TECHNICAL WORKING GROUP ON AGRICULTURAL GREENHOUSE GASES (T-AGG) SUPPLEMENTAL REPORT

Using Biogeochemical Process Models to Quantify Greenhouse Gas Mitigation from Agricultural Management Projects

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Duke
NICHOLAS INSTITUTE
FOR ENVIRONMENTAL POLICY SOLUTIONS

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What is T-AGG?

The **Technical Working Group on Agricultural Greenhouse Gases (T-AGG)** began work in November 2009 to assemble the scientific and analytical foundation to support implementation of high-quality agricultural greenhouse gas (GHG) mitigation activities. Mitigation activities that increase carbon storage in soil or reduce methane and nitrous oxide emissions could be an important part of U.S. and global climate change strategies. Despite the significant potential for GHG mitigation within agriculture, only a very few high-quality and widely approved methodologies for quantifying agricultural GHG benefits have been developed for various mitigation programs and markets. Much of the focus to date has been around forests on agricultural lands and manure management, rather than on production agriculture or grazing lands where we focus our attention. However, there are now a number of new agricultural protocols under development.

T-AGG is coordinated by a team at the Nicholas Institute for Environmental Policy Solutions at Duke University with partners in the Nicholas School of the Environment at Duke and at Kansas State University, and regularly engages the expertise of a science advisory committee and cross-organizational advisory board (details below). The work was made possible by a grant from the ***David and Lucile Packard Foundation***.

The project is producing a series of reports which survey and prioritize agricultural mitigation opportunities in the U.S. and abroad. The purpose is to provide a roadmap for protocol and program development, and provide in-depth assessments of the most promising approaches. Experts and scientists are providing guidance throughout the process, through the advisory groups, experts meetings, and individual outreach. We will also involve the agricultural community in order to gain their feedback and guidance on the approaches assessed in our reports. We hope these reports will be of use to private or voluntary markets and registries as well as regulatory agencies and corporate decision makers that may oversee similar programs or the development of regulatory carbon markets. We intend for these reports to provide the fundamental information necessary for the development or review of protocols designed for agricultural GHG mitigation projects or for broader programs that wish to address GHG mitigation.

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For more information see our website: http://nicholasinstitute.duke.edu/ecosystem/t-agg

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Summary

This paper provides an overview of how biogeochemical process models can be used to quantify greenhouse gases (GHG) in agricultural systems for use in developing GHG mitigation programs or protocols. Federal and state agencies, voluntary carbon market registries, and companies are all looking for ways to assess mitigation opportunities in agriculture and to track outcomes of various management options.

These process models may provide the most effective way of quantifying GHG impacts of agricultural management for a large-scale program, company, or market. Robust models have been developed and tested in the U.S. over the last few decades. Further development and improvement of these models and relevant research continue to be supported by the U.S. Department of Agriculture (USDA) and National Science Foundation (NSF). The models have strong coverage of all commodity crops but may be somewhat limited in their coverage for smaller-scale or specialty crops and more complex livestock systems due to a lack of research or experimental data with which to properly validate and calibrate the models. It has been over a decade since the last side-by-side comparison of the main biogeochemical models. It would be of value to update this comparison to allow better understanding of how structural error and other critical issues vary across the main models. For all models, development of a national network of long-term sampling sites would help to improve our understanding of the background changes in GHGs driven by climate shifts and improve the accuracy of model predictions.

If models are to be used for development of agricultural GHG programs or protocols, they will need to be applied in a standardized way, either at a regional scale to develop emissions factors for emissions calculations used in protocols, or at a farm scale to directly quantify net GHGs using a standardized user interface to collect data and allow for consistent model use. There are tradeoffs to be considered when selecting between regional and farm-scale applications of models. Regional applications may be best when there are less research and data available for the practices of interest or where critical site-level verification would be too complex or costly. Farm-level applications increase flexibility of management combinations and incorporation of farmer variability, but require additional farm-level data. To maintain accuracy at this finer scale, programs will need clear alignment of definitions of management practices and guidance on verification, which may increase complexity and costs.

Introduction

Numerous decision makers are looking toward the development of performance-based metrics for net GHG impacts of various agricultural practices in the U.S. and abroad. These include voluntary GHG offset registries, corporate and government supply-chain initiatives, international organizations (e.g., the Food and Agricultural Organization [FAO] of the United Nations), federal agencies (e.g., U.S. Department of Agriculture [USDA] and Environmental Protection Agency [EPA]) that are developing incentive and voluntary program requirements, and state and federal legislators who are considering the role of agriculture in various climate change, biofuels, and farm policies.

Agricultural lands (cropland, managed grassland, agroforestry, and bioenergy crops) cover 40%–50% of the Earth's land surface (IPCC 2007a) and account for 10%–12% of GHG emissions currently attributable to human activity. This is a conservative estimate that does not include the fuel use, transportation, buildings, and deforestation associated with agriculture. Agriculture now accounts for around 50% of human contributed methane (3.3 Gt CO_2e/yr)[1], and 60% of human-contributed nitrous oxide (2.8 Gt CO_2e/yr), (U.S. EPA 2006a; U.S. EPA 2006b). Many options exist for GHG mitigation in agriculture, including improved crop and grazing land management (e.g., nutrient use; tillage, rotation, and residue use; water and drainage), land-use changes (e.g., set-aside lands, forested buffers, agroforestry), and

[1] The term *ton* (abbreviated *t*) in this report refers to the metric ton (1 ton [or *tonne*] = 1,000 kg = 2,204.62 lbs). Hence, the abbreviations *Mt* and *Gt* refer to the megaton (1 million metric tons) and gigaton (1 billion metric tons), respectively.

improved livestock management (e.g., alternative feeds, selecting for feed efficiency, manure management). Shifts in land management can increase sequestration of carbon in soils and plants and reduce emissions of nitrous oxide (N_2O) and methane (CH_4). Sequestration of carbon in soils (enhancing sinks) provides almost 90% of the global potential for agricultural GHG mitigation.

GHG quantification is a critical step in protocols or programs that aim to track project performance. Models can be an effective way of quantifying GHG emission sources and sinks that are influenced by variable biological processes, dispersed across the landscape, and occur across mixed crop-livestock systems. Whatever quantification approach is used will need to be set within the context of the program objectives and within a comprehensive accounting approach that estimates uncertainty, clarifies project boundaries, and baseline conditions, and for carbon market approaches would include additionality, permanence, and leakage as well.[2] A number of these accounting issues such as specific boundaries and selected baseline approach, will need to be integrated with the quantification approach. Either the quantification tool or system will need to be adjusted to include the program-specific baseline and boundary requirements, or the protocol or guidance will need to explain how to make necessary adjustments for applying the tool.

While we have a rough but relatively clear picture as to where some of the biggest opportunities lie for changing agricultural practices to achieve greater efficiencies and mitigate GHGs (Smith et al. 2008), we have less clarity on how to quantify such changes at local scales. The Intergovernmental Panel on Climate Change (IPCC) has developed metrics (default factors; IPCC Tier 1) for estimating GHG emissions or sequestration at the national level, but these methods become less accurate as spatial scale decreases from the regional level to local and site levels and they do not account for many of the management practices that are expected to reduce emissions (e.g., changing fertilizer type). Thus, these metrics are not sensitive to management changes that farmers would implement on the ground. So, why not simply use direct field measurement to assess changes at local and site-level scales? While this may be a viable option for some projects, it may not work well for many others. Soils and soil carbon are extremely variable, and detecting changes in soil carbon using field measurement alone can be expensive. We are often looking for relatively small changes against a large background pool of stored carbon. Another difficulty is tracking other, more potent GHGs, namely, nitrous oxide and methane, which are, per molecule, 298 and 25 times more potent than carbon dioxide, respectively.[3] Field measurements of nitrous oxide and methane flux with current chamber and tower methods are expensive and difficult to use, and thus are not ready for wide-scale implementation. Changes in the emissions of these gases can be the goal of the shift in agriculture practice or just an unfortunate consequence, but we want to ensure that reducing emissions of one GHG does not simply increase emissions of another. Thus net accounting of all three GHGs as they are impacted by management is necessary. Given these difficulties with field measurement, programs in Canada and the U.S. are looking to modeling-based approaches for quantification. There are two types of modeling approaches used:

1. **Empirical models.** Regression analysis is used to extrapolate existing research and data to develop regionally explicit emissions factors. The regression equations produce GHG response curves for different management impacts. They are often specific to conditions at the ecozone or ecotype scale and thus are aggregated across sites. They can be developed without the use of a complex model and are relatively easy and transparent to use. They do not capture the effects of

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[2] *Additionality* criteria require that the project would not occur without the incentive offered by the program or market. *Permanence* criteria require that a project accounts for the risk that carbon sequestration is reversible. *Leakage* criteria require that the project accounts for emissions that shift outside the project boundary as a result of the project. Leakage results because demand for products (crop, timber) shifts to areas where the increase in emissions is not accounted for.

[3] See IPCC 2007b, Table 2.14, p. 212 at http://www.ipcc.ch/pdf/assessment-report/ar4/wg1/ar4-wg1-chapter2.pdf. For the sake of fungibility, most GHG programs use the SAR 100-yr values, according to which N_2O and CH_4 are 310 and 21 times more potent, respectively, than CO_2. We use the latest IPCC values here.

spatial and temporal variability on GHG dynamics at finer scales, and can be less flexible in handling variable management combinations.

2. **Process-based biogeochemical models.** These models use mechanistic equations based on substantial long-term research to represent growth, nutrient, water, soil, and GHG dynamics. The models can be used in two distinct ways:

    a. At an ecozone or regional (pTier 2) scale, covering area with similar soils and climate, to produce reasonable, regionally sensitive emissions factors that can be used to develop a protocol or program accounting methodology. This approach can be relatively simple, transparent, and low-cost. However, using models at this scale may not reflect the spatial/temporal variability of GHG dynamics at a particular local site in the region.

    b. At a farm or project (pTier 3) scale which can be used for a quantification tool within a protocol or program accounting methodology. At this scale models can capture fine-scale variability and dynamics but require significantly more site-level data inputs and detailed verification.

This paper focuses on the use of process-based models, providing an overview of how these models work, and a detailed review of three well-developed and commonly used models in the U.S. We discuss the limitations and uncertainties inherent in these models and options for how they can be used in the development of GHG protocols and programs. We close with a couple of examples, describing a few existing protocols that have used these models.

Project-level application of IPCC tiers
Given that many programs and quantification approaches under development are using the IPCC methods as a reference or default, we developed a similar typology to categorize approaches for quantifying greenhouse gases for mitigation projects or programs rather than for national inventories. To differentiate our typology, we use pTiers to indicate that we are referring to project- or program-scale approaches rather than national inventories.

pTier 1: IPCC Tier 1 default factors are used for projects. These are national-scale and annual-resolution, and have limited land-use and management activity and coarse delineation of soils and animal populations. They have high uncertainty when applied at a project scale.

pTier 2: Intermediate spatial and temporal scale input data, using process or empirical models to develop region-specific empirical equations with emissions factors which can and have been used for project-based accounting.

pTier 3: Field-, site-, and farm-scale quantification, which can be accomplished with field sampling and measurement using carefully established sampling scheme to meet acceptable levels of certainty. Process-based biogeochemical models that use field-scale data and daily time steps can also be used to quantify net greenhouse gases at this scale.

Process-Based Biogeochemical Models

Biogeochemical process models can simulate GHG dynamics under a range of changing environmental (soil physical properties, climate, topography, previous land management) and management (cropping, livestock, manure, grazing practices) variables while capturing temporal and spatial variability. These models are designed to work at the site-level scale, and are calibrated and tested using data from long-term controlled experiments and field observations. They can be scaled up and averaged for use at larger scales—a process that can result in a reasonable balance of accuracy and conservativeness, if uncertainties in the estimates can be quantified. One of these models (CENTURY/DAYCENT) is currently used for the national GHG inventory for land use in the United States and Canada. Process-based models can produce estimates of GHG change in response to changes in land use or management reasonably well when provided with significant environmental and agricultural data inputs and detailed site knowledge.[4] If the necessary data are available, they can simulate a baseline scenario (what would have happened without a program incentive), the changes in GHGs due to a shift in management, and the interactions of multiple changes in crops and practices over a complex landscape. However, even in the United States and Canada, where there are extensive high-quality national and regional databases and numerous long-term agricultural research sites, the availability of experimental data across all types of cropping, soils and livestock systems can be a limiting factor in validating the model and quantifying the uncertainty of the outcomes for various practices and crops.

The question of how the models handle multiple simultaneous practices that are typical of complex agricultural systems has been raised. Field measurement integrates everything that happens on a field, thus integrating across management changes. But what about models? Since the biogeochemical models are based on the processes and mechanisms that affect GHGs, they are designed to integrate multiple practices on the landscape. For example, shifting tillage results in changes in soil moisture and temperature as well as depth of aeration and soil organic matter placement in the soil profile; these changes to the physical and chemical environment are the changes that cascade through the model. If shifts in crop rotations occur at the same time, impacts of these shifts on total C and N in residue inputs, water use efficiency, and thus soil moisture interact with those from tillage and cascade through the model in tandem. The outcome is an integrated change in GHG fluxes.

Summary of the Main Biogeochemical Process Models

There are a number of process-based models that could be used to quantify GHG fluxes in agricultural systems. They vary somewhat in their approaches to modeling soil processes and in their calibration for different regions, management activities, and crops. Three of these models are well parameterized for use in the United States and are in wide use for quantifying agricultural GHGs: CENTURY/DAYCENT, DNDC, and EPIC/APEX. CENTURY/DAYCENT are two variations of the same model; CENTURY is a carbon cycle model, while DAYCENT operates at a finer time scale and can be used for other GHGs in addition to carbon. EPIC/APEX are also two variations of the same model, but here the difference is that APEX is the watershed version, allowing linked hydrological modeling. A fourth model, the NASA-CASA (Carnegie-Ames-Stanford Approach) model, uses a different fundamental approach where net primary production and soil heterotrophic respiration drive carbon and nutrient cycling at regional to global scales.[5] A fifth model described, RothC, is a soil carbon model and cannot produce net GHG impacts. It has been used more in Europe than the U.S. Table 1 provides a general comparison of these five models.

[4] Crop rotations and crop management factors like seeding dates, harvesting dates, tillage type, fertilizer rates, fertilizer type and timing, residue rates and management, etc.

[5] Little information about applications of the CASA model to regional or project scale quantification of GHGs is available publically. For more information on the CASA model contact Chris Potter. http://geo.arc.nasa.gov/sge/casa/

Table 1. Description of the major biogeochemical process models capable of quantifying GHG fluxes for the agricultural sector in the U.S.

Model	Description	Activities (1)/ GHGs(2)
DAYCENT*	DAYCENT simulates exchanges of carbon, nutrients, and trace gases among the atmosphere, soil, and plants. Flows of C and nutrients are controlled by the amount of C in the various pools, the N concentrations of the pools, abiotic temperature/soil water factors, and soil physical properties related to texture. Beginning in 2005, DAYCENT has been used to estimate N_2O emissions from cropped and grazed soils for the U.S. National GHG Inventory. The model is also used to investigate how land use and climate change impact plant growth and soil C and N fluxes. It is an expansion of the CENTURY model. http://www.nrel.colostate.edu/projects/daycent/index.html Contact: Stephen Del Grosso	1. Events and management practices such as fire, grazing, cultivation, residue management, and organic matter or fertilizer additions are modeled. A wide variety of crop, grass, and forest types are supported by the model. Primary model inputs are: soil texture, current and historical land use, and daily maximum/minimum temperature, and precipitation. 2. CO_2, N_2O, NO_x, NH_3,emissions; CH_4 uptake; NO_3 leached; crop/biomass yields.
DNDC**	DNDC is a family of models for predicting plant growth, soil C sequestration, trace gas emissions and nitrate leaching for cropland, pasture, forest, wetland, and livestock operation systems. The core of DNDC is a soil biogeochemistry model simulating thermodynamic and reaction kinetic processes of C, N, and water driven by the plant and microbial activities in the ecosystems. DNDC can be applied at various scales, ranging from site-specific applications to quantify within-field variability to county and regional scales to account for differences in environmental conditions and management practices. Soil organic C is divided into 4 compartments: litter, microbial biomass, active humus, and passive humus. The first 3 are further subdivided into pools that vary by their resistance to decomposition. As above, soil rate constants vary by abiotic factors of soil moisture, temperature, and texture. To relate C and N cycles, the output of soluble C drives denitrification. Carbon dynamics are computed on a daily time step, but N_2O is based on an hourly time step. http://www.dndc.sr.unh.edu/ Contact: William Salas or Changsheng Li	1. A relatively complete set of farming management practices such as crop rotation, tillage, residue management, fertilization, manure amendment, irrigation, flooding, grazing, etc., have been parameterized in DNDC to regulate their impacts on soil environmental factors (e.g., temperature, moisture, pH, redox potential, and substrate concentration gradients). 2. N_2O, NO_x, CH_4, and CO_2. From cropping systems (including rice CH_4), grazing systems and manure application/ management. Nitrate leaching loss (NO_3). Soil carbon sequestration, crop development, and biomass yields.
EPIC* (Erosion Productivity Impact Calculator)**	EPIC (Environmental Policy Integrated Climate) is a comprehensive terrestrial ecosystem model capable of simulating many biophysical processes as influenced by climate, landscape, soil, and management conditions. Salient processes modeled include growth and yield of numerous crops as well as herbaceous and woody vegetation; water and wind erosion; and the cycling of water, heat, carbon, and nitrogen. The carbon algorithms in EPIC are based on concepts used in the CENTURY model applied to entire soil profiles. In addition to soil respiration, EPIC calculates carbon losses in eroded soil sediments, runoff water, and percolating waters; carbon lost during vegetation burning; and carbon emissions due to management and inputs (e.g., tillage, fertilization). EPIC also uses a process-based algorithm to estimate N_2O flux during denitrification and N_2O and NO fluxes during nitrification. http://epicapex.brc.tamus.edu/ Contact: César Izaurralde or Jimmy Williams	1. A relatively complete set of farming management practices, including soil management, crop management, nitrogen management, land-use management, and livestock management. 2. Soil nutrient (C and N) stocks, CO_2 and N volatilization, and N_2O flux from denitrification.
APEX***	APEX is the watershed version of EPIC. It contains all of the algorithms in EPIC plus algorithms to quantify the hydrological balance at different spatial resolutions (farms to large watersheds) under different land covers and land uses. The fate of eroded carbon and nitrogen, as well as leached nitrate can be traced through the entire watershed. http://www.brc.tamus.edu/apex.aspx http://epicapex.brc.tamus.edu/ Contact: César Izaurralde or Jimmy Williams	

Model	Description	Activities (1)/ GHGs(2)
NASA-CASA (Carnegie-Ames-Stanford Approach) model	The model simulates net primary production (NPP) and soil heterotrophic respiration (Rh) at regional to global scales. Calculation of monthly terrestrial NPP is based on the concept of light-use efficiency, modified by temperature and moisture stress scalars. Soil carbon cycling and Rh flux components of the CQuest model are based on a compartmental pool structure, with first-order equations to simulate loss of CO_2 from decomposing plant residue and surface soil organic matter (SOM) pools. Model outputs include the response of net CO_2 exchange and other major trace gases in terrestrial ecosystems to interannual climate variability in a transient simulation mode. CASA EXPRESS CQUEST http://geo.arc.nasa.gov/sge/casa/index.html CQUEST online tool (slightly more limited in scope and customizability): http://sgeaims.arc.nasa.gov/website/cquest/viewer.htm	A relatively complete set of farming management practices, including soil management, crop management, nitrogen management, land-use management, and livestock management (as it pertains to grazing).
RothC	One of the very earliest soil carbon models. The compartments comprise labile plant residues, resistant plant materials, microbial biomass, and humified or inert organic soil organic carbon. The plant residues transform, through first-order kinetics, into microbial biomass or inert carbon, and in turn, a portion of these pools transform into CO_2, microbial biomass, and humified soil organic carbon. The inert soil fraction is resistant to microbial attack. Like the other models, soil moisture, temperature, and clay content control soil organic matter decay. http://www.rothamsted.bbsrc.ac.uk/aen/carbon/rothc.htm	1. Soil management, crop management. 2. Soil carbon.

*Description edited by Steven Del Grosso
**Description edited by William Salas
***Description edited by César Izaurralde

By working with model developers, we created the following detailed survey on three of these biogeochemical process models. The three we selected are those most widely used in the United States (and Canada) to quantify GHGs fluxes from agriculture and other land uses. We catalogue the GHGs, management practices, and crops included in these models, as well as the input data required to run them. We also share some insights into the accuracy and precision of these models. The three models covered here are DAYCENT, DNDC, and EPIC/APEX. Members of the modeling teams for each of these models contributed to this review. We acknowledge that the CASA and RothC models may also be of value for GHG quantification, but these have been less prominent for project- and program-level accounting to date, and members of their modeling teams were not available to contribute to our review.

Each of these models can quantify soil carbon dynamics and on-site nitrous oxide (Table 2). For off-site nitrous oxide emissions, the models estimate nitrogen leaching and volatilization loss rates, which can then be combined with the IPCC Tier 1 emissions factor to determine indirect nitrous oxide (N_2O) emissions from these sources. Only DNDC has fully modeled methane fluxes at this point, while EPIC is the only model that includes GHGs from upstream and offset energy and fuel use. Most of the models have relatively full coverage of common management practices, but a subset of these, such as those related to nitrous oxide, methane management, and biochar, need further testing and calibration (Table 3). Descriptions of these practices as well as information about regions and cropping systems where the practices are important, their mitigation potential, and possible impacts on soil quality, other GHGs, and ecosystem services can be found in the companion T-AGG paper "Assessing Greenhouse Gas Mitigation Opportunities and Implementation Options for Agricultural Land Management in the United States." The models include a wide variety of crop types, which vary somewhat by model (Table 4). Because the models have historically been used for commodity crops, specialty crops are often missing. However, there has recently been a significant effort to expand the models to include specialty crops. The models require a wide variety of data inputs (Table 5). While it seems like a daunting list of data inputs required for these process models, many of them can be found or extrapolated from national databases in North America, and other data are already collected and available to farmers. These models are all available online, but require significant training to use. A number of these models are being used to develop user-friendly and standardized decision support tools (Table 6), which may be the best way to incorporate them into protocols and program operations moving forward. While there are a wide range of decision support tools, the ones we describe in this paper are user-friendly interfaces for the full and complex biogeochemical process models.

Table 2. Greenhouse gases measured in three of the biogeochemical process models that can quantify GHG emissions from land use.

GHG Measured	DAYCENT	DNDC	EPIC/APEX
Electricity, fuel, and input energy	No	No	Yes, calculator for field operations (tillage, seeding, fertilizer application, etc.)
Soil carbon sequestration	Yes (Tier 3)	Yes (Tier 3)	Yes (Tier 3)
N_2O*	Yes (Tier 3): Leaky pipe approach** to N_2O emissions – calculated on basis of % of N mineralization subject to soil environment conditions	Yes (Tier 3): Soil Eh (measure of reducing conditions that drive production of N_2O - common in waterlogged soils)and microbial population dynamics	Yes (Tier 3): Based on electron flow, oxygen availability, and competitive inhibition among oxides of N.
CH_4	Uptake Only	Yes (Tier 3)	In progress

*On-site N_2O emissions are included directly in the models. For off-site N_2O, the models can estimate nitrogen lost through leaching and volatilization which can then be combined with the IPCC emissions factor to calculate off-site N_2O emissions.
**The controls on the production of nitric oxide and nitrous oxide demonstrate in "leaky pipe" model of Firestone and Davidson (1989). The concept of the model is that nitric oxide and nitrous oxide are the side products of nitrification and denitrification. Thus the production of these product depends on both the total of process (flow through the pipe) and the "leak" of nitric oxide and nitrous oxide (the size of the holes in the pipes).

Table 3. Management activities included in three of the biogeochemical process models that can quantify GHG emissions from land use.

Management Practice*	DAYCENT	DNDC	EPIC/APEX
Conventional to conservation till	Yes	Yes	Yes
Conventional to no-till	Yes	Yes	Yes
Conservation till to no-till	Yes	Yes	Yes
Switch from irrigated to dry land	Yes	Yes	Yes
Use winter cover crops	Yes	Yes	Yes
Eliminate summer fallow	Yes	Yes	Yes
Intensify cropping (more crops/year)	Yes	Yes	Yes
Switch annual crops (change rotations)	Yes	Yes	Yes
Include perennial crops in annual crop rotations	Yes	*Yes (new crops will need to be calibrated)*	*Yes (new crops will need to be calibrated)*
Short rotation woody crops	Yes	Yes	Yes
Irrigation improvements (drip, supplemental, etc.)	*Yes - model simulates irrigation, but can't distinguish types*	Yes (DNDC distinguishes sprinkler, flood, and drip; manual or automatic based on water stress)	Yes (different types; manual or automatic based on water stress)
Agroforestry (windbreaks, buffers, etc.)	Yes	Yes (by compartmentalizing the fields)	Yes - APEX
Herbaceous buffers	*Possible but has not been tested*	*Possible but has not been tested*	Yes - explicit in APEX
Application of organic materials (esp. manure)	Yes	Yes	Yes (beef, dairy, swine, poultry)
Application of biochar	*Possible but has not been tested*	*Possible but has not been tested*	*Under development*
Reduce N application rate	Yes	Yes	Yes
Change fertilizer N source	*Yes (only distinguished NO3 from NH4)*	Yes (7 distinct chemical fertilizer types)	Yes - single and compound fertilizers

Management Practice*	DAYCENT	DNDC	EPIC/APEX
Change fertilizer N timing	Yes	Yes	Yes - flexible application based on n test or plant n stress
Change fertilizer N placement	No	Yes (user prescribe depth, only limited testing)	Yes - (broadcast, banding)
Use nitrification inhibitors	*Yes (limited testing)*	*Yes (limited testing)*	*Not tested yet*
Improved manure application to soils management (N_2O)	Yes (amount and type)	Yes (amount and type)	*Not tested yet*
Irrigation management for N_2O	*Yes (only amount)*	*Yes (only amount)*	*Not tested yet*
Manage histosols to reduce GHG emissions	No	*Yes (new application in CA, needs calibration)*	*Not tested yet*
Drainage on croplands, N_2O & CH_4	*Yes (CH_4 not included)*	Yes	*EPIC/APEX can simulate drainage; no test of drainage and N_2O and CH_4*
Rice water management for CH_4	No	Yes	No
Improved grazing management, range	Yes	Yes	Yes
Improved grazing management, pasture	Yes	Yes	Yes
Fertilizing grazing lands	Yes	Yes	Yes
Irrigation management for grazing lands	Yes	Yes	Yes
Species composition on grazing lands	*Model represents vegetation mix, not species*	*No - users would have to define special mix*	Yes (up to 10 species)
Grazing land fire management	Yes	Yes	Yes
Rotational grazing	Yes	*Yes (grass model requires calibration and testing of physiological response to grazing intensity)*	Yes (new grazing model in APEX)
Manure management (lagoon, compost, etc.)	No	*Yes (new Manure model with enteric fermentation requires more testing, continued development)*	Yes (in APEX)
Transition to natural land (forests, native grasslands, wetlands)	Yes	Yes (wetland/forest DNDC)	Yes (in APEX) - in development (have not done wetlands)

* Inclusion of a management practice and variations on those activities (e.g., 7 chemical fertilizer types), means that the models include a process to estimate impacts of the practice, but does not guarantee that the science is fully developed. For example, biochar and fertilizer types are active areas of research with little scientific consensus on the basic process and outcomes of implementing the practice.

Table 4. Crops included in three of the biogeochemical process models that can quantify GHG emissions from land use.

DAYCENT	DNDC	EPIC/APEX
	CEREAL GRAINS	
Barley	Barley	Barley
Corn	Corn	Corn
Silage corn	Silage corn	Silage corn
	Edible amaranth	
Millet	Millet	Pearl millet
		Proso millet
Oat	Oat	Oat
	Paddy rice	Rice
	Rainfed rice	
	Dw rice	
	Upland rice	
Rye	Rye	Rye
Sorghum	Sorghum	Sorghum hay
		Grain sorghum
		Durum wheat
Spring wheat	Spring wheat	Spring wheat

DAYCENT	DNDC	EPIC/APEX
Winter wheat	Winter wheat	Winter wheat
VEGETABLE AND MELON		
	Artichoke	
		Asparagus
	Beet	
	CA broccoli	Broccoli
	Brussels sprout	Cabbage
		Cantaloupe
		Carrots
Cassava	Cassava	Cassava
		Cauliflower
	Celery	Celery
		Cucumber
		Eggplant
		Green bean
	Green onion	
		Honey dew melons
		Leaf lettuce
	Lettuce	Lettuce
		Lima bean
	Onion	Onions
	Pepper	Pepper
Potato	Potato	Potato
	Radish	
	Baby spinach	Spinach
		Sugarbeet
		Sweet corn
		Sweet potato
Tomato	Tomato	Tomato
	Vegetables	
		Watermelon
		Yam
LEGUMINOUS CROPS		
		Chick pea
Beans	Beans	
		Fava bean
		Lentil
		Lespedeza
	Soybean	Soybean
		Peas
		Cowpea
		Field pea
Austrian winter pea		Winter pea
OILSEED CROPS		
		Canola-argentine
		Canola-polish
	Flax	Flax
	Palm	
Peanut	Peanut	Peanut
Rapeseeds	Rapeseeds	
Safflower	Safflower	
Soybean		
Sunflower	Sunflower	Sunflower
FRUIT AND NUTS		
Apple		Apple
	Banana	
	Berries	
Citrus	Citrus	
	Fruit trees	
		Coffee
Grape	Grape	Grape
	Wine grape - high vigor	
	Wine grape - low vigor	
Peach		

DAYCENT	DNDC	EPIC/APEX
Pear		
Pecan		
	Strawberry	Strawberries
BEVERAGE, SPICE, AND SUGAR CROPS		
		Coffee
	Green tea	
	Hops	
Ratoon sugarcane	Ratoon sugarcane	
Sugarcane	Sugarcane	Sugarcane
OTHER CROPS		
Cotton	Cotton	Picker cotton
		Stripper cotton
	Nursery flowers	
Tobacco	Tobacco	Tobacco
	Truck crops	
FORAGE CROPS, HERBACIOUS AND SHRUBLAND SPECIES		
Alfalfa	Alfalfa	Alfalfa
Alpine grass		Altai wild rye
Annual grasses		Annual ryegrass
		Bahiagrass
		Big bluestem
		Bromegrass
		Buckwheat
		Buffalograss
		Cheatgrass
		Clover, alsike
		Coastal bermuda
		Cocklebur
		Crested wheatgrass
C3 grass		
C4 grass		
Clover		Red clover
		Sweet clover
Clover/grass mixture		
Grass clover pasture		
		Summer pasture
		Winter pasture
		Eastern gamagrass
Fallow	Fallow	
		Fescue
Grassland	Grassland	
		Giant foxtail
		Gramagrass
		Green foxtail
		Johnson grass
		Little blue stem
		Weeping lovegrass
Hairy vetch		
Legume hay	Legume hay	
Miscanthus		Miscanthus
Mixed cover crop	Mixed cover crop	
Non legume hay	Non legume hay	
		Northern wheatgrass
		Orchard grass
Perennial grass	Perennial grass	
		Poa spp.
		Range
		Russian wild rye
		Seabuck thorn
Sedge	Sedge	
		Sideoat grama
	Shrub blueoak	
		Slender wheatgrass
		Smooth brome

DAYCENT	DNDC	EPIC/APEX
Switchgrass		Switchgrass
		Timothy
Tropical grass		
		Vel vetleaf
		Western wheatgrass
TREE PLANTATIONS AND FORESTS		
		Ash
		Black locust
		Mesquite
		Oak
		Pine
		Poplar
		Sweetgum
Temperate mixed deciduous forest		Temperate deciduous forest
Temperate coniferous forest		Temperate evergreen forest
Topical evergreen forest		Tropical evergreen forest
Tropical deciduous forest		
OTHER BIOMES		
	Wetland grass	
Mediterranean shrubland		
Savanna		
Shrubland		

Table 5. Data inputs required for three process-based biogeochemical models.

		DAYCENT	DNDC * = included in simplified model	APEX (EPIC)
Soil	Texture class	Yes (% sand and % clay)	*Yes (texture or clay fraction - 12 soil types: sand, loamy sand, sandy loam, silt loam, loam, sandy clay loam, silty clay loam, clay loam, sandy clay, silty clay, clay, and organic soil)	Yes; user specifies % sand and % silt
	Depth of soil profile	Yes	*Yes for shallow profile (<1 meter) (new version with user specified soil layers, not yet extensively tested)*	Yes
	Bulk density	Yes	Yes (0-10 cm)	Yes (bulk density is dynamic and is affected by erosion (surface), tillage, and soil organic matter)
	Soil Organic C	No	Yes (0-5 cm)*	Yes
	pH	Yes	Yes*	Yes, and electrical conductivity
	Clay content	Yes	Yes	sand and silt content Clay by difference (as well as calcium carbonate)
	Drainage	Yes – water-logged soils	Yes – water-logged soils	Yes, full hydrology competent
Crop	Crop type	Yes	Yes*	Yes
	Crop rotation	Yes	Yes	Yes - including intercropping
	Planting dates	Yes – can estimate	Yes	Yes - can estimate
	Cover crop?	Yes	Yes	Yes
	Harvest dates	Yes – can estimate	Yes	Yes - can estimate
	Residue management (e.g., burned, removed, left, plowed in)	Yes	Yes (in terms of fraction of residue left in field)*	Yes
	Perennial crops	Yes	Yes	Yes

		DAYCENT	DNDC * = included in simplified model	APEX (EPIC)
Tillage	Tillage description	Yes	Yes (depth of each event)	Yes - need implements
	Tillage dates	Yes	Yes	Yes - can estimate
Fertilizer	Amounts	Yes	Yes*	Yes
	Application dates	Yes	Yes	Yes - can estimate
	Method	No	Yes (surface and injection)	Yes (surface and subsurface)
	Type	Nitrate vs. ammonium	Yes (7 chemical types)	Yes
	Stabilizer	Nitrification inhibitors	Yes (time release or nitrification inhibitor)	no
Manure input	Type	Yes	Yes (5 types farmyard, green, straw, liquid, compost)	Yes beef, dairy, pork, swine
	Amount	Yes	Yes	Yes
	C/N ratio	Yes	Yes	Yes, carbon, organic N, mineral N, NH_3 fraction
Irrigation	Amounts	Yes	Yes	Yes
	Dates	Yes	Yes (or modeled based on crop demand)	Yes
	Type (sprinkler, furrow, drip)	no	Yes	Yes
	Water pH and N content if known	Yes	Yes	Yes
Climate	Daily min/max temp	Yes - but can get independently	Yes - but can get independently	Yes - but can get independently
	Precipitation	Yes - but can get independently	Yes - but can get independently	Yes - but can get independently
	Solar radiation	no	Yes - but can get independently	Yes - but can get independently
	Atmospheric N deposition	Yes - but can get independently	Yes - but can get independently	Yes - but can get independently

Table 6. User-friendly interfaces or decision support versions of the biogeochemical process models.

Base Model	Decision support tools	Notes
CENTURY/DAYCENT	COMET-VR http://www.cometvr.colostate.edu/ COMET 2.0 http://www.comet2.colostate.edu/ COMET Farm (Beta available March 2011)	These tools are developed with support from USDA, NRCS. This tool is currently being updated into COMET-FARM, which is a whole farm/ranch greenhouse gas emission estimation tool that uses DAYCENT for estimating soil emissions and uptake of CO_2 and N_2O (and other models for livestock and other on-farm emissions). References: Paustian et al., 2010; Paustian et al., 2009
APEX/EPIC	Nutrient Trading Tool http://ntt.tarleton.edu/nttwebars/ ARCGIS APEX	This tool was developed with support from USDA NRCS. It tracks nitrogen impacts of agricultural practices on water quality, but can also but used to quantify GHG impacts. It is being linked to the DAYCENT model in current developments. A second decision support system for EPIC is under development by USDA and PNNL researchers with support from NASA.
DNDC	U.S. Cropland Greenhouse Gas Calculator http://www.dndc.sr.unh.edu/	ARCGIS version of the DNDC model for U.S. croplands.
NASA/ CASA	CASA EXPRESS CQUEST http://geo.arc.nasa.gov/sge/casa/index.html CQUEST online tool (slightly more limited in scope and customizability): http://sgeaims.arc.nasa.gov/website/cquest/viewer.htm	Observational tool to assess climate and land management trends and impacts on the landscape. Does not specifically model scenarios; however the model is capable of being run with pre-populated externally created scenario models. Especially effective in identifying current problems and sources of emissions. Tier 3 model using remote sensing with an easy-to-use ArcGIS interface, and background calculations based on user-provided data, satellite imagery and remote sensing data, and IPCC baseline information. Scalable to the 1/4 acre, as well as region and nation. Useable world-wide.

The DAYCENT, DNDC and EPIC/APEX models have many similarities, and a few critical differences, as explained below:

- All three models can be used at either a farm/site or an ecozone/regional level for quantifying CO_2 and N_2O emissions and C sequestration.
- DNDC simulates soil redox potential and methane (CH_4) emissions from saturated soils and CH_4 uptake; DAYCENT only models CH_4 uptake in non-saturated soils but is working on an emissions model; and EPIC/APEX currently does neither but is working on incorporating both.
- APEX places EPIC into a spatial context, where it can model hydrological flows using algorithms similar to those used in the SWAT model[7] and thus estimate runoff as well as transport and deposition of soil sediment, nutrients, and pesticides. They are working on adding estimates of indirect (off-site) N_2O emissions. The other two models can estimate nitrogen losses from leaching and volatilization, which can be used to calculate N_2O losses using an IPCC emissions factor, but the models do not do this directly.
- All three models cover common agricultural practices, but each has practices that are under development and not yet ready to run.
- All models can manipulate quantity of irrigation, but DAYCENT does not currently allow different types of irrigation (flood, sprinkler, drip). DNDC and EPIC/APEX do include irrigation type.
- All the models can control the amount of fertilizer. DAYCENT only includes nitrate versus ammonia fertilizers, while the other models have multiple types (~7). DAYCENT also does not have the ability to change method or placement of fertilization, but the other models do (e.g., surface versus injection).
- Nitrification inhibitors are in DAYCENT and DNDC, but not yet in EPIC/APEX.
- Nitrous oxide emissions from manure, irrigation, and other management can be predicted using DAYCENT, DNDC, and EPIC, but not yet with APEX, which uses empirical equations to predict denitrification.
- DNDC is the only model that current includes CH_4 emissions, thus it is the only one of the models that can look at water management in rice cultivation.
- The models differ slightly in the inputs they require, but all of them can use estimates or national databases to fill in most variables where site-specific information is not available. The quality of these national data and estimates vary.
- DNDC has a model for manure management, which includes intensive management systems with enteric fermentation. APEX includes a model for extensive grazing and confined area feeding. According to Gassman et al. (2010), up to 10 herds of groups of animals can be simulated with APEX, but only one herd can occupy a subarea at any given time. Livestock can rotate among subareas. Animals may be confined to a feeding area. Grazing can occur throughout the year or periodically according to limits. When no more grazing material is available, the owner can provide supplemental feeding.

While many of these models include some aspects of livestock management, they often present only a partial assessment of the beef production chain; significant opportunity for emission reductions exists in the confined feeding stages (drylots and feedlots) of the cattle's life cycle. In addition, quantification of CH_4 and N_2O emissions for livestock has complexity beyond that observed in crop management. The primary N_2O sources on grazed lands (i.e., N_2O from urine and dung patches) are spatially complex, making field measurement even more difficult. Further, the pasture-livestock interface needs to account for CH_4 production from enteric fermentation.

These models include water and fertilizer management of pasture lands, rotational grazing and fire management; some also include manure management. Other models are being developed for intensive animal feeding operation to predict GHG emissions from the entire operation, including land application of manures (e.g., Manure DNDC; Comet v2 2.0; CometFARM). Another model which could add some missing details is called the Integrated Farm System Model (IFSM) (ROTZ et al. 2011). IFSM is being developed by the USDA-ARS by Dr. Alan Rotz and colleagues.[6] The IFSM model is undergoing testing on recently added components that predict GHG emissions from the grazing animals as well as on-farm feed and manure sources. The model will include carbon sequestration in soils as well. In the interim, applying IPCC (2006) equations relating to grazing dry matter intake, enteric fermentation, and manure and N excretion rates, and then calculating subsequent emissions may be the best measurement methods to assess methane, carbon, and nitrous oxide fluxes from grazing systems.

Model accuracy and limitations

It is important to understand the potential limitations of these models. There are limits to the ability of these models to represent the ecological processes, which drive the GHG results. In some cases we do not have sufficient measured long-term data with which to test the models to ensure they are reasonably representing or predicting the impacts of the management practices for all locales. We need to be clear where the uncertainties lie in the use of these models if they are to be used to quantify GHG outcomes for developing programs and markets. Knowing the uncertainties can help programs apply model results in a conservative fashion, perhaps adjusting crediting based on accuracy and confidence in model outcomes.

Accuracy of model results is related to model error and uncertainty. Sources of model error can be partitioned into two categories:

1. errors due to uncertainty in model inputs
2. errors due to model structure

Model calibration is the process of parameterizing a model to the specific site or landscape application, incorporating detailed land-use and land-management history (for initializing soil C), soil maps, topography, daily or weekly climate data, initial soil carbon and nitrogen levels, among others. Errors from model input occur because model inputs are not precisely known. This uncertainty can be estimated by using sensitivity analysis such as a Monte Carlo approach, where thousands of possible scenarios are generated using random values varied across each input parameter to estimate this uncertainty. The set of modeled results is then analyzed statistically to generate the probability range and distribution of predictions. Environmental characteristics and crop and animal biophysical variables used in these models come primarily from national databases and can be provided as defaults in the models. National data on management and cropping practices are less robust, which can add significant uncertainty to model outcomes. As a result, a number of models are moving toward farmer-required inputs on management and cropping to run the models at farm level. If fine-scale (parcel-level) data are available, like in the U.S., models can be run at farm/project scale. Where fine-scale data do not exist, such as in many developing countries, it may make sense to run models at coarser scales, which may average out some of the uncertainty.

MODEL INPUTS
Management input variables: cropping systems (crop type, rotation sequence, field size, yield data), farm operations (seeding, tillage, harvest, residue management, spraying, irrigation data), fertilizer and manure N content, source, rate, placement and timing data, etc. These can be gathered at a regional scale (observational datasets) or at the farm level.

Environmental input variables: fine-scale soil map data with soil properties (soil type and texture, organic carbon and nitrogen levels, soil profile data, pH, etc), topographical information, daily or weekly climate data (precipitation, temperature), hydrography, etc. Information can be found in national databases or gathered at the site level.

Errors related to model structure result from the fact that equations in the models are imperfect representations of the real-world processes that result in GHG emissions. Model structure is usually considered to include the equations (e.g., the relationship between soil water content and the

[6] See http://ars-usda.gov/naa/pswmru.

decomposition rate multiplier) and model parameters that represent livestock and crop characteristics (e.g., root to shoot ratio, crop light use efficiency). The errors in the model structure can be estimated by statistically quantifying the agreement between model outputs and field measurements. Mixed-linear effects models can be used to see how much model outputs deviate from observed values (Del Grosso et al. 2010; Ogle et al. 2007; Ogle et al. 2010). Model validation is a term used for this process of assessing how well a model performs relative to an independent dataset (monitoring/benchmark sites, or flux tower/airplane data) that is different from the long-term data used to calibrate the model.

Sufficient field measurement for the desired range of practices, cropping systems, GHGs, and geographies is often a limiting factor in validating models and assessing the associated uncertainties. For example, we have little field data on specialty crops and how N fertilizer placement impacts N_2O emissions for a number of regions and cropping systems, and we need more research on rotational grazing and biochar. In one of the T-AGG companion reports, we reviewed the research literature to assess the state of knowledge on the mitigation potential of a wide range of agricultural land management activities. Out of 42 practices reviewed (Table 7),[7] 26 seem to have positive mitigation potential. Eleven of these 26 are supported by significant research (more than 20 field or lab comparisons), 13 are backed by a moderate level of research, and two, while promising, have little research. The remaining 16 practices are either too uncertain, due to questions of full life-cycle impacts or little data, or they appear to have little or negative GHG impact. The models cannot assess the uncertainty for practices, crops, and regions that have critical research and data gaps. Luckily research is under way to fill many of these gaps, which will allow even broader application of the models.

Another step in model use which can significantly impact accuracy is the initialization process through which models are calibrated to historic soil carbon levels and historic land-use and management practices. Most of the models described in this report have default soil carbon levels that have been validated against field data and research, and thus only require that land-use and land-management history be added. At a regional scale, aggregated data from farm agencies and USDA would likely be used, while at the farm scale landowner knowledge would be critical.

Table 7. Quantity of research on GHG mitigation potential of agricultural practices based on review in companion T-AGG paper "Greenhouse Gas Mitigation Potential of Agricultural Land Management in the United States: A Synthesis of the Literature."

Land Management Activity	# field or lab comparisons	Regional Representation*
Positive mitigation potential – significant research		
Conventional to no-till	526	1,2,3,5,7,8,9
Diversify annual crop rotations	93	1,2,7
Eliminate summer fallow	92	2,5,7
Use winter cover crops	76	1,3,6,9
Wetland restoration	70	2 (+ Canada)
Rice water management for CH_4 emission reduction	59	2 (+ Asia)
Short-rotation woody crops	56	1,2,3 (+ Canada)
Conventional to conservation till	53	1,2,6,7,9
Convert cropland to pasture	46	2,7,9
Cropland set-aside and herbaceous buffers	45	1,2,7,9 (+ Canada)
Reduce N fertilizer application rates	24	1,2,3,7 (+ Canada)
Positive mitigation potential – moderate research		
Improved grazing management, rangeland	17	2,7
Include perennial crops in rotations	18	1 (+ Canada)
Manage species composition on grazing lands	16	2 (+ Canada & global)
Change from annual to perennial crops	15	2,3
Rice variety development for CH_4 emission reduction	15	2 (+ Asia)

[7] This literature review did not include animal feed and manure management.

Land Management Activity	# field or lab comparisons	Regional Representation*
Use nitrification inhibitors	15	5 (+ Asia & Europe)
Change fertilizer N source – slow release	11	3,7
Change fertilizer N placement	9	3 (+ Canada & Europe)
Change fertilizer N timing	8	Canada
Improved grazing management, pasture	5	9
Agroforestry (e.g., windbreaks, buffers)	4	1,5
Irrigation improvements (e.g., drip)	4	Europe
Rotational grazing, pasture	4	9
Little available data – but seem to have potential		
Manage farmed histosols to reduce GHG emissions	2	1 (+ Europe)
Convert histosol cropland to natural	3	Canada and Europe
Uncertain GHG mitigation potential when considering life cycle		
Application of organic material (esp. manure)	28	1,4,5,8,9
Biochar application	0	
Fertilize grazing lands	7	2,7,9 (+ Canada & global)
Irrigation on grazing lands	8	7 (+ Australia & New Zealand)
Convert dryland to irrigated	15	2,7
Reduce rice acreage	0	-
Low or negative GHG mitigation potential		
Reduce chemical use (other than N)	n/a**	
Change fertilizer N – ammonium-based to urea	15	3,8 (+Europe & Canada)
Pasture to grassland – cease grazing	17	2,5,6,7
Little or no available data – uncertain GHG impact		
Increase cropping intensity	0	-
Drain agricultural land, humid areas	0	-
Improve manure management (N_2O)	1	Canada
Agroforestry on grazing land	0	-
Rotational grazing, rangeland	1	2
Fire management on grazing land	0	-
Improve fertilizer and manure NUE on grazing land	0	-

* Regions for the 48 coterminous states are as follows: (1) Corn Belt, (2) Great Plains, (3) Lake States, (4) Northeast, (5) Pacific Northwest, (6) Pacific Southwest, (7) Rocky Mountains, (8) South Central, and (9) Southeast.
** The GHG implication estimate for reducing chemical use does not require field comparisons, but relies on calculations of energy use for production, transport, etc., of these chemicals.

Assessing model performance

A number of different statistical measures should be used when evaluating model performance because each has strengths and weaknesses. For example, the correlation coefficient quantifies how well model outputs are correlated with measurements, but it is not influenced by model bias. For example, model outputs could be perfectly correlated with measurements (r^2=1.0) but highly biased if each model output is twice as high as the measured value. Model evaluation is also dependent on the variable of interest, the reliability of measured data, and the scale of model application. For example, grain yields are more accurately and precisely measured than GHG fluxes, so model errors tend to be smaller for grain yields than for GHG emissions.

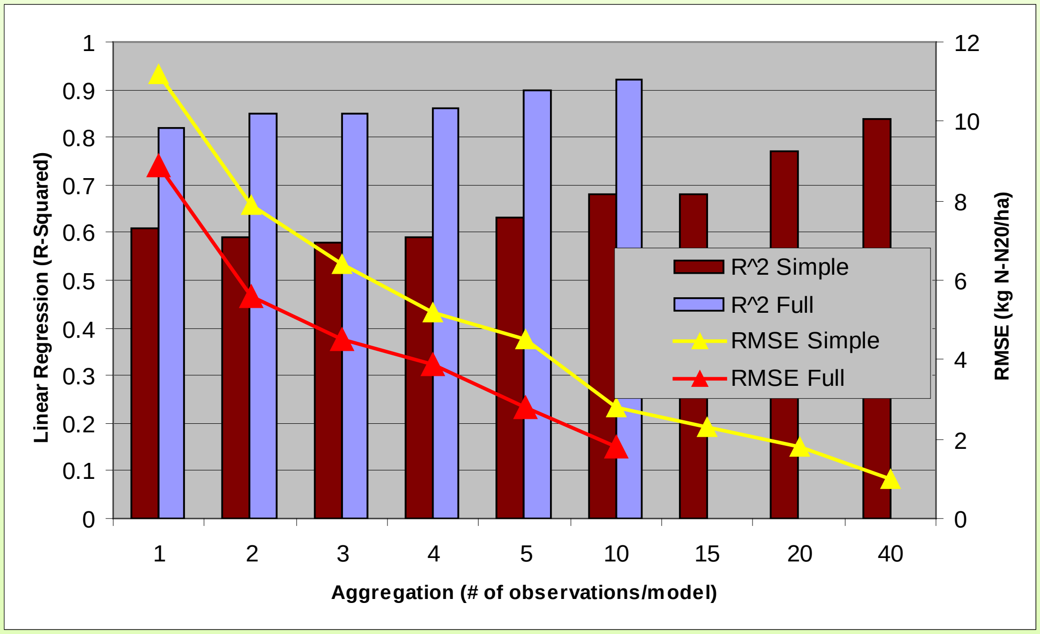
Scale dependency is complicated. When results from many model simulations are aggregated spatially and temporally, through averaging or scaling up, errors tend to shrink as scale increases. However, model errors for small plots of land can be small if all important inputs are well known. For example, individual landowners can provide detailed information on land-use history and land management and use site sampling where other databases are lacking. This can provide high accuracy for a small scale. However, gathering all of this detail can be time-consuming and expensive and can raise questions of data consistency across sites.

If we want to better understand and compare the uncertainties associated with various models, we need to have a parallel assessment of the models. At this time we do not have a side-by-side assessment of these models with comparable methods that explore both the structural uncertainty and the input uncertainties. The modeling teams are interested in developing such a comparison over the next few years, but for now we are limited in our ability to compare the models. Even so, it is possible to provide some indication of uncertainty for these models from the following examples for DNDC (Box 1), which provides an example of the scale dependency of uncertainty, and DAYCENT (Box 2), which provides an example of the structural and input uncertainties.

The process-based models are consistently being updated and calibrated as new information becomes available. While they are robust tools for quantifying GHG for many practices and cropping systems now, there are a number of opportunities to improve the function of these models, but they will require additional resources and research. Modelers need resources for further calibration of models to field studies, particularly those with research gaps, which is a continuing effort as the science evolves and refines remaining questions. Calibrating models for new crops and practices can cost from US$10,000 to US$50,000 when data are available, but there can be economies of scale if there are ways to combine crops. For some crops, the data can be collected from the literature and research sites; for others, particularly specialty crops, new data will need to be collected in partnership with growers and growers' groups (Del Grosso et al. 2010; Salas 2010). All of the models would benefit from the creation of a network of reference sites around the country to track background levels of change (Paustian et al. 2006; Paustian et al. 2004; vanWesemael et al. 2011). This would allow calibration of the models to background trends like decadal or longer shifts in climate, and more importantly, it would provide an independent set of data to better characterize model uncertainty. A national soil monitoring network, such as the USDA Natural Resources Inventory system, could leverage existing activities and expertise so that a fully built-out national system of about 5,000 monitoring locations could be established and maintained at a cost of US$2 to $3 million per year (K. Paustian, pers. comm.). The models would also benefit from greater information about what happens deeper in the soils (i.e., below the top 20–30 cm surface layer), which has become a consideration for quantifying soil carbon sequestration. It is becoming clear that the modeling community needs to have a focused, concerted effort of extensive independent model validation to develop statistically rigorous metrics of model uncertainties. Where there is sufficient data, these uncertainties can be assessed and quantified across regions, cropping systems, input data specifications, etc. In addition, such an effort would likely lead to finding out where the models do not perform well and lead to future improvements in the models. A new effort, the Agricultural Model Intercomparison and Improvement Project (AgMIP)[8] is focused on food security due to climate change and aims to enhance adaptation capacity in both developing and developed countries. Perhaps this could be expanded to include and integrate GHG modeling and mitigation outcomes.

[8] http://www.agmip.org/

Box 1. Uncertainty assessment for the DNDC model (by William Salas).
Given that uncertainty is higher for N_2O predictions than C, this assessment focused on N_2O. For the full DNDC model assessment (69 detailed, independent field validation datasets for N_2O emissions) at a single field/observation level, the model has an r-squared of 0.83 (measure of how well the model captures observed variability). In this case, the model captures well the observed variance in field measurements, but the precision is not great. To examine aggregation, we randomly selected groups of observations and compared the average emissions with the model. Aggregating four observations, the R-squared increases slightly to 0.86, but the RMSE (root mean squared error, measure of the precision of the model or typical error) drops to 3.9 kg N-N2O/ha (1.8 t CO_2e). At an aggregation of 10, the r-squared is 0.92 and RMSE is down to 1.8 kg N-N_2O/ha (840 kg CO_2e). The larger RMSE at the single-field scale is driven by a few sites with very high modeled or measured emissions. As the modelers compile a larger independent validation database, they will be able to provide more detailed estimates of model structural uncertainty. In addition, they will be able to assess the impacts of uncertainties in inputs on model estimates (Salas 2010).



The simplified DNDC model (Willey and Chameides 2007), which requires only eight inputs (annual precipitation, average temperature, soil carbon, soil texture, soil pH, crop type, amount of fertilizer, and amount of organic amendments), was compared with 434 independent field datasets. Based on this analysis the model captured 61% of the variance of field measurements with an RMSE of 11.2 kg N/ha. The model is accurate within 3 kg N_2O 60% of the time and within 5 kg 74% of the time at the field/plot scale. Note that most of the large differences between modeled and observed values occurred at sites with high emissions. The full DNDC model is more precise than the simplified model by approximately 3 kg (based on our analysis of 69 observation datasets). Assuming a similar distribution of errors between the simplified model and our full model, the full model should be within 2 kg N-N_2O of observed data approximately 74% of the time and within 5 kg N-N_2O of observed data 87% of the time at the field/plot scale. On average the simplified model is off by 2.5 t CO_2e. The 95% confidence interval on this is +/- 470 kg CO_2e. On average the full model is off by 1.6 t CO_2e (Salas 2010).

Box 3. Uncertainty analyses for EPIC/APEX (by R. César Izaurralde).
Wang et al. (2005) used data from a long-term field trial of continuous corn with varying N fertilizer levels to conduct sensitivity and uncertainty analyses of crop yields and soil organic carbon dynamics simulated with the EPIC model. Expert knowledge was used to select six crop and three soil parameters for sensitivity testing. The Generalized Likelihood Uncertainty Estimation (GLUE) procedure was used to generate output probability distribution functions and confidence limits based on likelihood weights. Observed corn yields fell within the 5% and 95% confidence limits calculated for all treatments from 1,500 simulations. Comparable results were obtained for soil organic carbon except for one treatment. A variance-based sensitivity analysis using the Fourier Amplitude Sensitivity Test (FAST) was used to assess sensitivity. High total sensitivity indices of corn yields were detected based on likelihood weights for the parameters investigated, suggesting that the good agreement between observed and simulated yields does not depend on a single parameter but on the interaction among several parameters. Similar results were obtained for soil organic carbon. Wang et al. (2006) conducted sensitivity analysis of the APEX model when used for the Conservation Effects Assessment Project (CEAP) National Assessment. Two sensitivity analysis methods (variance-based and enhanced Morris) were evaluated and the enhanced Morris method was selected. Influential parameters identified included the NRCS curve number index (e.g., for runoff, water erosion, nutrient losses), Hargreaves PET exponent, RUSLE C factor coefficient, and potential heat units.

Box 2. Uncertainty analyses for DAYCENT/CENTURY (by Stephen Del Grosso).
Several analyses of uncertainty have been conducted for the DAYCENT model (for N_2O emissions) and the closely related CENTURY model (for soil C dynamics), mainly in conjunction with U.S. national GHG emission estimates (Del Grosso et al. 2005; Del Grosso et al. 2010; Ogle et al. 2007; Ogle et al. 2010). Analyses have combined Monte Carlo approaches to estimate uncertainty in model inputs and a statistical approach (mixed-effect linear models) utilizing available long-term agricultural field experiments to estimate model structural uncertainty. Uncertainties for both N_2O and soil C estimates were strongly scale-dependent. For the structural uncertainty estimates for CENTURY, measurements from a total of 47 experimental studies, accounting for 872 treatment combinations (varying management, soil, slope, etc.), were included in the analysis (Ogle et al. 2007). At national scale, the 95% confidence limits on estimated changes in soil C stocks was around 20% of the mean, with the majority of the uncertainty attributable to model structural uncertainty (Ogle et al. 2010). For an individual major land resource area (MLRA[1]), total uncertainties in soil C stock changes exceeded 100%, illustrating the impact of sparse data for both model inputs and field experiments. For N_2O emissions, a total of 12 sites were used in developing the structural uncertainty estimate (Del Grosso et al. 2010; Ogle et al. 2010). For national-scale estimates, the 95% confidence limits for N_2O emissions had a lower bound of 34% below the mean and an upper bound of 51% greater than the mean. Of total uncertainty, around 80% was attributed to model structural uncertainty.

Using Models for Protocol or Program Development

Given the complexity of most process-based models and the amount of data they require, running them accurately and consistently requires a certain level of sophistication and expertise. Setting up the full process models and running them for individual projects is complex, requires substantial expertise, may be prone to error or bias, and may be cost prohibitive for a project. One of the primary challenges in using these process models for determining baseline and quantifying GHG impacts at farm- or regional-scales is to standardize how the technology can be made available to non-expert users such as project developers, consultants, and verifiers, in quantification protocols or program guidelines. Given the different model types, complex input variables, different scales of application, and range of sensitivities, the model selected and how it is used may have a profound impact on the GHG changes quantified (Dumanski et al. 1998). Therefore, developing approaches to apply models in a standardized, simple, and transparent way will enable their application in large-scale programs or environmental markets. As described above, these models can be used in two distinct ways, which correspond with the scale of use: regional or farm scale. The options are to have experts run the models to develop regional emissions factors (1 below), or to design a user interface for the models that standardizes model use for farm-scale quantification that fits within a program accounting framework (2 below). We use the terms *farm scale* versus *regional scale* to refer to the scale at which the models are run. Both lead to the development of programs or protocols that are implemented at a farm scale, where net GHG emission and verification occur at the farm scale and can be aggregated across multiple farms.

1. At an ecozone or regional (pTier 2) scale, covering areas with similar soils and climate, to produce reasonable, regionally sensitive emissions factors that can be combined with equations or formulae and embedded within a protocol or program accounting methodology. This is a top-down approach using regional averages of model runs tailored to soil type, agroclimatic zone, and cropping and management systems present in the region. Using models at this scale cannot reflect the spatial/temporal variability of GHG dynamics at a particular local site in the region. This approach tends to be more practice-specific, where emissions factors are determined for specific activities and gases, and perhaps for common combinations of activities, but is unlikely to offer as much flexibility in combining multiple practices.

2. At a farm or site (pTier 3) scale, which can be used as a quantification tool within a protocol or program accounting methodology. This is a bottom-up, fine-scale approach where GHGs from individual farms and their variability in cropping, management, and soil type are quantified at the farm/field level and aggregated for projects. This will require a decision support interface to allow non-experts to input data and run models. At this scale models can capture fine-scale variability and dynamics, but do require significantly more site-level data inputs and detailed verification. This approach can integrate across various practices in real time, allowing more flexibility.

A hybrid is also possible, where a farm-scale model uses Tier 1 or Tier 2 emissions factors for a particular activity when experimental data are insufficient to model that activity at the finer scales.

The choice of scale of model application is based on many factors. The choice between a regional and farm-scale approach will be a balancing act among precision, flexibility, and complexity of implementation. A regional approach might be used where we have less research and less confidence in fine-resolution outputs of the process models or where we do not have or cannot acquire sufficient site-level data, or if complexity of verification at a site level is too costly or difficult. Where models and data are considered sufficient or obtainable at reasonable cost a site-level approach may be viable and preferable. See Table 8 below for a side-by-side comparison.

Farm-scale quantification requires full resolution use of process models, which will require (1) significant user support, or even better, a model user (or decision support) interface that runs the model in the background and produces results in a readable form, and (2) additional farm-level data inputs. Due to the complexity of the models, standardization of model use is necessary to streamline the quantification process, simplifying the number of user-defined inputs; standardize the data used; and provide procedures for generating standard estimates of uncertainty. This will increase transparency and consistency in model use and simplify verification of model estimates. It reduces quantification risk for all components of the system, reduces costs for project developers and farmers, and assists with achieving project implementation at scale. One of the limitations of standardized user interface (decision support) tools such as COMET VR[9] has been a perception that there was not sufficient representation of relevant cropping and management combinations to represent farmer actions. While these standardized approaches do not include all crops and management options, they continue to evolve and newer versions will likely have very significant coverage of major crops and management options similar to the full models as depicted in Tables 3 and 4. These earlier tools did not run the full model in the background, but the new COMETFarm tool will have that capability, and others are under development (Table 6). Setting up such a user interface tool may be cost-prohibitive for a program. There will be a need for continual updating and enhancement to these existing tools as research moves forward, adding new management options or improving the accuracy of existing options. The models can also provide standardized estimates of uncertainty which can be used to adjust crediting based on confidence in the model estimates, at the

[9] http://www.cometvr.colostate.edu/

appropriate scale. Thus, the standardized tools can provide a transparent way to embed quantification uncertainties into protocols and crediting.

Farm-scale quantification also requires more detailed farm-level data. The U.S. has sufficient soils and climate data, but this may not be true elsewhere. We do not have sufficient collected information on management (past and current crops, fertilizer regime, tillage, number of animals, etc.) thus we need to have farmers provide this directly and have standardized ways to verify it (see Appendix for more detail). Again, a user interface to the models becomes important as a way to gather information in a standardized manner that aligns model and farmer definitions without being too onerous or costly. Modelers estimate that it should take a user 30 to 60 minutes to enter sufficient data into the user interfaces.

With the development of standardized user interfaces for quantification, the challenge for a farm-scale quantification approach primarily comes in implementation. The quantification process has to be applied within the typical carbon accounting processes used in most programs or registries. The program will have to develop the necessary alignment among the model-defined practices (e.g., a no-till system), how the farmer needs to implement the no-till management system to meet the model definition (e.g., one disturbance event to directly apply seed and fertilizer), and how the verifier assesses the supporting on-the-ground evidence of the practice that is gathered by the project developer or farmer (percent residue cover or disturbance indices of the no-till equipment, remote sensing to verify a single disturbance event). Given the potential complexity of verifying management at the farm level, the program will need to develop procedures and guidance for data and supporting records for assessing the validity of the farmer-entered management data. For project developers, who likely will be aggregating a number of farms into a project of suitable size, the complexity and cost of managing this farm-scale approach increases. Project developers will need to collect the supporting evidence from the participating farms in order verify that the farm-entered management data aligns with the modeled quantification. Other programs have developed explicit guidance on the necessary records and evidence required to meet protocol specifications. This can include receipts, shipping records, truck weights, invoices, crop insurance records, proof of farm equipment specifications for no-till and fertilizer band delivery, and remote sensing and aerial photography for field sizes and equipment passes (which are likely available through USDA and the U.S. Geological Survey). This greatly simplifies and enables a more efficient verification process. To ensure the resulting credits from the projects are quantifiable and verifiable, the farm-level approach requires much greater specificity of farm-level activities than a regional approach, but it is adding a higher level of precision that is not dependent on averaging across a large-scale program to achieve sufficient accuracy.

Complications in implementing programs at farm scale, particularly with verification and alignment of the verification method to the modeling approach, may make application at the farm level too difficult or expensive for some programs, making the regional scale preferable. The regional or ecozone approach may be used to increase transparency of project measurement, monitoring, and verification; to control quantification uncertainty; and to increase the practicality of implementation to project developers. The regional approach has been shown to achieve scale in Alberta, with large numbers of farmers engaged in GHG reductions relatively quickly. Uncertainty due to spatial and temporal variability of input variables can be reduced by averaging or aggregating modeled results in the standardized regional application. Averaging approaches work best in a large-scale program.

The following matrix may be useful to program operators when considering which approach to use (Table 8).

Table 8. Comparing regional versus farm-scale use of models for agricultural GHG program and protocol development.

Consideration	Regional Scale	Farm Scale
	Quantification	

Consideration	Regional Scale	Farm Scale
Data Availability	Uses regional databases; extrapolating results in an averaged fashion; useful where a lack of data or research exists and models are limited.	Uses detailed farm input data and experimental data to calibrate the models; not all systems in all regions are well-researched (livestock-pasture systems are a knowledge gap).
Quantification	Model-based, expert run to develop regionally explicit emissions factors, control on scale-up and uncertainty quantification to ensure conservativeness is applied.	Model-based, project-level application for baseline and project practices allows more flexibility in management and more user-defined inputs; this can lead to challenges in implementation and additional work to maintain transparency and consistency.
Uncertainty	Quantified at the regional scale	Currently quantified at a regional scale (MLRA). New soil inventory and monitoring may allow finer-scale uncertainty in future.
Accuracy	Lower accuracy, regional management data includes aggregated self-reported data that may not always have full alignments of definition, but on average can provide reasonable accuracy	Higher accuracy, if farm-level data have more specific alignment with definitions used in models and some level of verification.
Flexibility	Less flexible, but combined practices can be modeled	More flexible in combining practices and capturing farm-level management variability.
Implementation Considerations		
Verifiability	Standardized and transparent approach: typically verify practice and standard farm records for proof	Can be more complex; given greater farm-level data input, may want to verify a number of these inputs, probably focusing on those that have the most impact on model quantification outcomes. So information on model sensitivity would be helpful.
Cost	Cost burden on program; less transaction costs on the project developer	Cost burden on program for quantification method and alignment and on project developer for monitoring, reporting, and verification (MRV)
Risk	Risk managed by program; expert-generated emission factors; asserts greater control over protocol factors that can lead to risk.	Increased flexibility and complexity can increase risk of inconsistent application; program will need more explicit guidance on implementation.
Profit to project	Maybe greater due to low MRV cost	Depends on MRV requirements
Ease of aggregation	Aggregation process greatly simplified.	Greater level of detail needed and possible complexity for MRV

At this time, uncertainty will likely be quantified in a similar manner for both regional and farm-level applications. Modelers are not comfortable estimating uncertainties at a farm level unless there are field measurements to compliment the modeling, which would add cost and complexity in implementation. The COMETVR tool and newer version COMETFarm will calculate uncertainty at the MLRA scale, which corresponds with ecologically relevant variability and is a unit used widely by USDA for management and policy recommendations. The MLRA would also be a good choice for regional-scale modeling, suggesting similar estimates of uncertainty. Efforts under way to expand U.S. soil inventory and monitoring systems to up to 5,000–10,000 sampling locations may allow quantification of uncertainty at finer scales in the future.

The text boxes in the section on model accuracy above, review uncertainty assessments for each of the models detailed in this report. They suggest that programs and protocols will have to develop conservative accounting procedures that consider the level of uncertainty that is inherent in complex biological processes. Where data and research are robust, uncertainty around changes in soil carbon at the MLRA scale can be ±20%–30% of the mean with 95% confidence (95% CI limits),[10] and changes in nitrous oxide can be ±30%–50% of the mean. At the other extreme, where data and research are sparse the models may not have enough information to calculate uncertainty, which may limit their application in those regions or for those practices until more research can be incorporated.

[10] For example, if the estimate is 1 t CO_2/ha, 95% of a random sampling of those instances would fall between 0.8 and 1.2 t CO_2/ha.

Another important consideration in applying these models is how the baseline scenario is set. By default, most of these models assume that historic trends in climate, yield, and disturbance continue forward in time. On a shorter time horizon (e.g., 10 years), this may be a reasonable assumption; however, on a longer time horizon (e.g. 30 to 100 years), the impacts of climate change are likely to alter rainfall, temperature, and disturbance patterns in significant ways that could change the magnitude of GHG emission and carbon sequestration from agricultural systems. It may even result in a change of direction for carbon sequestration, where systems that were storing carbon are now releasing and vice versa, where systems that were releasing begin storing. Models of climate change at regional and local scales are still highly uncertain, which makes these longer-term projections difficult to incorporate into biogeochemical process models at this time. However, this is an active area of research that should inform future updates to these models and how they are used for mitigation programs and policies.

Questions to ask when selecting a modeling approach

Based on the discussion above, several key considerations need to be taken into account when setting up model application for GHG mitigation programs. Below is a list of these considerations posed as questions that a program administrator can ask when setting up a modeling approach for quantification.

1. Are there good biogeochemical models for the program or protocol under consideration?
    a. Do any of the models include all the relevant GHGs, crops, regions, and management practices that will be included in the program?
    b. Are they sufficiently calibrated and parameterized to run the management options of interest at sufficient levels of confidence? Assess how the model handles uncertainty from model structure, parameters, and input data. Has the model been adequately tested for structural uncertainty in the production system of choice?
    c. Do they include the appropriate default data (best databases) for soils, crops, livestock, and climate data?
    d. Do they handle land-use history sufficiently to address long-term trends in soil carbon stock changes? Has the model been appropriately initialized and calibrated for soil carbon and land-use history?
    e. Are there limits to the scale of model use? How does scale affect uncertainty?
2. Should the program consider user interface versions of biogeochemical process models for farm-scale quantification?
    a. If models are capable of farm-scale quantification, can it aggregate information across multiple fields/farms, crops, and management practices? How does that aggregation process affect the estimates (i.e., has it been conservatively done)?
    b. What user/farmer input is required? Is this information that the farmer will have and that the program can verify?
    c. What MRV procedures and guidance need to be built to make the farm input data, and supporting farm/project evidence match model definitions (e.g., tillage/seeding equipment, disturbance indices, crop yield evidence, irrigation scheduling, fuel usage, fertilizer type/rate per field evidence, field size)? If needed, can adjustments be made to the model to conform with implementation needs?
    d. Is a user interface tool available that covers desired management options? Check the tables in this document and ask model developers to see if a standardized user interface version of the biogeochemical process models is available and ready for use.
    e. If not, can one be readily developed or adapted to address needs?
    f. How is baseline calculated? If necessary can this be adjusted to meet protocol or program requirements?

3. Should the program consider regional-scale model runs for development of emissions factors and equations instead? If questions in #2 above suggest that farm scale is not viable, or if implementation

costs for project development, verification, and alignment or risks are too high, a regional approach may be preferred. If a regional approach is used, the program needs to align standardized equations with modeled emissions factors.

4. If no appropriate parameterized and calibrated model is available, can you build or calibrate a new one?
    a. All the same questions above apply in terms of which models to use.
    b. Additional questions include whether you would like to develop a tool to run at the farm/site scale, or use the model to develop soil-, climate-, region-specific default factors to have a more landscape-level tool.

Examples of How Modeling Is Being Incorporated into Protocols

Pearson and Brown (2010) and Pearson et al. (2010) explored the use of a Tier 2 approach versus a Tier 3 process modeling approach for quantifying N_2O. They tested a simpler model based on a study by Bouwman et al. (2002), but they found it insufficient for project-level calculations (Pearson and Brown 2010; Pearson et al. 2010) and opted to use the DNDC model for the U.S. instead. The nitrous oxide methodology they developed for the American Carbon Registry using a farm-scale application of the DNDC process model can quantify GHGs for changes in fertilizer quantity, type, placement, and timing, as well as use of timed-release fertilizers, nitrification inhibitors, shift to crops with lower N demand, and adoption of precision agriculture.[11] However, it does require significant site-specific soil, climate and N source for model inputs (see Appendix A). Uncertainties are estimated by the model and discounts for uncertainty are required. The methodology has been approved under the American Carbon Registry program. Many of the critical soil input data for running the DNDC model (or other process models) are available from the NRCS SSUGRO soil survey data.[12] However, there are several site-specific soil and crop parameters that need to be measured for model input. For nitrous oxide management there may be sufficient data available in the U.S. to fill in necessary inputs for complex process-based models. The project developer will need to have relatively sophisticated expertise in order to apply the methodology across a number of farms.

By way of contrast, the Alberta Compliance-based Offset System has a government-approved protocol for Tillage System Management that has been developed for regional-scale application.[13] The quantification methodology used in the protocol relies on Best Practice Guidance taken from the IPCC Tier 2 approaches used in Canada's National Emissions Inventory. The result is a series of performance standard baselines that are projection-based and applied at regional levels to quantify net changes in GHGs (carbon dioxide from fuel usage, nitrous oxide and carbon sequestration). The quantification for changes from full-till to reduced-till to no-till, and combinations in between, is set out in a series of equations with custom emission factors for baseline and project, applied at the regional scale. The DAYCENT model was run by experts at finer scales, with Monte Carlo analysis to derive uncertainty estimates for carbon sequestration rates (or reversals). The results were averaged across larger reporting zones, assuming the average represents the best value for use for GHG reporting on a regional basis. Standardized application of calibrated model estimates at Soil Landscape of Canada (SLC) units for each crop-soil-management type were rolled up to ecodistrict level (analogous to the MLRA scale) and aggregated conservatively so that the coefficients underestimate soil carbon gain on average by 25% or more when compared to averaged empirical data. This resulted in conservative estimates for ecodistrict-scale estimates. These

[11] http://www.americancarbonregistry.org/carbon-accounting/ACR Methodology for Emission Reductions through Changes in Fertilizer Management - public comment draft June 2010.pdf.
[12] http://soils.usda.gov/survey/geography/ssurgo/.
[13] Many of the details described here are in an updated version of the protocol which is not yet publically available. These document reflect the current non-updated version. Tillage Protocol - http://environment.alberta.ca/02308.html; Supporting Technical Paper - http://carbonoffsetsolutions.climatechangecentral.com/files/microsites/OffsetProtocols/ProtocolReviewProcess/1stCycleProtocolReview/Tillage/14_No_Till_Default_Protocol_SMTWG_Oct2006_mod.pdf.

would not necessarily be representative of the expected C change for a specific area of land, but would be representative on average. Averaging over larger zones was done by weighting by the area of agricultural land represented by that soil component-SLC polygon combination. These averages were used to develop the empirical equations and emission factors. In this manner the quantification risks/uncertainties are dealt with upfront.

With this standardized approach, the relevant farm activity data to calculate the emissions and verify the activity data accordingly is streamlined. Farm records are described as farm resource inventories held by the farmer or other agri-businesses (e.g., custom applicators, crop insurance agencies), including dated field records of tilled land and tractors or machinery used; soil disturbance measurements; production accounts of crop operations; crop/field records, including chemicals purchased, farm maps, or crop rotations; income and expense records for land, labor, or machinery; transaction journals; general ledgers; etc. These records may be augmented or substantiated through other information sources such as crop insurance, aerial photographs, and satellite imagery, and should be retained by both the farmer and project developer for the duration of the project. Definitions for tillage type and eligible cropping systems are explicit in the protocol, as is the requirement to prove soil disturbance levels through machinery measurements and documentation. Guidance to verifiers and sample data collection sheets are also provided in the appendices.

Conclusion

Biogeochemical models can provide a robust tool for quantifying GHG impacts of alternative management and cropping practices in the United States. These models have been in use and tested for decades, providing significant insights into model capabilities and uncertainties. The primary limitations of these models are due to gaps in research and data, which can and are being filled over time. These models can be used in mitigation programs or protocols in two different ways: (1) to develop regionally specific emissions factors that are embedded in protocol equations for quantifying GHGs in projects, and (2) to develop user interface decision support tools that allow use of the models by non-experts for farm-scale quantification of GHGs. The choice between a regional- and farm-scale approach will be a balancing act among precision, flexibility, and complexity of implementation. Models can provide a standardized, transparent, and low-cost means for quantifying GHGs.

Appendix A: Examples of Guidance and Standardization Necessary for Implementing Protocols That Use Models

The first two examples below show how different the verification of a protocol can be given how models are used. As noted above, these examples show how a farm-scale application of the models can require more guidance and standardization of the verification and reporting process. This is likely to be a continuum. Farm-scale application of models can be further standardized than the example provided here perhaps using defaults for factors that have little impact on quantification outcomes (because the model is not sensitive to that factor), or program managers may be able to verify certain factors, like residue, for the whole program instead of farm by farm by using remote sensing data.

The third example shows how the alignment of definitions between models and application were accomplished for a tillage protocol. Ideally, this type of alignment will occur whether models are used at farm or regional scales, but at regional scales, the definitions may be inherent in the default databases, somewhat limiting how precise the model and verification definition need to be.

Figure A1. Example of Data Inputs Required for the ACR Nitrous Oxide Reduction Methodology

Input Category	Code	Input	Units	Mandatory / Optional	Data Source			
					Project records	*Measured*	*Look-up*	*Default*
Location	*L1*	GPS location of stratum	decimal °	M		X		
Climate	*CI*	Atmospheric background NH_3 concentration	μg N/m³	M				X
	C2	Atmospheric background CO_2 concentration	ppm	M				X
	C3	N concentration in rainfall	mg N/l or ppm	M			X	
	C4	Daily meteorology	multiple	M		X	X	
Soils	*S1*	Land-use type	type	M	X			
	S2	Clay content	0-1	M		X	X	
	S3	Bulk density	g/cm³	M		X	X	
	S4	Soil pH	value	M		X	X	
	S5	SOC at surface soil	kg C/kg	M		X	X	
	S6	Soil texture	type	M		X	X	
	S7	Slope	%	M		X		
	S8	Depth of water retention layer	cm	M		X	X	
	S9	High groundwater table	cm	M		X	X	
	S10	Field capacity	0-1	M		X		
	S11	Wilting point	0-1	M		X		
Cropping system	*CR1*	Crop type	type	M	X			
	CR2	Planting date	date	M	X			
	CR3	Harvest date	date	M	X			
	CR4	C/N ratio of the grain	ratio	M		X		
	CR5	C/N ratio of the leaf + stem tissue	ratio	M		X		
	CR6	C/N ratio of the root tissue	ratio	M		X		
	CR7	Fraction of leaves and stem left in field after harvest	0-1	M		X		
	CR8	Maximum yield	kg dry matter/ha	M	X			
Tillage system	*T1*	Number of tillage events	number	M	X			
	T2	Date of tillage events	date	M	X			
	T3	Depth of tillage events	6 depths†	M	X			
N Fertilizer	*F1*	Number of fertilizer applications	number	M	X			
	F2	Date of each fertilizer application	date	M	X			
	F3	Application method	surface / injection	M	X			
	F4	Type of fertilizer	type*	M	X			
	F5	Fertilizer application rate	kg N/ha	M	X			
	F6	Time-release fertilizer	# days for full release	M	X			
	F7	Nitrification inhibitors		M	X			
Organic Fertilizer	*O1*	Number of organic applications per year	number	M	X			
	O2	Date of application	date	M	X			
	O3	Type of organic amendment	type	M	X			
	O4	Application rate	kg C/ha	M	X			
	O5	Amendment C/N ratio	ratio	M				X
Irrigation System	*I1*	Number of irrigation events	number	M	X			
	I2	Date of irrigation	date	M	X			

In the example above, the farm records that will need to be gathered are listed in the *project record* column. Evidence of the tillage system, N fertilizer, and organics and irrigation systems will need to be gathered. Project developers or the program will need to apply some standardized procedures to ensure consistency. In addition, lab results of measured N of the grain, leaf, and stem, and roots will need to be conducted and gathered on a per-crop basis, along with field capacity and wilting point (one-time measurement). Issues of appropriate field sampling procedures to avoid bias will need to be demonstrated by project developers, or laid out in additional guidance by the program. The amount of residues left after harvest (fraction of leaves and stems left in the field after harvest) input can have a large impact on the

GHG quantification; thus, programs will need to ensure that bias is minimized through standardized sampling procedures across the farms and projects. The ACR methodology states: "Project Proponents must retain a conservative approach: that is, if different values for a parameter are equally plausible, a value that does not lead to under-estimation of net GHG emissions must be selected." But this guidance may not be explicit enough to ensure consistency and transparent quantification and implementation of the aggregated farms across the project. Additional program guidance will likely be needed.

A2. Example of data inputs required for the Alberta Tillage System Management Protocol; additional guidance and required and supporting evidence

The standardized regional approach uses spatially and temporally aggregated default parameters for yield data (10-year averages), N fertilizer application rates, fuel use, soil characteristics, crop parameters, and other variables (finer spatial unit databases with modeled results scaled up to ecodistrict level). The scaling up procedures (see http://environment.gov.ab.ca/info/library/7921.pdf and Appendix A), average out variability introduced by the various combinations of crop-soil-management-climate interactions for an ecodistrict, resulting in a very streamlined set of farm-level inputs to be gathered for project accounting and verification. However, flexibility is limited in that there is no ability to influence the quantification due to changes in nitrogen management, residue management, different crop types (annual only), or improvements in yield, which should result in increased carbon sequestration. This is very much a performance-standard kind of approach.

Farm-based records and justification are required for the following factors:

- ownership of emission reductions;
- ownership of fields and associated reductions;
- number, size, and location of fields which are part of the project;
- crop type; and
- tillage practices.

Table A2-1 below is a summary of the data points and sources of evidence needed to ensure alignment with the model-based quantification and verification for the protocol.

Table A2-1. Data inputs and sources of evidence for the Tillage Management System Protocol.

	Evidence
Ownership of Emission Reductions	Aggregators: Agreements between aggregators and farmers; farm titles search to ensure landowner identity Farmers: Land Rental/purchase/financing agreements and/or agreements between farmer and landowners Landowners: Purchase/financing agreements
Ownership of Fields	Same as above
Number of Fields	A table comparing the fields from which emission reductions are being claimed and ownership documentation
Size of Fields[1]	• GPS track files from specific farm equipment; or • GPS shape files derived from field inspection; or • Re-measurement using Alberta soils viewer; or • Satellite data; or air photos
Location of Fields	Same as above
Crop Type	• Physical inspection • Seed purchase records, crop sales records, and harvest data reviewed by professional agrologist. Crop type data can also be further substantiated by crop insurance data, however, crop insurance data on its own is considered an insufficient data source.

	Evidence
Tillage Practice and number of passes	GPS output from specific farm equipment; or Satellite data interpretation (with ground truthing); or Aerial Photo interpretation (at specific times of year, if available, this can provide strong evidence of recent practices); and/or Physical inspection of field; Physical inspection of seeding/tillage equipment claimed as low till (openers divided by shank spacing); and Review of farm records by professional Agrologist in addition to a physical inspection of tillage equipment with accompanying statement of review

[1] – if field dimensions change, then measurements will need to be re-taken

The scalability of this kind of protocol has been demonstrated in the Alberta Offset System. To date, after three compliance cycles, over 4.4 million metric tons of verified soil sequestration offsets have been generated.

A3. Example of Aligning Definitions in the Alberta Tillage System Management Protocol

To ensure alignment with model-based definitions for tillage management systems in this protocol and farmer implementation the protocol sets out the guidance shown in Table A2-1.

Table A2-1. Definitions of tillage systems in the Parkland[1] and Dry Prairie protocol areas.

Tillage System	Cropped Land Period [2]	Fallow Period [3]
No-till	Up to two passes with low-disturbance openers (up to 38% each)[4,5] or one pass with a slightly higher disturbance opener (up to 46%) to apply seed, fertilizer or manure,[5] discretionary tillage of up to 10%,[6] no cultivation allowed. Manure applications are either injection or broadcast within these disturbance criteria – no incorporation.	No cultivations
Reduced till	Soil disturbance to apply seed, fertilizer, or manure exceeds no-till definition and/or one cultivation in fall or spring	One to two cultivations
Full till	More than one cultivation between harvest and subsequent seeding if no fallow in that period, or, more than three cultivations between harvest to subsequent seeding if fallow.	More than two cultivations

Notes:

[1] The Peace River Lowland ecoregion is contained within the Parkland zone.

[2] Cropped land period applies to the management cycle that terminates at harvest, (e.g., harvest to harvest defines the cropped land period). This includes land preparation for seeding which may occur in the previous fall.

[3] Fallow period extends from harvest for one full year to the next harvest, typically in the fall.

[4] Percentage values associated with openers are based on maximum opener width (e.g., 5 inch openers actually measure 5.5 inches) divided by the spacing between shanks of the implement.

[5] Additional operations with harrows, packers, or similar non-soil disturbing implements are accepted (e.g., rodweeders are not acceptable).

[6] Discretionary tillage of up to 10% means that up to 10% of the surface area of a single agricultural field may be cultivated to address specific management issues. These areas are determined on an annual basis, meaning that specific areas may change from year to year. Discretionary tillage of greater than 10% of field area must be disclosed and that field is not eligible to generate offsets. This must be disclosed in project documentation.

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