_2O $ha^{-1}yr^{-1}$)	Average (kg N_2O $ha^{-1}yr^{-1}$)	References[a]
All crop land	*193*	*-0.2*	*239*	*7.4*	--
Grass	83	-0.2	152	5.4	a, c, d, f
Alfalfa	5	1.7	6.6	4.0	a, f, g
Corn	65	0.2	239	13	a, d, e, f, g
Soybeans	14	0.3	6.2	2.2	g
Wheat	18	0.1	28	2.8	d, e, g
Mixed[b]	8	1.1	10	3.4	c, f
Bare soil	2	0.4	5.2	2.8	b

[a] References: a. Duxbury et al. (1982); b. Flessa and Beese (2000); c. Flessa et al. (2002); d. Kaye et al. (2004); e. Kaye et al. (2005); f. Mosier et al. (2005); g. Stehfest and Bouwman (2006)
[b] Mixed crop consists of a combination of the following: corn, soybean, wheat, and/or fallow.

Riddle et al., 1997). As a result, this data point does not accurately represent a minimum observed annual N_2O flux from grasslands. If this negative data point is removed, the minimum observed annual emission is 0 kg N_2O ha^{-1} yr^{-1}, with a negligible change in the average flux. Second, small negative emissions can be observed from grasslands during short periods in a year. When data are integrated over a full year though, net emissions are typically positive.

Although emissions of N_2O were historically associated with denitrification, research has shown that nitrification also contributes to emissions (Sahrawat and Keeney, 1986). These emissions have been found to correspond with wetting of dry soil (Davidson, 1992) and the application of nitrogen in manure or fertilizer (Mosier et al., 1982). Conversely, negative or zero emissions are observed during dry periods or under management practices with no nitrogen application. The negative observed emission in Table 2-3 occurred during the summer on a grass field with no manure application (Wagner-Riddle et al., 1997). The large emissions were measured on pasture lands, which had a large input of manure, and thus nitrogen, deposited by grazing cows. Grass without nitrogen application tended to have emissions at the low end of the range in Table 2-3. The variability observed in emissions from grass was due to vastly different management scenarios among grassland production systems.

All of the crops exhibit a relatively wide range of measured N_2O emissions. The crops that show the greatest variability are those that are typically heavily fertilized (e.g., corn), which suggests that this variability is due in part to different fertilization strategies. Tillage also accounts for some of this variability. Liu et al. (2006) observed that no-tillage systems resulted in greater N_2O emissions as compared to conventional tillage systems.

2.4 Animal and Housing Facility Emissions

Inside a barn, it is difficult to separate GHG emissions directly emitted by livestock from those emitted from manure. As a result, livestock and housing emissions are grouped into one category: emissions from livestock housing facilities (i.e., total emissions from livestock and manure inside housing facilities). Emissions from manure storages are reported as a separate category. Emissions from housing facilities are reported in kg LU^{-1}, where one livestock unit (LU) represents 500 kg of animal mass. Full-grown Holstein dairy cows average about 700 kg, so one LU represents a little less than one full-grown dairy animal.

Despite the limited data available on GHG emissions from storage and housing, manure storages and livestock facilities are clearly net emitters of GHGs. Emissions of CO_2 from manure storages averaged 59 kg CO_2 m^{-3} yr^{-1}, whereas CO_2 emissions from livestock respiration averaged 2,754 kg CO_2 LU^{-1} yr^{-1} (Table 2-4). These values represent the primary net emissions of CO_2 into the atmosphere from farms. Methane

Table 2-4. Typical CO_2 emission ranges for manure storage and animal housing facilities.

	Number of Data	Minimum	Maximum	Average	References[a]
Manure storage (kg CO_2 m^{-3} yr^{-1})					
All storages	*4*	*8.6*	*117*	*59*	--
Slurry tank	1	17	17	17	e
Stacked	3	8.6	117	72	a, f
Animal housing (kg CO_2 LU^{-1} yr^{-1})					
All facilities	*5*	*1,697*	*3,624*	*2,754*	b, c, d

[a] References: a. Hensen et al. (2006); b. Jungbluth et al. (2006); c. Kirchgessner et al. (1991); d. Pinares-Patiño et al. (2003); e. Sneath et al. (2006); f. Sommer and Dahl (1999)

emissions from manure storages averaged 4.0 kg CH_4 m^{-3} yr^{-1}, while emissions from enteric fermentation by livestock averaged 73 kg CH_4 LU^{-1} yr^{-1} (Table 2-5). Nitrous oxide emissions due to livestock were less than CO_2 or CH_4 emissions. Emissions of N_2O from manure storages averaged 0.1 kg N_2O m^{-3} yr^{-1}, while emissions from livestock facilities (probably manure on the barn floor) averaged 0.3 kg N_2O LU^{-1} yr^{-1} (Table 2-6).

Two differences were observed between CO_2, CH_4, and N_2O emissions from manure storage and livestock housing facilities. First, emissions of N_2O exhibited less variability than CO_2 or CH_4. Unlike emissions of N_2O, emissions of CH_4 and CO_2 are associated with livestock (i.e., CH_4 production in the rumen of dairy cows and CO_2 emissions due to animal respiration) and may be more difficult to measure from large animals whose metabolism varies throughout the day. In addition, one method of measuring CH_4 involves measuring animal respiration. As a result, errors in measuring respired CO_2 contribute to errors in measuring CH_4. Thus, both CO_2 and CH_4 measurements tend to be more variable than N_2O.

Second, the major sources of CH_4 from manure storages do not correspond to the major sources of N_2O from storage. Uncovered slurry storage causes the greatest emission of CH_4 from storage facilities, whereas uncovered slurry storage is on the low end of the range for N_2O emissions. Composting manure before storage has been suggested as a manure treatment because it drastically reduces CH_4 emissions (Table 2-5). However, composting has little effect on N_2O emissions (Table 2-6). No data were available on CO_2 emissions before and after composting. Emissions of GHGs during the composting process itself are dependent on the management of the compost.

One important similarity was observed between CO_2, CH_4 and N_2O emissions data: in all cases, more data are needed to reduce variability and improve our confidence in quantifying typical emissions.

Table 2-5. Typical CH_4 emissions from manure storage and livestock housing facilities. The first data row (in italics) shows the statistics for all types of manure storage with subsequent rows specific to a given type of system.

	Number of Data	Minimum	Maximum	Average	References[a]
Storage (kg CH_4 m^{-3} yr^{-1})					
All storages	*17*	*0.2*	*15*	*4.0*	--
Composted	2	0.2	1.1	0.6	a
Slurry-covered	2	5.7	7.3	6.5	m, n
Slurry-uncovered	8	1.2	15	5.4	g, j, l, m
Stacked	5	0.3	5.8	2.3	e, m
Housing (kg CH_4 LU^{-1} yr^{-1})					
All facilities	*18*	*1.0*	*169*	*73*	a, b, c, d, f, h, i, k

[a] References: a. Amon et al. (2001); b. Boadi and Wittenberg (2002); c. Flessa et al. (2002); d. Grainger et al. (2007); e. Hansen et al. (2006); f. Jungbluth et al. (2006); g. Kaharabata et al. (1998); h. Kinsman et al. (1995); i. Kirchgessner et al. (1991); j. Kϋlling et al. (2003); k. Møller et al. (2004); l. Pinares-Patiño et al. (2003); m. Sneath et al. (2006); n. Sommer et al. (2000)

Table 2-6. Typical N_2O emissions from manure storage (kg N_2O m^{-3} yr^{-1}) and livestock housing facilities (kg N_2O LU^{-1} yr^{-1}). The first data row (in italics) shows the statistics for all types of manure storage with subsequent rows specific to a given type of system.

	Number of Data	Minimum	Maximum	Average	References[a]
Manure storage (kg N_2O m^{-3} yr^{-1})					
All storages	*9*	*0.0*	*0.3*	*0.1*	--
Composted	2	0.0	0.0	0.0	a
Slurry-covered[b]	1	0.3	0.3	0.3	f
Slurry-uncovered	5	0.0	0.2	0.1	d, e
Stacked	3	0.1	0.1	0.1	a, e
Animal housing (kg N_2O LU^{-1} yr^{-1})					
All facilities	*5*	*0.0*	*0.6*	*0.3*	a, b, c

[a] References: a. Amon et al. (2001); b. Flessa et al. (2002); c. Jungbluth et al. (2006); d. Külling et al. (2003) e. Sneath et al. (2006); f. Sommer et al. (2000)

[b] Data for covered slurry storage reflect the effect of a natural crust, straw, or similar material that enhances nitrification and denitrification.

2.5 Farm-level GHG Emissions

The data presented in Table 2-1 through Table 2-6 provide ranges of GHG emissions from farms. However, because the units vary based on the emission source, it is difficult to compare the relative contributions of each source or to identify the impact of reduction strategies on overall farm emissions. In order to compare emission sources, we used a representative farm to compare farm-level emissions and to discuss potential reduction strategies and their impacts.

2.5.1 Representative Farm

The ranges and averages determined through this literature review were obtained for a wide range of farm and climate conditions throughout the U.S. and Canada. The emissions we estimate are not exact emissions for a specific farm, but they are useful for illustrating and comparing farm-level GHG emissions.

The representative farm used was based on a “typical” dairy farm in Pennsylvania with alfalfa, grass, and corn fields. The 89 ha farm included 100 Holstein cows (average mass of 690 kg), 38 heifers over one year in age (average mass of 470 kg), and 42 heifers under one year of age (average mass of 200 kg). This provided a total of 190 LU (500 kg per LU). Animals were housed in free-stall barns. Manure was removed daily, stored as slurry in a 3000 m^3 storage tank for up to six months, and spread on fields bi-annually. On average over the year, the storage contained about 1500 m^3 of manure. The farm area consisted of 19 ha of grass, 20 ha of alfalfa, and 50 ha of corn. We assumed that all crop nutrient requirements were met through manure nutrients generated on the farm.

Using the CO_2 equivalents of the average emissions reported in Table 2-7 and our farm characteristics, grass has a net flux of -92 Mg CO_2e yr^{-1}, alfalfa emits -104 Mg CO_2e yr^{-1}, and corn emits -430 Mg CO_2e yr^{-1}. The total cropland has a net flux of -626 Mg CO_2e yr^{-1}. Manure storage emits 384 Mg CO_2e yr^{-1} and animals and their housing facilities emit 859 Mg CO_2e yr^{-1}, for a total annual emission of 617 Mg CO_2e yr^{-1}.

As discussed previously, the crop data in Table 2-1 does not reflect the influence of a long-term history of manure application. To account for manure application, we assumed that 6000 m^3 of slurry were produced on the dairy farm in a given year. Using a manure dry matter content of 7% and a carbon content of 40% in the dry matter yields 168 Mg C in field-applied manure. Assuming that all of this carbon is subsequently

Table 2-7. Annual net contributions of each emission source and total emissions from a representative farm reported as mass of each specific gas and as mass of CO_2 equivalents (kg CO_2e).

	Carbon dioxide		Methane		Nitrous oxide		Total
	CO_2	CO_2e[a]	CH_4	CO_2e[a]	N_2O	CO_2e[a]	kg CO_2e
Cropland (kg ha^{-1})[b]							
Grass	-6,396	-6,396	-1.4	-32	5.4	1,480	-4,830
Alfalfa	-6,343	-6,343	-2.6	-60	4.0	1,184	-5,219
Corn silage[c]	-17,745	-17,745	-1.5	-35	13	3,848	-13,932
Corn grain[c]	-8,873	-8,873					-5,060
Manure storage (kg m^{-3})[b]	17	17	6.5	150	0.3	89	256
Animal housing (kg LU^{-1})[b]	2,754	2,754	73	1,679	0.3	89	4,522

[a] Assumes 1 CO_2e per unit of CO_2, 23 CO_2e per unit of CH_4, and 296 CO_2e per unit of N_2O.
[b] 100 Holstein cows plus 80 replacement heifers on 89 ha of land with 19 ha of grass, 20 ha of alfalfa and 50 ha of corn.
[c] Corn silage and corn grain have different emission rates for CO_2, but the same rates for CH_4 and N_2O. Emissions of CO_2 from corn silage were obtained from Table 2-1. Emissions from corn grain were assumed to be 50% of emissions from corn silage. For total CO_2e, CH_4 and N_2O contributions are counted toward both silage and grain so that these emission rates are applied to the entire corn area (i.e., 50 ha).

respired as CO_2, there are additional emissions of 616 Mg CO_2e yr^{-1} from the dairy farm for a net emission of 1233 Mg CO_2e yr^{-1}.

Optimistically assuming that the representative farm can continue to sequester carbon in the soil, the farm still has a net emission between 617 to 1233 Mg CO_2e yr^{-1}, or 3.2 to 6.5 Mg CO_2e LU^{-1} yr^{-1}. This example highlights that, despite the potential for farmland to serve as a sink of carbon, livestock agriculture is likely an overall source of GHG emissions when total net emissions are quantified.

Based on the representative farm emissions, the carbon sink present in the system due to carbon assimilation is offset by other emission sources. Individually, livestock CO_2 emissions offset the net assimilation. Taken collectively, fluxes of GHGs into the atmosphere are greater than fluxes of GHGs into the farm system, resulting in a net flux into the atmosphere.

Livestock production has been noted as the largest source of CH_4 from agriculture, with enteric fermentation contributing 63% of total agricultural CH_4 emissions (EIA, 2004). The data collected support the general observation that annual CH_4 emissions from livestock were greater than CH_4 emissions from all other farm sources. In fact, total GHG emissions from livestock were greater than GHG emissions from all other farm sources. As livestock production intensifies and the number of animals on a given farm increases, the GHG emissions will also increase, as shown by the estimated rate of 3.2 to 6.5 Mg CO_2e LU^{-1} yr^{-1}. However, this increase is highly dependent upon the amount of feed imported to the farm.

2.5.2 Carbon Sequestration and Emission Reduction Strategies

Because of the increasing concentration of GHGs in the atmosphere, scientists are investigating methods of mitigating, or reducing, emissions. Based on the data presented above, livestock agriculture can be a significant source of GHG emissions. However, current efforts to reduce GHG emissions are focused on reducing industrial emissions while largely ignoring farm emissions. If industrial emissions are reduced without reducing agricultural emissions, farms may play a larger role in U.S. GHG emissions in the future. As a result, reduction strategies should be identified to reduce farm-level contributions, particularly as agricultural production intensifies.

One proposed method is carbon sequestration, or the removal of CO_2 from the atmosphere to a sink. Natural carbon sinks include forests, oceans, and soil. Research has shown that implementing different tillage operations and crop management strategies can increase the carbon sequestered in farmland. In other words, with proper management more carbon can be incorporated into crop systems as plant biomass and soil organic matter than is emitted through respiration as CO_2. Various strategies have been shown to increase carbon storage in croplands. These strategies include using reduced tillage operations, incorporating legumes and perennial forages into a crop rotation, and eliminating fallow periods (Bruce et al., 1999; Robertson et al., 2000; Azam et al., 1985; Ladd and Amato, 1986; Post et al., 2004). However, soils have a maximum potential to sequester carbon, and the soil is typically saturated after approximately 50 to 100 years of using a given production strategy (Sauerbeck, 2001). As a result, sequestration is unlikely to be a long-term solution, and scientists must investigate alternative reduction strategies.

Gaseous emissions are affected by several factors that may be used to design reduction strategies. For example, if manure storage covers increase N_2O emissions (Table 2-6), then a potential reduction strategy is to eliminate the use of covers. However, these factors do not affect all GHGs and other environmental pollutants in the same way. The effect of these factors on CO_2, CH_4, and N_2O, as well as on ammonia (NH_3, as an example of another environmental pollutant), is shown in Table 2-8. The effect of these factors on one gas is often negated by the effect on another gas. In other words, implementing one reduction strategy may reduce emissions of one gas while increasing emissions of another gas. For example, reducing the total solids content of manure decreases CH_4 emissions from storage but increases N_2O emissions. A second example further highlights the importance of taking all aspects of a farm system into account. As milk production increases, dairy cows emit more CH_4. However, the primary goal of most farms is to maximize profit, not to minimize environmental problems.

Reduction strategies thus need to focus on reducing all GHGs, while accounting for the factors impacting emissions. However, the various factors described interact with each other as well as with the climate, hydrology, soil, and other components to affect net GHG emissions, making it difficult to predict their ultimate impact. Even when impacts are known, mitigation techniques are unlikely to be implemented if the practices decrease the profitability of the farm. As a result, all individual factors and their interactions must

Table 2-8. Potential qualitative impacts of selected farm management factors on the emissions of carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and ammonia (NH3).

Management Factor[a]	CO_2	CH_4	N_2O	NH_3
Cropland				
Manure incorporated immediately after application	+	+	+	–
Manure not incorporated (or long period after application)	+	–	+	+
Injection of manure slurry directly into soil	+	+	+	–
Seeding of crops using no-till practices	–	+	+	+
Livestock				
Increased milk production	0	+	–	0
Manure storage				
Increased manure solids content	0	–	+	0
Increased manure temperature	+	+	+	+
Use of covered storage	–	+	+	–
More frequent emptying of storage	+	+	+	+

[a] A positive sign (+) indicates that the factor increase emissions. A negative sign (–) indicates that the factor decreases emissions. A zero (0) indicates that the factor has no effect on emissions.

be analyzed to identify cost-effective management practices that minimize emissions from farms. Arguably, no field study could feasibly record all of these factors while measuring GHG emissions. Instead, a robust method for analyzing the impact of these factors is to use computer simulation to evaluate proposed reduction strategies in the context of a whole-farm system.

Current methods of predicting GHG emissions from farm sources are primarily stand-alone empirical emission factors that do not take into account factors that may change based on reduction strategies. For example, IPCC's Tier I methodology to calculate CH_4 emissions due to enteric fermentation uses default emission factors based on the number of cows. Changes in farm management (e.g., animal diet) will not impact CH_4 emissions using this default factor. As a result, a computer model needs to be developed that is based on mechanistic relationships or empirical equations that represent farm processes and the interacting affects of reduction strategies. By integrating this GHG module into a whole farm model that simulates other forms of pollution (e.g., NH_3 emissions, nitrate leaching, and phosphorus runoff pollution) as well as the economics of a farm, reduction strategies can be analyzed in the context of overall environmental impacts along with the effect on farm profitability.

The USDA Agricultural Research Service (ARS) has developed a model called the Integrated Farm System Model (IFSM; Rotz et al., 2007). As a process-based farm-level model, IFSM simulates farm production systems, including the major components of soil, crops, grazing, tillage and planting, crop harvest, feed storage, feeding, herd production, manure handling, and economics. IFSM can be used to examine how various management practices affect farm nutrient dynamics and economics. However, IFSM currently does not have the capability of simulating GHG emissions. Although other models exist that simulate GHG emissions from farms, the majority of these models use empirical relationships or emission factors to predict emissions, are overly complex and require calibration, do not look at the whole farm system, or have been developed primarily for use in Europe and are not applicable to U.S. dairy farms. Based on the work presented in this paper, we plan to develop and incorporate GHG emission modules into IFSM to analyze the impacts of reduction strategies on farm performance, the environment, and farm profitability.

2.6 Conclusions

Even though the data gathered in this review exhibit high variability, they can be used to guide further research. Experimental studies that quantify GHG emissions from agriculture, particularly manure storage and livestock facilities, are needed to better establish typical emission ranges for U.S. farms and the factors that affect these emissions.

Although agricultural lands can serve as a carbon sink through sequestration, the emissions of CH_4 and N_2O from animal-producing farms may result in net emissions of GHG from livestock agriculture. The actual rate of carbon sequestration and net GHG emissions are highly dependent on the management strategies implemented on a farm. A simple analysis of a representative 100-cow dairy farm in Pennsylvania gave a net annual emission of 617 to 1233 Mg CO_2e considering all major sources of CO_2, CH_4, and N_2O.

No experimental study could economically record all of the important factors and measure the relevant sources of pollution in order to determine the overall environmental impact of farm production systems. This emphasizes the need for a whole-farm computer simulation tool for evaluating mitigation strategies in farm production systems.

Chapter 3

Simulating Carbon Dioxide Emissions From Dairy Farms

Abstract. The reduction of greenhouse gas emissions is becoming more important world-wide. Farm practices have a large impact on the soil carbon cycle as well as on the net emissions of carbon dioxide into the atmosphere. The primary sources of carbon dioxide on a dairy farm are animal respiration, plant respiration, and soil respiration, with smaller contributions from manure storages and barn floors. Strategies designed to reduce carbon dioxide emissions from one source can cause an increase in emissions from another source. As a result, a whole-farm evaluation is needed to assess the overall impact of proposed reduction strategies. Cost-effective whole-farm evaluation can be done through computer simulation. One model that can perform this whole-farm evaluation is the Integrated Farm System Model, a processed-based computer model that simulates a farm as a whole system. This model was modified to include simulation of carbon dioxide emissions from animal respiration, manure storage, and barn floors. The model also included relationships to simulate the carbon cycle, photosynthetic fixation, and respiration from plants and the soil. We describe several relationships to predict each of these sources, criteria used to select model relationships, and final model components. We compare model simulations to average emission rates from dairy farms as well as to experimentally measured emissions from individual sources. In addition, we evaluated the model's cycling of carbon by analyzing the mass of carbon present in each pool at the end of a simulation. The model predicted carbon dioxide emissions within the expected emission ranges for both the specific sources and for overall farm emissions. Differences in net emissions from croplands were due to differences in manure applications, crop residue management, and crop yield. Also, IFSM predictions of carbon pools agreed with published reports of carbon cycling. This research shows that a whole-farm model that includes process-based relationships predicting carbon dioxide emissions can be effectively used to evaluate the carbon cycle and proposed carbon dioxide reduction strategies.

3.1 Introduction

In 2007, the Intergovernmental Panel on Climate Change (IPCC, 2007) reported that it is "extremely likely" (i.e., representing a 95% confidence level or higher) that anthropogenic emissions of greenhouse gases (GHGs) are causing a change in the global climate. In 2005, U.S. CO_2 emissions were 6,009 million metric tons, accounting for 84% of the total U.S. anthropogenic GHG emissions (EIA, 2006). The majority of these emissions were due to the combustion of fossil fuel, with contribution estimates varying from 75% (IPCC, 2001) to 98% (EIA, 2006). The second largest contributor is land use change, with small additional contributions due to oil and gas production, emissions from industrial processes, and waste combustion (IPCC, 2001; EIA, 2006).

Agriculture is not explicitly included in the categories described above, and, therefore, the contribution of CO_2 from farms may be considered negligible. However, agriculture has two important impacts on CO_2 emissions. First, the conversion of native land to agricultural land is a major cause of the increase in CO_2 emissions (IPCC, 2001; Schlesinger, 2000a, b). On-farm CO_2 emissions can result from respiration (animal, plant, and soil), loss of plant biomass, and increased decomposition of organic matter (SOM) in the soil and in manure storages (IPCC, 2001; Schlesinger, 2000a, b). Second, research suggests that farm land has the potential to sequester carbon (C) and negate increases in the atmospheric concentration of CO_2, with estimates ranging from 0.3 to 1.4 Pg C yr^{-1} (Bruce et al., 1999; Houghton et al., 1999; IPCC, 1996).

Multiple processes emit CO_2 from dairy farms. A review of agricultural emission experimental data shows that the majority of on-farm CO_2 emissions is due to animal respiration, followed by less signification emissions from manure storages, barn floors, and, depending on the operations utilized, croplands (Chapter 2).

Computer simulation is a cost-effective and efficient method of estimating CO_2 emissions from dairy farms and analyzing how management scenarios affect these emissions. The Integrated Farm System Model (IFSM), a model developed by the USDA Agricultural Research Service (ARS), is a process-based whole-farm simulation including major components for soil processes, crop growth, tillage and planting operations, feed storage, herd and feeding, manure storage, and economics, with each divided into smaller components (Rotz et al., 2007). IFSM can predict the effect of management scenarios on farm profitability and environmental pollutants such as nitrate leaching, ammonia volatilization, and phosphorus runoff, but does not currently predict CO_2 emissions.

The overall goal of this research was to develop a tool for quantifying CO_2 emissions from dairy farms and for analyzing how management scenarios affect these emissions. To accomplish this, we sought to incorporate a module into IFSM that simulates the C cycle, with subsequent emissions of CO_2, on dairy farms and to evaluate the effectiveness of this tool at predicting farm level emissions of CO_2. Specific objectives were to review published models that simulate C cycling and CO_2 emissions, to identify the relationships that best fit our modeling goals, to adapt these models for use in IFSM, and to evaluate the use of this tool in predicting whole-farm CO_2 emissions.

3.2 Model Criteria

Several models have been published that predict CO_2 emissions from ruminant animals and crop production. In order to develop our module, we selected relationships from these published models that best fit our research goals. Therefore, we identified a list of criteria used to evaluate potential models. These criteria were:

1. ***The model must be able to simulate processes that affect CO_2 emissions when farm management changes are employed***. Strategies to reduce CO_2 emissions from dairy farms include reducing tillage, managing crop residue, and utilizing different manure storage techniques. In order to analyze how these practices affect CO_2 emissions, the model must account for associated changes (e.g., tillage operations, manure type, and storage design).
2. ***The model should be process-based***. Our goal was to select physically- and biologically-based relationships that are more likely to satisfy criterion 1 as compared to models based on emission factors.
3. ***The model should satisfactorily predict observed data over a full range of potential conditions***. A primary goal of models is to simulate observed data. As a result, the chosen relationships should predict CO_2 emissions within the range of emissions measured or expected from dairy farms.
4. ***The model should be consistent with the current scale of other components in IFSM***. Currently, the intent of IFSM is to simulate realistic management scenarios that can be implemented by farmers. The characteristics of these scenarios are at the field- or farm-level (e.g., land area, crops grown, animal numbers, equipment operations, manure storage duration). Subsequently, IFSM simulates processes, normally on a daily time step, at the field- or farm-level according to the assumed farm characteristics. As a result, selected relationships, as well as associated inputs and parameters, should be applicable at the field- or farm-level as opposed to different scales (e.g., microbiological, watershed).
5. ***Model inputs and parameters should use readily available data***. Some of the available mechanistic models predict emissions with high accuracy; however, these models typically have many inputs or are highly parameterized. The

required values are often the result of calibrating the model against observed data, are difficult to obtain, or have no physical or biological basis. The uncertainty added by making assumptions for parameter values can outweigh the benefit of using a highly mechanistic model. In contrast, the majority of parameters and inputs in IFSM are not calibration parameters, are relatively easily obtained through on-farm measurements, and correspond to characteristics of the farm. As a result, our final criterion was that inputs and parameter values should be easily obtained within, or consistent with, the current structure of IFSM.

3.3 Cropland Emissions

Typically, over the course of a full year, croplands assimilate C in the form of CO_2. In other words, the plants capture more CO_2 through photosynthesis than the croplands emit through respiration. Currently, IFSM simulates the growth of plants (i.e., the capture of CO_2 through photosynthesis), although the model does not explicitly predict photosynthetic fixation. As a result, this section will focus on the total C fixed through photosynthesis and the emission of CO_2 through plant (i.e., autotrophic) and soil (i.e., heterotrophic) respiration. Models simulating the C cycle will be discussed, followed by a history and description of the chosen model, DAYCENT.

3.3.1 Soil C Models

Models have been developed which simulate the C cycle with varying levels of detail. Some of the more frequently used models include TEM, BIOME, and CENTURY. In-depth reviews and comparisons of these models have been published (e.g., Goldewijk and Leemans, 1995). Instead of reviewing these various models in detail, only two will be discussed: Fang and Moncrieff (1999), as an example of a model simulating production and transport; and CENTURY, as an example of a process-based model.

Fang and Moncrieff (1999) described a model to predict production and transport of CO_2 in the soil. This model used a first-order equation to simulate decomposition of organic matter in the soil and corresponding production of CO_2. The model then simulated the transport of CO_2 through the soil using Fick's first law. Additionally, Fang and Moncrieff (1999) simulate the dynamics of above and below ground litter by using equations with single and double integrals. This model satisfies criteria 1 and 2, and partially satisfies 3. The model is based on widely used decomposition and transport equations (i.e., first-order reactions; Fick's law) and is thus process-based. By incorporating litter dynamics, the model would be able to simulate changes in crop residue management. The model only partially satisfies criterion 3 because, although the model was shown to adequately simulate observed data (Moncrieff and Fang, 1999), a literature review yielded no agroecosystem applications. The model does not satisfy the final two criteria. Model parameters are not provided and would need to be obtained from other studies. Also, the structure of the model is not consistent with the current scale of IFSM.

Goldewijk and Leemans (1995) provided an overview of various terrestrial C models including LINKAGES, CENTURY, BIOME, and TEM. This study classified each model along two continuums: empirical vs. process-based and static vs. dynamic. The majority of models were classified in the middle of the range of each, although a few were classified on the edges of either extreme. One of the model criteria was to utilize process-based relationships. Based on the classification of Goldewijk and Leemans (1995), one of the models that satisfied this criterion is CENTURY.

CENTURY is one of the most frequently used models to simulate the C cycle in agroecosystems. The daily time-step version, DAYCENT, satisfies all five criteria. Because of this, as well as because of future projects seeking to compare IFSM and DAYCENT, the equations incorporated into IFSM to simulate the C cycle were based on relationships in DAYCENT. The following sections provide a brief history of DAYCENT, several applications of the model, and some of the main relationships incorporated into IFSM.

3.3.2 History of DAYCENT

DAYCENT is a derivative of CENTURY, with both models simulating soil organic matter dynamics. DAYCENT and CENTURY have been described in previous publications (e.g., Parton et al., 1987; Parton et al., 1998; Kelly et al., 2000); only a brief description of the development, main sub-models, and selected applications is provided here.

CENTURY was developed to simulate the long-term effects of climate on SOM as well as productivity (Parton et al., 1987). Parton et al. (1987 and 1994) described the sub-models in CENTURY for SOM and decomposition, plant production, and nitrogen cycling. The model, which operated on a monthly time step, simulated active, slow, and passive soil C, as well as structural and metabolic C derived from plant residues. The decomposition of SOM was based on the amount of C in the pool being decomposed, an intrinsic decomposition rate which is a function of the quality of the C in the pool (i.e., microbial C has a greater decomposition rate than passive C), and factors accounting for the effect of temperature and moisture.

Further development of CENTURY yielded a daily time step version called DAYCENT. The different time step allowed DAYCENT to simulate other environmental processes (e.g., trace gas fluxes) in addition to SOM dynamics (Del Grosso et al., 2001). Modifications to DAYCENT included a new soil respiration model (Del Grosso et al., 2005b) and sub-models for CH_4 (Del Grosso et al., 2000c) and N_2O emission (Parton et al., 1996; Del Grosso et al., 2000b; and Parton et al., 2001).

DAYCENT and CENTURY have been used for a variety of applications including analyzing trace gas fluxes from bioenergy crops (Adler et al., 2007), estimating N_2O emissions from croplands in the U.S. at the county level (Del Grosso et al., 2006), and investigating the interaction of C sequestration and N_2O flux from agricultural systems (Del Grosso et al., 2000a).

3.3.3 Cropland Model Description

The majority of relationships incorporated into IFSM were directly taken from DAYCENT Version 4.5. A brief description of several important equations is provided here, along with a description of relationships included in IFSM that differed from those in DAYCENT. Further details can be found in the DAYCENT model and documentation for both DAYCENT and CENTURY (CENTURY, 2007). In addition, the model equations can be found in Appendix I.

Photosynthetic fixation of C by plants is the main input of C for a farm system. DAYCENT simulates total potential production as:

$$C_{pot,photo} = R_{solar} \cdot F_{prod} \cdot F_{temperature} \cdot F_{H2Ostree} \cdot F_{bio} \cdot F_{seedling} \cdot F_{CO2} \cdot 4 \qquad (3.1)$$

where $C_{pot.photo}$ is the total potential production from photosynthetic fixation [kg C ha^{-1} day^{-1}], R_{solar} is the daily solar radiation at the desired location [ly day^{-1}], F_{prod} is a coefficient to calculate daily aboveground production [g biomass m^{-2} day^{-1}], $F_{temperature}$ is a function representing a temperature effect on photosynthesis [unitless], $F_{H2Ostress}$ is a function representing the effect of water stress on potential production [unitless], F_{bio} is a coefficient representing the effect of physical obstruction on potential crop growth [unitless], $F_{seedling}$ is a coefficient to account for restriction of seedling growth [unitless], F_{CO2} is a coefficient representing the effect of atmospheric CO_2 concentration on plant growth, and *4* is a unit conversion factor. The original values of F_{prod} in DAYCENT were monthly values (i.e., g biomass m^{-2} month^{-1}); in order to simulate daily production, the values were divided by 30.4 to yield daily values (i.e., g biomass m^{-2} day^{-1}).

In order to calculate plant respiration (i.e., autotrophic), the total potential production was divided between above and below ground potential production as:

$$C_{ag} = C_{pot,photo} \cdot \left(1 - F_{bg}\right) \tag{3.2}$$

$$C_{bg} = C_{pot,photo} \cdot \left(F_{bg}\right) \tag{3.3}$$

where C_{ag} is the total potential aboveground production [kg C ha^{-1} day^{-1}], C_{bg} is the total potential belowground production [kg C ha^{-1} day^{-1}], and F_{bg} is the fraction of production allocated belowground [kg C kg^{-1} C].

A fraction of the above and below ground potential production was assumed to be respired by the plants as:

$$C_{resp,ag} = C_{ag} \cdot \left(R_{ag}\right) \tag{3.4}$$

$$C_{resp,bg} = C_{bg} \cdot \left(R_{bg}\right) \tag{3.5}$$

where $C_{resp,ag}$ is aboveground respiration [kg C ha^{-1} day^{-1}], $C_{resp,bg}$ is belowground respiration [kg C ha^{-1} day^{-1}], R_{ag} is the fraction of aboveground production respired [kg C kg^{-1} C], and R_{bg} is the fraction of belowground production respired [kg C kg^{-1} C].

In Version 4.5 of DAYCENT (2007), above- and belowground respiration is not simulated. In other words, the model does not provide values for the parameters R_{ag} and R_{bg}. In order to simulate this process in IFSM, the parameters were calibrated so that the model would yield reasonable results for above-and belowground respiration, as well as reasonable values for C accumulation. Based on the calibration, IFSM currently assumes that 35% of aboveground and 20% of belowground production is respired as CO_2.

Microbial decomposition of organic matter is the driving force behind soil (heterotrophic) respiration. The C module in IFSM was developed to simulate three surface C pools (surface structural, metabolic, and microbial C), three soil C pools present in each soil layer (soil structural, metabolic, and microbial C), and two soil C pools for C with a long turnover rate (soil slow and passive C) (Figure 3-1).

For each C pool, a total flow of C out of the pool is calculated. A portion of the C is respired as CO_2, while the remaining C is cycled into a different pool. The total flow of C out of a given pool is calculated as:

$$C_{flow} = \min\left(C_{pool,current}, C_{\max flow}\right) \cdot F_{decomp} \cdot k_{decomp} \cdot F_{pH} \cdot F_{lignin} \cdot F_{cult} \cdot F_{texture} \cdot F_{anaerob} \quad (3.6)$$

where C_{flow} is the total flow of C out of a given pool [g C m^{-2} day^{-1}]; $C_{pool,current}$ is the current mass of C in the pool [g C m^{-2}]; $C_{max,flow}$ is the maximum mass of C that can leave the pool as obtained from DAYCENT [g C m^{-2}]; F_{decomp} is a decomposition factor based on the soil moisture and ambient temperature, and specific to above (e.g., surface) or belowground (e.g., soil) C pools [unitless]; k_{decomp} is an intrinsic decomposition rate specific to each pool [day^{-1}]; F_{pH} is a factor accounting for the effect of pH on decomposition [unitless]; F_{lignin} is the effect of the lignin content on decomposition [unitless]; F_{cult} is the effect of cultivation [unitless]; $F_{texture}$ accounts for the effect of soil texture [unitless]; and $F_{anaerob}$ accounts for the presence of anaerobic conditions [unitless].

The first five terms are calculated for C flows out of all pools. The lignin factor equals one for all pools other than the surface and soil structural pools. The surface and soil structural pools account for the effect of the lignin content of the structural pools as:

$$F_{lignin} = \exp\left(-R_{lig/str} \cdot C_{strlig}\right) \quad (3.7)$$

where $R_{lig/str}$ is a parameter accounting for the effect of the ratio of lignin to structural C on decomposition [unitless] and C_{strlig} is the ratio of lignin to structural C in the structural pool [g lignin C g^{-1} structural C].

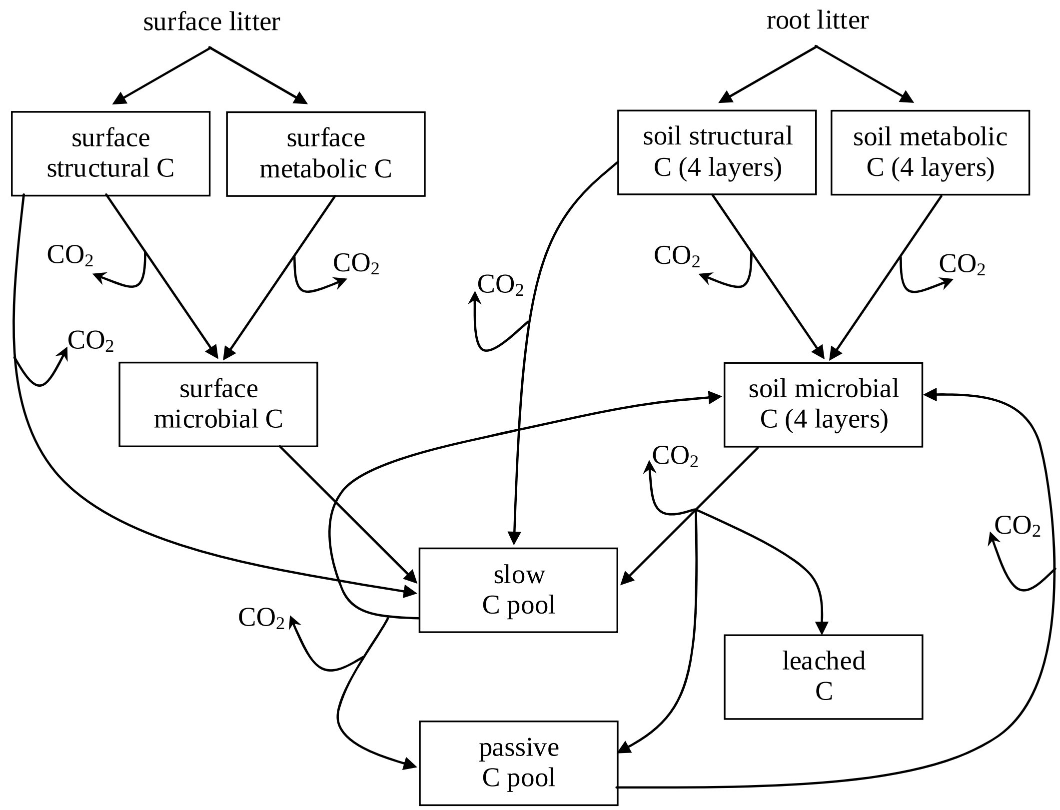

Figure 3-1. C flow diagram for the C module incorporated into IFSM (modified from Parton et al., 1994).

For the surface C pools (i.e., surface structural, metabolic, and microbial), the cultivation factor, F_{cult}, equals one. For the remaining pools, F_{cult} equals one on every day of the year that does not have a farm operation occurring. On days with a farm operation (e.g., tillage, harvest), the cultivation factors are assigned based on the type of operation and the type of machine (e.g., chisel plow, moldboard plow). The texture factor, $F_{texture}$, affects the decomposition from the soil microbial pool only, and is a function of the silt, sand, and clay contents. Finally, the anaerobic factor, F_{anerob}, only affects the decomposition of soil pools, and is calculated based on the soil moisture content.

Respiration of CO_2 is predicted assuming a set fraction of the total C flow out of the pool is respired as CO_2-C as:

$$C_{respired} = C_{flow} \cdot k_{resp} \tag{3.8}$$

where $C_{respired}$ is the daily amount of respired C [g C m^{-2} day^{-1}], C_{flow} is as defined above, and k_{resp} is the fraction of the daily total C flow that is respired [g C respired g^{-1} C flow]. These fractions vary and were obtained from DAYCENT input files (Table 3-1).

Table 3-1. Daily respiration rates used in IFSM as obtained from DAYCENT Version 4.5.

Source of C[a]	Daily respiration rate[b] [g C respired g^{-1} C flow]
Structural	
Surface pool (to microbial pool)	0.45
Surface pool (to slow SOM pool)	0.30
Soil pool (to microbial pool)	0.55
Soil pool (to slow SOM pool)	0.30
Metabolic	
Surface and soil pools	0.55
Microbial	
Surface pool	0.6
Soil pool	$0.17 + 0.68(F_{clay})$[c]
Passive pool	0.55
Slow pool	0.55

[a] Source of C represents the pool where the C originates. In other words, the respiration rate for "Surface pool (to microbial pool)" represents the fraction of C respired as CO_2 of the total C leaving the surface structural pool.
[b] Respiration rates were obtained from DAYCENT Version 4.5 input files.
[c] The respiration rate for the soil microbial pool is a function of F_{clay}, the soil clay content.

In addition to respired CO_2 losses, C is also lost from the system due to leaching and erosion. Leaching losses are predicted using relationships in DAYCENT by assuming a given fraction of the total C flow out of the microbial C pool is leached. This fraction is a function of the soil clay content, the water leached from the soil profile, and empirical parameters obtained from DAYCENT.

$$C_{leach} = \begin{cases} 0 & W_{leach} = 0 \\ C_{flow} \cdot K_{texture} \cdot F_{leach} & W_{leach} > 0 \end{cases} \tag{3.9}$$

$$K_{texture} = 0.03 + 0.12 \cdot F_{clay} \tag{3.10}$$

$$F_{leach} = \min\left[1.0, \quad 1.0 - \left(1.9 - W_{leach}\right) / 1.9\right] \tag{3.11}$$

Where C_{leach} is the amount of C leached from the soil microbial pool [g C m^{-2} day^{-1}], W_{leach} is the water flow out of the soil layer [cm], C_{flow} is the total flow of C out of the soil microbial pool [g C m^{-2} day^{-1}], $K_{texture}$ is the effect of soil texture on leaching [unitless], F_{leach} is the fraction of C leached [g C leached g^{-1} C flow], and F_{clay} is the soil clay content [decimal].

Sediment-bound organic matter represents another pathway of C loss from the system. Losses of C due to erosion are calculated as:

$$C_{erosion} = Y_{sed} \cdot C_{ER} \tag{3.12}$$

where $C_{erosion}$ is the amount of eroded C [kg C day^{-1}], Y_{sed} is the amount of daily erosion occurring from the given cropland [kg erosion day^{-1}], and C_{ER} is the C enrichment ratio [mg kg^{-1} erosion] (Sharpley 1985). Daily erosion is calculated in IFSM using the modified universal soil loss equation (MUSLE) as described in Sedorovich et al. (2007b). The enrichment ratio is calculated using relationships from Sharpley (1985) as:

$$C_{ER} = \exp(1.63 - 0.25 \cdot Y_{sed}) \tag{3.13}$$

3.4 Animal Respiration

Compared to emissions from fossil fuel combustion, CO_2 emissions from animal respiration are relatively minor. In addition, the IPCC (2001, 2007) does not include methodology to predict CO_2 due to animal respiration. This respired CO_2 is part of the C cycle that initially begins with photosynthetic fixation by plants. When the animals eat the crop (fixed C in the plant material), they convert it back to CO_2 that is respired (Kirchgessner et al., 1991; IPCC, 2001). On a farm, animal respiration of CO_2 is a major source relative to other CO_2 emissions. However, in the overall balance, the CO_2 released offsets the CO_2 sequestered in the plant material which is subsequently used as animal feed.

In order to develop a tool that comprehensively predicts GHG emissions from farms, animal respiration of CO_2 was included. This section describes several published models used to simulate CO_2 release by animals and the specific relationships chosen for use in the CO_2 module.

3.4.1 Animal Respiration Model Review

The majority of CO_2 respiration relationships reviewed were primarily empirical equations. The three relationships considered were two equations from Kirchgessner et al (1991) and one from Pinares-Patiño et al. (2007). All three relationships were similar and calculated CO_2 using a combination of animal mass, milk production, or feed dry matter intake (DMI) (Table 3-2). All of the models satisfied the five criteria to some extent. The two models from Kirchgessner had r-squared values of 70.5% (when a function of milk production) and 84.2% (when a function of feed dry matter intake), and the model from Pinares-Patiño et al. (2007) was based on data with standard error of the mean (SEM) of 5.5 and 4.2. Because Pinares-Patiño et al. (2007) was only a function of body weight, this relationship was not able to simulate differences in management scenarios as well as those of Kirchgessner et al. (1991). The relationship published by Kirchgessner et al. (1991) relating CO_2 emissions to DMI was chosen for use within the CO_2 module because this equation had a better fit to their original data and it better represented the natural process (i.e., C respired is a function of animal mass and carbon intake in feed). Although milk production is indirectly related to feed intake, prediction directly from feed intake was preferred since feed DMI was readily available for each animal group within IFSM. Relating CO_2 emissions to DMI was thus a more dynamic variable which simulated differences in management scenarios better than relating emissions to milk production.

Table 3-2. Summary of empirical models simulating CO_2 emissions from an individual animal due to respiration.

Model	Model core equations[a]	Units
Kirchgessner$_{milk}$[b]	$E_{CO2,resp} = 0.1 + 0.14*M_{prod} + 0.061*M_{BW}^{0.75}$ M_{prod} = mass of milk produced [kg day^{-1}] M_{BW} = mass of the animal [kg]	kg CO_2 day^{-1}
Kirchgessner$_{DMI}$[b]	$E_{CO2,resp} = -1.4 + 0.42*I_{DM} + 0.045*M_{BW}^{0.75}$ I_{DM} = dry matter intake [kg DM day^{-1}] M_{BW} = mass of the animal [kg]	kg CO_2 day^{-1}
Pinares-Patiño et al. (2007)[c]	$E_{CO2,resp} = 0.018*M_{BW}$ M_{BW} = mass of the animal [kg]	kg CO_2 day^{-1}

[a] $E_{CO2,resp}$ represents the emission of CO_2 from animals as predicted by the various models being used. The units of $E_{CO2,resp}$ are listed under the column "Units."
[b] Obtained from Kirchgessner et al. (1991)
[c] Equation calculated using data in Pinares-Patiño et al. (2007).

3.4.2 Animal Respiration Model Description

A detailed description of the development of the chosen model can be found in Kirchgessner et al. (1991). This section provides a description of the model, how the parameters were calculated, and how the model was integrated with IFSM.

The selected model of Kirchgessner et al. (1991) predicts CO_2 as:

$$E_{CO2,cow} = -1.4 \ + \ 0.42 \cdot M_{DMI} \ + \ 0.045 \cdot M_{BW}^{0.75} \tag{3.14}$$

where $E_{CO2,cow}$ is the emission of CO_2 from animal respiration [kg CO_2 cow^{-1} day^{-1}], M_{DMI} is the daily intake of feed dry matter for each animal [kg DM cow^{-1} day^{-1}], and M_{BW} is the animal's body weight [kg].

The DMI and body weight for each animal group were available in IFSM. IFSM calculated DMI based on animal nutrient requirements (i.e., energy and protein), the target milk production, the nutrient content of available feeds, and the amount of grazing available (Rotz et al., 1999). The body weight was a user specified parameter based on animal breed (e.g., Holstein, Brown Swiss, etc.) and the life stage of the animal (e.g., animal age and stage of lactation).

3.5 Other sources

As described previously, neither slurry storage nor barn floors are major sources of CO_2 emissions from farms. However, we included relationships to obtain a more comprehensive simulation of farm-level CO_2 emissions from all sources.

3.5.1 Manure Storages

Compared to other sources, slurry storages emit considerably less CO_2 (Chapter 2). Because this source contributes only minimally to whole-farm emissions of CO_2, there were few data available quantifying CO_2 emissions from slurry storages. We chose to use a constant emission factor to predict CO_2 emissions from uncovered slurry storages. Currently, the available data, as well as the relative importance of this loss to the overall farm emission do not justify using a more process-based model. As a result, a constant emission factor represented the best available method of predicting CO_2 emissions from slurry storages. To determine this emission factor, we obtained emission rates from two published studies and used the average for our emission rate (Table 3-3).

Table 3-3. Published and average emission rates of CO2 emitted from uncovered slurry storages.

Reference	Emission rate [kg CO_2 m^{-3} day^{-1}]
Jungbluth et al. (2001)	0.036
Sneath et al. (2006)	0.041
Average	***0.04***

The average emission of 0.04 kg CO_2 m^{-3} day^{-1} is applicable to uncovered slurry storage. However, some dairy farms utilize plastic covers to reduce gaseous emissions from manure storage. Since no data were available on CO_2 emissions from covered manure storages, and we were not able to quantify the differences between emissions from covered and uncovered storage. In order to simulate covered storages, we instead assumed that CO_2 emissions were reduced by a similar proportion when using a cover as found for other, more important gases. Because IFSM currently accounts for the reduction in ammonia emissions due to covers, we used ammonia as the base gas. IFSM simulations predicted about 80% reduction in loss with the use of a cover. To simulate CO_2 emissions from a covered storage, we applied the emission rate of 0.04 kg CO_2 m^{-3} day^{-1} to the storage and then assumed that a cover reduced this emission by 80%. In other words, the emission rate from covered slurry storage was assumed to be 0.008 kg CO_2 m^{-3} day^{-1}.

3.5.2 Barn Floor Emissions

Floors of housing facilities can be a source of CO_2 emissions due to decomposition of organic matter in manure deposited by animals. After cleaning and removal, some manure likely remains on the floor and continues to be a source of emissions. Using CO_2 emissions data measured from barn floors (Varga et al., 2007), an equation was developed relating CO_2 emissions to the ambient temperature (R^2 = 0.58).

$$E_{CO2,floor} = \max(0.0, 1.85T + 50.75) \cdot A_{barn} / 1000 \tag{3.15}$$

where $E_{CO2,floor}$ is the daily rate of CO_2 emission from the barn floor [kg CO_2 day^{-1}], T is the ambient temperature [°C], and A_{barn} is the area of the barn [m^2].

Equation 3.7 satisfies criteria 3 and 5; it is an empirical equation that correlates CO_2 emissions with temperature. This relationship was used because it represents the best available information that we currently have describing CO_2 emissions from barn floors. Also, because barn floor emissions are very low compared to other sources, a more sophisticated model was not justified. As a function of temperature, equation 3.7 is a simple, process-based equation, thus satisfying criterion 4 as well. This relationship predicts reasonable emission rates over ambient barn temperatures of 0°C and greater, with no loss at temperatures below 0°C.

3.6 Model Evaluation

The main goal of most models is to satisfactorily predict observed data. A model evaluation was performed on the soil C and animal respiration submodels to determine how well they represented real systems. Additionally, IFSM predictions were compared to typical emissions from a representative dairy farm in Pennsylvania. Model components were also analyzed to quantify the sensitivity of the model to various parameters.

3.6.1 Soil Carbon Model

Studies that have quantified CO_2 emissions or C pools often did not provide the specific input data required to simulate scenarios in IFSM. For C pools, many studies provided long-term change in C pools (e.g., g C m^{-2} 25 $years^{-1}$). However, because IFSM does an annual simulation, the model was not able to adequately simulate these long-term studies. As a result, although many studies have quantified CO_2 emissions and C pools, the number of studies available for model evaluation was limited. Two studies were used to evaluate the soil C model. Del Grosso et al. (2002) was chosen as the representative study to test the ability of IFSM to predict C pools. This study also allowed a direct comparison of IFSM predictions to DAYCENT predictions. However, because Del Grosso et al. (2002) did not quantify soil CO_2 emissions, a second study by Brye et al. (2002) was used to evaluate soil CO_2 emissions as well as changes in soil C pools.

Del Grosso et al. (2002) summarized previous experiments measuring soil organic C in three different cropping systems: no till wheat, conventional till wheat, and conventional till corn. In addition to the observed data, Del Grosso et al. (2002) also simulated these three systems using DAYCENT, and compared model predictions of C pools to observed values. As a result, this study allowed a comparison between IFSM and observed data, as well as IFSM and DAYCENT predictions.

The two wheat systems were located at the High Plains Agricultural Research Laboratory in Sidney, Nebraska. The soil type was a Keith silt loam (39% silt, 25% clay, 36% sand) with pH of 7.0 and organic matter content of 2%. One field utilized conventional tillage and one utilized no till; no fertilizer was applied to either system. Using the crop and soil characteristics described above, C pools were simulated using Sidney, Nebraska daily weather data from 1991 to 1998.

The corn system was located in Sterling, CO at a site designed to test the effects of dryland cropping on soil C levels and other agronomic parameters. Soil texture varied, but was predominantly a clay loam (36% silt, 30% clay, 34% sand). Fertilizer application rates ranged from 22 to 113 kg N ha^{-1}, for an average of 68 kg N ha^{-1}. No till was utilized in this system. With these characteristics, C pools were simulated with Akron, CO (approximately 30 miles south of Sterling) daily weather data from 1991 to 1998.

IFSM predictions closely matched the observed data and DAYCENT predictions, with average percent differences of 13% and 10%, respectively (Table 3-4). IFSM disagreed with DAYCENT predictions by predicting more C in no till corn than in conventionally tilled wheat. However, IFSM predictions followed the trend in observed data and predicted that the greatest soil C pool at the end of the simulation would be found in the no till wheat system, followed by no till corn and then conventionally tilled wheat. Based on these results, IFSM was determined to satisfactorily simulate the C cycle and total soil C.

Brye et al. (2002) measured gas fluxes from a prairie and maize agroecosystem in Wisconsin from 1995 to 1999. The objectives of their study were to compare respiration and C pools between prairie and corn fields and to identify the factors influencing interannual variability of these variables. Because this study quantified both soil CO_2 respiration and soil C pools, it allowed an evaluation of the ability of IFSM to simulate soil CO_2 fluxes as well as the cycling of C in the soil. For evaluation of IFSM, the maize data were used.

Table 3-4. Observed and predicted values for total soil carbon for no till wheat, conventionally tilled wheat, and no till corn.

	Total soil carbon [kg C ha^{-1} yr^{-1}]		
Cropping system	Observed	DAYCENT	IFSM
no till wheat	32,500	33,000	27,000
conventionally tilled wheat	30,000	30,100	26,800
no till corn	32,000	29,000	19,600

The corn fields were located at the Arlington Agricultural Research Station at the University of Wisconsin-Madison. The soil was a Plano silt loam (59% silt, 25% clay, and 16% sand) with an organic matter content of 3.3%, bulk density of 1.34 g cm^{-3}, and a slope of 2%. Four treatments were used: no till and no fertilizer (NT, nf); no till with fertilizer (NT, f); conservation till and no fertilizer (CT, nf); and conservation till with fertilizer (CT, f). Each treatment was established on individual plots measuring 111 m^2. Farm areas simulated in IFSM must be within the range of approximately 0.1 ha to 10000 ha. The original study area (i.e., 0.0111 ha) was less than the minimum area IFSM simulates. As a result, the area was increased to 11.1 ha when the farm was simulated with IFSM. The fertilizer treatments received 180 kg N ha^{-1} post planting broadcast on the surface. For tillage treatments, tillage occurred in the fall after harvest, with the seedbed prepared by disking in the spring before planting. With these characteristics, soil respiration and C pools were simulated with Madison, WI (approximately 22 miles north of Arlington) daily weather data over 25 years.

IFSM predictions slightly overestimated soil CO_2 emissions from CT,f, and significantly underestimated emissions from NT,f. Brye et al. (2002) observed no difference in CO_2 emissions between CT and NT. This is contrary to other studies concluding that reducing tillage reduces soil CO_2 emissions (Reicosky, 1997; Lal, 2004b). In addition, IFSM predictions of less CO_2 from NT as compared to CT agree with previously published DAYCENT simulations (Del Grosso et al., 2005a). IFSM also underestimated the loss of SOM, although model predictions followed the trend of observed data. The observed data showed a loss of 8 Mg C ha^{-1} and 11 Mg C ha^{-1}. These data represent the change in SOM over approximately five years. This five-year study began after the system was converted from a maize-soybean-alfalfa rotation into a maize system. Therefore, the data account for the change in crops grown on the field, in addition to the different tillage used. In contrast, IFSM is not intended to be a long-term model, but instead provides annual results over 25 years of weather. The systems simulated in IFSM are already in equilibrium. In other words, the IFSM data only account for differences between tillage systems, rather than converting from a crop rotation to a single crop. Changes in SOM are likely to be less important over one year as compared to long-term simulations (i.e., centuries), explaining why IFSM predicts less change in SOM as compared to the observed data.

Table 3-5. Observed and IFSM-predicted values for soil CO_2 respiration and change in soil organic matter.

	Soil CO_2 emissions [kg CO_2 ha^{-1}]		ΔSOM [kg C ha^{-1} yr^{-1}][a]	
System	Observed[a]	IFSM	Observed[b],[c]	IFSM
CT, f	25,600	26,800	11,150	2,700
NT, f	25,600	11,100	8,250	700

[a] A positive change in SOM represents a loss of soil.
[b] Observed values are obtained from Brye et al. (2002).
[c] Brye et al. (2002) reported ΔSOM values for both fertilizer treatment and tillage treatment. The values shown in the table represent the averages of these two values: CT,f (13,600; 8700); NT, f (7,800; 8,700).

3.6.2 Animal Respiration

IFSM predictions of CO_2 emissions from animal respiration were evaluated by comparing model predictions to published emissions from a chosen study. We chose individual studies that represented typical emissions within the ranges shown in Chapter 2, that included the input information required to simulate the study with IFSM, and that were not a source of data for the models used in the CO_2 module.

A study by Kinsman et al. (1995) was selected to test the ability of IFSM to simulate CO_2 emissions due to animal respiration. Kinsman et al. (1995) measured CO_2 emissions from 118 lactating cows weighing an average of 602 kg and with average milk production of approximately 10,403 kg cow^{-1} yr^{-1}. On average, animals were fed 17.5 kg DM $animal^{-1}$ day^{-1} (± 1.4 kg DM $animal^{-1}$ day^{-1}). The diet consisted of corn silage, alfalfa silage, hay, roasted soybean, barley, and other supplements (Table 3-6). Kinsman et al. (1995) reported that the CO_2 emissions ranged from 5032 to 7427 L CO_2 cow^{-1} day^{-1} (10 to 14.7 kg CO_2 cow^{-1} day^{-1}) with an average respiration rate of 6,137 L CO_2 cow^{-1} day^{-1} (12.2 kg CO_2 cow^{-1} day^{-1}). Using the average diet characteristics and milk production of the study, IFSM predicted 12.8 kg CO_2 cow^{-1} day^{-1}. This simulated emission is within the range, and close to the average, CO_2 respiration rate reported by Kinsman et al. (1995), illustrating that IFSM is capable of predicting CO_2 emissions from animal respiration. In addition, IFSM accurately predicted CH_4 emissions from this same study (Chapter 4).

Table 3-6. Ingredient composition of diet (Kinsman et al., 1995).

Feed type	Contribution (% of DM)
Corn silage	36
Wilted alfalfa silage	32
Hay (timothy and alfalfa)	12
Roasted soybean	13.6
Barley	3.2
Other[a]	3.2

[a] Other ingredients include small contributions from urea, limestone, dicalcium phosphate, cobalt-iodized salt, trace mineral premix, and vitamin premix.

3.6.3 Representative farm

In addition to testing IFSM's ability to simulate the C cycle and predict animal respiration, IFSM's ability to predict whole-farm emissions was also assessed using a representative farm. The representative farm was defined based upon a hypothetical "typical" dairy farm in Pennsylvania with alfalfa, grass, and corn production. The 89 ha farm included 100 Holstein cows and 80 replacement heifers with all animals housed in free-stall barns. Manure was removed daily, stored in an uncovered storage tank with a surface area of 730 m^2 for up to six months, and spread bi-annually. The farm area consisted of 19 ha of grass, 20 ha of alfalfa, and 50 ha of corn (20 ha for corn silage, 30 ha for corn grain harvest). We assumed that all crop nutrient requirements were met through fertilizer applications.

Using the above farm characteristics, IFSM predicted annual emissions of 595 Mg CO_2 from animal respiration and the barn floor (585 Mg from respiration, 10 Mg from the barn floor) and 17 Mg CO_2 from the manure storage. IFSM predicted that croplands sequestered C or, in other words, emitted -267 Mg CO_2 from croplands (Table 3-7). This gave 345 Mg CO_2 yr^{-1} of total emission from the representative dairy farm. IFSM predictions agreed with previously summarized dairy farm emissions from animal respiration and manure storages. For overall farm emissions, IFSM's predicted rate of 345 Mg CO_2 yr^{-1} was similar to the rate of 297 Mg CO_2 yr^{-1}previously estimated as a typical emission for a dairy farm of this size (Table 3-7, Chapter 2). The differences have several explanations. First, measured CO_2 emissions from housing quantified emissions due solely to animal respiration whereas IFSM simulated emissions from both animal respiration and manure on the barn floor. Second, the rate of manure application has a significant impact on the net CO_2 emission from a dairy farm. Finally, factors impacting net emissions include crop yield, type of harvest (e.g., corn silage vs. corn grain), amount of residue returned to the soil, and initial amount of soil C. Assumptions were made for all of these values in order to simulate the representative farm in IFSM. The selection of assumptions did not necessarily match the wide range of management practices represented in the previously estimated average emissions (Table 3-7, Chapter 2). Despite these caveats, IFSM prediction of whole-farm emissions matched typical value fairly well. Based on these evaluations, IFSM was determined to satisfactorily predict CO_2 emissions.

3.7 Conclusion

A module simulating the C cycle including CO_2 emissions from animal respiration, plant respiration, and soil respiration was developed and added to IFSM. Model equations were based on previously published relationships and experimental data. The C module represents the best available models consistent with our modeling objectives and with the current structure of IFSM. IFSM was shown to predict CO_2 emissions that were consistent with reported emissions from specific experiments and previously estimated whole farm emissions. With the incorporation of this C module, IFSM can simulate whole-farm emissions of CO_2 and can be used to evaluate the overall impact of management changes and reduction strategies.

Table 3-7. Typical and predicted CO_2 emissions from a representative farm

	Representative Farm[a] Total Emission [Mg]	IFSM predictions Total emission [Mg]
Housing	523	597[b]
Manure Storage	26	17
Croplands		
Grass	-122	--
Alfalfa	-127	--
Corn silage[c]	-355	--
Corn grain[c]	-266	--
Field-applied manure[d]	618	--
Total cropland	-252	-267
Total	297	345

[a] Emission rates were obtained from Chapter 2. Total emissions were calculated using the identified rates, 190 LU, 1500 m^3, 19 ha of grass, 20 ha of alfalfa, and 50 ha of corn.

[b] 585 Mg were emitted due to animal respiration; the remaining 10 Mg were emitted from the barn floor.

[c] The CO_2 emission data for corn does not provide separate emission rates from corn silage and corn grain. To accurately reflect conditions on the representative farm, we assumed that 20 ha of the corn area were devoted to silage (13 t DM/ha) and 30 ha were devoted to grain (6 t DM/ha). We calculated emission rates of 19 Mg CO_2e ha^{-1} silage and 8.8 Mg CO_2e ha^{-1} grain.

[d] The CO_2 data for crop emissions does not account for field-applied manure. To account for this, we assumed that 6000 m^3 of manure was produced on the farm in a year. With a 7% DM content and 40% carbon content, 658 Mg CO_2e were field-applied and respired as CO_2.

Chapter 4

Simulating Methane Emissions From Dairy Farms

Abstract. Legislation and initiatives on the national and international levels are focused on reducing the emissions of greenhouse gases. Although much of the focus is on carbon dioxide, methane is a stronger greenhouse gas. As a sector, agriculture is reported to be the third greatest contributor of methane in the U.S., emitting one-quarter of total U.S. methane emissions. The primary sources of methane on a dairy farm are animals and manure storages, with smaller contributions from field-applied manure, feces deposited by grazing animals, and manure on barn floors. Proposed reduction strategies must be evaluated on the whole-farm level to ensure that overall methane emissions are reduced. This assessment can be done through computer simulation. One tool that can perform this type of whole-farm evaluation is the Integrated Farm System Model, a process-based computer simulation model of farm production systems. This model was modified to include simulation of methane emissions from enteric fermentation in animals, manure storages, field-applied manure, feces deposited on pasture, and manure on barn floors. The model predicted animal emissions of 124 kg CH_4 cow^{-1} yr^{-1}, which fell within one standard deviation of measured emissions. For manure storage, the model simulated 3.2 kg CH_4 m^{-3} yr^{-1}, which was also consistent with reported emissions. This research shows that a whole-farm model that includes process-based relationships predicting CH_4 emissions can be effectively used to evaluate proposed CH_4 reduction strategies.

4.1 Introduction

In 2007, the Intergovernmental Panel on Climate Change (IPCC, 2007) reported that it is “extremely likely” (i.e., representing a 95% confidence level or higher) that anthropogenic emissions of greenhouse gases (GHGs) are causing a change in the global climate. Although many mitigation plans currently focus on reducing carbon dioxide (CO_2) emissions, methane (CH_4) is a stronger greenhouse gas and has a global warming potential around 23 times that of CO_2 (IPCC, 2007). The Food and Agriculture Organization of the United Nations has claimed that livestock emit more CH_4 in CO_2 equivalents than transportation (FAO, 2006). In 2005, agriculture was reported to contribute 25% of the total U.S. CH_4 emissions, behind only the energy sector (39%) and human waste management (36%) in overall impact (EIA, 2006). As a result, quantifying and reducing CH_4 emissions from livestock farms is important in reducing overall CH_4 emissions.

Multiple processes emit CH_4 from dairy farms including enteric fermentation in animals and microbial processes in manure on the barn floor, during storage, and following field application. A review of agricultural emission experimental data shows that the majority of CH_4 from dairy farms is created through enteric fermentation, followed closely by emissions from manure storages (Chapter 2). Recent research has shown that plants may also emit CH_4, although the mechanism is not currently known (Keppler and Röckmann, 2007). Field studies (e.g., Sherlock et al., 2002), as well as the review of agricultural emissions mentioned above, report croplands as a negligible source, or small sink, of CH_4 in the long term. However, field-applied slurry can result in significant emissions for several days after application (Chadwick and Pain, 1997; Sherlock et al., 2002). Thus, the primary emissions of CH_4 on a dairy farm are emissions from animals due to enteric fermentation and from manure during storage. In addition to these major sources, less significant emissions result from field-applied manure and from manure deposited by animals inside barns or on pasture.

Computer simulation can be a cost-effective and efficient method of estimating CH_4 emissions from dairy farms and analyzing how management scenarios affect these emissions. The Integrated Farm System Model (IFSM), a model developed by the USDA Agricultural Research Service (ARS), is a process-based whole-farm simulation including major components for soil processes, crop growth, tillage and planting operations, feed storage, herd and feeding, manure storage, and economics, with each divided into smaller components (Rotz and Coiner, 2005). IFSM can predict the effect of management scenarios on farm profitability and environmental pollutants such as nitrate leaching, ammonia volatilization, and phosphorus loss, but did not predict GHG emissions.

The overall objective of this research was to quantify CH_4 emissions from dairy farms and to analyze how management scenarios affect these emissions. To accomplish this, we sought to incorporate a module into IFSM that simulates emissions of CH_4 from dairy farms and to evaluate the effectiveness of this tool at predicting farm level emissions of CH_4. This expanded version of IFSM will provide a tool for evaluating the impact of various reduction strategies on CH_4 emissions, along with the effects on other environmental factors and farm profitability. Specific objectives were to review published models that simulate CH_4 emissions, to identify the relationships that best fit our modeling goals, to adapt these models for use in IFSM, and to use this tool to predict whole-farm CH_4 emissions.

4.2 Model Criteria

A number of models have been published that predict CH_4 emissions. In order to develop our module, we selected relationships from these published models that best fit our research goals. Therefore, we identified a list of criteria used to evaluate potential models. These criteria were:

1. ***The model must be able to simulate processes that affect CH_4 emissions when farm management changes are employed.***

   Strategies to reduce CH_4 emissions from enteric fermentation primarily involve diet modifications. Strategies to reduce CH_4 emissions from manure storages can include capturing and flaring the gas or implementing different storage practices. In order to analyze how these practices affect CH_4 emissions, the model must account for associated changes (e.g., animal ration, manure type and storage design).

2. ***The model should be process-based.***

   Several published models, as well as the IPCC, predict CH_4 emissions from farms using emission factors (e.g., Schils et al., 2005; Lovett et al., 2006). While these models are useful as simple tools for estimating CH_4 emissions from farms, they do not have the capability of representing the reduction strategies that affect CH_4 emissions. For example, Schils et al. (2005) simulate CH_4 emissions due to enteric fermentation in heifers and calves by multiplying a group-specific emission factor by the number of animals in each group. This model only accounts for the effect of reducing or increasing animal numbers and does not account for diet modifications. As a result, our goal was to select physically- and biologically-based relationships that satisfied criterion 1 as compared to models based on emission factors.

3. ***The model should satisfactorily predict observed data over a full range of potential conditions.***

   A primary goal of models is to simulate observed data. As a result, the chosen relationships should predict CH_4 emissions within the range of emissions measured from dairy farms.

4. ***The model should be consistent with the current scale of other components in IFSM.***

   The intent of IFSM is to simulate realistic management scenarios that can be implemented by farmers. The characteristics of these scenarios are at the field- or farm-level (e.g., animal diets, sequence of tillage operations, manure storage duration). Subsequently, IFSM simulates processes, normally on a daily time step, at the field- or farm-level according to the assumed farm characteristics. As a result, selected relationships, as well as associated inputs and parameters, must function well at the field- or farm-level as opposed to different scales (e.g., microbiological or watershed).

5. ***Model inputs and parameters should use readily available data.***

   Some of the available mechanistic models predict emissions with high accuracy; however, these models typically have many inputs or are highly parameterized. The required values are often the result of calibrating the model against observed data, are difficult to obtain, or have no physical or biological basis. The uncertainty added by making assumptions for parameter values can outweigh the benefit of using a highly mechanistic model. In contrast, the majority of parameters and inputs in IFSM are not calibration parameters, are relatively easily obtained through on-farm measurements, and correspond to characteristics of the farm. As a result, our final criterion was that inputs and parameter values should be easily obtained within, or consistent with, the current structure of IFSM.

4.3 Enteric Fermentation

Enteric fermentation in ruminants is the largest source of CH_4 emissions from dairy farms (EIA, 2006; Chapter 2). Ruminants (e.g., cattle, sheep) subsist primarily on forages like grasses and leafy plants. Like most animals, ruminants do not have the enzymes necessary to break down cellulose. Instead, enteric methanogens exist in a symbiotic relationship with other microorganisms in the rumen (i.e., the fore-stomach) and, through enteric fermentation, break down and obtain energy from cellulose. In the rumen, enteric methanogens prevent the build-up of the hydrogen produced during fermentation by using it to reduce CO_2 to CH_4. The CH_4 produced is released by the ruminant to the atmosphere by eructation, or belching. Other roles of these microorganisms are not fully understood (Madigan et al., 2003).

Although enteric fermentation allows ruminants to obtain energy from cellulose, this process also produces CH_4. The amount of CH_4 produced from enteric fermentation is impacted by various factors including animal type and size, digestibility of the feed, and the intake of dry matter, total carbohydrates, and digestible carbohydrates (Monteny et al., 2001; Wilkerson et al., 1995). Because of the role of CH_4 in climate change, various models have been published that attempt to predict the amount of CH_4 produced by ruminant animals.

4.3.1 Enteric Fermentation Model Review

Enteric fermentation models can be categorized as mechanistic and empirical. The more mechanistic models (e.g., Baldwin et al., 1987; Dijkstra et al., 1992; Mills et al., 2001) are based on the chemical or microbiological processes occurring in the rumen that produce CH_4. These models are highly detailed and require many state variables and equations to simulate CH_4 emissions from livestock. For example, Dijsktra et al. (1992) utilized 17 state variables and more than 100 equations to simulate enteric fermentation. Empirical models are based on equations relating CH_4 emissions to various factors. These models range from equations based solely on statistical correlations to biologically-based relationships.

The first widely used ruminant CH_4 model was an empirical model published by Blaxter and Clapperton in 1965 (Table 4-1). Methane production was correlated to level of feeding (i.e., a multiple of the recommended energy requirement for maintenance) and the digestibility of the animal's diet. Other empirical models have related CH_4 production to feed characteristics (Moe and Tyrrell, 1979), to milk yield and live weight (Kirchgessner et al., 1991), to dry matter intake and feed characteristics (Yates et al., 2000), and to metabolizable energy intake, a maximum potential CH_4 production, and feed characteristics (Mills et al., 2003) (Table 4-1).

Reviews of both mechanistic and empirical models have been published (Wilkerson et al., 1995; Benchaar et al., 1998; and Mills et al., 2003). Mechanistic

Table 4-1. Summary of empirical models simulating CH_4 production through enteric fermentation.

Model	Model core equations[a]	Units
Blaxter and Clapperton (1965)	$E_{CH4,ent}$ = 1.30+0.112*D–L*(2.37–0.05*D) L = multiple of maintenance level D = apparent digestibility	kcal CH_4 / 100 kcal feed
Moe and Tyrrell (1979)	$E_{CH4,ent}$ = 0.439+0.273*R+0.512*H+1.393*C R = residue (kg) H = hemicellulose (kg) C = cellulose (kg)	Mcal CH_4
Kirchgessner et al. (1991)	$E_{CH4,ent}$ = 55+4.5*M+1.2*W (grass) $E_{CH4,ent}$ = 26+5.1*M+1.8*W (corn silage) M = milk yield W = live weight	g CH_4/day
Yates et al. (2000)	$E_{CH4,ent}$ = 1.36+1.21*D_m-0.825*D_{mc}+12.8*N_d (all) $E_{CH4,ent}$ = -35.5+0.0216*N+27.6*S_{dm}+1.63*G_{dm} (silage) D_m = dry matter intake (kg) D_{mc} = dry matter concentrates (kg) N_d = ratio of NDF/D_m N = N intake S_{dm} = ratio of silage D_m/D_m G_{dm} = ratio of gross energy/D_m	MJ CH_4/day
Mills et al. (2003)	$E_{CH4,ent}$ = E_{max} - E_{max} * e^(-c*M_{EI})] E_{max} = maximum value of CH_4 production c = shape parameter M_{EI} = metabolizable energy intake	MJ CH_4/day

[a] $E_{CH4,ent}$ represents the emission of CH_4 from enteric fermentation as simulated by the various models being used. The units of $E_{CH4,ent}$ vary for each model and are listed under the column "Units."

models, such as Mills et al. (2001), explained more variation as compared to empirical models. However, although the mechanistic model of Mills et al. (2001) satisfied criteria 1, 2, and 3, the model did not satisfy the remaining two criteria. Mills et al. (2001) simulated CH_4 production by modeling the chemical reactions in the rumen. One section of their model predicts hydrogen production as a function of microbial biomass. As stated in the criteria, IFSM simulates processes at the field- or farm-scale, not the microbiological scale, and so the model did not satisfy criterion 4. More importantly, the inputs and parameters required by their models were not readily available. In order to use Mills et al. (2001), a number of assumptions had to be made to set input parameters, which may vary from farm to farm. These values may not be readily available or may be poorly defined for the wide range of animal management strategies found on different farms. As such, the uncertainty added from assuming values for these parameters outweighed the benefit of using a mechanistic model.

Instead, we used the Mitscherlich 3 (Mits3) equation developed by Mills et al. (2003). Mits3 is a simplified, process-based model that was originally developed using data from the U.K. Mits3 satisfies all five criteria. The model is based on dietary composition and is capable of accounting for management practices that alter the animal's intake and diet, satisfying criterion 1. Mits3 is process-based, relating CH_4 emissions to dietary intake as well as animal type and size, satisfying criterion 2. When compared to data from the U.S., Mits3 yielded a regression slope of 0.89 and an intercept of 3.50 (Mills et al., 2003). Also, as an indication of the overall error of prediction, the square root of the mean square prediction error (MSPE) was 34.1% for the American data. These results show that Mits3 satisfactorily predicts data from the U.S. even though it was developed using U.K. data, satisfying criterion 3.

In addition, Mits3 predicts realistic emissions at the extremes of the parameter ranges (i.e., with zero feed intake, the model predicts zero CH_4 production and, at the other extreme of very high feed intake, the nonlinear model predicts that CH_4 emissions approach a maximum possible emission). Thus, an additional benefit of the nonlinearity of Mits3 is that the model can be applied to conditions outside those for which it was originally developed without predicting unreasonable emissions since the model limits predicted emissions to a specified maximum value. In comparison, the other empirical models are linear models that predict CH_4 emissions outside the realistic range as feed intake increases (Mills et al., 2003; Kebreab et al., 2006).

Mits3 satisfies criterion 4, as the much simpler formulation is consistent with the scale of other processes predicted in IFSM. Finally, Mits3 satisfies criterion 5 by requiring only three model inputs that are easily obtained from the feed and animal components of IFSM: the starch content of the diet, the acid detergent fiber (ADF) content of the diet, and the metabolizable energy intake. Also, these three inputs are directly related to the animal's diet and indirectly related to the animal's characteristics. This allows prediction of changes in CH_4 production as effected by changes in animal nutrition and management.

4.3.2 Enteric Fermentation Model Description

A detailed description of the development of the selected model can be found in Mills et al. (2003). This section provides a brief description of the model, how the parameters were calculated, and how the model was integrated with IFSM.

Emission of CH_4 is predicted as:

$$E_{CH4,ent} = \left[E_{\max} - E_{\max} \exp\left(-c \cdot M_{EI}\right)\right] \cdot F_{kgCH4} \tag{4.1}$$

where $E_{CH4,ent}$ is the emission of CH_4 due to enteric fermentation [kg CH_4 cow^{-1} day^{-1}], E_{max} is the maximum possible emission of CH_4 [MJ CH_4 cow^{-1} day^{-1}], c is a shape parameter determining how emissions change with increasing M_{EI} [dimensionless], M_{EI} is the metabolizable energy intake [MJ cow^{-1} day^{-1}], and F_{kgCH4} is a conversion factor to convert megaJoules of CH_4 to kg CH_4 [0.018 kg CH_4 MJ^{-1}].

The maximum possible emission of methane, E_{max}, is defined as 45.98 MJ CH_4 cow^{-1} day^{-1}. Mills et al. (2003) determined this value by statistically analyzing observed U.K. data using the nonlinear mixed procedure in SAS (SAS Institute Inc., Cary, NC). Although this maximum possible emission is constant for all cows, the other inputs, namely MEI, indirectly account for the effect of different sizes and types of animals.

The shape parameter, c, is calculated as:

$$c = -0.0011 \cdot \left[\frac{starch}{ADF}\right] + 0.0045 \tag{4.2}$$

where *starch* is the starch content of the diet and *ADF* is the acid detergent fiber content of the diet. Equation 4.2 accounts for the tendency of CH_4 emissions to increase with fibrous diets (i.e., high ADF) and to decrease with high starch diets.

Based on the above equations, three inputs are needed for this model: the starch content of the diet, the ADF content of the diet, and the metabolizable energy intake, M_{EI}. Currently, IFSM determines the ration that each animal group is fed based on the animal nutrition requirements and the available feeds (Rotz et al., 1999). This information includes the total dry matter intake [kg DM day^{-1} cow^{-1}], the energy content of the diet [MJ kg DM^{-1}], and the specific type of feeds used. The first two parameters were used to calculate M_{EI}. The ADF content of the feeds used in IFSM (Table 4-2) was calculated by assuming a linear relationship with neutral detergent fiber (NDF) for each type of feed, with this relationship based on data from the National Research Council (NRC, 2001). The starch content of the feeds used in IFSM (Table 4-2) was calculated by assuming a linear relationship with the amount of nonfibrous carbohydrates (NFC) in the feed. The fraction of NFC was predicted by:

$$F_{NFC} = 1 - \left(F_{NDF} + F_{CP} + F_{fat} + F_{ash}\right) \tag{4.3}$$

where F_{NFC} is the fraction of NFC in the diet, F_{CP} is the fraction of crude protein (CP) in the diet, F_{fat} is the fraction of fat in the diet, and F_{ash} is the fraction of ash in the diet. The fractions of NDF and CP are available in IFSM; typical fractions of fat and ash were obtained from the National Research Council (NRC, 2001).

Table 4-2. Relationships used to model the starch and ADF content of feeds in IFSM.

Feed type	Starch[a],[b] [fraction]	ADF [fraction]
Alfalfa hay	$0.64*(1-F_{NDF}-F_{CP}-0.11)$	$0.78*F_{NDF}$
Alfalfa silage	$0.89*(1-F_{NDF}-F_{CP}-0.12)$	$0.82*F_{NDF}$
Grass hay	$0.45*(1-F_{NDF}-F_{CP}-0.11)$	$0.61*F_{NDF}$
Grass silage	$0.65*(1-F_{NDF}-F_{CP}-0.12)$	$0.64*F_{NDF}$
Corn grain	0.68	0.036
High moisture corn	0.52	0.004
Corn silage	$0.80*(1-F_{NDF}-F_{CP}-0.07)$	$0.62*F_{NDF}$
Perennial grass/legume	$0.48*(1-F_{NDF}-F_{CP}-0.14)$	$0.72*F_{NDF}$
Alfalfa pasture	$0.48*(1- F_{NDF}-F_{CP}-0.14)$	$0.55*F_{NDF}$
Protein supplement 1	0.0	0.0
Protein supplement 2	0.0	0.0
Fat additive	0.0	0.0

[a] The last value in the equation in the starch column represents an average total of fat and ash (see Fat + Ash column).
[b] F_{NDF} (fraction of neutral detergent fiber in feed) and F_{CP} (fraction of crude protein in feed) are available in IFSM.
[c] Average values for fat and ash were obtained from NRC (2001).

A given animal group is likely fed a mixture of different types of feed making up the whole diet. A weighted average of feeds in the ration was used to determine the starch and ADF content of the ration fed to each of the six possible animal groups making up the herd (Rotz et al., 1999).

4.4 Manure Storage

In addition to enteric fermentation, CH_4 is generated during manure storage. This reaction is similar to that described for enteric fermentation in many ways. The cellulose in the manure is degraded, with products of this process serving as substrates for methanogenesis. Temperature and storage time are the most important factors influencing CH_4 emissions from manure storage because substrate and microbial growth are generally not limited (Monteny et al., 2001). Although the processes are similar, there are important differences between the rumen and manure storage, including the following: the temperature in manure storages varies, in contrast to the relatively constant temperature in the rumen, and the conditions in manure storages are more heterogeneous (e.g., the substrate is less well mixed and some carbohydrates are already partially decomposed) as compared to the constancy of the rumen (Monteny et al., 2001).

4.4.1 Manure Storage Model Review

As with enteric fermentation, both mechanistic and empirical equations have been used to predict CH_4 emissions from manure storages. Unlike some of the empirical enteric fermentation models that simply utilize correlations that are not necessarily based on biological processes, the majority of manure storage models are biologically-based. Even the empirical manure storage models contain process-based components. Two mechanistic (Hill, 1982; and García-Ochoa et al., 1999) and four empirical models (Chen and Hashimoto, 1980; Hill, 1991; Zeeman, 1994; and Sommer et al., 2004) are described in this review. Although many models exist, these six models are representative of the main types of models that simulate emissions from manure storages.

Hill (1982) described a comprehensive and dynamic mechanistic model to predict CH_4 production through animal waste methanogenesis. The model satisfies criteria 1, 2, and 3 of our model requirements. The model is based on biological processes and thus satisfies criterion 2. Because it utilizes biological reactions, input parameters can be changed to account for different reduction strategies, satisfying criterion 1. Model results show high goodness of fit for dairy manure, satisfying criterion 3. However, the model simulates CH_4 production based on the chemical and microbiological reactions in the storage. As a result, the model scale is not consistent with that of IFSM. Additionally, there are many required model parameters that require iterative solutions, and input values may be difficult to obtain.

García-Ochoa et al. (1999) published a mechanistic kinetic model that used three stages to simulate anaerobic digestion and CH_4 production from animal waste. The three stages included (1) the conversion of complex biopolymers to simpler, more accessible substrates, (2) the conversion of hydrolyzed animal waste to volatile organic acids, and (3) the production of CH_4 from volatile organic acids. Assumptions made in developing the model included lumped parameter, pseudo-steady state, and first-order kinetics. This model satisfies criteria 1, 2, and 3. Model parameters can be modified to account for different reduction strategies, satisfying criterion 1. The model is based on biological reactions rather than empirical equations, satisfying criterion 2. Model results of anaerobic digestion and CH_4 production fall within the experimental uncertainty, satisfying criterion 3. However, the model must determine values for the ten parameters iteratively using a fourth-order Runge Kutta algorithm linked to a non-linear multiple response regression. Most parameters in IFSM are externally determined and hard-coded, or are set by the user through a graphical interface. The technique used by García-Ochoa et al. (1999) is thus not consistent with the current structure of IFSM.

Chen and Hashimoto (1980, Table 4-3) described an empirical model to predict volumetric CH_4 production from anaerobic digesters. This model satisfies all five criteria. The model is process-based, using a maximum possible CH_4 yield to predict emissions. The model accounts for the reduction of this possible yield due to various factors (e.g., volatile solids concentration, temperature, hydraulic retention time). As a result, it can be used to simulate reduction strategies such as changing storage temperature and storage period. When used to predict CH_4 production from the anaerobic digestion of beef cattle manure, the average ratio of experimental to predicted CH_4 production was 0.96 with a standard deviation of ±0.06 (Hashimoto, 1982a). These results show that the model can accurately predict observed data, satisfying criterion 3.

The model is also on the same scale as IFSM and utilizes readily available data for inputs and parameters (Hashimoto et al., 1981; Hashimoto, 1982b, 1983, and 1984).

Hill (1991, Table 4-3) described a single equation model to estimate CH_4 production based on volatile solids (VS) reduction. This model was based on Hill (1982), but was intentionally simplified: the model was intended for field use, where computing capabilities were limited to a calculator, and for undergraduate class simulations, where the goal is to teach students how to calculate CH_4 production rather than what causes the production. Hill (1991) fully satisfies criteria 2 and 3 and partially satisfies 5. The model was based on the concentration and reduction of VS and is thus based on biological principles. Hill (1991) reported that the simple model had prediction confidence of at least 97%, satisfying criterion 3. The model requires few inputs, which are readily available. However, the parameters for the model were empirically derived from model output as described by Hill and Bolte (1987). This model was developed for anaerobic digesters, and the empirical parameters thus may not be applicable to predicting emissions from manure storages with no treatment.

Zeeman (1994, Table 4-3) developed a model to predict the production of CH_4 in manure storages. The model was based on first-order hydrolysis of biodegradable polymers and Monod kinetics to simulate the growth of methanogenic bacteria. Zeeman's model is similar in concept to García-Ochoa et al. (1999), although much simpler. Unlike Hill (1991), experimentally-determined parameters are provided for both digested and fresh manure. The model satisfies criteria 1, 2, 3, and 5, and partially satisfies criterion 4. The equations are based on biological reactions, with parameters provided for storage of fresh manure. The model is accurate and can be used to simulate reduction practices, but it is not completely consistent with the structure of IFSM.

Sommer et al. (2004, Table 4-3) simulated the production and emission of CH_4 from fresh manure storages. Like many of the models previously described, this model bases CH_4 production on the degradation of VS. Additional factors affecting CH_4 production are temperature and storage time. Like Hashimoto et al. (1981), this model also satisfies all five criteria. The model utilizes biological reactions, and the inputs are derived from well-known equations (i.e., Bushwell's equation). Unlike the other models,

Table 4-3. Summary of empirical models simulating CH_4 emissions from manure storages.

Model	Model core equations[a]	Units
Chen and Hashimoto (1980)	$E_{CH4,man} = (B_oS_o/\theta) * [1 – (K/\theta\mu\text{-}1+K)]$ B_o = ultimate CH_4 yield S_o = influent volatile solids concentration θ = hydraulic retention time μ = maximum specific growth rate K = kinetic parameter	L CH_4 L^{-1} day^{-1}
Hill (1991)	$E_{CH4,man} = \gamma * \tau * \sigma$ γ = specific CH_4 productivity τ = volatile solids reduction σ = organic loading rate stress factor	L CH_4 L^{-1} day^{-1}
Zeeman (1994)	$E_{CH4,man} = \alpha * S_p$ α = first order hydrolysis constant S_p = concentration of biodegradable polymer substrate	g CH_4 L^{-1} day^{-1}
Sommer et al. (2004)	$E_{CH4,man} = V_{s,d} * b_1 * \exp[\ln(A) – E*(1/R*T)] +$ $V_{s,nd} * b_2 * \exp[\ln(A) – E*(1/R*T)]$ $V_{s,d}$, $V_{s,nd}$ = degradable and nondegradable volatile solids b_1, b_2 = rate correcting factors (1, 0.01) A = Arrhenius parameter E = activation energy R = universal gas constant T = temperature	g CH_4 day^{-1}

[a] $E_{CH4,man}$ represents the emission of CH_4 from manure storage as simulated by the various models being used. The units of $E_{CH4,man}$ vary for each model and are listed under the column “Units.”

Sommer et al. (2004) was developed more generally and can be easily applied to either digested or untreated manure.

Based on the above descriptions, we considered three of the six original models: Hashimoto et al. (1981), Zeeman (1994), and Sommer et al. (2004). We concluded that Zeeman (1994) was less suitable than the remaining two models for several reasons.

Hashimoto et al. (1981) and Sommer et al. (2004) do not use emission factors to determine the emission of CH_4; Zeeman (1994) uses biologically-based equations to predict CH_4 production, but requires emission factors or another method to predict the actual emission of CH_4. Sommer et al. (2004) questioned whether the parameters published in Zeeman (1994) were derived solely from anaerobically-digested manure data.

In contrast, values for the empirical parameters in Sommer et al. (2004) can be applied to either digested or fresh manure. Hashimoto et al. (1981) and subsequent publications (Hashimoto 1982b, 1983, and 1984) provide equations to calculate the empirical parameters as functions of temperature and VS concentration. Either of these two models can thus be applied to both digested and fresh manure. Additionally, both Hashimoto et al. (1981) and Sommer et al. (2004) utilize relationships that account for the effect of temperature on emission rates. Finally, the scale of either Hashimoto et al. (1981) or Sommer et al. (2004) is more consistent with IFSM than is that of Zeeman (1994).

Thus, the models of either Hashimoto et al. (1981) or Sommer et al. (2004) would fit our objectives. The models are similar, with both based on the VS content of manure. Sommer et al. (2004) utilize the VS content in the manure storage, while Hashimoto et al. (1981) require the influent concentration of VS. In order to use Sommer et al. (2004), the content of VS in the manure storage must be tracked throughout the simulation. This requires a separate model, which would unnecessarily complicate the code. In contrast, because the model of Hashimoto et al. (1981) only requires the influent concentration of VS, this model is more easily utilized. However, although Hashimoto et al. (1981) can be applied to fresh manure, several of the parameters were empirically determined based on data from anaerobic digesters. Sommer et al. (2004) employ commonly used empirical relationships (e.g., Arrhenius relationship) that are more general and can thus be more easily applied to conditions outside of which they were developed. Additionally, Sommer et al. (2004) is a more recent model and, as such, likely incorporates more recent developments than Hashimoto's model. As a result, despite the similarity between these two models, we chose to use Sommer et al. (2004).

4.4.2 Manure Storage Model Description

A detailed description of the development of the chosen model can be found in Sommer et al. (2004). This section briefly describes the model, how the parameters were calculated, and how the model was integrated with IFSM.

Sommer et al. (2004) predict CH_4 as:

$$E_{CH4,man} = \frac{V_{s,d} \cdot b_1}{1000} \cdot \exp\left[\ln(A) - \frac{E}{RT}\right] + \frac{V_{s,nd} \cdot b_2}{1000} \cdot \exp\left[\ln(A) - \frac{E}{RT}\right] \quad (4.4)$$

where $E_{CH4,man}$ is the emission of CH_4 from manure storage [kg CH_4 day^{-1}], $V_{s,d}$ and $V_{s,nd}$ are the degradable and nondegradable volatile solids [g kg^{-1} manure], b_1 and b_2 are rate correcting factors [dimensionless], A is the Arrhenius parameter [g CH_4 kg^{-1} VS h^{-1}], E is the apparent activation energy [J mol^{-1}], R is the gas constant [J K^{-1} mol^{-1}], and T is the temperature [K] (Table 4-4).

Sommer et al. (2004) estimates the fraction of degradable volatile solids as:

$$V_{s,d} = V_{s,tot} \frac{B_o}{E_{CH4,pot}} \quad (4.5)$$

where $V_{s,tot}$ is the volatile solids of the manure [g VS kg^{-1} manure], B_o is the achievable emission of CH_4 during anaerobic digestion [g kg^{-1} VS] and $E_{CH4,pot}$ is the potential CH_4 yield of the manure [g kg^{-1} VS] , which can be estimated using Bushwell's equation and the carbohydrate, fat, and protein content of the manure. For cattle slurry, Sommer et al. (2004) define B_o as 0.2 g CH_4 kg^{-1} VS and $E_{CH4,pot}$ as 0.48 g CH_4 kg^{-1} VS.

Rather than tracking the change in volatile solids content of the manure throughout the simulation period, we modified Sommer et al. (2004) to base CH_4 emissions on the influent volatile solids content. Total volatile solids, $V_{s,tot}$, can be estimated using the manure mass, the total solids content, and the volatile solids content:

$$V_{s,tot} = M_{manure} \cdot P_{TS} \cdot P_{VS} \quad (4.6)$$

where M_{manure} is the mass of manure entering the storage [kg], P_{TS} is the total solids content in the manure [g TS kg^{-1} manure], and P_{VS} is the content of volatile solids in the total solids [g VS g^{-1} TS].

The mass of nondegradable volatile solids, $V_{s,nd}$, is then calculated using a mass balance.

$$V_{s,nd} = V_{s,tot} - V_{s,d} \quad (4.7)$$

Table 4-4. Parameters and values for Sommer et al. (2004).

Parameter	Variable	Value	Units
total solids[a]	P_{TS}	0.107, 0.116, 0.125[b]	g TS g^{-1} manure
volatile solids[a]	P_{VS}	0.726, 0.698, 0.68[b]	g VS g^{-1} TS
achievable CH_4[c]	B_o	0.2	g CH_4 g^{-1} VS
potential CH_4[c]	$E_{CH4,pot}$	0.48	g CH_4 g^{-1} VS
correcting factors[3]	b_1, b_2	1.0, 0.01	dimensionless
Arrhenius parameter			
in-house[c]	$\ln(A)_{in}$	44.29	dimensionless
Outside[c]	$\ln(A)_{out}$	43.33	dimensionless
activation energy[c]	E	112,700	J mol^{-1}
gas constant[c]	R	8.314	J K^{-1} mol^{-1}

[a] From USDA-SCS (1999).
[b] Values for heifers, dry cows, and lactating cows.
[c] From Sommer et al. (2004).

Although B_o is defined for anaerobic digestion, this parameter can be applied to fresh manure storage. Both anaerobically-digested and fresh manure produce CH_4. Manure in anaerobic digesters typically produces more CH_4 than manure in regular storage because anaerobic digesters are kept at higher temperatures to maximize CH_4 yield. Because the model of Sommer et al. (2004) accounts for the effect of temperature, B_o can still be applied to fresh manure. The model predicts less CH_4 production from fresh manure (i.e., lower temperatures) than it does from digested manure (i.e., higher temperatures).

Based on the above equations, the inputs required for this model are the mass and temperature of the manure in storage. The mass of the manure in storage is simulated as the accumulation of that produced by the herd; daily manure excretion is determined in the animal component of IFSM (Rotz et al., 1999). Using relationships currently in IFSM, the temperature of the manure in storage is estimated as the average ambient air temperature over the previous ten days. Both the manure quantity produced and daily air temperatures are available in IFSM.

The relationships described above are applicable to uncovered slurry storage. However, some dairy farms utilize control technology to reduce emissions from manure storage. One such control is capturing and flaring the CH_4 gas. This method drastically decreases the emission of CH_4, although it does increase the emission of CO_2 due to the combustion of CH_4. To simulate a tightly enclosed storage, we assumed that the CH_4 was captured and then flared. The emission of CH_4 from an enclosed manure storage was calculated as:

$$E_{CH4,\mathrm{cov}} = E_{CH4,calc} \cdot \left(1-\eta_{eff}\right) \quad (4.8)$$

where $E_{CH4,cov}$ is the CH_4 emitted from the enclosed manure storage [kg CH_4 day^{-1}], $E_{CH4,calc}$ is the calculated emission of CH_4 from manure storage with no cover using equation 4.4 [kg CH_4 day^{-1}], and η_{eff} is the efficiency of the collector [unitless] (EPA, 1997). The efficiency of the collector and flare was assumed to be 99% (EPA, 1997).

The subsequent flaring of the captured CH_4 releases CO_2, which adds to the overall farm emission of this gas which was previously discussed in Chapter 3. The additional emission of CO_2 due to the flaring of CH_4 is calculated as:

$$E_{CO2,\,flare} = E_{CH4,\mathrm{cov}} \cdot 2.75 \quad (4.9)$$

where $E_{CO2,flare}$ is the emission of CO_2 due to flaring of CH_4 captured from manure storage [kg CO_2 day^{-1}] and 2.75 is the ratio of the molecular weights of CO_2 and CH_4.

4.5 Other Sources

As described previously, enteric fermentation and manure storage are the primary sources of CH_4 from farms, contributing 63% and 30%, respectively, of total agricultural CH_4 emissions (EIA, 2006). Even though manure applied on fields, feces deposited on pasture, and manure on barn floors do not contribute large amounts of CH_4 relative to the primary sources, we included relationships to simulate these emissions so that we could comprehensively predict farm-level CH_4 emissions from all sources.

4.5.1 Field-applied Manure

Research has shown that field-applied slurry is a source of CH_4 emissions for several days after application, emitting between 40 to 90 g CH_4 ha^{-1} day^{-1} (Sommer et al., 1996; Chadwick and Pain, 1997; Sherlock et al., 2002). Emissions drastically decreased within the first three days, and soils returned to being a neutral source, or slight sink, of CH_4 after 11 days (Sherlock et al., 2002).

Sherlock et al. (2002) relate CH_4 emissions from field-applied slurry to the volatile fatty acids (VFAs) concentration in the soil. The VFAs in the soil are due to the application of the slurry (Sherlock et al., 2002). As a result, we modified the model of Sherlock et al. (2002) to relate CH_4 emissions to the VFA concentration in the slurry as compared to the concentration in the soil. Emissions of CH_4 from field-applied slurry were predicted as:

$$E_{CH4,app} = (0.170 \cdot F_{VFA} + 0.026) \cdot A_{crop} \cdot 0.032 \tag{4.10}$$

where $E_{CH4,app}$ is the emission of CH_4 from field-applied slurry [kg CH_4 day^{-1}], F_{VFA} is the daily concentration of VFAs in the slurry [mmol kg^{-1} soil], and A_{crop} is the crop area [ha] where the manure is applied. Equation 4.10 is valid for CH_4 emissions within the first 11 days of application; after 11 days, CH_4 emissions are assumed to be negligible until the next application.

Sherlock et al. (2002) found that the daily VFA concentration exponentially decreased in the days following the application of manure slurry and approached background levels within approximately four days. Using this information, we derived a relationship predicting the daily concentration of VFA in the field-applied slurry.

$$F_{VFA} = F_{VFA,init} \mathrm{e}^{-0.6939 \cdot t} \tag{4.11}$$

where F_{VFA} is the daily concentration of VFAs in the slurry [mmol kg^{-1} slurry], $F_{VFA,init}$ is the initial concentration of VFAs in the slurry at the time of application [mmol kg^{-1} slurry], and t is the time since application [days], with t=0 representing the day of application.

Paul and Beauchamp (1989) developed an empirical model relating the pH of manure slurry to the VFA and total ammoniacal nitrogen (TAN).

$$pH = 9.43 - 2.02 \cdot \frac{F_{VFA,init}}{F_{TAN}} \tag{4.12}$$

where pH is the pH of the manure slurry [dimensionless] and F_{TAN} is the concentration of TAN (NH_4^+ + NH_3) in the slurry [mmol kg^{-1} slurry]. Rearranging Equation 4.12, we obtained an equation predicting the initial concentration of VFAs based on the pH and TAN of the manure slurry.

$$F_{VFA,init} = \frac{F_{TAN}}{2.02}(9.43 - pH) \tag{4.13}$$

To predict an emission from field applied manure, Equation 4.13 was used to determine an initial VFA concentration and equation 4.11 was used to track the VFA concentration through time following field application. Using this concentration, an emission rate was determined until the remaining VFA concentration approached zero.

4.5.2 Grazing Animals

In farming systems that incorporate grazing for a portion of the year, freshly excreted feces and urine are directly deposited by animals on pastures. Studies have shown that feces are a small source of CH_4 and that emissions from urine are not significantly different from background soil emissions (e.g., Jarvis et al., 1995; Yamulki et al., 1999). Because animal-deposited feces contribute only minimally to overall farm CH_4 emissions, there were few data quantifying these emissions. A 2004 review of emissions from grazing animals concluded that CH_4 emission rates from freshly deposited feces were influenced by environmental conditions and animal rations, which were highly variable and unable to be represented by a constant emission rate (Saggar et al., 2004b).

Despite this conclusion, we chose to use a constant emission factor to predict CH_4 emissions from feces deposited by grazing animals. The limited research data available and the relatively minor emission from this source do not justify using a more process-based model. As a result, a constant emission factor represented the best available method of predicting CH_4 emissions from pasture-deposited feces. To determine this emission factor, we obtained emission rates from four published studies and used the average of 0.086 g CH_4 kg^{-1} feces for our emission rate (Table 4-5). For grazing systems, the daily emission of CH_4 was predicted as the product of this emission rate and the daily amount of feces deposited by grazing animals.

Table 4-5. Published and average emission rates of CH_4 emitted from feces directly deposited by animals on pasture lands.

Reference	Emission rate [g CH_4 kg^{-1} feces]
Jarvis et al. (1995)	0.110
Flessa et al. (1996)	0.130
Holter (1997)	0.068
Yamulki et al. (1999)	0.036
Average	***0.086***

4.5.3 Barn Emissions

Floors of housing facilities can be a source of CH_4 emissions due to animal-deposited manure. Immediately after cleaning and removal, some manure likely remains on the floor and continues to be a source of emissions. No published model or data were found for this emission source. As a result, unpublished CH_4 emissions data measured from barn floors (Varga et al., 2007) were used to develop an equation relating CH_4 emissions to the ambient temperature (R^2 = 0.56).

$$E_{CH4,\,floor} = \max(0.0,\, 0.14T + 0.29) \cdot A_{barn} / 1000 \qquad (4.14)$$

where $E_{CH4,floor}$ is the daily rate of CH_4 emission from the barn floor [kg CH_4 day^{-1}], T is the ambient temperature [°C], and A_{barn} is the area of the barn floor covered with manure [m^2].

Equation 4.14 satisfies criteria 3 and 5. Equation 4.14 is an empirical equation that correlates CH_4 emissions with temperature. We chose to use this relationship because it represents the best available information that we currently have describing CH_4 emissions. The temperature dependence of CH_4 production is well-documented (Zeikus and Winfrey, 1976; van Hulzen et al., 1999), and equation 4.14 thus relates CH_4 emission to a well-known influencing factor. As a function of temperature, equation 4.14 is a simplified, process-based equation, thus satisfying criterion 4 as well. This simple relationship predicts reasonable emission rates for ambient temperatures of 0°C and greater. Because this emission source contributes relatively minor amounts to overall farm-level CH_4 emissions, development of a more detailed model was not justified.

4.6 Model Evaluation

Few data exist on overall emissions of CH_4 from dairy farms in the U.S. (Chapter 2). The studies that quantified CH_4 emissions from specific sources on farms often have not provided the specific input data required to simulate scenarios in IFSM. In addition, these studies tended to be small-scale or laboratory studies that could not be adequately simulated in IFSM, which simulates processes on a farm-scale. Because of this, we evaluated IFSM predictions of CH_4 emissions in three ways. First, for each emission source, we used an individual study to evaluate IFSM's ability to predict the observed emissions. We chose individual studies that represented typical emissions within the ranges in Chapter 2, that included the input information required to simulate the study with IFSM, and that were not a source of data for the models used in the CH_4 module (Table 4-6). Second, we used IFSM to simulate a representative farm and compared IFSM predictions to the ranges identified in Chapter 2. Finally, we performed a sensitivity analysis on the important parameters in each component of the CH_4 module.

4.6.1 Enteric Fermentation Emissions

We chose Kirchgessner et al. (1991) and Kinsman et al. (1995) as the representative studies to test the ability of IFSM to simulate CH_4 emissions due to enteric fermentation. Kirchgessner et al. (1991) measured CH_4 emissions from 67 lactating cows weighing an average of 583 kg and with average milk production of approximately 6000 L cow^{-1} yr^{-1}. The animals were fed diets consisting of an average of 57% roughage, which was composed of a mixture of grass hay and corn silage. They reported an average CH_4 emission of 300 g CH_4 cow^{-1} day^{-1} (± 39 g CH_4 day^{-1}), or 110 kg CH_4 cow^{-1} yr^{-1} (± 14 kg CH_4 cow^{-1} yr^{-1}). Using the average diet characteristics and target milk production, IFSM predicted 124 kg CH_4 cow^{-1} yr^{-1}. This simulated emission was within one standard deviation of the results reported by Kirchgessner et al. (1991), illustrating that IFSM is capable of predicting CH_4 emissions from enteric fermentation.

Table 4-6. Identified emission ranges (Chapter 2) and specific emission rates from chosen studies used for model evaluation.

	Chapter 2	Specific emission	Reference
Enteric fermentation [kg CH_4 LU^{-1} yr^{-1}]	1 – 169 (65)	96 – 124 (110)	Kirchgessner et al. (1991)
		104 – 173 (141)	Kinsman et al. (1995)
Manure storages [kg CH_4 m^{-3} yr^{-1}]	0.2 – 15 (4.1)	2.0	Külling et al. (2003)

Kinsman et al. (1995) measured CH_4 and CO_2 emissions from 118 lactating cows weighing an average of 602 kg and with an average milk production of approximately 10,100 L cow^{-1} yr^{-1}. On average, animals were fed 17.5 kg DM animal^{-1} day^{-1} (± 1.4 kg DM animal^{-1} day^{-1}). The diet consisted of corn silage, alfalfa silage, hay, roasted soybean, barley, and other supplements (Table 3-6). Kinsman et al. (1995) reported that CH_4 emissions ranged from 436 to 721 L CH_4 cow^{-1} day^{-1} (0.29 to 0.47 kg CH_4 cow^{-1} day^{-1}) with an average rate of 587 L CH_4 cow^{-1} day^{-1} (0.39 kg CH_4 cow^{-1} day^{-1}). Using the average diet characteristics and target milk production, IFSM predicted 0.42 kg CH_4 cow^{-1} day^{-1}. This simulated emission was within the range, and close to the average, CH_4 emission rate reported by Kinsman et al. (1995), illustrating that IFSM is capable of predicting CH_4 emissions from enteric fermentation. As discussed in Chapter 3, IFSM was also able to adequately predict CO_2 emissions from this same study.

4.6.2 Manure Storage Emissions

We chose Külling et al. (2003) as the representative study to test the ability of IFSM to predict CH_4 emissions from manure storages. Külling et al. (2003) measured CH_4 emissions from slurry manure from six dairy cows fed grass- and hay-based rations. Emissions were measured from 11.7 L buckets (diameter = 0.24 m, depth = 0.26m, surface area = 0.05 m^2, volume = 0.0117 m^3) containing approximately 8 L of dairy cattle slurry. Külling et al. (2003) reported emissions of 8.9 μg CH_4 m^{-2} s^{-1} and 20.1 μg CH_4 m^{-2} s^{-1} (SE = 4.07) for the different rations, with an average emission rate of 2.0 kg CH_4 m^{-3} yr^{-1}. To simulate this study using IFSM, we increased the scale of the manure storage dimensions, while keeping the original ratio of diameter to height (diameter = 2.4 m, depth = 2.6 m, surface area = 4.52 m^2, volume = 11.7 m^3). Using these dimensions and slurry characteristics, IFSM predicted 3.2 kg CH_4 m^{-3} yr^{-1}. The predicted emission is consistent with the results reported by Külling et al. (2003), indicating that IFSM can be used to predict CH_4 emissions from manure storages.

4.6.3 Representative Farm Emissions

The representative farm used was based on a hypothetical "typical" dairy farm in Pennsylvania with alfalfa, grass, and corn production. The 89 ha farm included 100 Holstein cows (average mass of 690 kg), 38 heifers over one year in age (average mass of 470 kg), and 42 heifers under one year of age (average mass of 200 kg). Animals were housed in free-stall barns. Manure was removed daily, stored in a 3000 m^3 storage tank for up to six months, and spread bi-annually. On average over the whole year, the storage contained about 1500 m^3 of manure. The farm area consisted of 19 ha of grass, 20 ha of alfalfa, and 50 ha of corn. We assumed that all crop nutrient requirements were met through manure nutrients generated on the farm.

Using the above farm characteristics, IFSM predicted annual emissions of 15,814 kg CH_4 from enteric fermentation and barn floors, 3,118 kg CH_4 from manure storages, and 23 kg CH_4 from field application (Table 4-7). This gave 18,955 kg CH_4 yr^{-1} for the total emission from the representative dairy farm. For overall farm emissions, IFSM's predicted rate of 18,955 kg CH_4 yr^{-1} is consistent with the rate of 19,201 kg CH_4 yr^{-1} that was previously estimated as a typical emission for a dairy farm of this size based upon a review of published emission data (Table 4-7).

Table 4-7. Previously estimated and model predicted CH_4 emissions from a representative dairy farm in Pennsylvania.

	Representative Farm[a]	IFSM
	Total emissions [kg CH_4]	Total emissions [kg CH_4]
Housing	13,900	14,907
Manure Storage	5,400	3,225
Croplands		
Grass	-27	--
Alfalfa	-52	--
Corn	-20	--
Total Cropland	-99	0
Field application	--	21
Total	19,201	18,184

[a] Emission rates were obtained from Chapter 2. Total emissions were calculated using the identified rates, 190 LU in the herd, 1500 m^3 manure storage, 19 ha of grass, 20 ha of alfalfa, and 50 ha of corn.

4.6.4 Sensitivity Analysis

Models are more sensitive to some parameters and inputs than others; it is therefore important to quantify this sensitivity to ensure that values for the variables with the most impact are accurate. A sensitivity analysis determines the impact various parameters have on model output.

A traditional sensitivity analysis involves varying a selected parameter by a selected percentage and calculating the percent change in the output. For example, to calculate how a 10% change in x affects the model output y, the original value of $x = 1$ (x_{base}) is used as an input to the model to obtain y_{base}. The parameter is then increased by 5%, $x_{+\%} = 1.05$, and decreased by 5%, $x_{-\%} = 0.95$, to represent an overall change of 10%. The model output is obtained at both of these values: $y_{+\%}$ and $y_{-\%}$, and the ratio of percent change in y to the change in x is calculated as:

$$P_{change} = \left(\frac{y_{+\%} - y_{-\%}}{x_{+\%} - x_{-\%}} \right) \cdot \left(\frac{x_{base}}{y_{base}} \right) \tag{4.15}$$

A value of one indicates that a 10% change in *x* corresponds to a 10% change in *y*; a lesser ratio indicates lesser sensitivity whereas a greater ratio indicates greater sensitivity. This method is useful when evaluating the sensitivity of variables with specific values (i.e., as opposed to categorical variables).

A traditional sensitivity analysis was performed on the modules developed for enteric fermentation, manure storage, and field-applied manure. The relationships for the CH_4 model were coded in Fortran using the Intel Fortran compiler (Intel Fortran Compiler Version 9.1, 2003) with Visual Studio .NET (Microsoft .NET Framework 1.1, 2003). All of the equations were integrated into the existing structure of IFSM rather than creating a stand-alone group of independent subroutines. During the development of each relationship, a parallel, or ad-hoc, model was created simultaneously in Matlab®. Unlike the parallel Fortran model, this ad-hoc model consisted of individual function files for each source of CH_4 emission from dairy farms (e.g., an enteric fermentation subroutine, a subroutine for emissions from manure storage, etc.). The results from the Matlab ad-hoc model were compared to output from the Fortran code to verify programming logistics. Modifications to the CH_4 relationships were made as necessary to achieve mathematically-correct and physically-realistic output while maintaining the scientific validity of the equations (i.e., no inclusion of arbitrary scaling factors). Because a function was created for each emission source, the inputs and parameters were easily changed and the relevant outputs obtained. This method allowed the sensitivity of important parameters to be quantified while maintaining the interaction among variables.

To perform the sensitivity analysis, the important parameters and inputs were first identified. Second, base values were set for each variable based on expected values from typical farm conditions or previously published studies. Third, a separate Matlab subroutine was created to generate the model inputs and to obtain the outputs by calling the relevant functions in the ad-hoc model. Finally, the data were compiled using a spreadsheet program, and the percent change was calculated using equation 4.15.

For the manure storage module, the majority of parameters had percent change values of 1.0. In other words, a given change in the input parameter caused the same change in the output (Table 4-8). However, the model was extremely sensitive to the Arrhenius parameter, as shown by a change in the output greater than 100. The Arrhenius parameter accounts for the temperature dependency of CH_4 emissions from manure storage. In the model, this parameter is not set by the user, but is an internally-set constant. The values for the Arrhenius parameters were calculated by the original developers of the manure storage model by fitting the parameters to observed data. Additionally, the values selected ensured that annual CH_4 emissions from slurry storage corresponded to emissions calculated using IPCC emission factors (Sommer et al., 2004). As a result, the present Arrhenius values represent the best available model; more studies quantifying CH_4 emissions from slurry storage are required to further evaluate and

Table 4-8. Sensitivity analysis results for the CH_4 module.

Manure storage			Field application			Enteric fermentation		
Variable[a]	%	Change[b]	Variable[a]	%	Change[a]	Variable[a]	%	Change[b]
P_{ts}, P_{vs}	25	1.0	M_{TAN}	25	0.99	MEI	25	0.7
B_o	25	0.98	M_{man}	25	0.01	$CH_{4,max}$	25	1.0
E_{maxCH4}	25	1.04[c]	pH	25	5.6	R_{diet}	25	0.2
b_1, b_2	25	0.99	Days	25	0.7[d]	C_{shape}	25	0.7
ln(A)[e]	25	>>100[e]	R_{app}	25	1.1[f]			
M_{man}	25	1.0						
T_{10C}	25	1.7						
T_{25C}	25	4.3						

[a] P_{ts}, P_{vs}: percent total solids and volatile solids (VS) [%]; B_o: achievable CH_4 yield [g CH_4 kg^{-1} VS; E_{maxCH4}: maximum potential CH_4 yield [g CH_4 kg^{-1} VS]; b_1, b_2: rate correction factor for degradable and nondegradable VS [unitless]; ln(A): Arrhenius parameter for inside and outside [g CH_4 kg^{-1} VS hr^{-1}]; M_{man}: mass of manure [kg]; T_{1OC}, T_{25C}: temperature [°C]; M_{TAN}: total ammoniacal nitrogen in manure [mmol kg^{-1} slurry]; pH: pH of the slurry [unitless]; days: days until incorporation [days]; R_{app}: manure application rate [kg m^{-2}]; MEI: metabolizable energy intake [MJ cow^{-1}]; CH_{4max}: maximum possible emission of CH_4 [MJ cow^{-1}]; R_{diet}: ratio of starch:ADF in diet [g g^{-1}]; and C_{shape}: shape parameter to calculate enteric fermentation.

[b] The value in the change column represents the percent the output changes based on the change in the input value. For example, if change = 1.0, then a 25% change in the input yielded a 25% change in the output.

[c] Varying E_{maxCH4} by 10% and 50% yielded 1.0 and 1.3, respectively.

[d] Varying Days by 10% and 50% yielded 1.7 and 0.5, respectively.

[e] The model was very sensitive to changes in the Arrhenius parameters for both inside and outside storage, with a change much greater than 100 for each parameter.

[f] Varying R_{app} by 10% and 50% yielded 1.0 and 1.3, respectively.

perhaps improve the calculation of this parameter (Chapter 2; Sommer et al., 2004).

As with the manure storage model, most parameters in the field applied manure module caused approximately the same percent change in output as the change in input (i.e., change equals 1.0). The pH of the manure slurry was the only variable that caused a major difference in the output, as evidenced by a five-fold change in output for a given change in input. Similar to the Arrhenius parameter, the pH of the slurry is not set by the user, but is an internal variable in IFSM. Currently, IFSM assumes that the pH of stored slurry is 8.0; future work may improve the prediction of CH_4 emissions by further developing the calculation of slurry pH.

The enteric fermentation model was not highly sensitive to any of the parameters. For a given percent change in the input, all of the parameters caused the same, or less, change in CH_4 emissions. The majority of CH_4 emissions from the farm were due to enteric fermentation. Even though the manure storage and field application modules were very sensitive to specific parameters, contributions from each of these sources were small relative to enteric fermentation. Thus, changes to parameters in the manure storage and field application modules had minimal impact on the whole-farm GHG emissions, even though some parameters were highly sensitive.

4.7 Conclusion

Modules simulating CH_4 emissions from enteric fermentation, manure storages, field-applied manure, feces deposited in pasture, and manure on barn floors were developed and added to IFSM. Model equations were based on previously published relationships as well as experimental data. The CH_4 modules represent the best available models that were consistent with our modeling objectives and with the current structure of IFSM. IFSM was shown to predict CH_4 emissions that were consistent with reported emissions from dairy farms, as well as from specific experiments quantifying emissions. The CH_4 manure storage module was highly sensitive to the Arrhenius parameter for indoor and outdoor storage. The contribution of the manure storage to whole-farm CH_4 emissions was small, so that varying the Arrhenius parameter has minimal effect on whole-farm GHG emissions. With the incorporation of this CH_4 module, IFSM provides a tool for simulating whole-farm emissions of CH_4 and evaluating the overall impact of management scenarios used to reduce emissions.

Chapter 5

Simulating Nitrous Oxide Emissions From Dairy Farms

Abstract. The reduction of greenhouse gas emissions is becoming more important world-wide. As a sector, agriculture is reported to be the greatest contributor of nitrous oxide in the U.S., emitting three-quarters of total U.S. nitrous oxide emissions. The primary source of nitrous oxide on a dairy farm is emissions from croplands, with smaller contributions from manure storages and from manure on barn floors. Strategies designed to reduce nitrous oxide emissions are not implemented in isolation and may affect other aspects of the farm. As a result, a whole-farm evaluation is needed to assess the overall impact of proposed reduction strategies. Cost-effective whole-farm evaluation can be done through computer simulation. One model that can perform this whole-farm evaluation is the Integrated Farm System Model, a computer model that simulates a farm as a whole system. This model was modified to include simulation of nitrous oxide emissions from croplands using relationships in DAYCENT. Relationships were also incorporated to simulate emissions from slurry storages and barn floors. The modified version of IFSM predicted N_2O emissions of 1.6 kg N_2O ha^{-1} yr^{-1} from an alfalfa field and 1.8 kg N_2O ha^{-1} yr^{-1} from a corn field. These emissions are consistent with observed data (2.1 kg N_2O ha^{-1} yr^{-1} and 1.86 kg N_2O ha^{-1} yr^{-1}) as well as with DAYCENT simulations (1.7 kg N_2O ha^{-1} yr^{-1} and 1.9 kg N_2O ha^{-1} yr^{-1}). IFSM also predicted whole-farm emissions within the expected emission ranges determined by a previous literature review. This extended whole-farm model can be effectively used to evaluate proposed N_2O reduction strategies along with effects on other greenhouse gas emissions, environmental issues of nitrogen and phosphorus losses, and farm profitability.

5.1 Introduction

In 2007, the Intergovernmental Panel on Climate Change (IPCC, 2007) reported that it is “extremely likely” (i.e., representing a 95% confidence level or higher) that anthropogenic emissions of greenhouse gases (GHGs) are causing a change in the global climate. Although many mitigation plans currently focus on reducing carbon dioxide (CO_2) emissions, nitrous oxide (N_2O) is a stronger GHG and has a global warming potential 296 times that of CO_2 (IPCC, 2007). In 2005, agriculture had the greatest overall impact on N_2O emissions, contributing 78% of the U.S. total (EIA, 2006). In fact, agriculture’s contribution to U.S. N_2O emissions has become increasingly important, with emissions increasing by 10% between 1990 and 2005 (EIA, 2006). As a result, quantifying and reducing N_2O emissions is necessary to reduce overall emissions of GHGs.

Multiple processes emit N_2O from dairy farms including emissions from the soil, from manure storages, and from manure deposited by animals in barns. A review of agricultural emission experimental data shows that the majority of N_2O from dairy farms is due to emissions from the soil, followed by less significant emissions from manure storages (Chapter 2). Relatively small amounts of N_2O are also emitted from manure deposited by animals inside barns where the manure is removed on a daily basis (e.g., tie-stall and free stall barns; Chapter 2); housing systems including a bedded pack or a dry lot would likely have higher emissions of N_2O (EPA, 2007).

Computer simulation is a cost-effective and efficient method of estimating N_2O emissions from dairy farms and analyzing how management scenarios affect these emissions. The Integrated Farm System Model (IFSM), a model developed by the USDA Agricultural Research Service (ARS), is a process-based whole-farm simulation including major components for soil processes, crop growth, tillage and planting operations, feed storage, herd and feeding, manure storage, and economics, with each divided into smaller components (Rotz et al., 2007). IFSM can predict the effect of management scenarios on farm profitability and environmental pollutants such as nitrate leaching, ammonia volatilization, and phosphorus loss, but does not currently predict GHG emissions.

The overall objective of this research was to develop a model that quantifies N_2O emissions from dairy farms and illustrates how management changes affect these emissions. To accomplish this, we sought to incorporate a module into IFSM that simulates emissions of N_2O from dairy farms and to evaluate the effectiveness of this tool at predicting farm level emissions of N_2O. The enhanced version of IFSM will provide a tool that can be used to evaluate the impact of various reduction strategies on N_2O emissions, along with the effect on other environmental factors and farm profitability. Specific objectives of this paper were to review published models that simulate N_2O emissions, to identify the relationships that best fit our modeling goals, to adapt these models for use in IFSM, and to use this tool to predict whole-farm N_2O emissions.

5.2 Model Criteria

A number of models have been published that predict N_2O emissions. In order to develop the N_2O module, we selected relationships from these published models that best fit our research goals. Therefore, we identified a list of criteria to evaluate potential models for incorporation into IFSM. These criteria were:

1. ***The model must be able to simulate processes that affect N_2O emissions when farm management changes are employed.***

   Strategies to reduce N_2O emissions from dairy farms can include changing the cropping system, altering manure handling and application methods, implementing different manure storage practices, or changing tillage practices. In order to analyze how these practices affect N_2O emissions, the model must account for associated changes (e.g., application timing and technique, manure type and storage design).

2. ***The model should be process-based.***

   Several published models, as well as the IPCC, predict N_2O emissions from farms using emission factors (e.g., Olesen et al., 2006). While these models are useful as simple tools for predicting N_2O emissions from farms, they do not have the capability of representing reduction strategies that affect N_2O emissions. For example, Olesen et al. (2006) predicted N_2O emissions from croplands by assuming that 1.25% of all N applied is emitted as N_2O. This model only accounts for the effect of reducing or increasing the total amount of N applied; it does not account for changing the timing or method of application (e.g., does the application coincide with a rain event). As a result, our goal was to select physically- and process-based relationships that more likely satisfied criterion 1 as compared to models based on emission factors.

3. ***The model should satisfactorily predict observed data.***

   A primary goal of models is to properly represent observed data. As a result, the chosen relationships should predict N_2O emissions within the range of emissions measured from dairy farms.

4. ***The model should be consistent with the current scale of other components in IFSM.***

   Currently, the intent of IFSM is to simulate realistic management scenarios that can be implemented by farmers. The characteristics of these scenarios are at the field- or farm-level (e.g., sequence of tillage operations, manure storage duration). Subsequently, IFSM simulates processes, normally on a daily time-step, at the field- or farm-level according to the assumed farm characteristics. As a result, selected relationships, as well as associated inputs and parameters, should be at the field- or farm-level as opposed to different scales (e.g., microbiological, watershed).

5. ***Model inputs and parameters should use readily available data.***

   Some of the available mechanistic models predict emissions with good accuracy; however, these models typically have many inputs or are highly parameterized. The required values are often the result of calibrating the model against specific data, they are difficult to obtain, or they have no physical or biological basis. The uncertainty added by making assumptions for these parameter and input values can outweigh the benefit of using a highly mechanistic model. In contrast, the majority of parameters and inputs in IFSM are not calibration parameters, are relatively easily obtained through on-farm knowledge, and correspond to characteristics of the farm. As a result, our final criterion is that input and parameter values should be easily obtained within, or consistent with, the current structure of IFSM.

5.3 Cropland Emissions

Emissions from croplands are the largest source of N_2O emissions from dairy farms (EIA, 2005; Sedorovich et al., 2007). Although undisturbed soils emit N_2O naturally, the rate of emission from cultivated soils is much greater because of the large N inputs on farmland. Two pathways can lead to emissions of N_2O: denitrification and nitrification. Denitrification is the microbial reduction of NO_3 to N_2 under anaerobic conditions, with the production of NO and N_2O as intermediates (Figure 5-1).

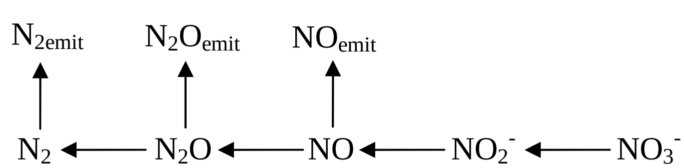

Figure 5-1. Pathway of denitrification in soils (Parton et al., 1996).

Historically, denitrification was believed to be the primary source of N_2O emissions; however, scientists have established that nitrification also contributes to emissions (Sahrawat and Keeney, 1986). Nitrification is an aerobic process that oxidizes NH_4^+ to NO_3, with the production of NO and N_2O as intermediates (Figure 5-2).

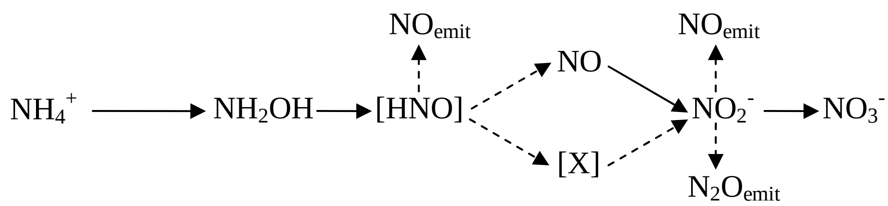

Figure 5-2. Pathway of nitrification in soils. Dashed lines and square brackets indicate incompletely understood processes and intermediates (Parton et al., 1996).

The emission of N_2O is thus dependent on both denitrification and nitrification. A conceptual model published by Davidson et al. (2000) described how denitrification and nitrification were connected (Figure 5-3). This model, known as the “hole-in-the-pipe” (HIP) model, connected the two pathways and thus linked the emission of NO and N_2O (Davidson et al., 2000).

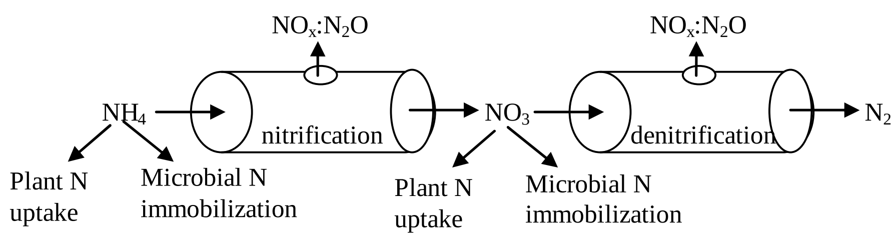

Figure 5-3. Conceptual model of controls on N gas emissions from soil using the leaky pipe metaphor (Parton et al., 2001).

5.3.1 Cropland Models Review

Both mechanistic and empirical equations have been used to predict N_2O emissions from soils. Reviews of both categories of models have been published (e.g., Heinen, 2006). We describe five models in this review (Table 5-1): one mechanistic (DNDC) and four other process-based models with less mechanistic detail (Bouwman et al., 2002; Olesen et al., 2006; DAYCENT; and WNMM;). Although many models exist, these five models represent the primary models used to simulate soil emissions of N_2O.

The DNDC model of Li et al. (1992a) simulates denitrification based on biochemical reaction kinetics as a function of the growth rate of denitrifiers. The production of N_2O from denitrification is then calculated as a mass balance between production and consumption, and as affected by gas diffusion out of the soil. Nitrification is simulated as a function of the concentration of ammonium in the soil, the biomass of nitrifiers, and soil pH (Li et al., 2000). DNDC satisfies criteria 1, 2, and 3.

Table 5-1. Summary of empirical models simulating N_2O production from soils.

Model	Model core equations[a]	Units
Bouwman et al. (2002)	$E_{N2O,soil} = \exp[C + \Sigma (F_i)]$ C = constant = -0.4136 F_i = individual values for each factor class[b]	kg N_2O-N/ha
Olesen et al. (2006)	$E_{N2O,\ soil} = 0.0125 * N_{input}$ (fields) $E_{N2O,\ soil} = 0.02 * N_{input}$ (grazing) N_{input} = all N inputs to a field	kg N_2O/ha
DAYCENT	$E_{N2O,soil,D} = [F_{WFPS} * \min(F_{NO3}, F_{CO2})]/(1+R_{N2/N2O})$ $E_{N2O,soil,N} = (R_{Nmin} * k_1 + k_{max} * N_{NH4} * F_T * F_{WFPS} * F_{pH}) * k_2$ F_{WFPS}, F_{NO3}, F_{CO2}, F_T, F_{pH} = effect of water-filled pore space, nitrate concentration, soil respiration, temperature, and pH on N_2O gas flux $R_{N2/N2O}$ = ratio of N_2 to N_2O produced k_1, k_2, k_{max} = fractions of nitrogen N_{NH4} = concentration of ammonium	μg N/g soil-day
WNMM	$E_{N2O,soil,N} = \alpha_n * R_n * F_T * F_{sw}$ $E_{N2O,soil,D} = 0.05 * R_d$ (WFPS $\geq$ 1.0) $E_{N2O,soil,D} = \alpha_d * R_d * (1-F_{sw})$ (WFPS < 1.0) α_n, α_d = maximum fraction of N_2O in nitrification and denitrification R_n, R_d = rate of nitrification and denitrification F_T, F_{sw} = effect of temperature and soil water	kg N/ha-day

[a] $E_{N2O,soil}$ represents the emission of N_2O from the soil as simulated by the various models being used. The units of $E_{N2O,soil}$ vary for each model and are listed under the column "Units."
[b] Each factor class (F_i) represents a factor impacting N_2O emissions (e.g., fertilizer type, N application rate, etc.) or an interaction between factors (e.g., N application rate · soil texture, N application rate · crop type, etc.). Values for each factor class, F_i, are given in Bouwman et al. (2002).

The model is process-based and simulates N_2O emissions based on the activity of nitrifiers. In addition, the model accounts for soil moisture content and substrate concentration, allowing the impact of changes in management practices to be simulated (Li et al., 1992a, 2000). Also, the model has been shown to accurately predict N_2O emissions and to follow temporal patterns of emissions (Li et al., 1992b; Li et al., 2000; Stange et al., 2000; Saggar et al., 2004a; Saggar et al., 2007). However, as stated in the criteria, IFSM simulates processes at the field- or farm-scale, not the microbiological scale. As a result, DNDC did not fit well with criterion 4. Finally, DNDC requires data on the mass of nitrifiers and denitrifiers, as well as validation of assumed values for certain parameter values. These data are not available in IFSM, nor are they easily obtained for a wide range of agricultural practices. In order to use DNDC, a number of assumptions would have to be made for these values. As such, the uncertainty added by assuming values for these parameters outweighed the benefits of using this detailed mechanistic model.

Bouwman et al. (2002, Table 5-1) developed a statistical N_2O emissions model through the Residual Maximum Likelihood (REML) technique with 846 N_2O measurements from 126 different studies. This model satisfies criteria 3, 4, and 5. The model of Bouwman et al. (2002) resulted in less uncertainty in N_2O predictions (-40% to +70%) as compared to the IPCC's 1997 default global emission factor (-80% to +100%), satisfying criterion 3. The model requires data on the N application rate, fertilizer type, crop type, and soil characteristics. These data are readily available in IFSM, satisfying criterion 4. Values for the constants and each factor class are provided in the original documentation, satisfying criterion 5 (Bouwman et al., 2002). However, by using a statistical technique (i.e., REML) for model development, the model may not adequately represent processes and reduction strategies not included in the original data. Also, the authors state that the model is not intended (i.e., not suitable) for use in predicting emissions at specific sites, but rather for landscape conditions. As a result, the model of Bouwman et al. (2002) did not satisfy our modeling objectives.

Olesen et al. (2006, Table 5-1) assumed that 1.25% of all N inputs are emitted as N_2O. The authors modified this factor to 2% to predict emissions from manure deposited by grazing animals. As with Bouwman et al. (2002), Olesen et al. (2006) satisfies criteria 3, 4, and 5. The model is simple to use and requires data readily available in IFSM, satisfying criteria 4 and 5. In addition, the emission factor of 1.25% is used as the default IPCC methodology, satisfying criterion 3. However, the model is not process-based and is thus not capable of simulating desired reduction strategies. In addition, although the default IPCC emission factor is an accepted method of predicting N_2O emissions, other models (e.g., Bouwman et al., 2002) are more accurate predictors of emissions. As a result, Olesen et al. (2006) did not satisfy our modeling objectives.

Parton et al. (1988, Table 5-1) developed an initial soil nitrification model in the late 1980s. NGAS, an updated general model for nitrification and denitrification, was later published by Parton et al. in 1996. NGAS was based on the original 1988 nitrification model and included a module for denitrification. Further improvements (Del Grosso et al., 2000; Parton et al., 2001) yielded the relationships found in DAYCENT and shown in Table 5-1. The relationships of DAYCENT satisfy all five criteria. The model is process-based and accounts for how management scenarios affect the moisture content, pH, nitrate concentration, and ammonium concentration in the soil, satisfying criteria 1 and 2. DAYCENT has been used to accurately simulate N_2O emissions for a variety of different applications. Comparisons with observed data showed that the gas module more accurately predicted observed data (r^2 = 0.74) as compared to the IPCC methodology (Del Grosso et al., 2005). In addition, Li et al. (2005) observed that DAYCENT's gas module follows the trend of observed data, although emission peaks were offset by one day. Finally, model parameters were provided in the documentation, and the remaining inputs were readily available in IFSM, satisfying criterion 5.

The water and nitrogen management model (WNMM, Table 5-1) is a process-based model that simulates water dynamics, crop growth, the C and N cycles, and land management (Li et al., 2007). The model assumes that N_2O is emitted as a set fraction of both nitrification and denitrification. WNMM satisfies all five criteria. The model is process-based and is capable of simulating changes in management scenarios. WNMM was found to simulate N_2O emissions accurately, although the model tended to miss the N_2O peaks (Li et al., 2007). Li et al. (2005) found that the model predicted observed N_2O emissions more accurately than either DAYCENT or DNDC. Finally, model parameters are relatively easy to obtain, and, as a result, the model can be easily integrated into IFSM.

Based on the above descriptions, we considered two of the original five models: DAYCENT and WNMM. Both models satisfied all five of our criteria. Li et al. (2005) reported that WNMM predicted N_2O emissions more accurately than DAYCENT, suggesting that WNMM may be the better choice. However, WNMM is a recently developed model, and, as such, there are fewer application and evaluation studies of the model. More importantly, the only published applications of WNMM are simulations of soils in China. Li et al.'s (2005) conclusion that WNMM was more accurate than DAYCENT was based on simulations of emissions from soils in the North China Plain, not from soils in the U.S. In contrast, DAYCENT has been widely used to simulate emissions from U.S. soils and found to accurately represent N_2O emissions (e.g., Del Grosso et al., 2006). We therefore chose to use DAYCENT's N_2O module.

5.3.2 Croplands Model Description

A detailed description of the development of the chosen model can be found in Del Grosso et al. (2000) and Parton et al. (2001). This section provides a brief description of the model, how the parameters were determined, and how the model was integrated with IFSM.

Emission of N_2O from soils is predicted as the sum of nitrification and denitrification losses:

$$E_{N2O,soil} = E_{N2O,soil,N} + E_{N2O,soil,D} \tag{5. 1}$$

where $E_{N2O,soil}$ is the emission of N_2O from soils [kg N_2O ha^{-1} day^{-1}], $E_{N2O,soil,N}$ is the emission of N_2O from soils due to nitrification [kg N_2O ha^{-1} day^{-1}], and $E_{N2O,soil,D}$ is the emission of N_2O from soils due to denitrification [kg N_2O ha^{-1} day^{-1}].

Emission of N_2O from nitrification is predicted as:

$$E_{N2O,soil,N} = K_2 \cdot R_{NO3} \cdot F_{N,conv} \tag{5. 2}$$

where K_2 is the fraction of nitrified N lost as N_2O flux [g N g^{-1} N], R_{NO3} is the soil nitrification rate [g N m^{-2} day^{-1}], and $F_{N,conv}$ is a conversion factor [28.57 (kg N_2O ha^{-1} day) (g N m^{-2} day^{-1})$^{-1}$]. Parton et al. (2001) define K_2 as 0.02 g N flux g^{-1} N nitrified. Parton et al. (2001) provide a model to calculate R_{NO3}, the soil nitrification rate. However, IFSM currently calculates soil nitrification (Rotz et al., 2007), and this rate was used rather than the method provided in Parton et al. (2001).

Emission of N_2O due to denitrification is predicted as:

$$E_{N2O,soil,D} = \left[\frac{\min\left(F_{d,NO3}.F_{d,CO2}\right)\cdot F_{d,WFPS}}{1+R_{Nratio}}\right]\cdot \rho_{soil} \cdot d_{soil} \cdot F_{N,mass} \tag{5. 3}$$

where $E_{N2O,soil}$ is the emission of N_2O from soil [kg N_2O ha^{-1} day^{-1}], $F_{d,NO3}$ is a factor for the effect of soil nitrate concentration [μg N g^{-1} soil day^{-1}], $F_{d,CO2}$ is a factor for the effect of soil respiration [μg N g^{-1} soil day^{-1}], $F_{d,WFPS}$ is a factor for the effect of soil moisture [dimensionless], R_{Nratio} is the ratio of N_2 to N_2O emission [μg N $μg^{-1}$ N], ρ_{soil} is the bulk density of the soil [g cm^{-3}], d_{soil} is the active soil depth [20 cm], and $F_{N,mass}$ is a unit conversion factor [0.286 (kg N_2O ha^{-1} day^{-1}) (μg N cm^{-2} day^{-1})$^{-1}$].

The effects of soil nitrate and CO_2 flux on denitrification are predicted by empirical equations as described in Parton et al. (2001). The effect of soil nitrate on the N_2O flux due to denitrification, $F_{d,NO3}$, is calculated as:

$$F_{d,NO3} = 1.15 \cdot \left(N_{NO3}\right)^{0.57} \tag{5. 4}$$

where N_{NO3} is the nitrate concentration in the soil [μg N g^{-1} soil]. The effect of soil respiration on the N_2O flux due to denitrification, $F_{d,CO2}$, is predicted as:

$$F_{d,CO2} = 0.1 \cdot \left(C_{CO2}\right)^{1.3} \tag{5. 5}$$

where C_{CO2} is the soil CO_2 flux [μg C g^{-1} soil].

The model of Parton et al. (2001) assumes that denitrification does not occur at soil moisture below approximately 55%. Above 55%, denitrification increases exponentially and asymptotically approaches a maximum as soils approach saturation. This effect is predicted as[1]:

$$F_{d,WFPS} = \frac{0.5}{\pi} \arctan\left[0.6 \cdot \pi \left(0.1 w_{wfps} - a\right)\right] \tag{5. 6}$$

where w_{wfps} is the water-filled pore space [percent] and a is a factor controlling the soil moisture content at which denitrification is assumed to be half of the maximum rate. This parameter a is calculated as:

$$a = 0.90 - M \cdot C_{CO2} \tag{5. 7}$$

$$M = 0.36 - 3.05 \cdot \min\left(0.113, D_{fc}\right) \tag{5. 8}$$

where M is a multiplier function representing the magnitude of the interaction between soil moisture and respiration [dimensionless] and D_{fc} is a gas diffusivity coefficient [dimensionless].

[1] The result of the arctangent term should be in radians to obtain the correct parameter values.

Multiple models have been suggested to calculate D_{fc}, the ratio of gas diffusivity in the soil to gas diffusivity in the air (Hillel, 1998). We predict D_{fc} using a relationship developed by Millington (1959):

$$D_{fc} = \left(\frac{f_a}{f}\right)^2 \left(f^{\frac{4}{3}}\right) \tag{5. 9}$$

where f_a is the air-filled porosity [cm^3 cm^{-3}] and f is the total porosity [cm^3 cm^{-3}]. This model is a simplified version of that used in DAYCENT. Although the relationship used in DAYCENT has been shown to be more accurate (Potter et al., 1996), equation 5. 9 is more easily parameterized and integrated into IFSM, and it provides an adequate representation of this process applied at the farm scale.

The ratio of N_2 to N_2O, R_{Nratio}, is predicted as:

$$R_{Nratio} = F_{r,NC} \cdot F_{r,WFPS} \tag{5. 10}$$

where $F_{r,NC}$ is a measure of the ratio of electron donor (NO_3) to substrate (CO_2) [dimensionless] and $F_{r,WFPS}$ is a function accounting for the effect of soil moisture on the relative emissions of N_2 and N_2O [dimensionless].

DAYCENT utilizes empirical equations to model $F_{r,NC}$ and $F_{r,WFPS}$. The effect of the ratio of NO_3 to CO_2 is predicted as:

$$F_{r,NC} = \max\left[(0.16 \cdot K_1), \left(K_1 \mathrm{e}^{-0.8r}\right)\right] \tag{5. 11}$$

$$K_1 = \max\left[1.7, \left(38.4 - 350 \cdot D_{fc}\right)\right] \tag{5. 12}$$

where K_1 is the intercept of $F_{r,NC}$ [dimensionless] and r is the ratio N_{NO3} to C_{CO2} [μg N μg^{-1} C]. The effect of soil moisture is predicted as:

$$F_{r,WFPS} = \max\left[0.1, \left(0.015 \cdot w_{wfps} - 0.32\right)\right] \tag{5. 13}$$

Based on the above equations, seven inputs are needed for this model: the soil nitrification rate, bulk density, the nitrate concentration in each layer, CO_2 flux, water-filled pore space, air-filled pore space, and total porosity. Currently, IFSM simulates the nitrogen cycle, and the soil nitrification rate and nitrate concentration are available in this module (Rotz et al, 2007). Specific soil properties, including bulk density, are available as inputs in the soil characteristics menu of IFSM; water-filled pore space and total porosity are then calculated using these user-defined soil properties. The air-filled pore space can be calculated from the water-filled pore space and total porosity. The soil CO_2 flux is available from the carbon module within IFSM (see Chapter 3).

5.4 Other Sources

As described previously, cropland is the primary source of N_2O from farms, contributing 75% of total agricultural N_2O emissions (EIA, 2006). Even though neither manure storages nor barn floors contribute large amounts of N_2O relative to croplands, we included relationships to represent these emissions to complete a comprehensive farm-level model.

5.4.1 Manure Storages

Nitrous oxide emissions from stored slurry or liquid manure were predicted as a function of the exposed surface area of the manure storage (Olesen et al., 2006). We used the emission rate determined by Olesen et al. (2006) to predict N_2O emissions.

$$E_{N2O,manure} = E_{F,N2O,man} \cdot A_{storage} / 1000 \quad (5.\ 14)$$

where $E_{N2O,manure}$ is the emission of N_2O from slurry storage [kg N_2O day^{-1}], $E_{F,N2O,man}$ is the emission rate of N_2O [0.8 g N_2O m^{-2} day^{-1}], and $A_{storage}$ is the exposed surface area of the manure storage [m^2]. This relatively simple model was justified because the N_2O emission from this type of manure storage is typically a relatively small portion of the whole farm emission (Olesen et al., 2006; Sedorovich et al., 2007),

The average emission of 0.8 g N_2O m^{-2} day^{-1} is applicable to uncovered slurry storage where a natural crust forms on the manure surface. However, some dairy farms utilize plastic covers to reduce gaseous emissions from manure storage. Few data were available on N_2O emissions from manure storages, and we were not able to quantify the differences between emissions from covered and uncovered storage. In order to simulate covered storages, we instead assumed that all gaseous emissions were reduced by the same percent when using a cover. Because IFSM can currently account for the reduction in ammonia emissions due to covers, we used ammonia as the base gas. We used IFSM to simulate ammonia emissions with and without a cover. We then calculated the percent reduction to be 80%. To simulate N_2O emissions from a covered storage, we applied the emission rate of 0.8 g N_2O m^{-2} day^{-1} to the storage and then assumed that a cover would reduce this emission by 80%. In other words, the emission rate from covered slurry storage was assumed to be 0.16 g N_2O m^{-2} day^{-1}.

Manure is sometimes added to the surface of the manure storage each day, which prevents the formation of the natural crust. Without this natural crust, no N_2O is formed and emitted (Külling et al., 2003; Sneath et al., 2006). Therefore, when a storage was used where manure was added to the surface, an emission rate of zero was used.

5.4.2 Barn Emissions

Floors of housing facilities can be a source of N_2O emissions due to manure deposited by animals. After cleaning and removal, some manure normally remains on the floor and continues to be a source of emissions. Emissions data (Varga et al., 2007) measured from barn floors showed that N_2O emissions were small compared to other greenhouse gases emitted in the barn and ranged from 0.005 g N_2O m^{-2} day^{-1} to 0.077 g N_2O m^{-2} day^{-1}. These measured emission rates were not found to be correlated to ambient barn temperature, so an average emission rate was used to predict N_2O emissions from barn floors:

$$E_{N2O,floor} = E_{F,N2O,floor} \cdot A_{floor} \Big/ 1000 \qquad (5.\ 15)$$

where $E_{N2O,floor}$ is the emission of N_2O from the barn floor [kg N_2O day^{-1}], $E_{F,N2O,floor}$ is an average emission rate of N_2O [0.02 g N_2O m^{-2} day^{-1}], and A_{floor} is the manure covered surface area of the barn floor [m^2].

Use of this simple relationship was justified because the contribution of this source to overall N_2O emissions is minimal. In addition, a more process-based or detailed relationship was not justified based upon the current data available.

5.5 Model Evaluation

One of the main goals of models is to adequately simulate observed data. Thus, we evaluated the process-based components of the N_2O module (i.e., croplands module) by comparing simulated and measured emissions. Stehfest and Bouwman (2006) published a review of N_2O emissions from agricultural fields in various countries. In addition, typical emission ranges from U.S. farms were reviewed in Chapter 2. However, the studies that have quantified N_2O emissions from specific crops often have not provided the necessary input information required to simulate scenarios in IFSM.

IFSM predictions of N_2O emissions were evaluated in four ways. First, we used two studies to evaluate IFSM's ability to predict observed emissions from cropland. We chose individual studies that represented typical emissions within the ranges reported in Chapter 2, that included the soil and crop information required to simulate the study with IFSM, and that were not a source of data for the models used in the N_2O module. The two chosen studies were for irrigated corn fields in Colorado (Mosier et al., 2005) and corn and alfalfa production in Michigan (Robertson et al., 2000). Since our soil N_2O emission model was based on relationships from DAYCENT, the predictions from both IFSM and DAYCENT should be similar. In addition to meeting the criteria for individual studies, the study published by Robertson et al. (2000) was also simulated with DAYCENT (Del Grosso et al., 2005). As a result, the data of Robertson et al. (2000) was also used for a second evaluation method: comparing IFSM predictions to DAYCENT predictions. As a third type of evaluation, IFSM was used to simulate a representative farm in Pennsylvania, and IFSM predictions of N2O emissions were compared to the ranges identified in Chapter 2. As a final fourth evaluation procedure, a sensitivity analysis was performed on selected parameters of the cropland module.

5.5.1 Irrigated Corn Fields

Mosier et al. (2005) measured N_2O emissions from irrigated corn fields near Fort Collins, CO. The soil was a clay loam soil (44% silt, 36% clay, and 19% sand) with 1.3% organic carbon. The corn fields were continuously cropped with corn and were fertilized with 0, 134, or 202 kg N ha^{-1} and 56 kg P ha^{-1}. Conventional tillage was employed on the corn field for all three levels of fertilization. Weekly measurements were obtained from April 2002 to April 2003 using flux chambers. The flux chambers were used to obtain gas samples which were then analyzed using a gas chromatograph to obtain N_2O emissions.

Using the crop and soil characteristics described above, N_2O emissions were simulated with IFSM using Fort Collins daily weather data for 2002 and 2003. IFSM predicted greater N_2O emissions for greater fertilization rates, which followed the trend of observed data (Table 5-2). Although IFSM predictions were consistent with the observed emissions, IFSM over-predicted the lowest emission with no N fertilizer application and under-predicted the greatest emission that occurred when 202 kg N ha^{-1}

was applied. This inconsistent difference indicates that IFSM was less able to predict emissions at either of the extremes. However, this also implies that IFSM is less likely to over-predict N_2O emissions from farms with greater than average N fertilization rates.

There are two possible explanations for the difference between IFSM predictions and observed data. The first explanation is that an assumption was made regarding fertilization date. Mosier et al. (2005) specifies that the crop was fertilized prior to planting, which was represented in the model inputs. However, the study does not specify the planting dates and, consequently, does not specify the actual fertilization date. As a result, dates for planting and fertilization had to be assumed when simulating this scenario in IFSM. The N_2O model is sensitive to the interaction between water-filled pore space and soil respiration (see Section 5.5.4). Because the water-filled pore space is affected by the precipitation, simulation results are affected by the timing of precipitation and fertilization events. If the planting dates, and thus the fertilization dates, were known, model results would likely improve.

The second explanation is that the initial soil N level was not specified in the study of Mosier et al. (2005). The simulated emissions of N_2O are influenced by the amount of N fertilizer applied, as well as by the initial concentration of N in the soil. An assumption was made regarding this initial concentration, which may have affected model results.

5.5.2 Alfalfa and Corn Fields

Robertson et al. (2000) measured N_2O emissions from alfalfa and conventionally tilled corn at the Kellogg Biological Station (KBS) Long-Term Ecological Research (LTER) site in southwest Michigan. The LTER covered approximately 1600 ha, including 26 different research sites. The main field site consisted of 60 ha divided into 1 ha cropping systems. The predominant soil for the site was Kalamazoo loam, although field characteristics varied. For the IFSM simulation, the soil characteristics assumed were 1.8% organic carbon with 50% silt, 35% clay, and 15% sand. The conventionally tilled corn received conventional chemical inputs including fertilizer at 123 kg N ha^{-1}.

Table 5-2. Emissions of N_2O as measured from conventionally tilled and irrigated corn fields near Fort Collins, CO (Mosier et al., 2005) and as predicted using IFSM.

N fertilization	Observed[a],[b]		IFSM
[kg N/ha]	[kg CO_2e ha^{-1} yr^{-1}]	[kg N_2O ha^{-1} yr^{-1}]	[kg N_2O ha^{-1} yr^{-1}]
0	148	0.5	0.98
134	418	1.41	1.23
202	567	1.92	1.34

[a] Observed data are from Mosier et al. (2005)
[b] 1 kg N_2O = 296 kg CO_2e

Using the crop and soil characteristics for the site and daily weather data for Battle Creek, MI, IFSM was used to simulate N_2O emissions from 1991 to 1999. The predictions from IFSM were similar to the observed data, although IFSM predicted less N_2O emissions from alfalfa as compared to corn. This does not follow the trend of observed data, although it does agree with the trend predicted by DAYCENT (Del Grosso et al., 2005). From a review of observed emissions (Chapter 2), N-fertilized corn fields are typically expected to emit more N_2O as compared to alfalfa fields not receiving N fertilizer. Robertson et al. (2000) concludes that the N_2O emissions from alfalfa and corn were more similar than that from cropping systems and other perennial crops (i.e., poplar) or unmanaged sites. The similarity of predictions from alfalfa and corn agreed with this overall conclusion, although the model did not follow the observed trend.

However, Robertson et al. (2000) indicates that there was no significant difference between emissions from the alfalfa and conventionally tilled corn fields. Both DAYCENT and IFSM predictions agree with this observation, as there is little difference between emissions from these two fields.

Because DAYCENT has been extensively tested and used to simulate N_2O emissions and because of the lack of significance between alfalfa and corn emissions, the more important test for this evaluation was whether IFSM predictions were similar to those of DAYCENT (Table 5-3). The slight difference between predictions from IFSM and DAYCENT was likely due to other components of the models that differed. Based on this evaluation, IFSM was determined to satisfactorily predict N_2O emissions similar to DAYCENT.

Table 5-3. Emissions of N_2O as measured from alfalfa and conventionally tilled corn fields at the KBS LTER in Michigan (Robertson et al., 2000) and as predicted using DAYCENT and IFSM.

	Observed	DAYCENT	IFSM
	[kg N_2O ha^{-1} yr^{-1}]	[kg N_2O ha^{-1} yr^{-1}]	[kg N_2O ha^{-1} yr^{-1}]
Alfalfa	2.1	1.7	1.6
Corn with 123 kg N/ha	1.86	1.9	1.8

5.5.3 Representative Farm Emissions

A representative farm was used based upon a hypothetical "typical" dairy farm in Pennsylvania with alfalfa, grass, and corn production on a medium clay loam soil. The 89 ha farm included 100 Holstein cows and 80 replacement heifers with all animals housed in free-stall barns. Manure was removed daily, stored in a tank with an open surface area of 730 m^2 for up to six months, and spread bi-annually. The crop area consisted of 19 ha of grass, 20 ha of alfalfa, and 50 ha of corn. All crop nutrient requirements were met through manure nutrients generated on the farm. The farm was simulated for 25 years using State College, PA, weather data for 1981 to 2005.

Using the above farm characteristics, IFSM predicted annual emissions of 4 kg N_2O from animal housing, 184 kg N_2O from manure storages, and 538 kg N_2O from croplands (Table 5-4). This gave 726 kg N_2O yr^{-1} of total emission from the representative dairy farm.

IFSM predicted 4 kg N_2O emitted from housing, whereas the typical farm shows 57 kg N_2O. The average values obtained from Chapter 2 were based on emissions from various housing types, including bedded packs. Bedded packs typically emit more N_2O as compared to animal facilities where the floor is regularly scraped and only minimal manure remains on the floor (e.g., Flessa et al., 2002). The lower emission from a free stall barn floor compared to a general number over various housing types explains the difference between predicted and average estimated emissions from housing.

For overall farm emissions, IFSM's predicted rate of 726 kg N_2O yr^{-1} was approximately 30% less than the rate of 1,040 kg N_2O yr^{-1} previously summarized as a typical emission for a dairy farm of this size and cropping system (Chapter 2; Table 5-4). The reported data shown in Table 5-4 represent a wide range of management practices, nitrogen application rates, and soil types, and are calculated averages from a wide range

Table 5-4. Typical and predicted N_2O emissions from a representative farm.

	Representative farm Total Emission [kg]	IFSM predictions Total emission [kg]
Housing	57	4
Manure Storage	150	184
Croplands		
Grass	103	--
Alfalfa	80	--
Corn	650	--
Total cropland	833	538
Total	1,040	726

[a] Emission rates were obtained from Sedorovich et al. (2007). Total emissions were calculated using average emission rates for 100 cows plus replacement heifers, 1500 m^3 manure storage, 19 ha of grass, 20 ha of alfalfa, and 50 ha of corn.

of emission rates (Chapter 2). For example, reported emission rates from corn ranged from 0.2 to 239 kg N_2O ha^{-1}. As described in the next section, the N_2O model is sensitive to several factors, and is particularly sensitive to soil texture. In order to simulate the representative farm in IFSM, assumptions were made regarding each of these parameters to reflect conditions found on a typical farm in Pennsylvania. Consequently, these assumptions likely contributed to the lesser emissions than those reported in Table 5-4. Even with this wide range of conditions, IFSM predicted a whole-farm emission consistent with the ranges reported in Chapter 2.

5.5.4 Selected Parameter Analysis

Models are typically more sensitive to some parameters and inputs than others; it is therefore necessary to quantify this sensitivity to ensure that values for the variables with the most impact are accurate. A sensitivity analysis determines the impact various parameters have on model output.

In IFSM, several user inputs are categorical variables. In other words, these inputs provide options that represent a range of values, with a specific, average value assigned in the model code. For example, farm topography is a categorical variable on the IFSM user input menu. One option, gently rolling, covers slopes from 3% to 8%; within the code, the specific slope is assigned to 5.5%. Other variables, such as soil texture, are categorical variables with default values. Although the user can modify these default values, these variables are essentially categorical assuming that the user does not modify the default values. The sensitivity of categorical variables is not effectively quantified using the traditional sensitivity analysis described in Chapter 4 and used for the analysis of the CH_4 module. Instead, these variables were analyzed using a different method.

In a conceptual model for N_2O emissions, Davidson et al. (2000) described how soil water content influences the ratio of N_2O:NO emissions. Del Grosso et al. (2000b) also observed this trend using DAYCENT's trace gas subroutine, but extended the analysis. This study found that there was a significant interaction between water-filled pore space (WFPS) and heterotrophic respiration (CO_2) in clay soils, and that this interaction was less significant than the primary effect of WFPS in coarser textured soils (Del Grosso et al., 2000b). Figure 5-4 shows WFPS and corresponding N_2O emissions for observed data (circles), along with the best fit lines used by DAYCENT to simulate this interaction (solid line). A parameter analysis was performed on soil texture to determine whether the N_2O module in IFSM reflected this behavior.

The effect of soil texture on N_2O emissions was determined by replicating the analysis in Del Grosso et al. (2000b). To do this, soil textures were chosen to reflect those specified in Del Grosso et al. (2000b). The soil texture was varied between a high clay (27% silt, 47% clay, and 26% sand), a clay (30% silt, 36% clay, and 34% sand), and a sandy loam (13% silt, 13% clay, and 74% sand). In addition, the heterotrophic respiration in IFSM was forced to either a high rate (37 μg C g^{-1} soil) or a low rate (5 μg C g^{-1} soil), which resulted in six model simulations. The horticultural clay (HC) site had a history of wheat and barley production, and both the pasture clay (PC) and silty loam (SL) sites were moderately grazed. All three study sites were located near Fort Collins, CO, and all simulations used weather data from this location from 2000 to 2005. Only N_2O emissions are shown because N_2 relationships from DAYCENT were not incorporated into IFSM.

Although only N_2O emissions are shown (Figure 5-5) and the units differ from those in Figure 5-4, the same trend is observed in IFSM predictions as in DAYCENT predictions. For clay soils with greater respiration rates, greater N_2O emissions were observed at greater WFPS. Also, lesser respiration rates tended to result in lesser N_2O emissions regardless of soil texture or crop system.

As simulated by IFSM, the inflection point for each soil type was different (Figure 5-5). For the HC, PC, and SL soils with high respiration, Del Grosso et al. (2000b) reported that water was strongly limiting when WFPS was less than 50%, 65%, and 80%, respectively. IFSM results follow this trend of DAYCENT, although the inflection point does not agree with the exact published water contents for the three soils. Although IFSM predicts maximum emissions at different WFPS than published by Del Grosso et al. (2000b), the maximum emissions do follow the response curves shown in Figure 5-4.

Also, Figure 5-4 shows both N_2O and N_2 emissions, whereas we are only concerned with N_2O emissions from IFSM. Emissions of N_2 are simulated within IFSM, but are not predicted using DAYCENT relationships. Including N_2 emissions predicted using DAYCENT relationships in the IFSM analysis may generate a graph more similar to Figure 5-4.

Similarly, for HC, PC, and SL with low respiration, DAYCENT results show that water strongly limits emissions when WFPS is less than 80%. As shown by the graphs in Figure 5-5, minor emissions occurred in this scenario. Because IFSM did not simulate WFPS greater than 80% for these soils, we were unable to assess how the model reacted at greater WFPS. However, IFSM is expected to predict greater emissions, as a slight increase in emissions was observed as the WFPS approached 80% in the HC with low respiration.

Despite these similarities, several differences were noticed between Figure 5-4 and Figure 5-5. One of the main distinctions is that the left edges (i.e., lowest WFPS) of the graphs in Figure 5-5 are much sharper. There are two explanations for this difference. First, Parton et al. (1996) shows N_2O emission data from clay and loam soils as a function of WFPS from a study in Sweden. A sharp edge similar to those in Figure 5-5 was evident in the data. Second, the graphs in Figure 5-5 were generated by forcing CO_2 emissions to equal either 5 or 37 $\mu g\ C\ g^{-1}$ soil day^{-1}, and, as a result, the actual range of potential respiration was not covered. Instead of showing a range of WFPS and CO_2 interactions as in Figure 5-4, the interaction between WFPS and a specific respiration rate is shown in Figure 5-5. Although this analysis does not exactly replicate the analysis in Figure 5-4, it is useful in quantifying the specific threshold for when WFPS starts to strongly limit N_2O emissions. However, the results would only be applicable to a specific respiration rate. A more in-depth analysis that varied both the WFPS and the respiration rate would likely yield the exact threshold of limiting WFPS and CO_2.

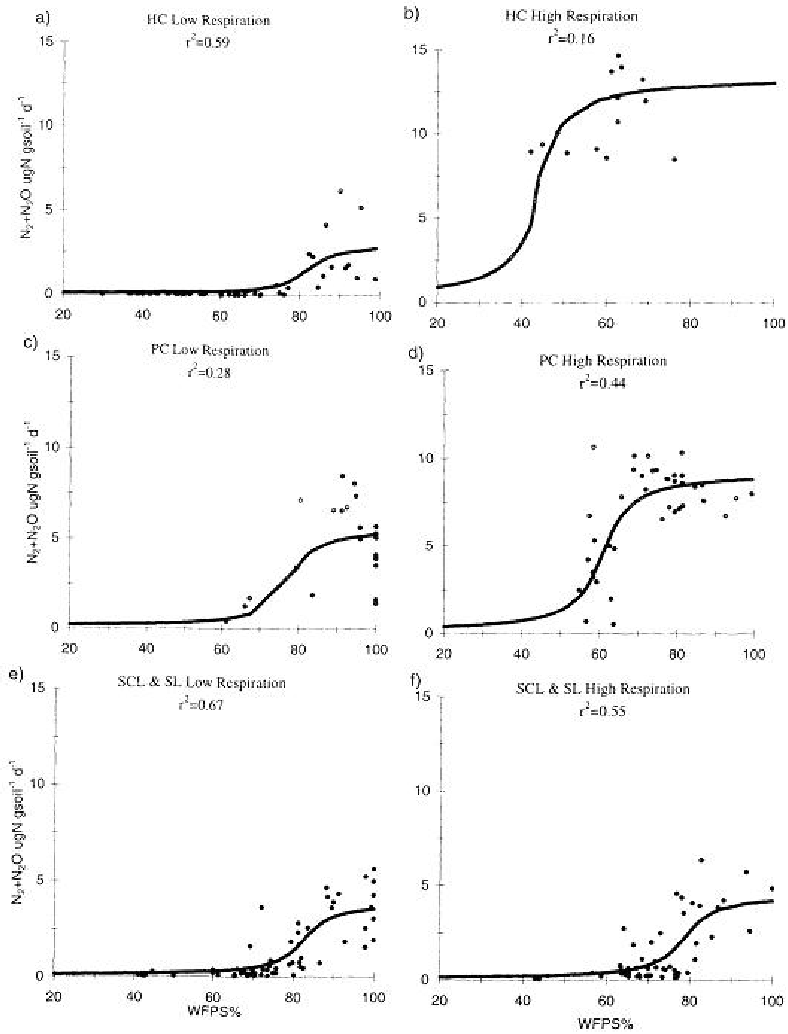

Figure 5-4. Response of denitrification to soil water-filled pore space with NO_3 not limiting and best fitting arctangent functions for the intact soils under high (>37 μg C g soil^{-1} day^{-1}) and low (<37 μg C g soil^{-1} day^{-1}) CO_2 emissions (Del Grosso et al., 2000b). The circles represent observed data while the lines represent the best fitting lines, with the equations of these lines used by DAYCENT to simulate the interaction of WFPS and respiration. The soil types used were horticultural clay (HC), pasture clay (PC), silty clay loam (SCL), and silty loam (SL).

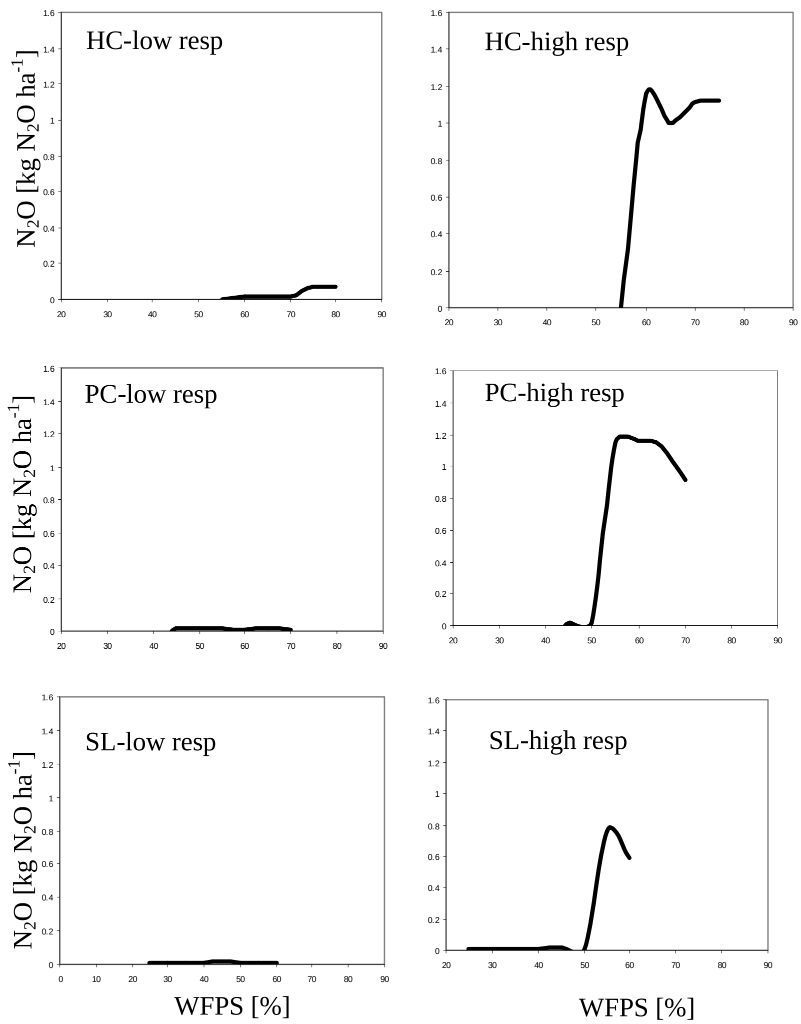

Figure 5-5. Response of IFSM predicted N_2O emissions to water-filled pore space with high (37 μg C g soil^{-1} day^{-1}) and low (5 μg C g soil^{-1} day^{-1}) CO_2 emission (HC = high clay, PC = clay, and SL = silty loam).

5.6 Conclusion

A module simulating N_2O emissions from croplands, manure storages, and barn floors was developed and added to the farm simulation model, IFSM. Model equations were based on previously published relationships and experimental measurements. The N_2O module represents the best available model that is consistent with our whole-farm modeling objectives and with the current structure of IFSM. IFSM was shown to predict N_2O emissions that were consistent with reported emissions from various field level studies and DAYCENT simulations, and reasonably represented emissions measured in specific experiments quantifying emissions. The soil N_2O emissions module was highly sensitive to the clay content of the soil, and this sensitivity agrees with previous analyses published on the selected model relationships (Del Grosso et al., 2000b). With the incorporation of this N_2O module, IFSM can simulate whole-farm emissions of N_2O. This provides a tool for evaluating the overall impact of farm management and the implementation of reduction strategies on N_2O emissions along with other measures of farm performance, environmental impact, and economics.

Chapter 6

Analyzing Greenhouse Gas Fluxes From Farm Scenarios

Abstract. The reduction of greenhouse gas (GHG) emissions is becoming more important world-wide. As a sector, agriculture is reported to be the greatest contributor of nitrous oxide and the third greatest contributor of methane in the U.S. Thus, strategies must be designed to reduce or eliminate net emissions of greenhouse gases. However, reduction strategies may reduce the emissions of one gas while increasing the emissions of another gas. The whole-farm evaluation tool IFSM can perform an analysis on the farm as a whole system to determine the overall impact of a reduction strategy. IFSM was used to simulate and evaluate scenarios in five main categories: manure handling strategies, tillage systems, use of rBST growth hormone, dietary forage concentration, and confined versus grazing production systems. In addition to quantifying GHG emissions from a whole farm, IFSM also provides information on the profitability of each scenario to determine if the farming practices are economically viable for the farmer. Based on the simulation results, the following practices resulted in the least emissions: covered manure storage with surface application, no till, using rBST, high forage:grain ratio with additional forage produced on-farm, and winter confinement with summer pasture. Although a full economic analysis is out of the scope of this paper, the results show that the most profitable system may not be the system with the least emissions. This highlights the need to use IFSM to perform a more in-depth economic analysis on potential reduction strategies. Future regulations restricting the emission of GHGs will likely change the analysis and identification of these feasible systems by affecting the economics of each scenario. IFSM was shown to be a useful whole-farm evaluation tool that can be utilized to analyze the effects of changing management strategies on GHG emissions and farm profitability.

6.1 Introduction

Reduction of GHGs has become an important global concern. As a sector, agriculture is the greatest contributor of N_2O emissions and the third greatest contributor of CH_4 emissions. As a result, scientists and policy makers are investigating methods of reducing emissions and mitigating the atmospheric concentration of GHGs. Several studies have been published that quantify GHG emissions from various farm management scenarios. However, these studies tended to focus on one gas, quantify emissions from one source of GHGs on a farm, or ignore important aspects of agroecosystems (i.e., profitability). The objective of this study was to quantify the GHG emissions from various dairy production scenarios in five main categories. The five categories analyzed were manure handling methods, tillage systems, hormone use, dietary composition, and confinement feeding versus grazing. The results from these scenarios will be discussed in terms of total mass of GHGs emitted, as well as emissions of GHGs normalized by a production parameter (e.g., mass of produced milk). The emissions include those sources discussed in Chapters 3 through 5, as well as emissions from combustion of fuel used in farm operations. For this analysis, the boundaries of the system are assumed to be the farm. In other words, the emissions reported do not include fuel used for transportation of purchased feed or fertilizers. In addition, the economics of each scenario will be presented. Many factors influence the selection of management practices on a farm. Identifying ideal or optimal management scenarios is not in the scope of this study; however, the economics are presented as one factor influencing that decision.

Section two describes a representative dairy farm used as the base for the system comparison. When the scenario being analyzed created differences in the representative farm, the revised farm conditions are specified in the given section. Section three describes the effect of covered manure storage and manure application methods, section four describes the effect of tillage systems, and section five describes the effect of adding bovine growth hormone. Section six addresses dietary forage content while section seven compares full confinement feeding to systems including pasture. Finally, overall conclusions are provided in section eight.

6.2 Representative Farm

The representative farm used was based on a “typical” dairy farm in Pennsylvania with alfalfa, grass, and corn fields on a medium clay loam soil (model inputs are listed in Appendix A). The 100 ha farm included 100 Holstein cows (average mass of 690 kg), 38 heifers over one year in age (average mass of 470 kg), and 42 heifers under one year of age (average mass of 200 kg). Animals were large Holsteins with a target milk production of 10,000 kg, and were housed in free-stall barns. Random calving was utilized on the farm. Manure was removed from the farm daily, stored in a 3000 m^3 storage tank for up to six months, and applied to cropland bi-annually. The farm area consisted of 20 ha of grass, 30 ha of alfalfa, and 50 ha of corn. The grassland was a mixed sward of approximately 90% orchard grass and 10% white clover. It received 90 kg N ha^{-1} of inorganic fertilizer and 30% of the available manure. The corn area received 20 kg N ha^{-1} of inorganic starter fertilizer and 70% of the available manure. All fields were seeded using conservation tillage, which consisted of chisel plowing, field cultivation, and planting. We assumed that all additional crop nutrient requirements were met through manure nutrients generated on the farm. Manure was field-applied through a custom-hired service using truck-mounted slurry tank spreaders. The systems were assumed to be well-managed dairy farms operated on productive soil (i.e., no marginal lands). All scenarios were simulated over each of 25 years of historical State College, Pennsylvania weather data (1982-2006).

6.3 Manure handling

Although few data were available on GHG emissions from covered versus uncovered slurry storages, using plastic covers was expected to reduce overall GHG emissions from manure storage (Chapter 2). The use of plastic covers was simulated using the method described in Chapter 4. This method assumed that the cover was 99% effective at capturing CH_4. It then assumed that the captured CH_4 was flared and converted to CO_2. As a result, plastic covers would increase emissions of CO_2, but would decrease emissions of CH_4. It was hypothesized that this would lead to an overall reduction of GHGs in CO_2 equivalents from the manure storage.

In addition to covered storages, another alternative handling strategy involves injection as compared to surface application. Injection was expected to reduce, or eliminate, emissions of CH_4, that occur in the days immediately following application. Additionally, injection was expected to increase N_2O, as observed by Drury et al. (2006), who found a significant interaction between N_2O emissions and nitrogen placement depth.

Three scenarios were analyzed to quantify the effect of each handling system on GHG emissions and farm profitability. These scenarios were no cover on the slurry storage with surface application of manure (no cover), covered slurry storage with surface application of manure (cover-SA), and covered slurry storage with injection of manure (cover-Inj). The representative farm was used for no cover with surface application. To simulate a covered slurry storage, the type of tank (Appendix A, Table 15) was changed to a covered tank rather than the concrete tank in the representative farm. For the third scenario, the type of manure storage remained the same as in the previous scenario. To simulate injection, the machine used for manure handling (Appendix A, Table 5) was changed to a truck-mounted slurry tank injector. The initial cost of the storage cover was \$17,500 or \$24 per m^2 of surface area, which was applied to both the second and third scenarios. The use of manure injection increased the initial cost of the manure applicator by $8000; this also increased the power required for applying the manure and reduced the operating capacity of the spreading operation. This additional cost was only applied to the last scenario.

Based on the results, manure storage covers decrease overall GHG, as shown by comparing the results from no cover and cover-SA. This comparison shows that covering the manure storage can reduce the overall global warming potential of emissions by approximately 14% (Figure 6-1). Manure injection does not have much impact on emissions, as shown by comparing the results from cover-SA to cover-Inj. These results show that injection may slightly reduce CO_2 and CH_4; however, this decrease is offset by an increase in N_2O emissions (Figure 6-1). Overall, manure storage covers with surface application of manure emitted the least amount of GHG (i.e., cover-Inj). Because manure handling strategies do not affect milk production, the amount of milk produced was the same in each scenario. The same trend was evident when emissions were normalized by milk production: manure storage covers with surface application emitted the least amount of GHGs.

Including a cover on the manure storage increased the annual production cost by $1400, as shown by the cost difference between no cover (no cover) and a cover with no injection (cover-SA). However, transitioning to a covered storage with injection (cover-Inj) decreased the annual production cost by $1900. With the same total income across all three scenarios (i.e., $370,780), the covered storage with injection gave the greatest net return of all three systems at $79,000.

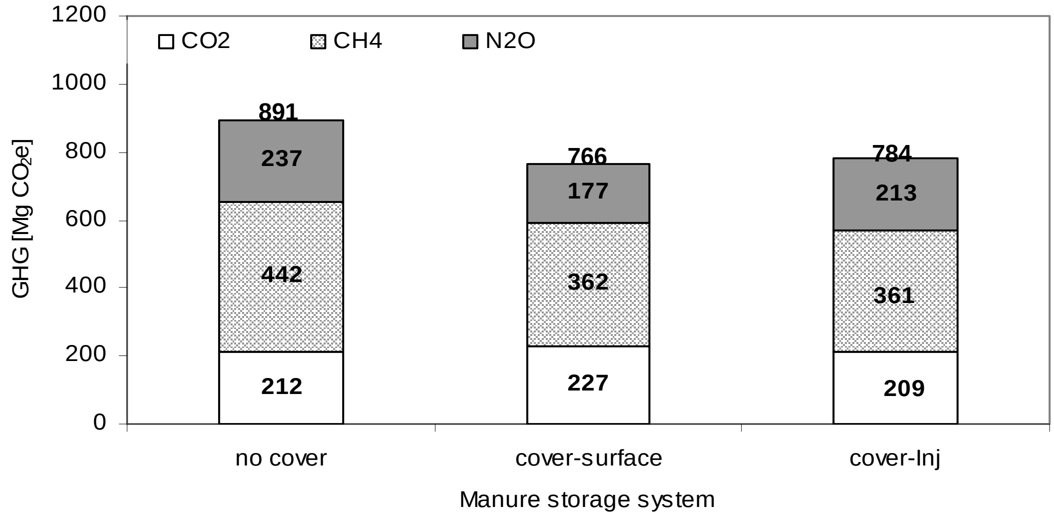

Figure 6-1. GHG emissions from dairy farms with three different manure handling systems.

Table 6-1. Effect of a covered manure storage on annual manure handling costs, production costs, and net return of a representative dairy farm in central Pennsylvania.

	no cover[a]	cover-SA[a]	cover-Inj[a]
Production costs [$]			
Net feed cost[b]	143,010	142,847	140,744
Total manure cost	19,057	20,582	20,750
Animal facilities cost	24,656	24,656	24,656
Other cost and labor[c]	63,307	63,307	63,307
Livestock expenses	36,900	36,900	36,900
Property tax	5,323	5,323	5,323
Total production costs	$292,168	$293,615	$291,680
Milk and animal sales income	$370,780	$370,780	$370,780
Net return to management	$78,612	$77,165	$79,100
Milk production [L/cow]	9,690	9,690	9,690
GHG emissions [g CO_2e/L milk]	920	790	809

[a] "No cover" represents slurry storage with no cover and surface application, "cover-SA" represents a covered storage and surface application, and "cover-Inj" represents a covered storage with injection.
[b] Net feed costs represents the difference between total feed costs and income from surplus feed sales.
[c] Other costs and labor represents milking and milk handling equipment costs; milk and animal handling labor costs, and milk hauling and marketing fees.

6.4 Tillage Systems

The three tillage systems evaluated were conventional (CT), conservation (CS), and no-till (NT). The first two categories, conventional and conservation, mix the soil in two stages, primary and secondary tillage. As compared to secondary tillage, primary tillage is deeper, leaves a rougher surface, and reduces soil strength. Secondary tillage occurs at shallower soil depths, with the main goals being to mix the soil and surface amendments and to level and firm the soil. Conventional tillage used a moldboard plow, which inverted the soil surface. Conservation tillage used a chisel plow to break up the soil, which resulted in more crop residue left on the soil surface as compared to a moldboard plow. The no-till system involved only a planting operation where the soil was minimally mixed to allow seed placement, and surface amendments and the soil surface were left relatively undisturbed.

Changing the tillage system can affect GHG emissions. Tillage systems affect net carbon emissions in three ways. First, tillage operations mechanically disrupt the soil structure, which plays an integral role in the physical protection of SOM. Organic matter becomes physically protected when it is incorporated into soil macroaggregates. When either the quantity or quality of these aggregates is decreased because of tillage operations, SOM is more likely to be decomposed (Post et al., 2004). In the absence of tillage operations, macroaggregates are more likely to form. This increases the physical protection of SOM, decreases decomposition, and reduces the associated release of CO_2 (Six et al., 2000). In addition, reducing tillage allows organic matter to remain on the surface, where conditions are less favorable for decomposition as compared to incorporation in the soil (Bruce et al., 1999). However, reducing tillage can potentially reduce the incorporation of crop residue, an important source of SOM input that can be sequestered into stable soil C pools with a long turnover time (Bruce et al., 1999).

Second, intense tillage operations cause soils to be more prone to both water and wind erosion. Total erosion under a conventional tillage system was observed to be greater than total erosion under reduced (i.e., conservation or no-till) tillage systems, in some cases by two orders of magnitude (Blevins et al., 1990, Seta et al., 1993). Erosion does not cause direct GHG emissions; however, it can lead to indirect emissions depending on the fate of the eroded carbon. Erosion causes losses of organic matter through sediment-bound carbon and loss of particulate organic matter. Because sequestered carbon represents negative GHG emissions (i.e., net carbon emissions = carbon emitted – carbon sequestered), increased erosion can indirectly result in increased GHG emissions. The eroded carbon is available for future decomposition and associated CO_2 release (Post et al., 2004).

The effect of tillage on N_2O emissions is less certain. Beauchamp (1997) suggested that reducing tillage operations was a method for controlling N_2O emissions. Supporting this, Drury et al. (2006) and Malhi et al. (2006) observed that no tillage resulted in less N_2O emissions than conventional tillage. However, Drury et al. (2006) reported that zone tillage (i.e., tilling in the center of the crop row) emitted less N_2O than either no tillage or conventional tillage.

Because of these often conflicting effects of tillage systems on GHG emissions, IFSM was used to simulate a farm under CT, CS, and NT. The representative farm conditions were used, with only a change in tillage system for crop establishment. The representative farm assumed conservation tillage was used. As a result, the representative farm was used to simulate the second scenario, CS. In order to simulate CT, a moldboard plow replaced the coulter-chisel plow for tillage machinery (Appendix A, Table 5). To simulate NT, the representative farm was used but with only planting included as a tillage operation (Appendix A, Table 3).

The GHG emissions did not differ greatly among the three systems, with only 4 Mg CO_2e yr^{-1} difference between the least emissions from CT and the greatest emissions from CS (Figure 6-2). As expected, there was no difference in CH_4 emissions among the three systems. Emissions of N_2O increased under CS, and were the least under NT. Emissions of CO_2 decreased from CT to CS to NT; this decrease was largely due to a decrease in the emissions of CO_2 associated with combustion of fuel. Under a no tillage system, there are fewer operations required on the farm. As a result, there is less fuel consumed and less emission of CO_2 associated with combustion.

From these results, no tillage was shown to have the least GHG emissions among the three systems. Like manure management, changing the tillage system also does not affect the milk produced on the farm. When emissions were normalized per unit of milk produced, the differences among the three systems were further minimized. Conventional, conservation, and no till emitted 920, 910, and 920 g CO_2e kg^{-1} milk produced respectively.

There was a greater difference when comparing the economics of the three systems. All of the three systems had the same income of $370,780. The total production cost was similar for conventional and conservation tillage, with only $1300 separating the two systems. The production costs for no till included an additional cost of $25 ha^{-1} to account for the additional cost of chemicals needed in no-till systems (e.g., herbicide, insecticide). Even with these additional costs, overall production costs for no till were the least of the three systems at $289,254. As a result, the greatest net return to management was under the no till system, which returned $81,526. The other two systems had net returns approximately 5% less than no till.

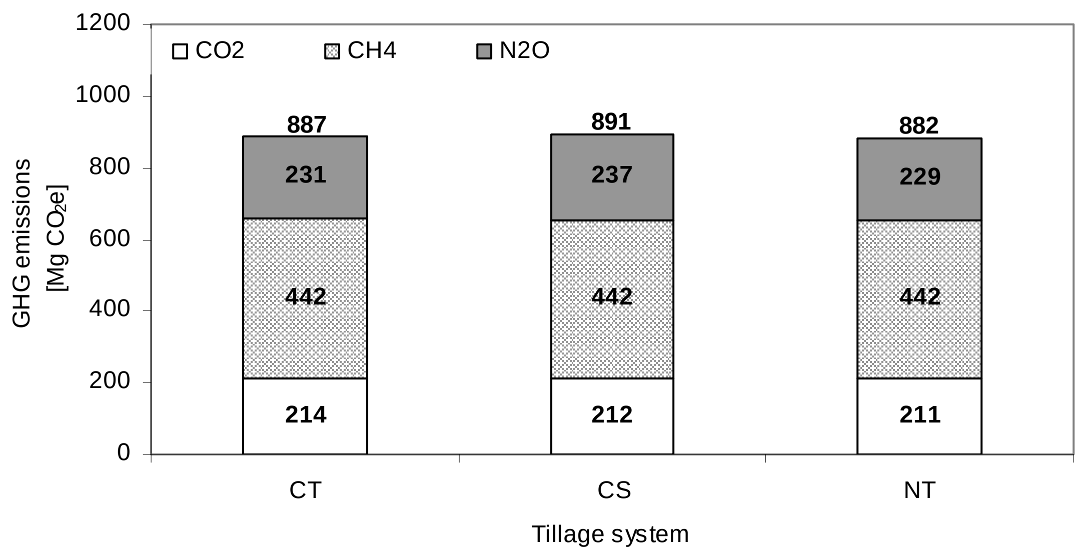

Figure 6-2. GHG emissions from conventional, conservation, and no till.

Table 6-2. Effect of tillage systems on annual manure handling costs, production costs, and net return of a representative dairy farm in central Pennsylvania.

	Conventional	Conservation	No-till
Production costs [$]			
Net feed cost[a]	144,342	143,010	137,578
Total manure cost	19,057	19,057	19,075
Animal facilities cost	24,656	24,656	24,656
Other cost and labor[b]	63,307	63,307	63,307
Livestock expenses	36,900	36,900	36,900
Property tax	5,238	5,238	5,238
Total production costs	$293,500	$292,168	$289,254[c]
Milk and animal sales income	$370,780	$370,780	$370,780
Net return to management	$77,280	$78,612	$81,526
Milk production [L/cow]	9,690	9,690	9,690
GHG emissions [g CO_2e/L milk]	920	920	910

[a] Net feed costs represents the difference between total feed costs and income from surplus feed sales.
[b] Other costs and labor represents milking and milk handling equipment costs; milk and animal handling labor costs, and milk hauling and marketing fees.
[c] Production costs for no-till include an additional $25/ha, representing $15/ha for a broadcast herbicide application prior to planting and $10/ha for a broadcast insecticide application.

6.5 Growth Hormone

Bovine somatotropin (BST) is a naturally-occurring growth hormone in dairy cows. Recombinant BST (rBST) is synthetically produced BST, which was approved by the FDA for use on dairy farms and released for sale in 1994 (EPA, 1999). Monsanto, the only seller of rBST at the time, reported that approximately one-third of all dairy cows in the U.S. were in herds utilizing rBST (McBride et al., 2004). McBride et al. (2004) found that using rBST increased annual milk production by approximately 1,200 kg per cow. Increasing the efficiency of dairy cows by using rBST has been suggested as a method to reduce CH_4 emissions per unit of milk produced (EPA, 1999).

In order to simulate the use of rBST, the representative farm was used with the potential milk production increased from 9,690 L cow^{-1} yr^{-1} to 14,000 L cow^{-1} yr^{-1} (Appendix A, Table 14). The milk production was increased to this high value so that the animals would be forced to produce as much milk as possible. The use of rBST then controlled the amount of milk produced on the diet resulting from the available feed. The farm using rBST was set to the same target milk production with the use of rBST at an annual cost of \$100 cow^{-1} (Appendix A, Table 14). Emissions from both systems were compared.

The results show that the farm using rBST emitted more GHGs than the farm without (Figure 6-3). This increase was due to higher feed intake necessary to achieve the higher milk production stimulated by the use of rBST. Neither farm reached the target milk yield; instead, this target was simply to force the animals to produce as much milk as possible. However, the animals on the farm that used rBST produced 10% more milk than the base case (Table 6-3). When the emissions were normalized based on milk production, the two systems had similar emissions (900 and 880 g CO_2e L^{-1} milk). The simulation results indicate that the use of the hormone may provide a small (2%) reduction in the overall emission per unit of milk produced.

The farm using rBST had increased production costs as compared to the farm without rBST. These costs accounted for the actual cost of the rBST and the additional feed required by the animals, and totaled approximately \$17,000. However, because of the higher milk production, the farm using BST had a 15% greater net return than the farm without BST.

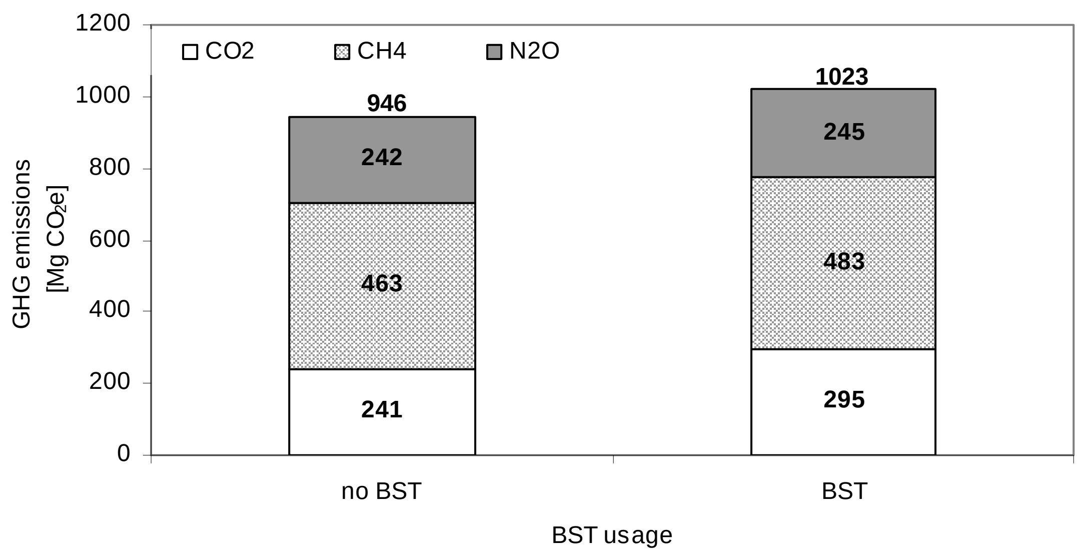

Figure 6-3. GHG emissions from farms utilizing and not utilizing BST.

Table 6-3. Effect of BST adoption on annual manure handling costs, production costs, and net return of a representative dairy farm in central Pennsylvania.

	no rBST	rBST
Production costs [$]		
Net feed cost[a]	151, 639	161,010
Total manure cost	19,264	19,504
Animal facilities cost	24,656	24,656
Other cost and labor[b]	64,880	67,073
Livestock expenses	36,900	46,900
Property tax	5,238	5,238
Total production costs	$302,577	$324,381
Milk and animal sales income	$398,303	$436,677
Net return to management	$95,726	$112,296
Milk production [L/cow]	10,476	11,573
GHG emissions [g CO_2e/L milk]	900	880

[a] Net feed costs represents the difference between total feed costs and income from surplus feed sales.
[b] Other costs and labor represents milking and milk handling equipment costs; milk and animal handling labor costs, and milk hauling and marketing fees.

6.6 Dietary Forage Content

Dairy cows include a rumen, which contains microorganisms with the ability to break down cellulose. The rumen flora thus allows the animals to subsist on grasses and leafy plants. However, research has shown that feeding grains to dairy cows can facilitate rapid weight gain and increase milk production (Huffman, 1961; Madigan et al., 2003). Tessman et al. (1991) varied the forage to grain ratio in Holstein cows to quantify the effect on milk quantity and quality. As percent of diet, forage composition ranged from approximately 38% to 98%. Tessman et al. (1991) observed that milk and milk protein production were relatively constant and then decreased as the percentage of forage in the diet increased beyond approximately 60%. Additionally, feed efficiency decreased as more forage was added to the diet beyond this threshold.

The observations of Tessman et al. (1991) agree with the conventional suggestions of many studies indicating that feeding grain increases the efficiency and productivity of dairy cows up to a limit of about 60% grain (e.g., Huffman, 1961; Smith, 1976). However, a rapid switch to high levels of grain feeding, or feeding too much grain, can lead to acidosis and potential death of the animal (Madigan et al., 2003). In addition, feeding grain can lead to greater populations of acid-tolerant bacteria in the rumen, such as *E. coli*, which can potentially be transferred to products intended for human consumption (Madigan et al., 2003).

Feeding dairy cows a greater percentage of fiber (i.e., forage) as compared to starch (i.e., grain) has been shown to increase CH_4 emissions due to enteric fermentation (Moe and Tyrrel, 1979; Mills et al., 2003). In order to study the effects of a low versus high forage:grain ratio, the representative farm was used to evaluate three scenarios: low ratio, high ratio-purchased feeds, and high ratio-farm produced feeds. The representative farm, where animals were fed a low forage:grain ratio, was used for the first case. For the second case, the animals were switched to a high forage:grain ratio without changing other farm parameters (Appendix A, Table 14); therefore the additional forage required was purchased and purchased grain was reduced. Finally, for the third case, the size of the corn silage storage on the farm was increased so that more forage was produced on the farm and fed to the animals (Appendix A, Table 12). The storage size was increased so that no forage was purchased and only a very minimal amount was sold on the average over the 25 years of weather.

Dairy farms with cows fed a high forage:grain ratio where the additional forage was purchased emitted more GHGs than dairy farms with cows fed a low forage:grain ratio (Figure 6-4, Table 6-4). The least emissions occurred from farms feeding a high forage:grain ratio with the additional forage produced on the farm. Emissions of CH_4 increased in both high ratio systems; this increase agrees with the observation that increasing the dietary fiber intake increases the CH_4 emissions from enteric fermentation. The difference in CH_4 emissions between the two high ratio systems was likely due to different types of forage being fed. For the system with on-farm production of additional forage, more corn silage was fed to the animals as compared to the other scenario where purchased forage was high-quality alfalfa forage.

The farm producing additional forage to meet the high forage:grain ratio also yielded the greatest net return at \$825 cow^{-1} (Table 6-4). The net return for the farm purchasing additional forage was the lowest because of the greater net feed cost. The manure handling costs increased because of the greater mass of manure produced on the farm due to increased forage intake by the animals.

These results indicate that feeding a higher percentage of forage in dairy diets can provide a similar GHG emission as obtained with a high grain diet provided that the additional forage is corn silage produced on the farm. With purchased alfalfa providing the additional forage, there was a 16% increase in overall GHG emission. The next section describes a more in-depth comparison of forage versus grain diets in whole-farm production systems.

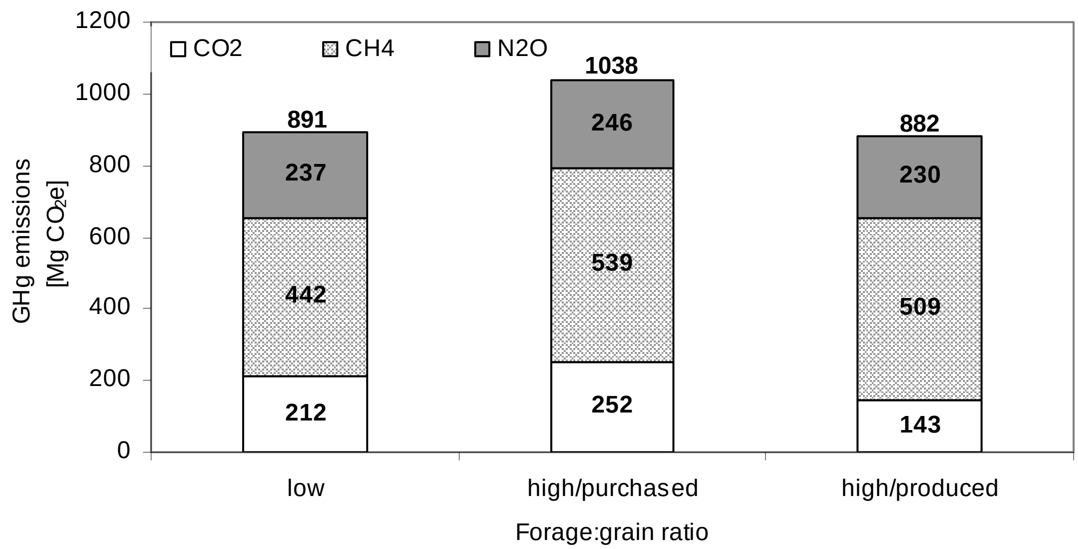

Figure 6-4. GHG emissions from animals fed a low forage:grain ratio, a high forage:grain ratio with additional forage purchased as alfalfa hay, or a high forage:grain ratio with additional forage produced on the farm as corn silage.

Table 6-4.Effect of forage:grain ratio on annual manure handling costs, production costs, and net return of a representative dairy farm in central Pennsylvania.

	low ratio	high - purchased	high - on farm
Production costs [$]			
Net feed cost[a]	143,010	150,557	138,815
Total manure cost	19,057	19,650	19,332
Animal facilities cost	24,656	24,656	24,656
Other cost and labor[b]	63,307	63,307	63,307
Livestock expenses	36,900	36,900	36,900
Property tax	5,238	5,238	5,294
Total production costs	$292,168	$300,308	$288,304
Milk and animal sales income	$370,780	$370,780	$370,780
Net return to management	$78,612	$70,472	$82,476
Milk production [L/cow]	9,690	9,690	9,690
GHG emissions [g CO_2e/L milk]	920	1071	910

[a] Net feed costs represents the difference between total feed costs and income from surplus feed sales.
[b] Other costs and labor represents milking and milk handling equipment costs; milk and animal handling labor costs, and milk hauling and marketing fees.

6.7 Confined Systems vs. Grazing

Grass-based dairy production has been suggested as a healthier alternative for both the animals and the consumer compared to production using more traditional confinement feeding. In the U.S., there is currently a growing demand for organic food products, including organic milk produced on pasture-based systems (Buragas, 2005; Croissant et al., 2007). In addition, pasture-based systems have been shown to decrease soil erosion and downstream nutrient pollution of surface waters (Parker et al., 1991). Casey and Holden (2006) evaluated the differences in GHG emissions between conventional and organic suckler-beef farms in Ireland. However, little data were available on GHG emissions from various production options within the U.S.

Feeding a higher fiber diet of pasture can increase enteric CH_4 production, and pastures may emit greater amounts of N_2O than cropland. However, reducing the use of manure storage and related manure handling processes can reduce the total emission of all three gases. In order to assess the effects of different systems on emissions of GHGs, IFSM was used to simulate three systems: full confinement, winter confinement with summer pasture, and year-round pasture. The full confinement system was the representative farm described in section 7.2. The winter confinement with summer pasture was a combination of confinement and grazing. The 20 ha of grass were available for grazing during the growing season, with both older heifers and all cows grazed using intensively managed rotational grazing. The diet was switched to a high forage:grain ratio to better utilize pasture forage. Animals were assumed to be average-sized Holsteins with an average annual milk production of 8500 kg. The year-round pasture system was an entirely grass-based dairy farm; all 100 ha were devoted to perennial grassland. Animals were assumed to be mixed Holstein and Jersey breeds with an average annual milk production of 6000 kg. Because of the smaller animal size and lower production, the farm was assumed to support 120 animals, with 96 heifers. All of the animals were maintained outdoors year-round (i.e., out-wintered); 30 ha were available for spring grazing, 70 ha were available for summer grazing, and the entire farm area was available for fall grazing. No silos or choppers were used in the grass-based system; excess pasture in the spring and early summer was harvested as baled silage and stored in wrapped bales. As with the winter confinement with summer pasture system, the animals were assumed to be on a high forage:grain diet. The farm utilized spring calving where all animals were bred to calve in March.

Based on the results, the winter confinement with summer pasture system emitted the least amount of GHGs. The negative value for CO_2 emissions accounts for C sequestered in feed on the farm and subsequently fed to animals. The sequestration rate observed in this system was greater (i.e., more negative) than in the other two systems, contributing to the overall lesser emission of GHGs. In addition, the N_2O emissions were less than either full confinement or year-round pasture. Grazing animals reduced the need for manure storage, which is a source of N_2O. However, grazed pastures can emit more N_2O than nitrogen-fertilized crop fields. Although the year-round pasture system eliminated manure storage, the greater emission rate from outwintering on pastures outweighed the contribution from manure storages, explaining why the grass-based system showed the greatest N_2O emission. Grazing the animals only part of the year increased N_2O emission during the grazing period, while greatly reducing emissions from the manure storage during that time. This interaction likely explains why N_2O emissions were the lowest from the winter confinement/summer pasture system.

Similar to this interaction between N_2O emissions from manure storages and from pastures, there was an interaction between CH_4 emissions from manure storages and from the animals. Incorporating grazing into a farm reduces the need for manure storage; however, higher forage diets tend to increase CH_4 emissions from enteric fermentation. As a result, CH_4 emissions were the greatest under the year-round pasture system. Although the CH_4 emissions from manure storage decreased by 74% between the confined and combined system, the increased emission from enteric fermentation resulted in an overall increase in CH_4 emission from the combined system.

All of these systems had different milk productions. Normalizing emissions by milk production rate also showed that winter confinement/summer pasture showed the least emissions. This system emitted 764 g CO_2e per unit of milk as compared to 920 or 1433 g CO_2e per unit of milk for full confinement and year-round pasture, respectively.

The production costs decreased as the farms incorporated grazing; however, the income also decreased. The full confinement system showed the greatest net return. This system had a net return of \$786 cow^{-1}, as compared to \$650 cow^{-1} for year-round pasture, and \$636 cow^{-1} for winter confinement/summer pasture. This simple economic analysis does not take into account the potential increase in product value for the grass-based system. Recently, consumer interest in grass-based products (e.g., grass-fed beef and dairy) has increased. As a result, products from the year-round pasture system may potentially have a higher value than shown here, which could increase the net return from the year-round system.

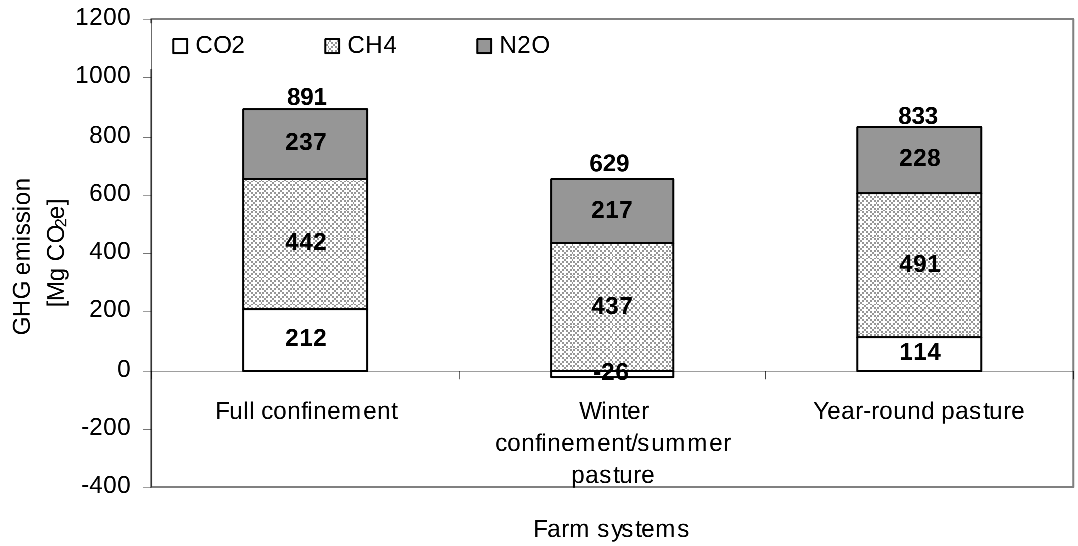

Figure 6-5. GHG emissions from confined, seasonal grazing, and grass-based dairy farms.

6.8 Conclusions

A representative dairy farm in central Pennsylvania was used as the basis to perform an analysis of five management scenarios including different manure handling strategies, different tillage systems, the use of rBST growth hormone, high and low forage concentrations in diets, and the use of grazing. Under each scenario, the systems with the least GHG emissions per unit of milk produced were: covered manure storage with injection, no-till system, using rBST, high forage:grain ratio with additional forage produced on-farm, and winter confinement with summer pasture.

The economics of each system showed a slightly different picture. The scenarios with the greatest net return were: covered storage with injection, no-till system, using rBST, high forage:grain ratio with additional forage produced on-farm, and full confinement. This seems to indicate that the scenario resulting in the least GHG emissions may not always be the most profitable. However, the simulation results were intended to illustrate the capability of IFSM to simulate both GHG emissions and economics. A full economic, or life cycle, analysis, would need to take into account more factors than addressed in this paper. Additionally, the current analyses were based on no GHG emission regulation in the U.S.; if legislation is passed to restrict GHG emissions from farms or if producers can receive economic benefit for reducing emissions, the economics of the systems would likely change.

Table 6-5. Annual manure handling costs, production costs, and net return of full confinement, winter confinement/summer pasture, and year-round pasture dairy farms in central Pennsylvania.

	full confinement	winter confinement/ summer pasture	year-round pasture
Production costs [$]			
Net feed cost[a]	143,010	119,556	97,530
Total manure handling cost	19,057	14,055	4,937
Animal facilities cost	24,656	24,656	9,330
Other cost and labor[b]	63,307	60,399	62,748
Livestock expenses	36,900	34,900[c]	39,480[d]
Property tax	5,238	5,169	3,761
Total production costs	$292,168	$258,735	$217,786
Milk and animal sales income	$370,780	$322,361	$282,856
Net return to management	$78,612	$63,626	$65,070
Milk production [L/cow]	9,690	8,236	5,814
GHG emissions [g CO_2e/L milk]	920	764	1433

[a] Net feed costs represents the difference between total feed costs and income from surplus feed sales.
[b] Other costs and labor represents milking and milk handling equipment costs; milk and animal handling labor costs, and milk hauling and marketing fees.
[c] Livestock expenses decrease for winter confinement/summer pasture because average-sized Holsteins are used rather than large Holsteins.
[d] Livestock expenses increase for year-round pasture because more animals are present on the farm.

Chapter 7

Conclusions

7.1 Summary

The overall objective of this research was to develop a tool for evaluating whole-farm emissions of GHGs from dairy farms and to explore how management scenarios impact emissions. A suite of subroutines was developed and incorporated in IFSM to allow simulation of CO_2, CH_4, and N_2O emissions from animal facilities, manure storage, and croplands. The SoilGHG module predicted CO_2 emissions within the expected emission ranges for specific sources and for overall farm emissions. Also, IFSM predictions of C pools agreed with published reports of C cycling. IFSM was shown to predict CH_4 emissions that were consistent with typical emissions from a representative dairy farm, as well as from specific experiments quantifying emissions. The CH_4 manure storage module was highly sensitive to the Arrhenius parameter for indoor and outdoor manure storage. However, the contribution of manure storages to CH_4 emissions is minimal, so that varying the Arrhenius parameter would have minimal effect on whole-farm GHG emissions in any case. IFSM predicted N_2O emissions within the ranges of reported emissions from various field level studies and DAYCENT simulations, and reasonably represented emissions measured in specific experiments quantifying emissions. The soil N_2O emissions module was highly sensitive to the clay content of the soil, and this sensitivity agrees with previous analyses published on the selected model relationships (Del Grosso et al., 2000b).

With the incorporation of the SoilGHG module, IFSM was able to simulate whole-farm emissions of CO_2, CH_4, and N_2O and was used to evaluate the overall impact of farm management and the implementation of reduction strategies. Using a representative dairy farm in central Pennsylvania as a basis, IFSM was used to analyze scenarios within five management categories: manure handling strategies, tillage systems, the adoption of rBST growth hormone, forage concentration in animal diets, and the use of grazing-based production systems. The following scenarios resulted in the least GHG emissions: covered manure storage with injection, no till, use of rBST, high forage:grain ratio with additional forage produced on farm, and winter confinement/summer pasture.

The model simulated the economics of each system, with the following systems yielding the greatest net return: covered manure storage with injection, no till, use of rBST, high forage:grain ratio with additional forage produced on farm, and winter confinement/summer pasture. However, a more in-depth economic analysis is needed in order to determine the best practice to reduce GHG emissions while maintaining farm profitability. Additionally, this simple economic analysis was performed in the absence of legislated GHG restrictions.

7.2 Scope and Limitations

Applications of IFSM with the SoilGHG model incorporated are restricted by the original limitations of IFSM as well as the added limitations of the SoilGHG model. IFSM was developed to simulate farms located primarily in the Northern U.S. and southern Canada. The model has the capability of simulating a wide range of management scenarios; however, when used to simulate scenarios outside of the intended range of applications, the model assumptions and results should be reassessed and verified. Necessary parameters must be appropriately assigned when simulating new conditions (Rotz et al., 2007).

The spatial scale of IFSM is the farm; system boundaries are assumed to be the farm boundaries so that only effects within the farm system are analyzed. As a result, the interaction of external markets (e.g., dairy market, fertilizer production) with farm economics is ignored. In addition, IFSM is not spatially distributed and treats all areas of each crop as a field with uniform growing conditions. For example, if a farm consists of two corn fields separated by another crop field, IFSM models the two spatially-separate corn fields as one area with the same characteristics.

The temporal scale of IFSM is one year; the model runs over each year of up to 25 years of weather data. Model results represent average values over the time period selected. In other words, the model predicts average annual emissions over 25 years of weather data. When comparing short-term predictions for a specific year, more error may be introduced as described by Rotz et al. (2007). Conversely, IFSM does not predict the effect of management scenarios over longer time periods (e.g., centuries).

However, despite these limitations, IFSM was shown to be capable of evaluating whole-farm emissions of GHGs and analyzing the effect of management scenarios on emissions and farm profitability. The refined model is beneficial to farm managers and researchers as an effective and efficient tool to determine the effects of management scenarios on GHG emissions. By providing this whole-farm evaluation tool, economically-feasible GHG reduction strategies can be identified and evaluated by farmers.

Appendix
Parameter Tables

Parameters used to describe the base farm simulation used in chapter 6.

Table 1. Land and crop parameters

Land and crop	Value
Owned land	100 ha
Rented land	0 ha
Alfalfa	20 ha
Life of alfalfa stand	4 years
Yield adjustment factor	91 %
Maximum annual irrigation	0.0 cm
Nitrogen	0.00 kg N/ha
Phosphate	0.00 kg P2O5/ha
Potash	0.00 kg K2O/ha
Manure	0 % of that collected
Grass	30 ha
Life of grass stand	4 years
Yield adjustment factor	98 %
Legume portion in sward	10 %
Maximum annual irrigation	0.0 cm
Nitrogen	90.00 kg N/ha
Phosphate	0.00 kg P2O5/ha
Potash	0.00 kg K2O/ha
Manure	30 % of that collected
Corn	50 ha
Relative maturity index	110 days
Grain yield adjustment factor	89 %
Silage yield adjustment factor	109 %
Maximum annual irrigation	0.0 cm
Preplanting Nitrogen	20.00 kg N/ha
Postplanting Ammonia	0.00 kg N/ha
Phosphate	0.00 kg P2O5/ha
Potash	0.00 kg K2O/ha
Manure	70 % of that collected

Table 2. Soil characteristics

Soil Characteristics	Value
Predominant soil type	Medium Clay Loam
Available water holding capacity	150.0 mm
Fraction of available water when stress begins	0.500
Bare soil albedo	0.110
Soil evaporation coefficient	5.994 mm
Moist bulk density	1.200 kg/m3
Organic carbon concentration	1.800 %
Silt content	45.000 %
Clay content	45.000 %
Sand content	10.000 %
Runoff curve number	85.000
Whole profile drainage rate coefficient	0.350
Soil pH	6.500
Tractability coefficients	
Spring tillage and planting, upper soil	0.920
Fall tillage and planting, upper soil	0.990
Fall harvest and planting, upper soil	1.030
Spring tillage and planting, lower soil	0.940
Fall tillage and planting, lower soil	1.000
Fall harvest and planting, lower soil	1.010

Table 3. Tillage and planting parameters

Operation	Starting Date
Alfalfa	
Operation #1 Field cultivator/conditioner	10 April
Operation #2 Field cultivator/conditioner	10 April
Operation #3 Alfalfa seeding	25 April
Grass	
Operation #1 Chisel plow	10 September
Operation #2 Tandem disk	15 April
Operation #3 Field cultivator/conditioner	20 April
Operation #4 Field cultivator/conditioner	20 April
Operation #5 Grass seeding	25 April
Corn	
Operation #1 Chisel plow	10 September
Operation #2 Tandem disk	25 April
Operation #3 Field cultivator/conditioner	30 April
Operation #4 Row crop planting	03 May
Maximum operations performed simultaneously:	2
Time available for tillage and planting operations	8.0 hrs/day

Table 4. Grazing parameters

Parameter	Value
Spring grazing area	0 ha
Summer grazing area	0 ha
Fall grazing area	0 ha
Investment in perimeter fence	0 $
Investment in temporary fence	0 $
Investment in watering system	0 $
Annual cost for seed, fertilizer and chemicals	0 $/ha
Grazed forage yield adjustment factor	0 percent
Labor for grazing management	0 h/week
Grazing strategy	Older heifers only

Table 5. Harvest, feeding, tillage, and planting machine parameters.

Machine	Num	Type and Size(Initial Cost)	Tractor(Initial Cost)
Mowing	1	Disk mower-conditioner, 10 ft (3.0 m)	($ 19200)
		87 hp (65 kW) tractor	($ 36400)
Raking	1	Tandem rake, 18 ft (5.4 m)	($ 14000)
		47 hp (35 kW) tractor	($ 10000)
Baling	1	Small round baler	($ 13800)
		87 hp (65 kW) tractor	($ 36400)
Forage chopping	1	Medium forage harvester	($ 22700)
		108 hp (80 kW) tractor	($ 65700)
Grain Harvesting	1	Large corn combine, 12 row	($ 89000)
Feed mixing	1	Medium mixer (9 ton, 8.5 t)	($ 22000)
		87 hp (65 kW) tractor	($ 36400)
Silo filling	1	Small silage bagger (8-9 ft)	($ 20700)
		87 hp (65 kW) tractor	($ 36400)
Manure handling	2	Truck mounted slurry tank spreader	($ 40000)
Plowing	1	Coulter-chisel plow, 12 ft (3.7 m)	($ 10000)
		108 hp (80 kW) tractor	($ 65700)
Disking	1	Tandem disk harrow, 12 ft (3.7 m)	($ 11400)
		108 hp (80 kW) tractor	($ 65700)
Field Cultivation	1	Field cultivator, 12 ft (3.7 m)	($ 9400)
		87 hp (65 kW) tractor	($ 36400)
Row crop planting	1	Corn planter, 6-row (4.6 m)	($ 18000)
		87 hp (65 kW) tractor	($ 36400)
Drill seeding	1	Drill seeder	($ 6000)
		47 hp (35 kW) tractor	($ 10000)

Table 6. Miscellaneous machine parameters

Machine Type	Number	Tractor
Transport tractors	1	47 hp (35 kW) tractor
Feed /manure loader	1	Medium skid-steer loader
Manure nurse tankers	0	
Round bale loader		87 hp (65 kW) tractor
Manure Agitator		87 hp (65 kW) tractor
Initial machine shed cost		60000 $
Custom Operations		
Grain harvest		64.25 $/ha
Manure hauling		60.00 $/hour

Table 7. Feed transport parameters

Feed transport	Machine	Number	Haul distance
Hay	Round bale wagons	1	1.00 km
Hay crop silage	Dump wagons	2	1.00 km
Grain crop silage	Dump wagons	2	1.00 km
Grain	Grain wagons	2	1.00 km

Table 8. Alfalfa harvest parameters
Preferred harvest schedule: 4 Cuttings - Bud first 2 cuttings, early flower last 2

Harvest	Type	Earliest Harvest Date	Drying Treatment
First	Wilted silage harvest by chopping	28 May	Mechanical conditioning, narrow swath
Second	Hay harvest by baling	4 July	Mechanical conditioning, wide swath
Third	Wilted silage harvest by chopping	17 August	Mechanical conditioning, narrow swath
Fourth	Wilted silage harvest by chopping	15 October	Mechanical conditioning, narrow swath

Table 9. Alfalfa harvest parameters

Harvest	Rate	% NDF at Harvest	%Moisture at Harvest	Critical NDF for HQ	Raking treatment	Tedding treatment
First	0.00 L/ha	36	68	42	No raking	No tedding
Second	0.00 L/ha	36	20	42	Raking before harvest	No tedding
Third	0.00 L/ha	39	68	42	Raking before harvest	No tedding
Fourth	0.00 L/ha	0	68	42	Raking before harvest	No tedding

Table 10. Grass harvest parameters
Preferred harvest schedule: 4 Cuttings - early boot first, 35 days to second, 50 days to others

Harvest	Type	Earliest Harvest Date	Drying Treatment
First	Wilted silage harvest by chopping	20 May	Mechanical conditioning, narrow swath
Second	Hay harvest by baling	29 June	Mechanical conditioning, wide swath
Third	Wilted silage harvest by chopping	18 August	Mechanical conditioning, narrow swath
Fourth	Wilted silage harvest by chopping	7 October	Mechanical conditioning, narrow swath

Harvest	Chemical Cond. Rate	% NDF at Harvest	%Moisture at Harvest	Critical NDF for HQ	Raking Treatment	Tedding Treatment
First	0.00 L/ha	45	68	42	No raking	No tedding
Second	0.00 L/ha	45	20	42	Raking before harvest	No tedding
Third	0.00 L/ha	55	68	42	Raking before harvest	No tedding
Fourth	0.00 L/ha	55	68	42	Raking before harvest	No tedding

Table 11. Corn harvest Parameters

Starting dates	
Corn silage	7 September
High moisture corn	1 October
Dried grain	21 October
Maximum silage moisture content at harvest	68 %
Corn silage processing	None
Corn silage cutting height	6.0 cm
High moisture corn type	w/ little or no cob & husk

Table 12. Storage parameters

Forage Type	Storage Type	Capacity (t DM)	Initial Cost ($)	Annual Cost ($/t DM)
High quality forage (1)	Bunker silo	186	32580	1.65
High quality forage (2)	No storage	0	0	0.00
Low quality forage (1)	No storage	0	0	0.00
Low quality forage (2)	No storage	0	0	0.00
Grain crop silage (1)	Bunker silo	292	45828	1.65
Grain crop silage (2)	No storage	0	0	0.00
High moisture grain	Stave silo	325	19441	0.00
Dry Hay	Inside a shed	136	10000	0.00
Dry grain storage	----	----	----	9.91

Table 13. Preservation treatment parameters

Preservation Treatments	Value
High moisture hay drying type	None
Dryer capacity	0.00 t DM
Additional labor	0.00 man h/t DM
Hay preservation procedure	No preservation used
Hay preservation treatment	Buffered/ dilute acid solution
Hay preservation application rate	0.00 %DM
Hay preservation equipment cost	0.00 $

Table 14. Herd and feeding parameters

Herd/Facility Parameters	Value
Animal type	Large Holstein
Target milk production	9690 liter/cow/year
First lactation animals	35 %
Number of lactating animals	100
Number of young stock (over 1 year)	38
Number of young stock (under 1 year)	42
Animal facilities	
Milking center structure: Double six parlor	93000 $
Milking and milk handling equipment	120000 $
Cow housing: Free stall barn	100000 $
Heifer housing: Free stall barn	53700 $
Feed facility: Commodity shed	7000 $
Labor for milking and animal handling	4.0 minutes/cow/day
Feeding Method	
Grain	Loader and mixer wagon
Silage	Loader and mixer wagon
Hay	Self fed round bales
Ration constituents	
Minimum dry hay in rations	0.0% of forage
Relative forage to grain ratio	Low
Crude protein supplement	Soybean meal, 44%
Undegradable protein supplement	User defined feed
Energy supplement	Grain with animal/vegetable oil
Phosphorus feeding level in rations	100.0% of NRC recommendation
Livestock expenses	
Bovine somatotropin injection	0.00 $/cow
Veterinarian and medication	100.00 $/cow
Semen and breeding	45.00 $/cow
Animal and milking supplies	100.00 $/cow
Insurance of animals	10.00 $/cow
Utilities for milking and animal handling	85.00 $/cow
Animal hauling	7.00 $/cow
DHIA, registration, etc.	22.00 $/cow

Table 15. Manure parameters

Manure Parameters	Value
Manure collection method	Scraper with slurry pump
Manure type	Slurry (8 - 10% DM)
Average hauling distance	1.00 km
Average time between manure spreading and incorporation	2 day(s)
Manure storage	
Method	6 month storage
Type	Concrete tank
Loading position	Bottom
Storage capacity	3078 t
Initial storage cost	68717 $
Bedding	
Type	Straw
Amount of bedding per mature animal	1.36 kg/day
Imported manure	
Imported manure	
Quantity	0 t
Type	Dairy
Dry matter content	10.00 %
Nitrogen content	3.80 % DM
Organic nitrogen content	70.00 % DM
Phosphorus content	0.80 % DM
Potassium content	2.40 % DM
Exported manure	
Quantity	0 % of that collected
Form	Fresh manure

Table 16. Economic parameters

General Information	Value
Rates	
Diesel fuel	0.60 $/liter
Electricity	0.10 $/kWh
Grain drying	2.20 $/pt/t DM
Labor wage	10.00 $/hour
Land rental	125.00 $/ha
Property tax	2.30 %
Treatment prices	
Drying agent	0.00 $/kg
Hay preservative	0.00 $/kg
Hay crop silage additive	0.00 $/kg
Grain silage additive	0.00 $/kg
Economic life	
Machinery	10.00 years
Structure	20.00 years
Salvage value	
Machinery	30.00 %
Structure	0.00 %
Interest rate	
Medium term	6.00 %
Long term	6.00 %
Other unaccounted farm overhead	0.00 $

Table 17. Cropping parameters

Cropping Information	Value
Cost of seeds and chemicals	
New forage stand	275.00 $/ha
Established forage stand	20.00 $/ha
Corn land	75.00 $/ha
Soybean land	110.00 $/ha
Additional for corn following corn	35.00 $/ha
Fertilizer prices	
Nitrogen	0.992 $/kg
Phosphate	0.838 $/kg
Potash	0.375 $/kg

Table 18. Commodity parameters

Commodity Information	Value
Buying prices	
Crude protein supplement	264.55 $/t DM
User defined	385.80 $/t DM
Corn grain	135.00 $/t DM
Hay	180.00 $/t DM
Fat	550.00 $/t
Minerals / vitamins	385.00 $/t
Bedding material	65.00 $/t
Selling prices	
Grain crop silage	80.00 $/t DM
High moisture corn	135.00 $/t DM
Corn grain	135.00 $/t DM
Soybeans	231.48 $/t DM
None grain	137.79 $/t DM
Alfalfa hay	180.00 $/t DM
Milk	35.00 $/hL
Cull cow	0.93 $/kg
Heifer	1500.00 $/animal
Calf	100.00 $/animal
Milk hauling, marketing & advertizing fees	2.000 $/hL

Table 19. Custom operations parameters.

Custom Operations	Value
Forage crop tillage and planting	98.84 $/ha
Grain crop tillage	61.78 $/ha
Grain crop planting	39.54 $/ha
Mowing	33.36 $/ha
Raking	17.30 $/ha
Tedding	17.30 $/ha
Baling	16.53 $/t
Grain crop silage chopping	8.27 $/t
Hay crop chopping	8.27 $/t
Grain harvest	64.25 $/ha
Manure hauling	60.00 $/hour

References

Adler, P.R., S.J. Del Grosso, and W.J. Parton. 2007. Life-cycle assessment of net greenhouse-gas flux for bioenergy cropping systems. *Ecol. Appl.* 17(3):675 – 691.

Amon, B., Th. Amon, J. Boxberger, and Ch. Alt. 2001. Emissions of NH_3, N_2O, and CH_4 from dairy cows housed in a farmyard manure tying stall (housing, manure storage, manure spreading). *Nutr. Cycl. Agroecosyst.*, 60:103 – 113.

Baldwin, R.L., J.H.M. Thornley, and D.E. Beever. 1987. Metabolism of the lactating cow. II Digestive elements of a mechanistic model. *J. Dairy Res.* 54:107-131.

Benchaar, C., J. Rivest, C. Pomar, and J. Chiquette. 1998. Prediction of methane production from dairy cows using existing mechanistic models and regression equations. *J. Anim. Sci.* 76:617-627.

Beauchamp, E.G. 1997. Nitrous oxide emission from agricultural soils. *Can. J. Soil Sci.* 77:113 – 123.

Blaxter, K.L. and J.L. Clapperton. 1965. Prediction of the amount of methane produced by ruminants. *Br. J. Nutr.*19:511-522.

Boadi, D.A. and K.M. Wittenberg. 2002. Methane production from dairy and beef heifers fed forages differing in nutrient density using the sulphur hexafluoride (SF6) tracer gas technique. *Can. J. Anim. Sci.*, 82:201-206.

Bouwman, A.F., L.J.M. Boumans, and N.H. Batjes. 2002. Modeling global annual N_2O and NO emissions from fertilized fields. *Global Biogeochem. Cy.* 16(4): doi:10.1029/2001GB001812.

Brye, K.R., S.T. Gower, J.M. Norman, and L.G. Bundy. 2002. Carbon budgets for a prairie and agroecosystems: Effects of land use and interannual variability. *Ecol. Appl.* 12(4):962 – 979.

Bruce, J.P., M. Frome, E. Haites, H. Janzen, R. Lal, and K. Paustian. 1999. Carbon sequestration in soils. *J. Soil Water Conserv.*, 54(1): 382 – 389.

Buragas, A. 2005. Organic dairy demand exceeds supply; new farmers needed. *Cheese Market News*. 25:1, 12.

CARB. 20007. Climate Change. California Air Resources Board webpage. Sacramento, CA: California Air Resources Board. Available at: http://www.arb.ca.gov/cc/cc.htm. Accessed 5 March 2007.

Casey, J.W. and N.M. Holden. 2006. Greenhouse gas emissions from conventional, agri-environmental scheme, and organic Irish suckler-beef units. *J. Environ. Qual.* 35:231 – 239.

CCX. 2007. CCX. Chicago, IL: Carbon Climate Exchange. Available at: http://www.chicagoclimatex.com. Accessed 5 March 2007.

CENTURY. 2007. CENTURY user's guide and reference. Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, CO. Available at: http://nrel.colostate.edu/projects/century5/reference/index.htm.

Chadwick, D.R. and B.F. Pain. 1997. Methane fluxes following slurry applications to grassland soils: laboratory experiments. *Agr. Ecosyst. Environ.* 63:51 – 60.

Chen, Y.R., and A.G. Hashimoto. 1980. Substrate utilization kinetic model for biological treatment processes. *Biotechnol. Bioeng.* 22: 2081 – 2095.

Croissant, A.E., S.P. Washburn, L.L. Dean, and M.A. Drake. 2007. Chemical properties and consumer perception of fluid milk from conventional and pasture-based production systems. *J. Dairy Sci.* 90:4942 – 4953.

Davidson, E.A. 1992. Sources of nitric oxide and nitrous oxide following wetting of dry soil. *Soil Sci. Soc. Am. J.*, 56: 95 – 102.

Davidson, E.A., M. Keller, H.E. Erickson, L.V. Verchot, and E. Veldkamp. 2000. Testing a conceptual model of soil emissions of nitrous and nitric oxide. *Bioscience* 50(8):667 – 680.

Del Grosso, S.J., W.J. Parton, A.R. Mosier, D.S. Ojima, and M.D. Hartman. 2000a. Interaction of soil carbon sequestration and N_2O flux with different land use practices. In *Non-CO_2 greenhouse gases: Scientific understanding, control and implementation*, 303 – 311. J. van Ham et al., eds. Netherlands: Kluwer Academic Publishers.

Del Grosso, S.J., W.J. Parton, A.R. Mosier, D.S. Ojima, A.E. Kulmala, and S. Phongpan. 2000b. General model for N_2O and N_2 gas emissions from soils due to denitrification. *Global Biogeochem. Cy.* 14(4):1045 – 1060.

Del Grosso, S.J., W.J. Parton, A.R. Mosier, D.S. Ojima, C.S. Potter, W. Borken, R. Brumme, K Butterbach-Bahl, P.M. Crill, K. Dobbie, and K.A. Smith. 2000c. General CH_4 oxidation model and comparisons of CH_4 oxidation in natural and managed systems. *Global Biogeochem. Cy*. 14(4):999 – 1019.

Del Grosso, S.J., W.J. Parton, A.R. Mosier, M.D. Hartman, J. Brenner, D.S. Ojima, and D.S. Schimel. 2001. Simulated interaction of carbon dynamics and nitrogen trace gas fluxes using the DAYCENT model. In *Modeling Carbon and Nitrogen Dynamics for Soil Management*, 303 – 332. M.J. Shaffer, L. Ma, and S. Hansen, eds. Boca Raton, FL: CRC Press.

Del Grosso, S.J., A.R. Mosier, W.J. Parton, and D.S. Ojima. 2005a. DAYCENT model analysis of past and contemporary soil N_2O and net greenhouse gas flux for major crops in the USA. *Soil Till. Res.* 83: 9 – 24.

Del Grosso, S.J., W.J. Parton, A.R. Mosier, E.A. Holland, E. Pendall, D.S. Schimel, and D.S. Ojima. 2005b. Modeling soil CO_2 emissions from ecosystems. *Biogeochemistry* 73:71 – 91.

Del Grosso, S.J., W.J. Parton, A.R. Mosier, M.K. Walsh, D.S. Ojima, and P.E. Thornton. 2006. DAYCENT national-scale simulations of nitrous oxide emissions from cropped soils in the United States. *J. Environ. Qual.* 35:1451 – 1460.

Dijkstra, J., H. D. St.C.Neal, D.E. Beever, and J. France. 1992. Simulation of nutrient digestion, absorption, and outflow in the rumen: Model description. *J. Nutr.* 122:2239-2256.

Drury, C.F., W.D. Reynolds, C.S. Tan, T.W. Welacky, W. Calder, and N.B. McLaughlin. 2006. Emission of nitrous oxide and carbon dioxide: Influence of tillage type and nitrogen placement depth. *Soil Sci. Soc. Am. J.* 70:570 – 581.

Energy Information Administration (EIA). 2006. Emissions of greenhouse gases in the United States 2005. DOE/EIA-0573 (2004). U.S. Department of Energy, Washington, D.C. Available at: http://www.eia.doe.gov/oiaf/1605/ggrpt/. Accessed 12 November 2007.

EPA. 1999. U.S. methane emissions 1990 – 2020: Inventories, projections, and opportunities for reductions. EPA 430-R-99-013. U.S. Environmental Protection Agency, Washington, D.C. Available at: http://www.epa.gov/ghginfo. Accessed 23 November 2007.

Fang, C. and J.B. Moncrieff. 1999. A model for soil CO_2 production and transport 1: Model development. *Agr. Forest Meterol.* 95:225 – 236.

FAO. 2006. Livestock's long shadow. H. Steinfeld, P. Gerber, T. Wassenaar, V. Castel, M. Rosales, and C. de Haan, eds. Rome, Italy: FAO.

Flanagan, L.B., L.A. Wever, and P.J. Carlson. 2002. Seasonal and interannual variation in carbon dioxide exchange and carbon balance in a northern temperate grassland. *Global Change Biol.* 8:599-615.

Flessa, H. and F. Beese. 2000. Laboratory estimates of trace gas emissions following surface application and injection of cattle slurry. *J. Environ. Qual.*, 29:262-268.

Flessa, H. P. Dörsch, F. Beese, H. Konig, and A.F. Bouwman. 1996. Influence of cattle wastes on nitrous oxide and methane fluxes in pasture land. *J. Environ. Qual.* 25: 1366 – 1370.

Flessa, H., R.Ruser, P.Dörsch, T.Kamp, M.A.Jimenez, J.C.Munch, and F.Beese. 2002. Integrated evaluation of greenhouse gas emissions (CO2, CH4, N2O) from two farming systems in southern Germany. *Agr. Ecosyst. Environ.* 91:175-189.

Frank, A.B. and W.A. Dugas. 2001. Carbon dioxide fluxes over a northern, semiarid, mixed-grass prairie. *Agr. Forest Meteorol.* 108:317-326.

Franzluebbers, A.J., F.M. Hons, and D.A. Zuberer. 1995. Tillage and crop effects on seasonal dynamics of soil CO_2 evolution, water content, temperature, and bulk density. *Appl. Soil Ecol.* 2:95-109.

García-Ochoa, F., V.E. Santos, L. Naval, E. Guardiola, and B. López. 1999. Kinetic model for anaerobic digestion of livestock manure. *Enzyme Microb. Tech.* 25:55-60.

Gilmanov, T.G., S.B. Verma, P.L. Sims, T.P. Meyers, J.A. Bradford, G.G. Burba, and A.E. Suyker. 2003. Gross primary production and light response parameters of four Southern Plains ecosystems estimated using long-term CO2-flux tower measurements. *Global Biogeochem. Cy.* 17(2):doi:10.1029/2002GB002023.

Ginting, D., A. Kessavalou, B. Eghball, and J.W. Doran. 2003. Greenhouse gas emissions and soil indicators four years after manure and compost applications. *J. Environ. Qual.* 32:23-32.

Goldewijk, K.K. and R. Leemans. 1995. Systems models of terrestrial carbon cycling. In *Carbon sequestration In the biosphere: Processes and Prospects*, 129 – 150. M.A. Beran, ed. New York, New York: Springer.

Grainger, C., T. Clarke, S.M. McGinn, M.J. Auldist, K.A. Beauchemin, M.C. Hannah, G.C. Waghorn, H. Clark, and R.J. Eckard. 2007. Methane emissions from dairy cows measured using the sulfur hexafluoride (SF_6) tracer and chamber techniques. *J. Dairy Sci.* 90:2755 – 2766.

Gregorich, E.G., P. Rochette, A.J. Vandenbygaart, and D.A. Angers. 2005. Greenhouse gas contributions of agricultural soils and potential mitigation practices in Eastern Canada. *Soil Till. Res.*, 83:53-72.

Hashimoto, A.G. 1982a. Effect of mixing duration and vacuum on methane production rate from beef cattle waste. *Biotechnol. Bioeng.* 24: 9-23.

Hashimoto, A.G. 1982b. Methane from cattle waste: Effects of temperature, hydraulic retention time, and influent substrate concentration on kinetic parameter $(K)^*$. *Biotechnol. Bioeng.* 24:2039-2052.

Hashimoto, A.G. 1983. Conversion of straw-manure mixtures to methane at mesophilic and thermophilic temperatures. *Biotechnol. Bioeng.* 25: 185-200.

Hashimoto, A.G. 1984. Methane from swine manure: Effect of temperature and influent substrate concentration on kinetic parameter $(K)^*$. *Agr. Wastes.* 9:299-308.

Hashimoto, A.G., V.H. Varel, and Y.R. Chen. 1981. Ultimate methane yield from beef cattle manure: Effect of temperature, ration consituents, antibiotics and manure age. *Agr. Wastes.* 3:241-256.

Heinen, M. 2006. Simplified denitrification models: Overview and properties. *Geoderma* 133: 444 – 463.

Hensen, A., T.T. Groot, W.C.M. van den Bulk, A.T. Vermeulen, J.E. Olesen, and K. Schelde. 2006. Dairy farm CH_4 and N_2O emissions, from one square metre to the full farm scale. *Agr. Ecosyst. Environ.* 112:146-152.

Hill, D.T. 1982. A comprehensive dynamic model for animal waste methanogensis. *Trans. ASAE* 28(3): 850-855.

Hill, D.T. 1991. Steady-state mesophilic design equations for methane production from livestock wastes. *Trans. ASAE* 34(5):2157-2163.

Hill, D.T. and J.P. Bolte. 1987 Modelling fatty acid relationships in animal waste anaerobic digesters. *Trans. ASAE* 30(2):502-508.

Hillel, D. 1998. Environmental soil physics. San Diego, CA: Academic Press.

Holter, P. 1997. Methane emissions from Danish cattle dung pats in the field. *Soil Biol. Biochem.* 29(1): 31 – 37.

Houghton, R.A., E.A. Davidson, and G.M. Woodwell. 1998. Missing sinks, feedbacks, and understanding the role of terrestrial ecosystems in the global carbon balance. *Global Biogeochem. Cycles* 12(1):25 – 34.

Intergovernmental Panel on Climate Change (IPCC). 2007. Climate change 2007: The physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor, and H.L. Miller, eds. United Kingdom and New York, NY, USA: Cambridge University Press.

Intergovernmental Panel on Climate Change (IPCC). 2001. Climate change 2001: The scientific basis. Contribution of Working Group I to the third assessment report of the Intergovernmental Panel on Climate Change. J.T. Houghton, Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson, eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jarvis, S.C., R.D. Lovell, and R. Panayides. 1995. Patterns of methane emission from excreta of grazing animals. *Soil Biol. Biochem.* 27(12): 1581 – 1588.

Jungbluth, T., E. Hartung, and G. Brose. 2001. Greenhouse gas emissions from animal houses and manure stores. *Nutr. Cycle Agroecosyst.*, 60:133-145.

Kaharabata, S.K., P.H. Schuepp, and R.L. Desjardins. 1998. Methane emissions from aboveground open manure slurry tanks. *Global Biogeochem. Cy.*, 12(3):545-554.

Kaye, J.P., I.C. Burke, A.R. Mosier, and J. P. Guerschman. 2004. Methane and nitrous oxide fluxes from urban soils to the atmosphere. *Ecol. Appl.* 14(4): 975 – 981.

Kaye, J.P., R.L. McCulley, and I.C. Burke. 2005. Carbon fluxes, nitrogen cycling, and soil microbial communities in adjacent urban, native and agricultural ecosystems. *Global Change Biol.* 11: 575 – 587.

Kebreab, E., K. Clark, C. Wagner-Riddle, and J. France. 2006. Methane and nitrous oxide emissions from Canadian animal agriculture: A review. *Can. J. Anim. Sci.* 86:135-158.

Kelly, R.H., W.J. Parton, M.D. Hartman, L.K. Stretch, D.S. Ojima, and D.S. Schimel. 2000. Intra- and interannual variability of ecosystem processes in shortgrass steppe: a new model, verification, simulations. *J. Geophys. Res.: Atmospheres* 105:93 – 100.

Keppler, F. and T. Röckmann. 2007. Methane, plants, and climate change. *Sci. Am.* Vol:52-57.

Kinsman, R., F.D. Sauer, H.A. Jackson, and M.S. Wolynetz. 1995. Methane and carbon dioxide emissions from dairy cows in full lactation over a six month period. *J. Dairy Sci.* 78:2760 – 2766.

Kirchgessner, M., W. Windisch, H.L. Müller, and M. Kreuzer. 1991. Release of methane and of carbon dioxide by dairy cattle. *Agribiol. Res.*, 44(2-3):91-102.

Kucharik, C.J., K.R. Brye, J.M. Norman, J.A. Foley, S.T. Gower, and L.G. Bundy. 2001. Measurements and modeling of carbon and nitrogen cycling in agroecosystems of Southern Wisconsin: Potential for SOC sequestration during the next 50 years. *Ecosystems* 4:237-258.

Külling, D.R., H. Menzi, F. Sutter, P. Lischer, and M. Kreuzer. 2003. Ammonia, nitrous oxide and methane emissions from differently stored dairy manure derived from grass- and hay-based rations. *Nutr. Cycl. Agroecosyst.* 65: 13 – 22.

Lal, R. 2004a. Agricultural activities and the global carbon cycle. *Nutr. Cycl. Agroecosys.* 70:103 – 116.

Lal, R. 2004b. Soil carbon sequestration impacts on global climate change and food security. *Science*, 5677:1623 – 1627.

Lee, D.K., J.J. Doolittle, and V.N. Owens. 2007. Soil carbon dioxide fluxes in established switchgrass land managed for biomass production. *Soil Biol. Biochem.* 39:178-186.

Li, C., S. Frolking, and T.A. Frolking. 1992a. A model of nitrous oxide evolution from soil driven by rainfall events: 1. Model structure and sensitivity. *J. Geophys. Res. – Atmos.* 97(D9): 9759 – 9776.

Li, C., S. Frolking, and T.A. Frolking. 1992b. A model of nitrous oxide evolution from soil driven by rainfall events: 2. Model applications. *J. Geophys. Res. – Atmos.* 97(D9): 9777 – 9783.

Li, Y., D. Chen, Y. Zhang, R. Edis, and H. Ding. 2005. Comparison of three modeling approaches for simulating denitrification and nitrous oxide emissions from loam-textured arable soils. *Global Biogeochem. Cy.* 19: doi:10.1029/2004GB002392.

Li, Y., R. White, D. Chen, J. Zhang, B. Li, Y. Zhang, Y. Huang, and R. Edis. 2007. A spatially referenced water and nitrogen management model (WNMM) for (irrigated) intensive cropping systems in the North China Plain. *Ecol. Model.* 203: 395 – 423.

Liu, X.J., A.R. Mosier, A.D. Halvorson, and F.S. Zhang. 2006. The impact of nitrogen placement and tillage on NO, N_2O, CH_4 and CO_2 fluxes from a clay loam soil. *Plant Soil*, 280:177 – 188.

Lovett, D.K., L. Shalloo, P. Dillon, F.P. O'Mara. 2006. A systems approach to quantify greenhouse gas fluxes from pastoral dairy production as affected by management regime. *Agr. Syst.* 88:156 – 179.

Madigan, M.T., J.M. Martinko, and J. Parker. 2003. Brock biology of microorganisms. NJ:Prentice Hall.

MATLAB. 2007. The MathWorks. Natick, MA, USA.

McBride, W.D. S. Short, and H. El-Osta. 2004. The adoption and impact of bovine somatotropin on U.S. dairy farms. *Rev. Agr. Econ.* 26(4):472 – 488.

Millington, R.J. and R.C. Shearer. 1971. Diffusion in aggregated porous media. *Soil Sci.* 111: 372 – 378.

Mills, J.A.N., J. Dijkstra, A. Bannink, S.B. Cammell, E. Kebreab, and J. France. 2001. A mechanistic model of whole-tract digestion and methanogenesis in the lactating dairy cow: Model development, evaluation, and application. *J. Anim. Sci.* 79:1584-1597.

Mills, J.A.N., E. Kebreab, C.M. Yates, L. A. Crompton, S. B. Cammell, M.S. Dhanoa, R.E. Agnew, and J. France. 2003. Alternative approaches to predicting methane emissions from dairy cows. *J. Anim. Sci.* 81(12):3141-3150.

Moe, P.W. and H.F. Tyrrell. 1979. Methane production in dairy cows. *J. Dairy Sci.* 62:1583-1586.

Møller, H.B., S.G. Sommer, and B.K. Ahring. 2004. Biological degradation and greenhouse gas emissions during pre-storage of liquid animal manure. *J. Environ. Qual.* 33:27-36.

Moncrieff, J.B. and C. Fang. 1999. A model for soil CO_2 production and transport 2: Application to a Florida Pinus elloitte plantation. *Agr. Forest Meterol.* 95:237 – 256.

Monteny, G.J., C.M. Groenestein, and M.A. Hilhorst. 2001. Interactions and coupling between emissions of methane and nitrous oxide from animal husbandry. *Nutr. Cycl. Agroecosyst.* 60:123-132.

Mosier, A.R., G.L. Hutchinson, B.R. Sabey, and J. Baxter. 1982. Nitrous oxide emissions from barley plots treated with ammonium nitrate or sewage sludge. *J. Environ. Qual.*, 11:78 – 81.

Mosier, A.R., A.D. Halvorson, G.A. Peterson, G.P. Robertson, and L. Sherrod. 2005. Measurement of net global warming potential in three agroecosystems. *Nutr. Cycl. Agroecosyst.*, 72:67-76.

NAEMS. 2007. The National Air Emissions Monitoring Study. West Lafayette, IN: Purdue University. Available at: http://cobweb.ecn.purdue.edu/~odor/NAEMS/index.htm. Accessed 14 September 2007.

NRC. 2001. Nutrient requirements of dairy cattle. 7th ed. Washington, D.C.:National Academy Press.

Olesen, J.E., K. Schelde, A. Weiske, M.R. Weisbjerg, W.A.H. Asman, and J. Djurhuus. 2006. Modelling greenhouse gas emissions from European conventional and organic dairy farms. *Agric. Ecosyst. Environ.* 112:207 – 220.

Owensby, C.E., J.M. Ham, and L.M. Auen. 2006. Fluxes of CO2 from grazed and ungrazed tallgrass prairie. *Rangeland Ecol. Manag.* 59:111-127.

Parker, W.J., L.D. Muller, and D.R. Buckmaster. 1992. Management and economic implications of intensive grazing on dairy farms in the Northeastern States. *J. Dairy Sci.* 75:2587 – 2597.

Parton, W.J., D.S. Schimel, C.V. Cole, and D.S. Ojima. 1987. Analysis of factors controlling soil organic matter levels in Great Plains grasslands. *Soil Sci. Soc. Am. J.* 51:1173 – 1179.

Parton, W.J., A.R. Mosier, and D.S. Schimel. 1988. Rates and pathways of nitrous oxide production in a shortgrass steppe. *Biogeochemistry* 6: 45 – 48.

Parton, W.J., D.S. Ojima, C.V. Cole, and D.S. Schimel. 1994. A general model for soil organic matter dynamics: Sensitivity to litter chemistry, texture and management. In *Quantitative Modeling of Soil Forming Processes*, 147 – 167. R.W. Arnold, eds. Madison, WI: SSSA Special Publication 39.

Parton, W.J., A.R. Mosier, D.S. Ojima, D.W. Valentine, D.S. Schimel, K. Weier, and A.E. Kulmala. 1996. Generalized model for N_2 and N_2O production from nitrification and denitrification. *Global Biogeochem. Cy.* 10(3):401 – 412.

Parton, W.J., M. Hartman, D.S. Ojima, and D.S.Schimel. 1998. DAYCENT: its land surface sub-model: description and testing. *Global Planet. Change* 19:35 – 48.

Parton, W.J., E.A. Holland, S.J. Del Grosso, M.D. Hartman, R.E. Martin, A.R. Mosier, D.S. Ojima, and D.S. Schimel. 2001. Generalized model for NO_x and N_2O emissions from soils. *J. Geophys. Res.* 106(D15):17403 – 17419.

Paul, J.W. and E.G. Beauchamp. 1989. Relationship between volatile fatty acids, total ammonia, and pH in manure slurries. *Biol. Waste.* 29:313 – 318.

Pinares-Patiño, C.S., P. D'Hour, J.-P. Jouany, and C. Martin. 2007. Effects of stocking rate on methane and carbon dioxide emissions from grazing cattle. *Agr. Ecosyst. Environ.* 121: 30 – 46.

Post, W.M., R.C. Izaurralde, J.D. Jastrow, B.A. McCarl, J.E. Amonette, V.L. Bailey, P.M. Jardine, T.O. West, and J. Zhou. 2004. Enhancement of carbon sequestration in US soils. *BioScience* 54(10):895 – 908.

Potter, C.S., E.A. Davidson, L.V. Verchot. 1996. Estimation of global biogeochemical controls and seasonality in soil methane consumption. *Chemosphere* 32(11): 2219 – 2246.

Reicosky, D.C. 1997. Tillage-induced CO2 emission from soil. *Nutr. Cycl. Agroecosys.* 49:273-285.

RGGI. 2007. Regional Greenhouse Gas Initiative. Available at: http://www.rggi.org. Accessed 5 March 2007.

Robertson, G.P., E.A. Paul, and R.R. Harwood. 2000. Greenhouse gases in intensive agriculture: Contributions of individual gases to the radiative forcing of the atmosphere. *Science*, 289(5486):1922-1925.

Rotz, C.A. 2004. Management to reduce nitrogen losses in animal production. *J. Animal Sci.* 82 (E. Suppl.):E119 – E137.

Rotz, C.A., D.R. Mertens, D.R. Buckmaster, M.S. Allen, and J.H. Harrison. 1999. A dairy herd model for use in whole farm simulations. *J. Dairy Sci.* 82(12):2826 – 2840.

Rotz, C.A., G.W. Roth, K.J. Soder, and R.R. Schnabel. 2001. Economic and environmental implications of soybean production and use on Pennsylvania dairy farms. *Agron. J.* 93(2):418 – 428.

Rotz, C.A., G.W. Roth, and W.L. Stout. 2002a. Economic and environmental implications of small grain production and use on Pennsylvania dairy farms. *Appl. Eng. Agric.* 18(4):417 – 428.

Rotz, C.A., A.N. Sharpley, L.D. Satter, W.J. Gburek, and M.A. Sanderson. 2002b. Production and feeding strategies for phosphorus management on dairy farms. *J. Dairy Sci.* 85(11): 3142 – 3153.

Rotz, C.A., M.S. Corson, and C.U. Coiner. 2007. *Integrated Farm System Model: Reference Manual*. Pasture Systems and Watershed Management Research Unit, USDA Agricultural Research Service: University Park, PA. Available at: http://www.ars.usda.gov/Main/docs.html?docid=8519. Accessed 31 October 2007.

Saggar, S., R.M. Andrew, K.R. Tate, C.B. Hedley, N.J. Rodda, and J.A. Townsend. 2004a. Modelling nitrous oxide emissions from dairy-grazed pastures. *Nutr. Cycl. Agroecosyst.* 68: 243 – 255.

Saggar, S., N.S. Bolan, R. Bhandral, C.B. Hedley, and J. Luo. 2004b. A review of emissions of methane, ammonia, and nitrous oxide from animal excreta deposition and farm effluent application in grazed pastures. *New Zeal. J. Agr.* 47: 513 – 544.

Saggar, S., D.L. Giltrap, and K.R. Tate. 2007. Modelling nitrous oxide emissions from grazed grasslands in New Zealand. *Agric. Ecosyst. Environ.* 119: 205 – 216.

Sahrawat, K.L. and D.R. Keeney. 1986. Nitrous oxide emissions from soils. *Adv. Soil Sci.* 4:103 – 148.

Sauerbeck, D.R. 2001. CO_2 emissions and C sequestration by agriculture – perspectives and limitations. *Nutr. Cycl. Agroecosyst.* 60:253-266.

Schils, R.L.M., A. Verhagen, H.F.M. Aarts, and L.B.j. Sebek. 2005. A farm level approach to define successful mitigation strategies for GHG emissions from ruminant livestock systems. *Nutr. Cycl. Agroecosyst.* 71:163 – 175.

Schlesinger, W.H. 2000a. Carbon sequestration in soils. *Science* 284:2095.

Schlesinger, W.H. 2000b. Carbon sequestration in soils: some cautions amidst optimism. *Agr. Ecosyst. Environ.* 82:121 – 127.

Sedorovich, D., C.A. Rotz, and T.L. Richard. 2007a. Greenhouse gas emissions from dairy farms. ASABE Paper No. 074096. St. Joseph, Mich.:ASABE.

Sedorovich, D.M., C.A. Rotz, P.A. Vadas, and R.D. Harmel. 2007b. Simulating management effects on phosphorus loss from farming systems. *Trans. ASABE* 50(4):1443 – 1453.

Sharpley, A.N. 1985. The selective erosion of plant nutrients in runoff. *Soil Sci. Soc. Am. J.* 49:1527–1534.

Sherlock, R.R., S.G. Sommer, R.Z. Khan, C.W. Wood, E.A. Guertal, J.R. Freney, C.O. Dawson, and K.C. Cameron. 2002. Emission of ammonia, methane and nitrous oxide from pig slurry applied to a pasture in New Zealand. *J. Environ. Qual.* 31:1491-1501.

Sims, P.L. and J.A. Bradford. 2001. Carbon dioxide fluxes in a southern plains prairie. *Agr. Forest Meteorol.* 109:117-134.

Six, J., E.T. Elliott, and K. Paustian. 2000. Soil macroaggregate turnover and microaggregate formation: a mechanism for C sequestration under no-tillage agriculture. *Soil Biol. Biochem.* 32:2099 – 2103.

Sneath, R.W., F. Beline, M.A. Hilhorst, and P. Peu. 2006. Monitoring GHG from manure stores on organic and conventional dairy farms. *Agr. Ecosyst. Environ.*, 112:122-128.

Sommer, S.G., R.R. Sherlock, and R.Z. Khan. 1996. Nitrous oxide and methane emissions from pig slurry amended soils. *Soil Biol. Biochem.* 28(10/11):1541 – 1544.

Sommer, S.G. and P. Dahl. 1999. Nutrient and carbon balance during the composting of deep litter. *J. Agric. Eng. Res.* 74:145-153.

Sommer, S.G., S.O. Petersen, and H.T. Søgaard. 2000. Greenhouse gas eission from stored livestock slurry. *J. Environ. Qual.*, 29:744-751.

Sommer, S.G., S.O. Petersen, and H.B. Møller. 2004. Algorithms for calculating methane and nitrous oxide emissions from manure management. *Nutr. Cycl. Agroecosyst.* 69:143-154.

Stange, F., K. Butterbach-Bahl, H. Papen, S. Zechmeister-Boltenstern, C. Li, and J. Aber. 2000. A process-oriented model of N_2O and NO emissions from forest soils. 2. Sensitivity analysis and validation. *J. Geophys. Res.* 205(D4): 4385 – 4398.

Stehfest, E. and L. Bouwman. 2006. N_2O and NO emission from agricultural fields and soils under natural vegetation: summarizing available measurement data and modeling of global annual emissions. *Nutr. Cycl. Agroecosyst.*, 74:207 – 228.

Suyker, A.E. and S.B. Verma. 2001. Year-round observations of the net ecosystem exchange of carbon dioxide in a native tallgrass prairie. *Global Change Biol.* 7: 279 – 289.

Suyker, A.E., S.B. Verma, G.G. Burba, and T.J. Arkebauer. 2005. Gross primary production and ecosystem respiration of irrigated maize and irrigated soybean during a growing season. *Agr. Forest Meteorol.* 131:180-190.

Tessman, N.J., H.D. Radloff, J.Kleinmans, T.R. Dhiman, and L.D. Satter. 1991. Milk production response to dietary forage:grain ratio. *J. Dairy Sci.* 74(8):2696 – 2707.

U.S. EPA. 1997. Emission factor documentation for AP-42 Section 2.4: Municipal solid waste landfills – Revised. In Compilation of Air Pollutant Emission Factors. Research Triangle Park, NC: US EPA.

USDA-SCS. 1999. Chapter 4. Agricultural waste characteristics. In *Agricultural Waste Management Field Handbook*, 4-1 to 4-23.

van Hulzen, J.B., R. Segers, P.M. van Bodegom, and P.A. Leffelaar. 1999. Temperature effects on soil methane production: an explanation for observed variability. *Soil Biol. Biochem.* 31:1919 – 1929.

Varga, G.A., R.E. Graves, J. Heinrichs, and E.F. Wheeler. 2007. Unpublished data from *Reducing ammonia emissions from dairy farms – Evaluating whole farm strategies*. USDA Special Grants 2004-2007. University Park, PA: The Pennsylvania State University.

Verma, S.B., A. Dobermann, K.G. Cassman, D.T. Walters, J.M. Knops, T.J. Arkeabuer, A.E. Suyker, G.G. Burba, B. Amos, H. Yang, D. Ginting, K.G. Hubbard, A.A. Gitelson, and E.A. Walter-Shea. 2005. Annual carbon dioxide exchange in irrigated and rainfed maize-based agroecosystems. *Agr. Orest Meteorol.* 131:77-96.

Wagner-Riddle, C., G.W. Thurtell, G.K. Kidd, E.G. Beauchamp, and R. Sweetman. 1997. Estimates of nitrous oxide emissions from agricultural fields over 28 months. *Can. J. Soil Sci.* 77: 135 – 144.

Wilkerson, V.A., D.P. Casper, and D.R. Mertens. 1995. The prediction of methane production of Holstein cows by several equations. *J. Dairy Sci.* 78:2402-2414.

Yamulki, S., S.C. Jarvis, and P. Owen. 1999. Methane emission and uptake from soils as influenced by excreta deposition from grazing animals. *J. Environ. Qual.* 28: 676 – 682.

Yates, C.M., S.B. Cammell, J. France, and D.E. Beever. 2000. Prediction of methane emissions from dairy cows using multiple regression analysis. *Proc. Br. Soc. Anim. Sci.* 2000:94.

Zeeman, G. 1994. Methane production/emission in storages for animal manure. Fert. Res. 37:207-211.

Zeikus, J.G., and M.R. Winfrey. 1976. Temperature limitation of methanogenesis in aquatic sediments. *Appl. Environ. Microbiol.* 31:99 – 107.

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EDUCATION

Engineer-In-Training, Pennsylvania

Ph.D., Agricultural and Biological Engineering, The Pennsylvania State University, Degree Expected May 2008. Dissertation: Simulating the emissions of greenhouse gases from dairy farms.

M.S., Agricultural and Biological Engineering, The Pennsylvania State University, May 2005. Thesis: Analyzing the effect of phosphorus management strategies on farm profitability and the environment.

B.S., Biological and Environmental Engineering, Cornell University, May 2003.

EXPERIENCE

Research Associate, ENVIRON International Corporation, 2008 – present

Analyze air emissions from facilities including the oil and gas production sector. Review relevant literature for dairy farm air emissions. Summarize proceedings from workshops addressing the implementation of legislation to reduce greenhouse gas emissions in California.

Doctoral Research, Penn State, 2005 – 2008

Create a computer model to simulate the carbon cycle and greenhouse gas emissions from dairy farms. Analyze the impact of reduction strategies on greenhouse gas emissions from dairy farms.

Research Associate, ENVIRON Corporation, 2006

Sampled indoor air quality to analyze the effects of a chemical plume in groundwater. Analyzed the emissions of volatile organic compounds from a major airline. Completed air quality reports, including Title V reports and California Annual Emissions Reports, for a major airline and two poultry farms.

Masters Research, Penn State, 2003 – 2005

Created a FORTRAN computer model simulating phosphorus transport in the soil and on the surface. Quantified the effects of phosphorus management on farm profitability and the environment

Teaching Assistant – Agricultural and Biological Engineering, Penn State 2007

Held office hours for a heat and mass transfer class with approximately 25 students. Developed and taught several mass transfer lectures. Graded homework assignments for mass transfer material.

PUBLICATIONS

Sedorovich, D., C.A. Rotz, and T. Richard. 2008. Estimated greenhouse gas emissions from a Northeastern dairy farm. Submitted to the Journal of Environmental Quality. ABE.

Sedorovich, D.M., C.A. Rotz, P.A. Vadas, and R.D. Harmel. 2007. Simulating management effects on phosphorus loss from farming systems. Transactions of the ASABE. 50(4):1443 – 1453.

AWARDS AND AFFILIATIONS

- Penn State's College of Engineering Research Symposium – 3rd place (2007)
- NASA Space Grant Fellowship Award (2005 – 2007)
- American Society for Agricultural and Biological Engineers (ASABE) (2005 – present)