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Quantifying Greenhouse Gas Emissions from Agricultural and Forest Landscapes for Policy Development and Verification

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Abstract

The emergence of policies to reduce greenhouse gas (GHG) emissions motivated a rapid shift in ecosystem modeling, especially concerning agricultural and forest management effects on nitrous oxide (N_2O) emissions and soil carbon (C). First, we review models for estimating GHG fluxes in agricultural and forest landscapes. Second, we investigate the interplay of models with institutions that develop and implement climate change policy. Limited GHG flux observations constrain our understanding of process controls, especially with respect to N_2O flux. Even when simulation models explicitly include N_2O flux, this capability is infrequently applied or validated. In the policy arena, tools used to estimate aboveground forest biomass C rely on robust inventory data. Such data are scarce outside of the industrialized world. Compared with biomass C, soil C storage in both forest and agricultural systems is difficult to quantify. Widely used estimates depend on critical assumptions such as the extent to which erosion contributes to C loss from fields and the mechanisms by which C is stabilized in soil, both of which are the subject of serious debate. As evidenced by at least one instance we explore, institutions dedicated to policy development and implementation can rapidly achieve a nuanced understanding of these limitations, given sufficient engagement of the research community. Our review illuminates challenges that affect land-based GHG mitigation initiatives as a result of current knowledge gaps, institutional capacity, and decision-making frameworks. We suggest key points that should be communicated to model users and raise questions that could be fruitfully addressed by model developers and consumers of modeled estimates.

Abbreviations: AB32, Assembly Bill 32; ACR, American Carbon Registry; APEX, Agricultural Policy/Environmental eXtender; C-AGG, Coalition for Agriculture and Greenhouse Gases; CAR, Climate Action Reserve; CDM, Clean Development Mechanism; CMPP, cropland management project protocol; CO2e, CO2 equivalents; CSA, Climate Smart Agriculture; DAYCENT, Daily CENTURY; DNDC, Denitrification–Decomposition; EF, emission factor; EPIC, Environmental Policy Integrated Climate; EUETS, EU Emissions Trading System; FIA, Forest Inventory and Analysis; FVS, Forest Vegetation Simulator; GHG, greenhouse gas; GPP, gross primary productivity; LCA, life-cycle analysis; LTE, long-term experiment; NI, nitrification inhibitor; NPP, net primary productivity; OM, organic matter; RGGI, Regional Greenhouse Gas Initiative; RZWQM2, Root Zone Water Quality Model 2; SL, slow-release; SOC, soil organic carbon; SOM, soil organic matter; T-AGG, Technical Working Group on Agriculture and Greenhouse Gases; UNFCCC, United Nations Framework Convention on Climate Change; WFPS, water-filled pore spaces.

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Synthesis and Modeling of Greenhouse Gas Emissions and Carbon Storage in Agricultural and Forest Systems to Guide Mitigation and Adaptation
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In this chapter, we draw together research and thinking centered on land use management and climate change mitigation. Three topics have their roots in ecosystem science. First, a long history of experimentation and modeling has examined changes in soil organic carbon (SOC) over time and the response of SOC to different management practices. Second, more recent efforts have measured and modeled nitrous oxide (N_2O) emissions from agricultural soils, and some of these studies have targeted the influence of management practices on GHG emissions. Third, a rich history of measuring tree growth across the United States has provided the foundation for estimating accumulation of carbon in aboveground biomass in forests. The empirical measurements and associated models that developed in each of these areas have recently been called into service to estimate GHG balances in agricultural fields and forests and to project changes in GHG budgets that would result from specific land management changes.

Our investigation differs from previous analyses in three respects. In our review of models and model projections, we consider both complex process-based simulation models and simpler empirical models. We discuss model strengths and weaknesses given the data available to parameterize them. Furthermore, we discuss how limitations in both data availability and conceptual understanding affect how different models represent ecosystem processes. For example, while models of soil carbon cycling have taught us a great deal and sometimes effectively project the trajectory of SOC over time, they remain limited by fundamental gaps in our understanding of processes that stabilize or destabilize SOC (Kramer et al., 2012, references therein; Kleber and Johnson, 2010; Guggenberger and Kaiser, 2003). While we are not the first to illuminate limitations to understanding these processes (e.g., Baker et al., 2007, for soil carbon responses to tillage practices in agriculture), our analysis is more synthetic, including both N_2O and SOC and both agricultural and forest management. In addition, we place our model comparisons in historical contexts, showing how disciplinary roots of different models have influenced the complexity with which they represent different ecosystem processes (e.g., hydrology versus soil biogeochemistry).

In addition to this technical overview, we discuss how particular institutions that develop market-based GHG trading systems have used available science, illustrate how groups of research scientists and policy developers have influenced each other, and discuss the institutional commitments that have structured those interactions. This kind of analysis should help us make the best use of ecosystem science to support land use management for climate change mitigation.

Finally, by placing our analysis of data and model limitations directly adjacent to a summary of selected policy initiatives, we show how policies can benefit from model projections, but we also show the limitations of current models and data sets and the need for further development of both models and data.

Our intent is to ground policy application of cutting-edge research tools in an understanding of their limitations, to emphasize that the natural evolution of models in response to new scientific knowledge conflicts with the need for policy methodologies to be standardized and implemented over multiple years or decades, and to reinforce the need for continued model development apart from the immediate policy applications. This level of analysis supports the research community's responsibility to provide best-available research for near-term management and policy decisions while simultaneously helping to retain a focus on studies that build deeper understanding over longer time frames.

The remainder of this chapter is divided into four sections. We begin by describing policy initiatives that have created demand for modeling tools that quantify net GHG emissions from agricultural and forest land management. We then review models for agricultural landscapes, including quantification of carbon dioxide (CO_2), methane (CH_4), and N_2O fluxes, with a particular focus on N_2O because of agriculture's dominant role as an N_2O source as well as the persistent challenges in modeling N_2O emissions. Our review complements recent work by Shepherd et al. (2011), which outlined the broad process-level capabilities of 30 currently available simulation models in agricultural systems, but did not focus on model capacity with respect to N_2O emissions. We subsequently review empirical models because they figure prominently in efforts to implement climate change mitigation policies and discuss challenges for improving our modeling tools with respect to SOC dynamics. For forest ecosystems we focus on modeling tools currently applied in policy settings to assess changes in biomass and soil carbon storage. We conclude by summarizing both the lessons learned and outstanding questions for the following three themes: (i) model structure and scale of application, (ii) data limitations and nonlinearity, and (iii) applications to GHG offset projects.

Institutions that Link Science and Policy to Reduce Net GHG Emissions

International

Since its adoption in 1992, the United Nations Framework Convention on Climate Change (UNFCCC) has spurred substantial international efforts to quantify annual GHG emissions from various sources, including agriculture and forestry. Most directly, the Kyoto Protocol established the Clean Development Mechanism

(CDM), which enables industrialized nations to meet emission reduction targets by supporting activities in less developed countries. A search of CDM agricultural projects demonstrates an emphasis on reclaiming CH_4 from improved manure management or biomass processing. Land-management-based strategies such as REDD (and REDD+)—projects designed to prevent forest clearing or promote C sequestration through reforestation or afforestation—have also received considerable attention.

Similarly, the EU Emissions Trading System (EUETS) has focused on reducing emissions from power stations and manufacturing facilities—sources that can be measured, reported, and verified with a high level of accuracy. Regulated entities can trade allowances with each other, so that facilities that reduce emissions more than required can sell unneeded allowances to companies that have not achieved required targets. While EUETS projects do not focus on land management, these projects can indirectly affect agricultural landscapes. Biomass energy plants initiated as EUETS projects have disrupted traditional agricultural uses for unharvested crop biomass (Gilbertson and Reyes, 2009), with the subsequent reduction in plant residue incorporation into soil potentially reducing SOC stocks.

A number of countries and provinces have developed climate change mitigation programs that include market-based mechanisms. Some of these (e.g., Alberta, Canada) incorporate offsets that include agriculture and forestry management. Others, such as the nascent provincial markets in China (Qiu, 2013), could adopt land management offsets as they evolve, particularly if robust protocols for estimating GHG emission reductions have already been developed. Other nations recognize the need to mitigate climate change and would like to harness the potential of land management to reduce emissions using other policy levers.

All these efforts to develop land-based climate change mitigation policy rely on a strong science base to quantify the relationship between specific land management practices and GHG emissions. Many nations support research on the climate change mitigation potential of agriculture and forestry, and the Global Research Alliance on Agricultural Greenhouse Gases facilitates information sharing among nations to accelerate the design and adoption of land management practices that reduce GHG emissions (http://www.globalresearchalliance.org, accessed 15 Sept. 2015). The United States, with its strength in scientific research and its culture of research collaboration across borders, is a major contributor to this effort. Identifying data needs to improve quantification of management effects, and the resources required to collect and interpret the data, will support wider adoption of agricultural and forest management practices that mitigate climate change. The scientific knowledge and research expertise of US researchers should provide a useful guide on quantifying management effects because of the substantial investment in research that has been made for decades and the associated availability of landscape- and national-scale data.

Major international efforts to promote Climate Smart Agriculture (CSA) include the work by the World Bank and the UN Food and Agriculture Organization (FAO), and the nascent CSA Alliance. Although these organizations have not focused on quantifying emissions, they have played a major role in drawing attention to the potential to reduce GHG emissions via land management. In December 2013, the Climate Change, Agriculture, and Food Security research program of the CGIAR system partnered with Future Earth to convene the third Global Conference on Agriculture, Food and Nutrition Security and Climate Change. The purpose of the conference was to promote a CSA Alliance (http://ccafs.cgiar.org/global-conference-agriculture-food-and-nutrition-security-and-climate-change#.UzniR_ldWgY, accessed 15 Sept. 2015). A number of governments are now working to define the structure and objectives of this nascent organization. At over 550 pages, the FAO's CSA sourcebook defines a framework for linking climate change and agriculture in a landscape context and applies this framework to row crops, livestock, forestry, and fisheries (Food and Agriculture Organization, 2013). Leading institutions with leverage over the trajectory of development initiatives have made the connection between climate change and agriculture a centerpiece of their work. And while the need for adaptation appears to have been the main driver of these initiatives, the role for agriculture in mitigation has also received a great deal of attention.

The US government is also paying attention to CSA and land use in an international context. Secretary of State John Kerry's initial policy guidance statements to the Department of State and the US Agency for International Development. This guidance focused on climate change and included the directive to slow, halt, and reverse emissions from land use.

United States

Before 2009, in anticipation of federal climate-and-energy legislation in the United States (e.g., HR2454, the American Clean Energy and Security Act), numerous organizations began to develop the analysis necessary for agriculture and forestry to participate in a cap-and-trade program (Broekhoff, 2008). The motivations for considering land use management in policy aimed primarily at reducing GHG emissions included (i) the need to make climate protection policy as affordable (hence feasible) as possible, coupled with analyses suggesting that emissions associated with land use change could be reduced at low cost relative to other emission reduction opportunities (Creyts et al., 2007); (ii) preexisting commitments of some stakeholders to protect forests, and the opportunity to find an additional lever to achieve that end; and (iii) the possibility of finding a revenue stream for farmers linked to climate change mitigation and hence enrolling their support for (or at least reducing opposition to) policies that promote climate change mitigation. Most efforts to take advantage of GHG emission reductions associated with land use change assumed a policy structure in which directly regulated entities such as power plants could purchase carbon credits from growers who reduced emissions by using management practices they would not have employed without this market opportunity. However, for carbon credits to have robust value, there was a critical need for agreed-on, defensible methods to quantify the degree to which various agricultural and forest management practices reduce emissions.

Following the failure of the US Congress to pass this legislation, efforts to take advantage of agriculture's potential role in climate change mitigation continued in several initiatives that also support the need for improved methods to quantify how much changes in agriculture and forest management lead to reduced GHG emissions. Within the United States, prominent public initiatives that include the agriculture and forestry sectors in climate change mitigation efforts are guidance provided to growers for voluntary use by the Climate Change Office of the US Department of Agriculture (Biggar et al., 2013); the Northeast Regional Greenhouse Gas Initiative (RGGI) (Regional Greenhouse Gas Initiative, 2013a, 2013b); and the carbon offsets program administered by the California Air Resources Board, as it implements the California Global Warming Protection Act (Assembly Bill 32 [AB32]) (California Air Resources Board, 2013).

Under AB32, offsets can be used to meet up to 8% of required emission reductions and can originate anywhere in the United States, even though emission reduction requirements apply only to California. To take full advantage of this provision in the law, regulated entities would require approximately 200 million metric tons of CO_2 equivalents (CO_2e) in offsets; generating that many offsets would require substantial tracts of land across the country (Stevenson et al., 2012). Approved offset protocols grant credits for projects that destroy ozone-depleting substances that have high global warming potential and for projects that sequester carbon in US forests (California Air Resources Board Cap-and-Trade Protocols). However, existing offset protocols do not provide the opportunity to generate 200 million metric tons of CO_2e. Project eligibility for offset credits under California's global warming protection law mandates that emission reductions would not have occurred in the absence of the regulation; because a suite of regulations and incentive programs in California are already reducing emissions from many activities, the number of potential offset opportunities is rather limited.

Indeed, whether enough offset opportunities exist to generate 200 million tons of CO_2e is an open question. Agriculture is typically unregulated, making the sector an appealing source of offset projects if the necessary quantification tools can be developed and if risks of emission reductions being temporary can be adequately addressed. Agricultural practices that might qualify as offsets include ones that sequester carbon in soil and ones that reduce emissions of nitrous oxide and methane (California Air Resources Board, 2011a, 2011b). The urgency behind efforts to identify offset opportunities and develop quantification methods and protocols has eclipsed a more fundamental question: When will research on agriculture and GHG emissions be able to credibly support these efforts?

In anticipation of a market-based GHG emissions reduction program, institutions like the Climate Action Reserve (CAR), the American Carbon Registry (ACR), and the Voluntary Carbon Standard (VCS) have produced protocols that define management practices eligible to earn carbon credits and quantify the GHG emissions reductions from specific management practices. Our treatment of carbon registries focuses on CAR. In contrast to the global distribution of CDM, EUETS, and REDD projects, for CAR these protocols primarily outline projects to be implemented within the United States. Exceptions include landfill, livestock, and forestry protocols developed specifically for implementation in Mexico (Climate Action Reserve, 2013). This national scope is consistent with requirements under California's AB32. The California Air Resources Board, which administers AB32, is a potential user of CAR's protocols.

Although research linking land management to GHG emissions and carbon storage in soil and forest biomass has been evolving for decades, only recently have a number of initiatives focused on synthesizing the science in a policy-relevant form. These initiatives are framing how technical understanding is incorporated into policy. For example, with funding from the Packard Foundation, the Technical Working Group on Agriculture and Greenhouse Gases (T-AGG) reviewed the literature to produce a current assessment of the GHG emission reduction potential of dozens of agricultural practices (Eagle et al., 2012). A set of USDA Conservation Innovation Grants (CIGs) focused on climate change mitigation included projects to assess barriers to farmers' use of GHG reduction protocols (USDA-NRCS, 2011). The Coalition for Agriculture and Greenhouse Gases (C-AGG) provides a regular forum for information exchange among project developers, scientists, growers' organizations, investors, and government agencies (www.c-agg.org).

As organizations like C-AGG and USDA-NRCS have recognized, quantification tools can be used in a variety of contexts apart from environmental markets or regulatory arenas. For example, COMET-FARM couples a complex biogeochemical model with a user-friendly interface and incorporates many default values for parameters. It therefore allows growers to estimate “best guesses” about GHG emission reductions that might result from practice changes on their land (http://cometfarm.nrel.colostate.edu/, accessed 15 Sept. 2105).

The limited number of landscapes, climate regimes, and agricultural and forestry practices for which protocols have been approved can be attributed largely to a scarcity of affordable, robust tools that can currently be used to quantify the relationship between changes in land management and GHG emissions. The status of tool development, in turn, can be traced to limited data and understanding. In the following sections we discuss the development and limitations of available GHG quantification tools and subsequently discuss how these limitations have influenced protocol development.

Quantifying GHG Emissions from Agricultural Land Management

Globally, agriculture is a dominant source of N_2O and CH_4, accounting for 82% and 43% of anthropogenic emissions, respectively (USEPA, 2012). In US agricultural systems, soils account for about 70% of total anthropogenic N_2O emissions, The majority of US anthropogenic CH_4 emissions result from losses in the natural gas industry (~36%), landfill emissions (~19%), and enteric losses (20%), with manure management (<10%) also contributing significant emissions; in contrast rice cropping systems only account for approximately 1% of US anthropogenic CH_4 emissions. Therefore, in the US context, cropping system management decisions impact net N_2O flux, but agricultural impact on CH_4 emissions depends mainly on the number of livestock raised and how manure is managed. Because cropping system management is a primary driver of US net N_2O flux, we focus our review of agricultural simulation models on tools that quantify N_2O flux in response to agricultural management decisions.

The contribution of agricultural land management to CO_2 emissions results from a net decrease in SOC on existing farms due to management practices; the influence of agricultural expansion on SOC and vegetation C; and fossil fuel combustion for farm management, fertilizer production, pesticide production, and manufacturing agricultural equipment. In the US context, CO_2 emissions from agricultural inputs and operations are about 14% of total agricultural GHG sources (Del Grosso and Cavigelli, 2012) and represent a small contribution to net CO_2 emissions relative to commercial, industrial, residential, and transportation CO_2 emissions. However, changes to agricultural land management could produce a significant sink for atmospheric CO_2 via SOC sequestration (e.g., Smith et al., 2008b). We discuss challenges regarding the accurate measurement of SOC accumulation in the section entitled "Managing Agricultural Landscapes to Promote SOC Storage."

Our ability to accurately model agroecosystem biogeochemical dynamics, and therefore net GHG emissions, remains constrained by limited data sets with spatially and temporally concurrent measurements of multiple C and N cycle processes. This challenge applies to both empirical models and mechanistic simulation models, though model performance has improved significantly after decades of model development and validation (e.g., Smith et al., 1997; Shepherd et al., 2011). We recognize that the distinction between mechanistic simulation models and empirical models is imprecise, as empirically derived functions relating ecosystem properties to GHG flux rate have served as the basis of both complex simulation model development (e.g., Parton et al., 1996), as well as simple empirical model development (e.g., Millar et al., 2010). However, we find the categorization of models as complex simulation or simple empirical models useful for understanding how models are being adopted in the policy arena. Below we review (i) agricultural models that explicitly simulate N_2O flux, (ii) simple empirical modeling tools for quantifying N_2O flux in agricultural landscapes, and (iii) broader challenges to accurately quantifying SOC response to agricultural management practices.

Simulation of Cropping System GHG Flux

Modeling net GHG emissions from agricultural landscapes requires accurate model description of (i) net CO_2 flux as the balance between CO_2 uptake resulting from C fixation during plant growth, and CO_2 emissions from plant respiration and heterotrophic soil respiration due to organic matter decomposition, (ii) N_2O emissions resulting from aerobic pathways during nitrification and anaerobic pathways during denitrification, and (iii) CH_4 emissions by explicit modeling of methanogenesis and CH_4 uptake through oxidation in non-saturated soils.

All agroecosystem models include the dominant processes of the C cycle, though mechanistic details vary. Models differ in how organic matter (OM) substrate pools are defined, which OM pools are explicitly tracked, and how environmental properties control decomposition rates. Models commonly distinguish between OM substrate quality in determining decomposition rate and OM residence time. Due to our incomplete mechanistic understanding of controls on carbon stabilization and decomposition, many modeled OM pools are conceptual rather than measurable pools. In other words, although models typically recognize that some OM decomposes easily and some resists decay, the division of the total OM pool into different fractions has only limited basis in a mechanistic understanding of why these decay rates vary. Therefore, model ability to project how decay rates will change in response to changes in management practices or environmental conditions is also limited. Without the ability to mechanistically simulate C stabilization, we cannot adequately study a major mechanism of long-term SOC accumulation in agricultural systems. We discuss recent mechanistic work regarding SOC accumulation and stabilization in the section entitled "Managing Agricultural Landscapes to Promote SOC Storage." Models also differ in how they simulate plant growth, with some models explicitly modeling gross primary productivity (GPP) and plant respiration, while other models calculate net primary productivity (NPP).

The complexity of N cycle description differs significantly among agroecosystem models. Models differ in their assumptions regarding controls on net N mineralization during decomposition, as well as subsequent nitrification rates. The most important difference in N cycle description among agricultural models is whether the model explicitly simulates N_2O emissions. We focus our simulation model review on models that explicitly partition N_2O and N_2 flux. Since anthropogenic N_2O emissions are largely controlled by agricultural soils, agroecosystem model capacity to track N_2O emissions is a critical model feature for application to GHG accounting questions. We complement the model review by Shepherd et al. (2011) by comparing simulation model commonalities and differences with respect to model description of C, N, and hydrologic cycles.

Overview of Models

We compare key features of agroecosystem models that are commonly applied to study environmental impacts of agricultural management and that explicitly quantify N_2O emissions. These models have a varied history in terms of original purpose of model development, as well as coordination of model development with management objectives. The disciplinary roots of the development team and the primary objectives of model development influence the complexity or simplicity of process representation. Historically hydrologic models originated with simplified C and N cycle descriptions, while models focused on C and N cycles started with relatively simplified hydrology. However, over the course of model development all ecosystem models have increased the complexity of C, N, and hydrologic cycle descriptions

We review five ecosystem models—three with a historical focus in C and N cycling and two with a historical emphasis on hydrology. DAYCENT (Daily CENTURY) (Parton et al., 1987, 1998, 2001) is a daily time-step model that tracks both N_2O and N_2 flux from agricultural systems and is based on the CENTURY model. CENTURY was originally developed as a monthly timescale model to quantify decadal and century-scale processes of SOC dynamics and soil development. The development of the daily time-step DAYCENT model allowed the CENTURY description of soil organic matter (SOM) dynamics to be applied toward agricultural management questions. Model application to address GHG emissions from agricultural landscapes has been a key goal over the course of DAYCENT development. The Denitrification–Decomposition (DNDC) model (Li et al., 1992) is grounded in the explicit representation of microbial populations and environmental constraints that control C and N process rates. Throughout DNDC's history, model developers have focused on describing GHG emissions. As a result, DNDC has been broadly applied to estimate agricultural GHG emissions and model development has been coordinated with various international research teams focused on quantifying GHG emissions for policy compliance, including NitroEurope and Landcare Research in New Zealand. The ECOSYS model (Grant et al., 2001a) uses a highly detailed, mechanistic approach to simulate C and N processes, describing microbial control on C and N dynamics by representing populations of different microbial functional groups. ECOSYS model development has frequently been coordinated with model validation against flux tower measurements, offering a unique opportunity to test and refine modeled CO_2 dynamics. Similar to other models reviewed, a fundamental goal of ECOSYS model development has been model application to support improved land management planning with respect to environmental impacts. The Agricultural Policy/Environmental eXtender (APEX) model (Williams et al., 2008) is derived from the Environmental Policy Integrated Climate (EPIC) model (Williams, 1995), which was originally developed to study watershed dynamics and soil erosion. The APEX model combines the hydrologic sophistication of EPIC with a complex N cycle and a CENTURY-like description of SOC decomposition processes. The Root Zone Water Quality Model 2 (RZWQM2) (Ma et al., 2001) is a widely applied model developed by USDA-ARS scientists. This model has been used to study various agricultural management scenarios, including tillage, fertilizer, manure, and pesticide management. The direct involvement of USDA-ARS scientists in APEX and RZWQM2 development has resulted in models that are well suited to addressing major management practices in US agricultural landscapes. Below we summarize key similarities and differences in how these five models describe C, N, and hydrologic processes and agricultural management practices. An overview of model similarities and differences is also summarized in Table 1.

C and N Process Description

A key distinction among models is whether C and N processes are described as explicit functions of microbial biomass with rates grounded in microbial metabolism or whether descriptions are derived from empirical observations of process

Table 1. Comparison of ecosystem models that partition N_2 and N_2O emissions.†

	DAYCENT	DNDC	ECOSYS	APEX-EPIC	RZWQM2
C cycle					
Vegetation growth					
GPP description‡	no	radiation use efficiency	Michaelis–Menten enzyme kinetic model	no	radiation use efficiency
GPP controls		plant C, temperature, precipitation, PET, soil moisture, [CO_2], soil N, leaf N, fPAR	LAI, PAR, [CO_2], leaf temperature, leaf nonstructural C:N, leaf structural C:N, leaf water potential, leaf stomatal conductance		plant C, plant N, light, temperature, soil moisture
NPP controls	plant C, temperature, precipitation, PET, soil moisture, soil N, LAI	plant C, temperature, precipitation, PET, soil moisture, soil N, leaf N, fPAR	GPP – autotrophic respiration	light-use efficiency, temperature, soil N, soil moisture	plant C, temperature
Soil processes					
SOM pools	6	9	9 in each of 5 substrate–microbe complexes	6	8 (including 3 microbial pools)
Microbial biomass explicitly controls C, N processes	no	yes	yes	no	yes
Decomposition function	first order	first order	Michaelis–Menten (substrate) × active microbial biomass	first order	first order
Decomposition controls	substrate, temperature, moisture	substrate, temperature, moisture, clay adsorption	substrate concentration, temperature, moisture, microbial biomass	substrate, temperature, moisture	substrate, temperature, soil moisture, microbial population, O_2, pH
Methane function	first order	Michaelis–Menten	Michaelis–Menten		first order
Methane controls	substrate, soil moisture, temperature, Eh	substrate, temperature, Eh, pH	DOC, acetate, [CO_2], [O_2]		
Decomposition temperature response	unimodal	unimodal, second-order polynomial	Arrhenius	unimodal	Arrhenius temperature limitation
Decomposition moisture response	unimodal	unimodal, second-order polynomial	through effect on microbial access to substrate	unimodal	piecewise step function

Table continued.

Table 1. Continued.

	DAYCENT	DNDC	ECOSYS	APEX-EPIC	RZWQM2
			N cycle		
Gross N mineralization	SOC decomposition	SOC decomposition	microbial decomposition	SOC decomposition	SOC decomposition
Net N mineralization-immobilization	OM C to N ratio	OM C to N ratio	microbial C:N	OM C to N ratio	explicit microbial growth
Nitrification function	empirical fit to observations across a gradient of NH_4^+, WFPS, temperature, and pH	Michaelis–Menten	Michaelis–Menten for NH_3	first order	first order for low $[NH_4^+]$, zero order for high $[NH_4^+]$
Nitrification controls	substrate, temperature, texture, WFPS, pH	substrate, temperature, moisture, pH	substrate, CO_2, nitrifier biomass	substrate, temperature, WFPS, pH	substrate, temperature, soil moisture, microbial population, O_2, pH
Plant uptake function		first order	coupled diffusion and active uptake (Michaelis–Menten)	evapotranspiration	Michaelis–Menten (active), transpiration (passive)
Plant uptake controls	root biomass, soil N, plant N need	daily plant growth, soil N, moisture	soil N, water, O_2, soil temperature	soil N, moisture	plant N need, soil N
N_2O and N_2 flux	empirical fit to observations across a gradient of NO_3^-, WFPS, and respiration	Michaelis–Menten dentrifier growth rate	Michaelis–Menten	first order	first order
N_2O and N_2 flux controls	substrate, temperature, texture, WFPS, pH	substrate, temperature, pH, Eh (soil anaerobic volumetric fraction)	substrate, temperature, O_2, and nitrifier and denitrifier biomass	substrate, temperature, moisture	substrate, temperature, moisture, pH
N_2/N_2O ratio	based on WFPS	clay, WFPS, temperature	from sequential reduction of NO_3^-, NO_2^-, N_2O	moisture	based on WFPS
N_2 and N_2O source	nitrification and denitrification	nitrification and denitrification	nitrification and denitrification	denitrification	nitrification and denitrification
N fixation	difference between plant N demand and soil available N	fraction of legume N uptake	root-nodule exchange of nonstructural C and N	fraction of legume N uptake	difference between plant N demand and soil available N (generic model); simulated nodule dynamics (DSSAT)
N cycle temperature response	nitrification exponential increase with temperature	nitrification monotonically increasing with temperature, fourth-order polynomial	common Arrhenius equation for all biological transformations		Arrhenius temperature limitation
N cycle moisture response	unimodal in nitrification, monotonically increasing in denitrification (shape dependent on soil texture)	unimodal, fourth-order polynomial; soil divided into aerobic and anaerobic fractions on the basis of Eh controlled by moisture and other oxygen consumption processes	through effects on soil $[O_2]$, aqueous microbial concentrations		piecewise step function

	DAYCENT	DNDC	ECOSYS	APEX-EPIC	RZWQM2
Hydrology					
Soil layers	10	20+	15	15	10
Infiltration and runoff		SCS curve		Green–Ampt, SCS curve	Green–Ampt, difference between rainfall intensity and Ksat
Drainage and redistribution	gravitational drainage (above field capacity); Darcy's Law (unsaturated soil)	gravitational drainage of soil moisture in excess of field capacity; empirical capillary rise	Richards' equation (unsaturated), Green–Ampt (saturated) for water flux; Fick's Law for vapor flux	gravitational drainage of soil moisture in excess of field capacity	Richards' equation using Brooks–Corey equation for soil water retention curves
Lateral flow	no	no	yes, surface and subsurface	yes	yes (for tile flow)
Management					
Tillage	yes	yes	yes	yes	yes
Fertilization method	yes	yes	yes	yes	yes
Irrigation	yes	yes	yes	yes	yes
Fertilizer type	yes	yes	yes	yes	yes
Manure	yes	yes	yes	yes	yes
Management schedule	yes	yes	yes	yes	yes
Complex rotations	approximated	yes (6 simultaneous crops)		yes (10 simultaneous crops)	yes
Model history					
Application	field, regional, national	field, regional, national	field, regional, continental	field, regional, national	field, regional
Original goal	long-term SOC dynamics	short-term C and N processes	short-term C and N processes	water quality	water quality
References	Del Grosso et al. (2000); Parton et al. (1996)	Zhang et al. (2002); Deng et al. (2011); Giltrap et al. (2010)	Grant et al. (2001a)	Williams et al. (2008); Williams (1995); Gassman et al. (2010)	Ahuja et al. (2000); Ma et al. (2011); Jones et al. (2003)

† A draft of this table was emailed to model developers, and we incorporated their comments. Blank cells denote processes for which we could not determine descriptions on the basis of model documentation. Abbreviations: APEX, Agricultural Policy/Environmental eXtender; DAYCENT, Daily CENTURY; DNDC, Denitrification–Decomposition; DOC, dissolved organic carbon; DSSAT, Decision Support System for Agrotechnology Transfer; EPIC, Environmental Policy Integrated Climate; fPAR, fractional photosynthetically active radiation; GPP, gross primary productivity; Ksat, saturated hydraulic conductivity; LAI, leaf area index; OM, organic matter; NPP, net primary productivity; PAR, photosynthetically active radiation; PET, potential evapotranspiration; RZWQM2, Root Zone Water Quality Model 2; SCS, Soil Conservation Service runoff curve number; SOM, soil organic matter; WFPS, water-filled pore spaces.

‡ GPP and NPP description from NACP model intercomparison (http://daac.ornl.gov/SURVEY8/survey_results.shtml). RZWQM2 has various plant growth models.

rates across a gradient of environmental controls. Decisions regarding representation of C and N processes affect the method of coupling dynamics across C and N cycles and the parameterization requirements for model use. When microbial biomass controls process rates, model reliability depends on robust parameterization of microbial metabolism rates. When empirical relationships determine process rates, model reliability depends on sufficient observations to parameterize key functional relationships. Ideally empirical functions describe process rate response to environmental gradients relevant to the particular cropping system, climate, and soil type being studied. Currently available data sets are best suited for the parameterization of empirical relationships, because C and N process rates have been studied in the field and lab across a gradient of environmental conditions such as soil texture, soil moisture, soil temperature, and cropping system.

CO_2 Flux

Models have used two approaches to estimate plant uptake of CO_2. One group of models bases plant uptake of CO_2 on leaf carboxylation rate as a function of leaf traits (leaf area, leaf N or RuBisCO content, and the saturation function limited by leaf CO_2 concentration). The other group models CO_2 uptake on the basis of photosynthetically active radiation with downregulation controlled by nutrient, water, and temperature stress. Plant release of CO_2 through respiration depends on stored C, N content, water balance, and temperature.

Most of the models we reviewed use first-order decay to represent the release of CO_2 from soil microbial respiration. An alternative approach to modeling OM decomposition applies Michaelis–Menten kinetics to explicitly simulate microbial population controls on decomposition. When using Michaelis–Menten kinetics, the decomposition rate depends on both substrate concentration and density-dependent microbial activity. Organic matter decay varies depending on the type of OM, and models differ in the categories of OM substrate explicitly represented and the decay rates of these substrates. Finally, models differ in how they represent environmental conditions such as water-filled pore spaces (WFPS), pH, temperature, and O_2 and the response of decomposition to these environmental constraints. The description of which environmental properties and how environmental properties affect decomposition rates is a key distinction among models. While a first-order rate equation is the dominant description of OM decomposition, models differ in their simulation of OM decomposition because decomposition rates are dynamically affected by environmental controls. Model assumptions regarding environmental controls and model ability to adequately model gradients in these environmental drivers across a range of soil texture and climates ultimately determines simulated decomposition rates and is a key reason for differences in model outcomes.

N Gas and Denitrification Description

Models represent denitrification and N_2:N_2O partitioning, as well as N_2O lost during nitrification, with varying degrees of complexity. The models describe N_2O flux using first-order kinetics, Michaelis–Menten kinetics, or empirically derived functions. No single functional form dominated model representation of N_2O flux, N_2:N_2O partitioning, or N_2O lost during nitrification. As with decomposition, controls on N gas flux differ among models. The activity of denitrifying microbes primarily responds to soil aerobic status, with the observed relationship between WFPS and N_2O flux varying across soil textures (e.g., Parton et al, 1996). Simulated denitrification is controlled by a combination of soil properties including substrate, temperature, moisture or O_2 concentration, texture, and pH. While all models calculate N_2O flux on the basis of some measure of soil moisture or O_2 state, only DAYCENT and DNDC explicitly include soil texture as a control on N_2O flux.

C and N Coupling

Model assumptions regarding how C to N ratios constrain decomposition and N mineralization are an important link between simulated C and N dynamics; these assumptions control decomposition as well as soil inorganic N available for plant uptake, or loss as NO_3^- or N_2O. For models with explicit simulation of microbial populations, net N immobilization is modeled on the basis of the C:N stoichiometry of the microbial population. In models driven by substrate composition, net immobilization and net mineralization are based on observed threshold C:N relationships across different OM substrate classes.

CH_4 Flux

For models that consider methane flux, model representation of methanogenesis applied either Michaelis–Menten kinetics or first-order kinetics. Methane flux is mainly relevant in flooded rice production systems, waterlogged ecosystems such as wetlands and bogs, or during decomposition of manure stored where anaerobic conditions can develop. In models that explicitly simulate microbial populations, the rate of CH_4 production is described using a Michaelis–Menten saturating function limited by substrate, soil acetate, CO_2 or O_2 concentration, Eh, or pH.

Water Cycle

Hydrologic complexity varies significantly among the ecosystem models reviewed. Models developed primarily to investigate C and N dynamics commonly limit drainage to vertical flow, while models developed primarily as hydrologic models consider both vertical and lateral flow. The most simplistic representation of drainage is based on gravitational flow, with flow volume determined as soil layer water in excess of water holding capacity or field capacity. More complex representation of drainage includes information about the physical soil matrix by applying Darcy's Law or Richards' equations to describe flux on the basis of soil hydraulic properties of a given soil layer. An increasingly mechanistic modeling approach includes water vapor flux using Fick's Law of diffusion.

A fundamental limitation to modeling denitrification is our inability to accurately model pore-scale soil moisture dynamics. Because it is currently not possible to accurately model the true distribution of pore-scale O_2 or moisture conditions, structural model uncertainty is an inevitable component of denitrification model description. However, simulated denitrification dynamics are often able to track observed trends in seasonal flux, implying that an approximation of soil properties using average, aggregate soil conditions is capable of approximating flux patterns that are actually occurring in temporal (hot moment) and spatial (hot spot) peak events.

Agricultural Management

Management practices that affect N_2O flux include (i) tillage and its effect on soil physical properties, (ii) N fertilization rate, timing and type, and its effect on soil available N, (iii) crop rotation and its effect on N uptake and water balance, and (iv) residue management and its effect on C availability and water and nutrient retention. All the models that we reviewed have been extensively applied in agricultural systems and include common conventional agricultural management practices: tillage, irrigation, fertilization rate and method, inorganic N or P fertilizer type, manure, plant residue management, planting density, planting date, harvest date, harvest amount, and a range of crop types (see Olander et al. [2011] for more details on model management capabilities). Models used in rangeland applications can also simulate grazing and burning. The majority of model applications have focused on conventional rotations.

Model capacity to represent complex management options and ecological complexity is more limited. Techniques such as frost seeding and intercropping are not universal capabilities of agroecosystem models. The lack of capacity to simulate multiple species concurrently limits model applicability for testing ecological management as a means of GHG emission reduction. Agroecosystem models rarely simulate disease or pest effects, which can influence the accuracy of plant productivity modeling as well as soil biogeochemical processes. The effects of flooding on plant productivity or soil biogeochemical processes are also rarely modeled. Such ecological perturbations can significantly alter biogeochemical cycling and may become more frequent under climate change. Therefore, improved model representation of ecological complexity is necessary for assessing climate change scenarios.

While all models reviewed herein simulate common management practices, the sensitivity of modeled ecosystem dynamics to management scenarios differs among models. In models with a hydrologic development history (APEX/EPIC, RZWQM2), simulated changes in tillage affect soil physical properties and water dynamics. In contrast, management decisions in models with a development history emphasizing C and N dynamics (DNDC, ECOSYS) have more resolution in the ecology of different cropping systems. Increased capacity to differentiate soil physical properties resulting from management is useful for testing management impacts on physical processes such as erosion, as well as moisture-driven biogeochemical processes such as denitrification. Enhanced complexity with respect to the cropping system description allows model application to study ecological rotations and more generally the role of litter substrate in controlling net C and N process rates.

Model Limitations

More accurate simulation of the C cycle in agricultural systems depends on improved simulation of the biophysical impact of agricultural management (especially tillage), improved simulation of ecosystem processes such as decomposition and SOC stabilization, and improved simulation of diverse management strategies such as rotation complexity, nutrient amendment strategy, and residue management (see the section entitled "Managing Agricultural Landscapes to Promote SOC Storage" for further discussion of SOC dynamics). However, even when models represent detailed management practices, there are limited data to validate whether a model mechanistically captures land management effects on SOC accumulation and soil erosion, especially across a wide range of soil types and climatic conditions. Furthermore, the impacts of individual management practices on biogeochemical cycles are often studied independently. In the absence of improved data, a conservative modeling approach would assume an additive relationship for quantifying biogeochemical dynamics in complex landscapes under multiple management practices; this assumption is likely to be erroneous in many cases. Therefore, model validation for diversified cropping systems will require improved access to long-term data sets under different management strategies.

The fundamental challenge to mechanistically simulating N_2O flux is accurately modeling the spatial and temporal variation in soil environmental conditions. A classic study of N flux from structurally intact soil cores by Parkin (1987) demonstrated that 85% of N gas flux occurred in a soil aggregate representing <0.1% of the original core mass and largely resulted from the decay of a piece of pigweed substrate. This study exemplifies the extent to which extreme soil conditions, rather than the mean, control cumulative N_2O flux, and therefore clarifies the challenge to achieving a truly mechanistic model description of N gas flux.

Even though N_2O flux from soils is part of an N cycle that potentially responds to numerous factors, in agricultural lands these emissions respond primarily to changes in soil aerobic state and the availability of labile forms of nitrogen. Simulation models generally describe average system properties, while in the agricultural landscape N_2O flux occurs in microsites, with the majority of emissions occurring during ephemeral "hot moment" periods when high soil N availability coincides with optimal soil moisture (Groffman et al., 2009). Therefore, simulation models have been conceptualized to aggregate the temporal and spatial diversity of soil environmental state to generate an aggregated N flux emission rather than explicitly characterizing diversity. Despite these simplifications in the spatial and temporal resolution of simulated N_2O flux, models have been successfully calibrated to simulate annual N flux observations. They generally produce seasonal patterns where the highest emissions correspond to periods when heavy rainfall coincides with fertilization or with pulses in N mineralization under bare fallow. Both of these patterns are consistent with our mechanistic understanding and observations of N gas flux dynamics.

Global change adds to current limitations on accurate modeling of complex C and N dynamics. Empirical observations of N_2O flux, plant growth, and SOM decomposition across current climate, atmospheric chemical composition, and soil environmental conditions form the basis of both simulation and simple empirical models. Uncertainty about long-term, ecosystem-scale C and N process response to global change (e.g., Norby and Luo, 2004; Reich et al., 2006; Rustad, 2006; Lukac et al., 2009) reduces confidence in ecosystem model accuracy. In particular, it remains challenging to mechanistically model ecosystem process response to moisture, temperature, and anthropogenic forcing of biogeochemical element concentrations for SOM decomposition (e.g., Giardina and Ryan, 2000; Torbert et al., 2000; Norby et al., 2001; Ågren and Bosatta, 2002; Davidson and Janssens, 2006; Davidson et al., 2006; Erhagen et al., 2013; Stockmann et al., 2013; Gabriel and Kellman, 2014), net N mineralization-immobilization (e.g., Kätterer et al., 1998; Thornley and Cannell, 2001; Reichstein et al., 2005; West et al., 2006; Guntiñas et al., 2012), and plant physiology (e.g., Karnosky et al., 2003; Ainsworth and Long, 2004; Li et al., 2007; Ziska and Bunce, 2007; Sun et al., 2009). In addition most ecosystem models do not consider the complexity of plant community response to global change (e.g., Araújo and New, 2007; Thuiller et al., 2008; Beale and Lennon, 2012; Svenning and Sandel, 2013). These responses depend not only on plant growth responses to novel climate conditions but also on climate-driven shifts in the behavior of invasive species (e.g., Whitney and Gabler, 2008; Bradley et al., 2010; Peltzer et al., 2010; Corbin and D'Antonio, 2012; Ibáñez et al., 2014) or pest dynamics (e.g., La Porta et al., 2008; Dukes et al., 2009; Ziska et al., 2011; West et al., 2012; Sutherst, 2014). While modeling remains our best tool for assessing long-term implications of land management, improving the mechanistic description of C and N dynamics as well as community dynamics will make ecosystem model predictions more robust for global change applications.

Making these improvements requires innovation in model development, and adequate model documentation is a barrier to innovation. The USDA-ARS supported model APEX/EPIC provides a stellar example of documenting the current state of a model's scientific framework (Williams et al., 2008). Because comprehensive model documentation is a time-consuming, unrewarded activity, models developed in an academic environment often rely on peer-reviewed publications to document model development. As a result, model documentation may be scattered among various journal articles, white papers, or technical reports. While individual advances in model components may be described in specific publications, it is generally difficult to get a comprehensive understanding of the current functional foundation of a particular model. Further limitations arise when the model code is not open source, which prohibits a researcher from reviewing how ecosystem processes are represented.

If the ecosystem modeling community were to establish documentation standards, benefits would be widespread. Standards could include guidelines for documenting the current conceptual framework of widely applied agricultural management models and for making model descriptions readily available on a website where model executable files are available for downloading. Additionally, open-source code and detailed documentation within the code should be encouraged. A transparent understanding of how processes are described will allow developers to learn which functional forms are best suited to particular simulation scenarios, facilitating the development of new, improved hybrid modeling approaches.

Empirical Models for Estimating Cropping System GHG Flux

While complex simulation models define interdependencies between multiple ecosystem processes and drivers, simple empirical models determine N_2O flux as a function of observed relationships between gas flux and one or two independent variables, with limited additional environmental information. Simple empirical models for GHG accounting are typically expressed as emission factors (EFs) that define N_2O emissions as a percentage of N addition. The database of N_2O emissions compiled by Stehfest and Bouwman (2006) has served as a basis for estimating EF values across different cropping systems. The Intergovernmental Panel on Climate Change (2006) recognized two categories of empirical N_2O models. Tier 1 models based on globally aggregated flux observations represent the coarsest approach to estimating N_2O in agricultural systems. The Intergovernmental Panel on Climate Change (2006) Tier 1 function for deriving N_2O flux as a function of fertilizer inputs is based on the analysis of Stehfest and Bouwman (2006). Tier 2 approaches can be developed when national or regionally relevant N_2O flux data are available. Because N gas flux is controlled by microbial response to oxygen state, and C and N availability, Tier 2 models define regionally specific functional relationships on the basis of observations relevant to specific cropping systems, soil textures, or climates (e.g., Dalgaard et al., 2011; Leip et al., 2011; Millar et al., 2010; Tonitto et al., 2009). Because empirical models do not mechanistically and dynamically describe environmental state, they cannot capture nuanced patterns of N_2O flux resulting from spatial and temporal variation in environmental properties. The absence of a mechanistic basis for prediction also means that Tier 2 models cannot be applied outside specific conditions and systems that the underlying data represent. However, for environmental conditions representative of the observation site, especially soil texture, climate, and cropping system, empirical model outcomes integrate the effect of environmental complexity on N_2O flux.

Quantifying landscape N_2O flux is difficult because N cycle processes are nonlinear. Nonlinear functions exhibit the property that function evaluation for the mean value of a controlling parameter is not equivalent to taking the mean of the function evaluated over the entire range of a controlling parameter, a property known as Jensen's Inequality. In a study of N losses from Danish agricultural landscapes, Dalgaard et al. (2011) demonstrated the problem of up-scaling nonlinear N cycle processes by calculating that landscape-scale N loss estimates are 30% higher when empirical EF models are applied using farm-specific data compared with estimates using landscape-averaged data. Millar et al. (2010) addressed the nonlinearity of N_2O flux by defining a nonlinear functional response of N_2O flux to N fertilization rate using flux observations from an N addition gradient experiment. Because investigators applied a gradient of fertilizer application rate within a site, the shape of the N_2O-N fertilizer rate relationship provides insight into the nonlinear trend in N_2O loss. This data-intensive approach provides a robust method for quantifying N_2O flux in response to changes in fertilizer rate for corn (*Zea mays* L.) grown on coarse textured soils, but few data sets exist for flux across an N addition gradient in other soil textures, cropping systems, or climates. The Millar et al. (2010) analysis serves as the basis of the Tier 2 MSU–EPRI model (developed by Michigan State University and the Electric Power Research Institute) applied in the CAR Nitrogen Management Project Protocol (Climate Action Reserve, 2012a) and the ACR N management protocol (American Carbon Registry, 2012), allowing for increased data support relative to the Tier 1 linear extrapolation of N_2O emissions as a function of N applied. Recent N_2O reviews by Kim et al. (2013) and Van Groenigen et al. (2010) confirmed the applicability of a nonlinear N_2O flux response across an N input gradient, though Kim et al. (2013) reviewed studies where a linear response to N addition is the best fit to the data.

Various approaches have been applied to integrate existing data and quantitative tools into Tier 2 models. Leip et al. (2011) develop a hybrid approach to quantifying N_2O flux by defining EF values using simulation modeling. Leip et al. (2011) implemented spatial simulations using DNDC-Europe to establish a range of EF values for different SOC, fertilizer scenarios, and climate zones in Europe, and they ultimately contrast these simulated EF ranges to Intergovernmental Panel on Climate Change Tier 1 outcomes. They found simulated EF values paralleled Tier 1 results at large scales (national estimates), but for higher-resolution estimates simulation methods allowed for better accounting of the effect of spatial variation in management practices. Dechow and Freibauer (2011) contrasted a fuzzy logic model to empirical N_2O functions (Bouwman, 1996; Freibauer and Kaltschmitt, 2003; Stehfest and Bouwman, 2006; Intergovernmental Panel on Climate Change, 2006). Their MODE model includes uncertainty due to variation in soil properties and climate. Their model often predicts lower N_2O flux than Bouwman (1996) and Stehfest and Bouwman (2006) models. Tonitto et al. (2009) applied Monte Carlo sampling to a subset of the Stehfest and Bouwman (2006) database to define potential N_2O flux ranges for specific grain cropping system and soil texture combinations under rainfed management. They found that observations supported the potential for N_2O flux rates that exceed 5% of available soil inorganic N, a rate significantly larger than Tier 1 estimates; however, these high flux events occurred with low probability.

While agricultural management has great potential for reducing N_2O emissions, the spatial and temporal resolution of emissions data remains poor because of the cost of implementing N trace gas measurements with sufficient sampling intensity. When field observations are available for specific cropping systems on representative soil textures and in relevant climates, empirical models are a robust tool for bounding the range of N_2O flux. Increased funding and improved N gas measurement methods are expanding the spatial coverage and management scenarios included in observations. These data will allow Tier 2 models to be developed for more cropping systems covering a larger geographic range.

Accurately integrating the effect of seasonal flux variation currently remains a challenge for Tier 2 models. Groffman et al. (2000) concluded that multi-year, continuous data are necessary to derive meaningful patterns for establishing ecosystem N_2O flux at regional scales. Their analysis of long-term data sets demonstrated patterns of N_2O flux related to soil N, C, and moisture state for cropland, forest, and grassland ecosystems, but did not find a single unifying description that could be applied broadly. For cropping systems in Ontario, Desjardins et al. (2010) demonstrate good agreement across measurement methods for a transect of tower and aircraft measurements, as well as simulations using DNDC. However, their work demonstrated the importance of spring snow melt in driving high N_2O flux, with variable moisture controlling peak N_2O flux events and thereby controlling annual flux totals. This nonlinear response to weather makes Intergovernmental Panel on Climate Change Tier 2 equations inadequate for capturing flux trends with respect to pulse climatic events, though they may parallel multi-year average flux. Because experiments that measure N_2O flux in the field typically do not continue over many years (or even a full calendar year), observations are unlikely to capture the full climate variation a site can experience. In the absence of measurements focusing on N_2O flux response to extreme weather events, empirical models are unlikely to accurately capture the occurrence of pulse N_2O flux events that often compromise the bulk of emissions.

Model inaccuracy due to the limited ability of empirical models to reflect ecosystem response to extreme weather events may be amplified as ecosystems respond to climate change. Direct limitations will result for systems that experience more frequent extreme weather events. For instance, empirical relationships derived from observations with a uniform distribution of mean annual precipitation may not adequately describe a system in which the same total precipitation largely falls in extreme events. The application of empirical models under climate change is also complicated in systems where climatic change affects plant physiology. In systems experiencing substantial physiological perturbation, historic observations will no longer adequately describe aggregate biogeochemical dynamics.

GHG Data Availability and Model Validation Studies

Simulation models are often applied to combinations of crops, management practices, and environmental conditions for which there are limited or no GHG flux data. Even if GHG flux data are available, there are very rarely enough auxiliary data to support a mechanistic understanding of environmental drivers on net flux. For example, rarely are there measurements of N_2O fluxes and water and nitrate leaching below the rooting zone throughout an entire year. Simulations of these systems do not focus on improved mechanistic representation of GHG flux. Instead, in these systems model-measurement comparisons are typically conducted for output variables such as SOC or crop yield.

In managed landscapes, long-term SOC data sets have sometimes been available, allowing validation of the C cycle (e.g., Smith et al., 1997) and constraining modeled CO_2 emissions resulting from plant and soil respiration, for a given set of assumptions about erosion rates. While some studies have validated models against observed steady state SOC at sites with long-term measurements, SOC response to management is difficult to measure accurately over shorter timescales and is therefore infrequently available for model validation. (We discuss this issue in more detail in the section entitled "Managing Agricultural Landscapes to Promote SOC Storage.") With the exception of the ECOSYS model, validation of modeled CO_2 flux against measurements is limited, though the increasing availability of flux tower data is making these comparisons possible (e.g., Schaefer et al., 2012; Dietze et al., 2011; Schwalm et al., 2010). Methane outcome validation exists for rice cropping systems (e.g., Fumoto et al., 2008; Smakgahn et al., 2009; Zhang et al., 2011a), and is not an important GHG source in other cropping systems. However, for croplands managed with manure inputs, manure storage is an important methane source. Methane loss responds to livestock management, especially manure management and diet selection, topics that are outside the scope of this chapter. Crop yield is the easiest C stock to measure and the most frequently validated model outcome. However, validating a model solely against crop yield provides limited constraint on the total C cycle and does not mean that the model delivers sound estimates of GHG flux. As models are increasingly applied in policy design and verification, model users should assess that a particular model has been adequately validated for the system and process of interest.

The full complexity of the N cycle remains a challenge to validate in model studies. Limited validation of modeled N cycle dynamics is largely due to the difficulty and expense of sampling nitrate leaching (Addiscott, 1996) and trace gas emissions (Groffman et al., 2006). Recent multi-scale N_2O emission studies by Desjardins et al. (2010) provide rigorous data for both model validation as well as understanding issues of integrating local-scale chamber measurements to landscape-scale emissions estimates, but high quality N_2O emissions data are unavailable for most agricultural systems.

We conducted a comprehensive survey of model application for the five simulation models reviewed in this chapter. Our survey emphasized the spatial extent of model application, the primary goal of application, the model outcomes reported in the study, and the type and success of model validation studies. Our survey demonstrated that model application was dominated by field-scale studies, though small- and large-scale regional applications were significant for hydrologic-centered applications of APEX, applications of DNDC to well-studied rice systems of China as well as grain and grassland systems in Europe, and DAYCENT application in the United States (Fig. 1a). The primary goal of most studies was to address ecological impacts of agricultural management (Fig. 1b), though some model applications were focused on more agronomic questions such as yield. A few model applications were explicitly concerned with the economic viability of land management scenarios. The models were generally applied to simulate conventional agricultural systems, though model application included ecologically based management scenarios (e.g., cover cropping or buffer strip management) or addressed the sustainability of agricultural management with respect to climate change.

Model development history influenced choices about how and where to apply a model. Studies applying models with a development history focused on hydrology (APEX, RZWQM2) frequently reported hydrologic outcomes, while studies applying models with a development history focused on carbon and nitrogen cycling (DAYCENT, DNDC, ECOSYS) had the most frequent reporting of GHG outcomes (Fig. 1c). Model application frequently included other ecosystem properties such as soil inorganic N status, NO_3^- or P leaching, soil temperature, or system energy balance (Fig. 1c). Models rooted in biogeochemistry (DAYCENT, DNDC, ECOSYS) were used predominantly in ecological studies (studies addressing GHG emissions, C storage, or water pollution). For models rooted in hydrology, APEX was generally used to address water quantity and quality questions, while RZWQM2 was applied to simulate water quantity and crop yield. In many applications the specific metric of the study (water quality or quantity, GHG emissions, C storage, or yield) was framed in a larger context of supporting ecosystem services.

Studies applying DNDC and ECOSYS most frequently validated biogeochemical outcomes, while APEX and RZWQM2 had the highest occurrence of hydrology validation (Fig. 1d). Lack of model validation (applied to manuscripts where no validation data were presented and prior validation work relevant to

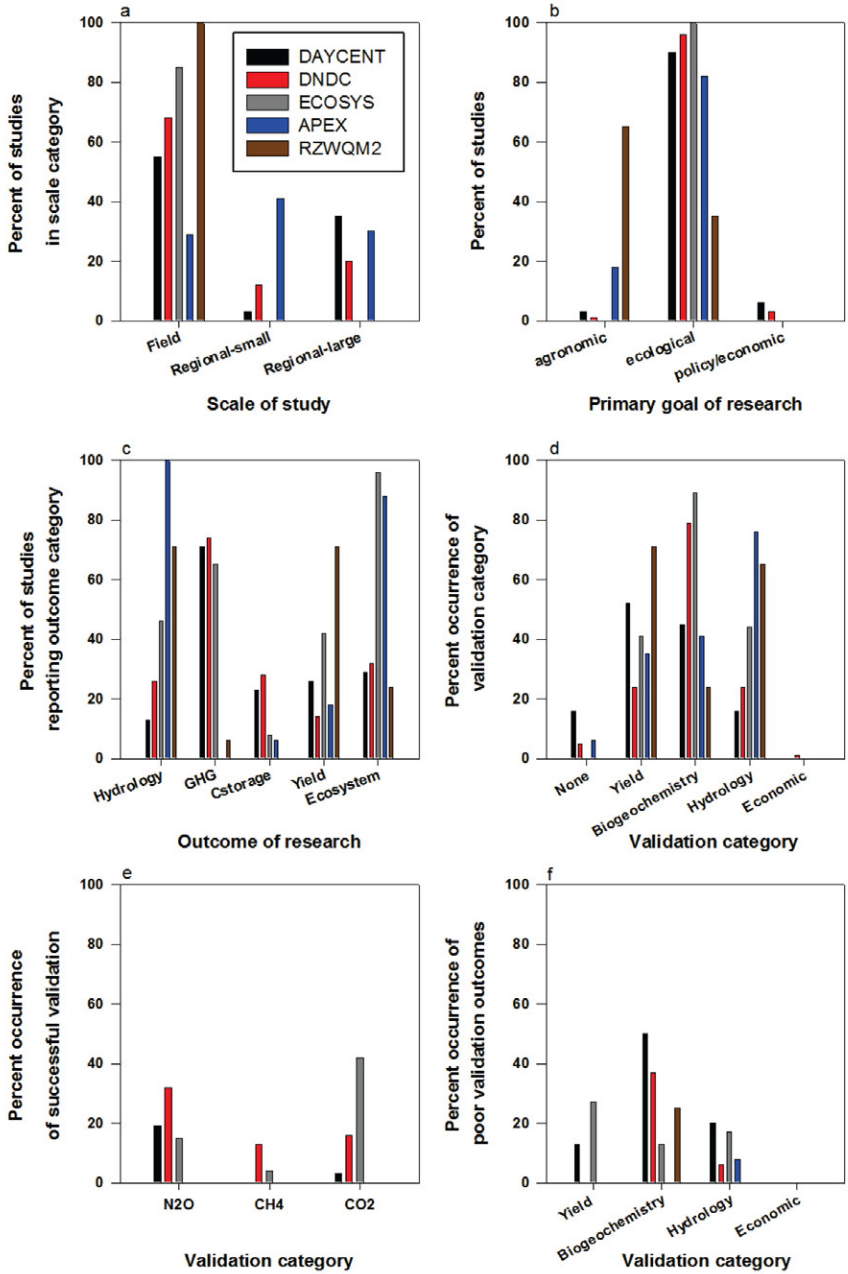

Fig. 1. Simulation model application and validation.

the study was not referenced) occurred in 5, 6, and 17% of the studies for DNDC, APEX, and DAYCENT, respectively. While all of the models reviewed can simulate GHG emissions, GHG outcomes have not been broadly validated (Fig. 1e). Nitrous oxide emissions have been most frequently validated for DNDC, but N_2O validation was also conducted in studies using DAYCENT and ECOSYS. Methane emissions have mostly been validated for rice cropping systems in China using the DNDC model. Net ecosystem CO_2 emissions have been validated most frequently by comparing ECOSYS outcomes with sites on the basis of flux tower observations. APEX and RZWQM2 have not been validated with respect to GHG flux. Biogeochemical trends remain difficult to model, especially at seasonal timescales (Fig. 1f). At least one instance of poor model–data agreement for biogeochemical trends occurred in 13, 25, 37, and 50% of biogeochemical validation studies for ECOSYS, RZWQM2, DNDC, and DAYCENT, respectively. Few model applications concurrently validated all relevant agroecosystem properties: yield, biogeochemical cycles, and hydrology. While the modeling studies surveyed represent a comprehensive use of available data, limited observations remain a challenge for model validation of biogeochemical outcomes.

Whereas data availability limits development and application of both empirical and process-based models, the availability of dedicated, trained experts is a limitation primarily in the application of process-based models. Accurate application of biophysical models requires significant training to understand how to interpret results or estimate uncertainty. While a rigorously validated process-based model can be expected to generate GHG flux outcomes that reflect the system studied, many model validation studies have demonstrated initial inconsistency in comparisons between model outcomes and measured data, highlighting the need for model improvement (e.g., Beheydt et al., 2007). An individual responsible for model application needs to have a general familiarity with the range of plausible ecosystem fluxes in the system studied, an understanding of the mechanisms that drive ecosystem fluxes, and an understanding of how the applied model describes particular ecosystem processes to judge if model structural error is leading to spurious outcomes. The amount of training required to accurately apply a simulation model is a limitation to the widespread deployment of simulation models as policy verification tools.

Managing Agricultural Landscapes to Promote SOC Storage

Carbon turnover times have been studied in agricultural soils for well over 100 yr, and biogeochemical models such as Roth-C and CENTURY, developed to test and refine hypotheses about SOM in crop fields, appear to have been well validated for slow turnover SOC pools at steady state (Smith et al., 2012). However, the past decade has witnessed a vibrant debate among competing hypotheses to explain why SOM is sometimes quickly mineralized by microbes and at other times persists for decades to centuries. Inherent biochemical recalcitrance, protection from attack by virtue of position in the soil matrix, and physical stabilization on mineral surfaces have all received support as stabilization mechanisms (Giardina and Ryan, 2000; Kramer et al., 2012; Mikutta et al., 2006; Sollins et al., 2006; Torn et al., 1997, 2005). In contrast, models of SOM decomposition generally assume decay is primarily based on OM substrate chemistry mediated by environmental factors such as soil texture, moisture, and temperature. Because our understanding of SOM dynamics is undergoing a major shift, models cannot incorporate a fully mechanistic description of SOM stabilization and destabilization. It is therefore worth asking whether SOM models capture how management practices influence soil carbon stability on short timescales and how those changes cascade to influence long-term SOC dynamics. If models cannot mechanistically describe the nuanced ways in which management changes the chemical and physical stabilization of SOM, will they provide a sufficiently unbiased comparison of how management techniques influence GHG budgets to develop policy recommendations?

Within the research community, opinions diverge regarding the extent to which the science behind soil carbon storage is robust, and several factors contribute to that split. First, biogeochemical models of soil carbon cycling rely on conceptual definitions of carbon pools (fast-cycling, slow-cycling, and passive) that are based on long laboratory incubations (Paul and Clark, 1996) rather than incubations under field conditions. This is necessary because of the long timescale of SOC decomposition dynamics, though SOC turnover times derived using ^{14}C isotope methods have been applied to gauge SOC turnover rate in situ (e.g., Gaudinski et al., 2000) and serve as a foundation for SOM model development (e.g., Tonitto et al., 2014). Because models built using these data can predict changes in total soil carbon that match data from long-term experiments (LTEs), they can be argued to provide a sufficient empirical foundation for model structural development and parameterization. However, as explained above, the underlying mechanisms have not been clearly established. A second school of thought holds that until mechanistic knowledge and understanding advances, it will be challenging to form robust expectations about how long SOM will persist and about how that persistence will change in response to a wide variety of management decisions (Crow et al., 2007) and global change.

Second, experiments comparing SOM content among different land uses and management practices appear to yield clear results, but assumptions and knowledge gaps across most experiments leave potentially important processes unmeasured. Eagle et al. (2012) list 11 agriculture management practices with "significant" research, 8 of which appear to increase soil carbon storage compared with fields managed without that practice. However, empirical knowledge about plant–soil interactions belowground lags behind the understanding of aboveground processes, and sometimes even well-understood interactions are not always incorporated into models. For example, several studies indicate that plant roots and plant shoots do not decompose at the same rate and do not contribute equally to soil carbon storage (Puget and Drinkwater, 2001). Roots may add more carbon to soil than shoots, but we know much less about their growth and decomposition (Freschet et al., 2013; Karlen and Cambardella, 1996; Merrill et al., 2002). In addition, roots can stimulate decomposition of native SOM, including deep SOM that otherwise likely would remain in situ for years or longer (Dijkstra and Cheng, 2007; Fontaine et al., 2007; Fu and Cheng, 2004; Zhang et al., 2013). Despite the complexity of rhizosphere dynamics, most research on soils has focused only on shallow horizons. The dearth of research below 20 to 30 cm in the soil profile means that biophysical processes and different types of tillage that are known to affect deeper parts of the soil profile are not considered in most analyses (Baker et al., 2007). Although models vary in their ability to represent processes such as root growth explicitly, they do not generally capture the type of nuanced result from field experiments discussed above. Similarly, biogeochemical models tend to exclude soils deeper than 1 m from the system boundary, so projections from models largely ignore gains or losses in deep soil. Improved mechanistic representation of management effects on the surface to 1-m depth is the most relevant scale for improving modeled response to management of most grain cropping systems in the United States; however, in cropping systems such as perennial grasses a deep and complex rooting zone can influence C accumulation below 1-m depth. Current efforts to create a community platform for quantitative assessment of agricultural systems (e.g., The Agricultural Model Intercomparison and Improvement Project [AgMIP] or The Global Research Alliance on Agriculture and Greenhouse Gases) may improve our collective ability to systematically address shortcomings in empirical knowledge and model development.

Third, few data sets are available that show changes in soil C in response to agriculture management practices and that enable us to ascertain whether these changes resulted from decomposition or erosion (Van Oost et al., 2007). Where soil carbon stocks have been observed to decline over time, it is often uncertain whether the decline represents a transfer of C from soil to atmosphere or movement of C across the landscape. If the latter, SOM may actually be deposited in streams or ponds, where low oxygen concentrations retard rather than accelerate decomposition. While the mechanism of OM loss is relatively unimportant from the perspective of soil fertility on the field, which declines in either case, it is critical from the perspective of GHG emissions. While simulation models with a hydrologic development history have often been validated with respect to runoff and sediment yield (e.g., Wang et al., 2008b, 2009), erosion processes have often been ignored in models with a development history emphasizing soil C and N dynamics. The assumption that C losses all result from decomposition is a critical weakness in model projections.

Fourth, to establish empirical relationships between a change in practice and soil carbon storage, experiments usually need to run for many years before a response can be detected (Richter et al., 2007). The need for long-term data arises because the soil carbon pool is very large, which means that even if the rate of soil carbon storage increases significantly, the total amount of carbon in the soil will not change enough over 1 to 5 yr for the change to be captured with a feasible number of samples (Paul et al., 1997). Consequently, detecting a change in soil carbon in response to a change in land management requires soil samples taken many years apart, ideally on fields where different management practices have been maintained following initially similar histories (Rasmussen et al., 1998; Richter et al., 2007). These data can come either from experiments that run for at least 15 to 20 yr (Paul et al., 1997) or from working farm fields that have been managed differently but consistently for many years and where we have good reason to believe the soils were similar at the beginning (Reganold et al., 1993). We identified 22 studies focused on agricultural ecosystems that have been running for at least 15 yr in the United States and Canada and that measured soil carbon. The longest-running of these include the Morrow Plots in Illinois, established in 1876, the Sanborn Plots in Missouri, begun in 1888, the Bretton Plots in Canada, initiated in 1929, and the Pendleton Plots in Oregon, started in 1931.

Despite their scientific importance, LTEs in the United States and Canada have included only a few of the many management systems a grower might consider, and they occur in a relatively small subset of the soil, climate, and landscape conditions where agriculture is practiced. For example, only three LTEs—two in the Mid-Atlantic and one in the Midwest—measured soil carbon in organic vs. conventional systems. And although LTEs in the United States and Canada capture large variations in soils and climates, there is a major gap in data showing how soil carbon responds to management change across the significant variation in soil and climate within regions. Similarly, LTEs have tended to focus on commonly used practices—a valuable approach to support choices among familiar options but much less useful for identifying practices with unrecognized promise (Stockmann et al., 2013).

One way to validate agroecosystems models without establishing numerous LTEs—a costly proposition that would not yield the desired answers for many years—might be to periodically resample soil carbon from marked locations at a wide variety of working farms (Spencer et al., 2011). As long as biophysical characteristics are known, and management history has been well-documented, data from farms that vary broadly in crop rotations, fertilizer management, pesticide use (or lack thereof), soils, and climate would enable the research community to calibrate and validate models that project the response of soil carbon storage to changes in agriculture management. The National Resources Inventory (NRI) is a statistical survey of land use and natural resource conditions and trends on non-federal lands in the United States that includes about 200,000 sample points on cultivated cropland. Existing resources already support periodic visits to these plots for sampling purposes, and the data collection for a subset of these plots could readily incorporate soil carbon measurements.

Reducing Agricultural GHG Emissions through Management of Agricultural Systems

Achieving sustainable, low GHG emitting agricultural landscapes will ultimately include more systemic management changes, such as diversified cropping systems and a more integrated distribution of animal and cropping systems to allow for efficient usage of manure. Current land management GHG mitigation strategies often focus on a single practice change to reduce GHG emissions. For example, the CAR nitrogen management protocol enables growers to earn carbon credits for reducing N_2O flux by reducing N application rate. The structure of C market policy does not promote integrative management approaches, because verifying outcomes is more challenging for these systems. Simulation and empirical modeling tools are most easily applied to quantify how changes in conventional management practices (i.e., tillage, fertilizer method, fertilizer type) lead to net GHG reductions. The recently developed Manure-DNDC model (Li et al., 2012) is one tool for studying more integrated landscapes. Improved capacity for life-cycle analysis (LCA) of complex agricultural systems is needed to accurately quantify net GHG emissions from more diversified landscapes.

There are fundamental inconsistencies between current GHG policy norms and an ecosystem management or LCA approach. Standard GHG accounting methodologies award CO_2 reductions due to reduced fertilizer production to the fertilizer factory (Climate Action Reserve, 2013). While factory management can reduce CO_2 emissions as a result of improved efficiency (lower CO_2 per unit fertilizer), it is the decisions and actions of the land manager that result in lower fertilizer per unit area. In rainfed grain cropping systems of the US Corn Belt, fertilizer accounts for over 30% of fossil fuel energy inputs (Kim et al., 2009). Therefore, agricultural land managers can reduce CO_2 emissions by increasing N fixation or improving nutrient retention through rotation diversification, or by applying manure as an N source, all of which reduce the need for fertilizer N application. Under current market approaches to GHG accounting, practices that reduce CO_2 emissions by reducing fertilizer use cannot be incentivized.

In the US context, policy focusing on N management is relevant for reducing our GHG emissions from agriculture. The USEPA (2012) estimates direct N_2O emissions are 215.9 Tg CO_2-eq yr^{-1} (3.1% of all US GHG emissions), while total GHG emissions from agriculture are about 6% of total US emissions (USDA, 2011). However, in the global context, policies and economic structures that promote building SOC have a greater potential to reduce net GHG emissions while promoting the maintenance of soil fertility. Smith et al. (2008b) estimate the GHG mitigation potential of global agriculture as 5500 to 6000 Tg CO_2-eq yr^{-1} by 2030, mostly resulting equally from cropland and grazing land management that promotes SOC accumulation and from the restoration of cultivated organic soils, with each sequestering on the order of 1300 to 1350 Tg CO_2-eq yr^{-1}. Restoration of degraded lands is also an important SOC accumulation strategy comprising about half of the mitigation potential of cropland and grazing land management scenarios (~650 Tg CO_2-eq yr^{-1}), while improved rice and livestock management can reduce CH_4 flux by ~250 to 300 Tg CO_2-eq yr^{-1}. In contrast, improved cropland management is only predicted to decrease N_2O flux by ~200 Tg CO_2-eq yr^{-1}. However, a reduction in N_2O flux is realized each year best management practices are implemented in contrast to SOC accumulation in response to management, which ultimately achieves a steady state, after which further SOC accumulation is negligible.

Eagle and Olander (2012) reviewed the GHG mitigation potential of 42 agricultural management strategies and determined sufficient data exist to promote 20 strategies for their GHG reduction potential. Significant accumulation of SOC across the agricultural landscape requires management changes to rotation, tillage, and organic amendments in cropland, and improved grazing land management. However, with SOC accumulation, future changes in management could again reduce SOC stocks, so the issue of permanence must be addressed carefully. While small changes to management practices are the easiest policies to initiate, management that promotes building SOC will require different economic incentive structures.

Quantifying GHG flux from Land Use Change and Forestry

Similar to agricultural systems, in forest ecosystems there are two general modeling approaches used to estimate carbon cycling: (i) simulations of forest stand growth based on climatic and soil conditions and (ii) empirical estimates of stand growth based on repeated measurements of forest carbon stocks. Each approach can be used for plantations and naturally regenerated forests. In this section, we focus on how carbon cycling is modeled in the United States for (i) national-scale reporting under the UNFCCC and (ii) project-scale accounting using tools developed by CAR and RGGI. In these cases, the approaches are primarily empirical and are based on periodic measurements of the key carbon pools, either directly in the parcel of interest for the compliance programs or based on systematic forest surveys from similar forests within the region for voluntary programs and county, state, and national estimates of forest carbon fluxes. Therefore, we focus on empirical models and tools that are based on periodic measurements of forest carbon stocks. Because environmental markets use multiple GHG accounting tools, we briefly discuss how land-based empirical carbon flux estimates compare with those from ecosystem models and atmospheric inverse modeling.

Carbon accumulates in forest ecosystems because of the balance between fixation by photosynthesis and emission from respiration. The sum of these processes is termed net ecosystem productivity (NEP). Both fixation and respiration are strongly affected by forest management. Forested ecosystems store large quantities of carbon in living and dead biomass and soil, and changes in these carbon pools are a significant part of the global carbon budget. Globally, forest ecosystems are major net sinks for CO_2 (Pan et al., 2011), and in the US net CO_2 uptake by forests is equivalent to approximately 16% of total CO_2 emissions from fossil fuel combustion (USEPA, 2013). In many forests, the largest C pools are aboveground live biomass and mineral soils, with lesser amounts in belowground biomass and surface detritus (forest floor). But some of these pools, such as mineral soils, usually change slowly, while vegetation and forest floor pools can change quickly over short timescales in response to natural disturbance or forest management. In the United States, most of the change in forest carbon stocks (carbon sink) is in the aboveground biomass (49%) with an additional 27% in wood products in landfills and the remainder in down dead wood, wood products in use, and forest floor and soil (Woodbury et al., 2007b). However, in some forest ecosystems under some types of management or natural disturbance situations, changes in other pools such as forest floor and coarse woody debris can be very important.

The aboveground biomass of living trees is the most important carbon sink. Tree diameter and height can be readily measured using well-established protocols, and allometric equations then used to estimate aboveground forest carbon stocks. Modeling efforts have focused primarily on forest stands that do not already have measurements and for projecting the effects of changes due to disturbances such as fire and insect pests and management practices such as different types of harvest and pre-commercial thinning.

National-, State-, and County-Scale Estimates Based on Forest Inventory Measurements

Flux of CO_2 from Living Vegetation

At national, regional, state, and county scales in the United States, the Forest Inventory and Analysis (FIA) program of the USDA Forest Service provides data from many thousands of permanent sampling plots on both private and public lands, and these data are available online (http://fia.fs.fed.us, accessed 15 Sept. 2015). Historically, the main purpose of the FIA program has been to estimate timber supply. However, the measurements taken to estimate timber supply include forest area and the species, diameter, and height of individual trees. These data can be used to estimate the amount of wood in entire trees using allometric equations.

To estimate the change in carbon over time, or net carbon flux based on inventory data, a "stock change approach" is used. In this approach, carbon stocks are estimated at two or more times, and net annual carbon flux is estimated by subtracting one stock estimate from the other and dividing by the number of years between stock estimates. These FIA data have been used for decades to estimate forest carbon stocks and stock changes. Over time the data have generally become available at finer spatial and temporal scales. Recently, additional measurements of carbon pools beyond trees, including down dead wood, forest floor, and soil, have been included (reviewed by Heath, 2013). Forest inventory data are a useful basis for estimating carbon stocks and net fluxes for the sampled area. However, forest carbon pools such as coarse woody debris, soils, and understory have been difficult to estimate on the basis of data collected in inventories until very recently, so there is a need to augment inventory data with data from intensive research sites and models. Using FIA data supplemented with models for carbon pools other than trees, carbon stocks, and stock changes throughout the United States have been estimated for decades, for example, as part of the annual greenhouse gas inventory required under the UNFCCC (e.g., Woodbury et al., 2007a; USEPA, 2013, as reviewed by Heath, 2013). Over time, these estimates have expanded to cover non-forest land to represent effects of afforestation and deforestation, including changes in soil and forest floor carbon stocks, as discussed further in subsequent sections (Woodbury et al., 2007b; Heath, 2013).

Tools Based on Forest Inventory Data

Publically available tools that use FIA data to calculate forest carbon fluxes include the Carbon Online Estimator (COLE) (Proctor et al., 2005; Van Deusen and Heath, 2010) and the Carbon Calculation Tool (CCT) (Smith et al., 2007, 2010). The COLE was developed to allow easy estimation of forest carbon stocks for a user-specified region of interest (Proctor et al., 2005). During the US voluntary carbon program known as "1605b," the Forest Service adopted COLE as the official web tool for the forest portion of that program (Heath, 2013). Users can select specific forest regions of interest and generate a report that estimates the carbon accumulated in each forest carbon pool over time (Van Deusen and Heath, 2010). The CCT is a program that allows a user to download the latest FIA data and produce estimates at the state scale matching those in the national GHG inventories, and it can be used to develop estimates of state carbon fluxes since 1990 (Smith et al., 2010).

Flux of CO_2 from Coarse Woody Debris

In many forests, large quantities of C accumulate in the form of coarse woody debris also called "down dead wood." Unfortunately, the size of this pool is not closely related to aboveground biomass or forest age, so it is difficult to estimate coarse woody debris on the basis of frequently measured aboveground stand characteristics (Woodall et al., 2008). At state and national scales, estimates have been made on the basis of predictions of residues produced during harvesting. These modeled estimates were recently compared with those based on field measurements. The total stock estimate for the United States differed by only 9% between modeled and measured estimates, with the models underestimating total coarse woody debris in stands with little coarse woody debris and overestimating carbon in stands with high coarse woody debris (Domke et al., 2013). There were also regional differences in model accuracy, with greater accuracy in the Southeast and lower accuracy in the North Central and Northeast. On a regional basis, these discrepancies caused significant differences in coarse woody debris carbon stocks by region and ownership. On the basis of these results the authors suggest that the United States conduct systematic field sampling for the purpose of national inventories.

Flux of CO_2 from Forest Floor, Soil, and Roots

The forest floor is defined broadly as the organic layer above the mineral soil including woody debris smaller than 7.5 cm in diameter. The forest floor contains fine woody debris, a litter layer (designated O_i and O_e), and humus (O_a). In most forests in the conterminous United States, these layers generally store smaller amounts of C than do mineral soils, but they can change much more rapidly following harvest or fire, highlighting their importance when assessing effects of management. Changes in forest floor carbon for broad forest types and large regions of the United States have been modeled on the basis of available research and inventory data (Smith and Heath, 2002), and these models have been used to estimate national carbon stock changes for UNFCCC reporting. Root biomass is extremely challenging to measure directly, but it is usually closely correlated with aboveground biomass (typically 0.26 of aboveground biomass; Cairns et al., 1997), and thus it can be modeled on the basis of measurements made in forest inventories. Changes in forest soil carbon are discussed in the subsequent section on land use change.

Land Use Change—Deforestation and Afforestation

When forest regrows immediately following a natural or anthropogenic disturbance, there may not be large, long-term (multi-decadal) changes in forest floor and soil carbon stocks, unless the soil surface is physically disturbed, for example, is burned or plowed. However, if there is a change in land use from forest to plowed agriculture, there can be large and long-term decreases in these carbon stocks. In tropical regions, such deforestation to agriculture causes large emissions of CO_2 (Ramankutty et al., 2007). In the United States, afforestation on abandoned agricultural land has acted as a major C sink, especially in the Northeast. This is supported by survey and experimental data for forest floor and soil and an empirical model (Woodbury et al., 2007a) as well as increased tree carbon stocks based on FIA data supplemented with models (Woodbury et al., 2007b). Effects of land use change have also been estimated using ecosystem models rather than empirical survey data (e.g., Houghton and Hackler, 2000; Houghton et al., 2000; Pielke et al., 2002).

It is important to note that carbon in forest floor litter and organic horizons is lost within a few years after deforestation to plowed agriculture, but is gained only over many decades after afforestation (Woodbury et al., 2007a). For this reason, at regional and national scales it is important to model simultaneous afforestation and deforestation on the basis of gross land use changes, not just net land use changes. If only net land use change is modeled, the "lag" effect of afforestation can cause a large bias in the estimates (Woodbury et al., 2007a).

A comparison of tools for estimating the effect of land use change on carbon stocks demonstrates that alternative modeling approaches, which apply different types of input data, result in model outcomes that differ even at the national scale. Estimates based on FIA data supplemented with models (land-based estimates) can be compared with those from ecosystem models. For example in a study of

US forest carbon stocks, Hurtt et al. (2002) estimate 330 Tg of net change in soil, forest floor, and woody debris, which is fivefold greater than a land-based estimate (Woodbury et al., 2007b). Despite these differences, changes in aboveground (tree) carbon still dominate the total carbon stock change from land use change, due to the large stocks in temperate forests and relatively rapid changes compared with forest floor and soil carbon after afforestation (Woodbury et al., 2007b).

Flux of CO_2 and CH_4 from Wood Products

Up to now we have focused on changes in carbon stocks within forests. However, after harvest, wood products are usually not instantly decomposed or combusted; instead, wood products may be stored for decades or centuries when incorporated into buildings or other long-lived structures. Eventually, wood products are combusted or decayed to produce CO_2 or CH_4 (see methane discussion below). When wood products are disposed of in landfills, the carbon may be released many years or decades later, or may be stored almost permanently in the landfill. “Book-keeping” type accounting models have been used for many years to estimate the half-life of various types of wood products and their rate of decay after different types of disposal, including combustion with or without energy recovery (e.g., Skog and Nicholson, 1998; Skog et al., 2004). These approaches have been used for national GHG inventory reporting under the UNFCCC (e.g., USEPA, 2013). In landfills, because of intentionally anaerobic conditions, both CO_2 and CH_4 may be produced from wood products and other wastes (USEPA, 2013). Because CH_4 has such a high global warming potential (circa 23-fold higher than CO_2), assumptions about CH_4 versus CO_2 emission are very important. Surprisingly, landfills are among the fastest growing carbon pools in the United States, where wood products such as paper and construction waste break down only very slowly (Miner and Perez-Garcia, 2007; Skog, 2008). Emissions from landfills are modeled using a book-keeping approach as well as ongoing surveys of waste management practices and of different categories of solid waste, and on measured emissions of CO_2 and CH_4 from experiments and field studies (USEPA, 2013). A certain proportion of carbon is assumed to be stored indefinitely in landfills. The remainder is assumed to decay over time according to first-order kinetics.

Forest Stand and Project-Scale Estimates

At the scale of individual forest stands or carbon offset projects, there are limitations to using FIA data and models based on them. First, FIA data are intended to measure forest attributes over wide areas, especially county and larger scales, so they may not represent a small forest parcel. Second, as mentioned above, information on carbon stocks in coarse woody debris, soils, and understory often must be modeled using data from research plots that may not represent the actual site conditions. Third, depending on the location, the sampling interval may be many years or longer and thus may not always represent current conditions. For these reasons, while data from FIA have been used for general planning purposes for estimating the potential value of carbon offsets, they are not generally appropriate for specific offset projects. Instead, such projects generally required repeated sampling of the actual parcel of forest being used as an offset. For both voluntary programs such as the 1605b, and compliance markets such as the former Chicago Climate Exchange (CCX) and the current CAR and RGGI, verifiable estimates of carbon stock changes are required (as reviewed by Fahey et al., 2010).

To obtain carbon credits under compliance programs such as CAR and RGGI, applicants must submit a detailed application that explains how C sequestration will be quantified, monitored, and verified. The project area is divided into relatively homogeneous units on the basis of factors such as forest type, stand age, slope, etc. For each unit, C pools must be sampled to achieve specific statistical confidence, such as >95% confidence that results are within 10% of the true value. Carbon pools include aboveground biomass, belowground biomass, coarse woody debris, soil, and harvested wood products. As discussed in subsequent sections, measuring changes in pools other than aboveground trees can be challenging, and may be very costly to achieve the required precision, but models may be used in some cases to supplement these measurements. Measurements must be repeated periodically, but may be estimated annually using models. Such precision of measurement for multiple pools and requirements for frequent resampling may increase transactions costs so much as to discourage participation in compliance markets.

Climate Action Reserve Forest Management Protocol

The CAR forest management protocol allows credits for CO_2 emission reductions due to improved management associated with US projects supporting reforestation (forest regrowth on previously forested lands) and afforestation (establishment of forests in areas previously under non-forest landcover). Onsite forest carbon pools are broadly grouped into living biomass, dead biomass, and soils. Living biomass includes biomass in live trees and shrubs and herbaceous understory (live non-tree biomass). Onsite dead biomass includes biomass in dead trees, lying dead wood, and litter. Offsite dead biomass includes harvested wood products. A combination of modeling and measurements is used, similar to the forest inventory methods reviewed above, but with forest sampling data collected from the parcel. Projects must be verified by approved third-party verifiers and by the CAR program. A report must be completed each year for 100 yr, although measurements do not need to be made annually. All projects must use the appropriate biomass equations for the project location. The required biomass equations are found on the Reserve's Forest Project Protocol webpage. The calculation of CO_2e for each inventoried tree must be conducted in a manner that provides project estimates for several components, as follows. Whole tree biomass (roots, stump, bark, bole, top, and branches) is used to provide project totals and estimates of emissions associated with harvest activities. Bole biomass is the portion of harvested trees delivered to facilities for processing into wood products. The aboveground portion (stump, bark, bole, top, and branches) is used to compare project data with common practice statistics for improved forest management projects. Further information is available in publications (Climate Action Reserve, 2012b, 2012c) provided on the project website, which should be reviewed for updates (http://www.climateactionreserve.org/how/protocols/adopted/forest/current/, accessed 15 Sept. 2105).

Regional Greenhouse Gas Initiative Forest Management Protocol

The RGGI protocol allows credits for CO_2 emission reductions resulting from reforestation and afforestation projects in RGGI member states in the northeastern United States. The focus is on afforestation with native species to promote restoration and sustainable management of native forests on lands that have not been forest for at least 10 yr before project initiation. Emissions reductions or carbon sequestration must be real, additional, verifiable, enforceable, and permanent. To ensure permanency a relevant state agency must approve a legally binding "permanent conservation easement." This easement must require that all land within the offset project boundary be maintained in a forested state in perpetuity, and the carbon density within the project be maintained at or above that achieved at the end of the CO_2 offset crediting period. The net carbon sequestered during the reporting period is also discounted by 10% to account for potential reversals of carbon sequestration, unless the project sponsor retains long-term insurance, approved by the relevant state agency where the offset project is located. Such insurance must guarantee replacement of any lost sequestered carbon for which CO_2 offset allowances were awarded. Similar to the CAR protocol, it uses a combination of modeling and measurements including forest sampling data collected from the parcel.

When direct sampling is not possible or cost-effective, empirical models are used to project the results of direct field sampling through simulated forest management activity. Models are also used to assist in updating inventory plots. By modeling tree growth in plots, these plots can represent a reporting year subsequent to the actual sampling date. As of February 2013, RGGI had approved the following growth models for deriving these estimates:

- CACTOS: California Conifer Timber Output Simulator,
- CRYPTOS: Cooperative Redwood Yield Project Timber Output Simulator,
- FVS: Forest Vegetation Simulator,
- SPS: Stand Projection System,
- FPS: Forest Projection System,
- FREIGHTS: Forest Resource Inventory, Growth, and Harvest Tracking System,
- FORESEE: FORESt Ecosystems in a Changing Environment.

Additional models are allowed following approval of a state forestry authority and meeting quality criteria to assure that the model will perform adequately for the forest type and location.

All projects must be verified by approved third-party verifiers. Further information is available in publications (Regional Greenhouse Gas Initiative, 2013a, 2013b) provided on the project website, which should be reviewed for any updates (http://www.rggi.org, accessed 15 Sept. 2105).

Forest Vegetation Simulator

To project future forest stand growth, carbon sequestration, and the effects of silvicultural treatments, tools such as the Forest Vegetation Simulator (FVS) can be used (Crookston and Dixon, 2005; www.fs.fed.us/fmsc/fvs). The FVS consists of a suite of growth and yield models that have been calibrated using FIA and other data to forests across the United States. The FVS has been approved for use by CAR and RGGI in conjunction with periodic sampling to meet their criteria for providing verifiable estimates of C sequestration for forestry offset projects. We discuss this particular tool because it has been used for decades to model forest stand growth and the effect of silvicultural treatments for many forest types throughout the United States on the basis of FIA data. The FVS is an individual-tree, distance-independent growth and yield model. More recently, the FVS-CarbCalc tool has been added to simulate stand level carbon stocks and changes in forests and in harvested wood products using the approaches discussed above. The methods are consistent with the US 1605b program (USDOE, 2007) calculating and reporting guidelines as well as the Intergovernmental Panel on Climate Change (2003). The following carbon pools are modeled: aboveground live biomass, aboveground dead biomass, belowground carbon, litter and duff (forest floor) biomass, and harvested merchantable biomass. The FVS uses FIA data or project data to describe initial stand conditions. Further information is available at the FVS website (http://www.fs.fed.us/fmsc/fvs/index.shtml, accessed 15 Sept. 2105).

The FVS is a useful tool, but as with any modeling tool, users must be aware of the strengths and limitations of the model and follow guidance to obtain useful results (Hoover and Rebain, 2011). To investigate the utility of the FVS model for carbon offset projects, data from three long-term forest sites were compared with FVS predictions of carbon stock changes (Fahey et al., 2010). For northern hardwood forests in New Hampshire and Allegheny hardwoods in New York State, aboveground tree biomass was predicted accurately over 37-yr and 50-yr measurement intervals, respectively. For a spruce–fir–birch forest in New Hampshire, projections were accurate from 1965 to 1987, but subsequent pollution-induced decline of red spruce (*Picea rubens*) resulted in a substantial overprediction by the model. The response to whole-tree harvest in New Hampshire was also modeled, and FVS greatly underestimated subsequent biomass accumulation, because it did not predict the occurrence of pin cherry (*Prunus pensylvanica*), a fast-growing tree species that can dominate initial biomass accumulation in this region (Fahey et al., 1998). These results suggest that no model simulation can represent events that are not anticipated, such as the decline of a dominant species. But these results also show that even commonly used models may not be correctly parameterized, in this example failing to include a fast-growing tree species.

Comparing and Evaluating Different Approaches to Modeling Forest Carbon

Estimates of net change in forest carbon stocks often seem to converge when scaling up to regional and national scales. However, this convergence in the overall net change is based on conflicting estimates for particular pools and processes. For example, forest carbon flux estimates of ecosystem models driven by satellite measurements were similar to those derived from land-based surveys supplemented with models, with the exception of the Terrestrial Ecosystem Model, which was only half that of other estimates (Woodbury et al., 2007b). However, estimates of specific carbon pools were extremely variable. For example, the overall estimate of net US forest C change for the ecosystem model of Hurtt et al. (2002) is 330 Tg yr^{-1}, which is more than double a land-based estimate of 163 Tg yr^{-1} (Woodbury et al., 2007b). On the basis of an ecosystem growth model, Hurtt et al. (2002) estimate changes in tree carbon stocks similar to the land-based estimate, but they estimate an additional very large change of 100 Tg yr^{-1} due to woody encroachment on non-forest land in the arid Southwest. Furthermore, their estimate of net change in soil, forest floor, and woody debris is fivefold greater than the land-based estimate. As in other ecosystem models, wood products are not included

(Hurtt et al., 2002). At the national, continental, and global scale, improved estimates of forest carbon flux will depend on reconciling estimates derived from different methods such as atmospheric inversion modeling, inventory-based approaches, ecosystem modeling, and land use change modeling.

During recent years, increased spatial and temporal resolution of forest inventory data and increased availability of measurements of additional pools have reduced uncertainties for some carbon pools including coarse woody debris and forest floor (Domke et al., 2013; Woodall et al., 2012). However, there will still be uncertainty in belowground pools that are impractical to measure directly and also because of changes that are not represented in models. For example, the spread of exotic earthworms can greatly reduce the thickness of organic layers, increase the bulk density of soils, and incorporate litter and humus materials into deeper horizons of the soil profile. All of these earthworm impacts could alter carbon stocks in the forest floor and mineral soil, and if this change is not measured or included in a model, it could result in substantial errors in carbon stock changes (Frelich et al., 2006).

At the project or forest stand level, estimates may differ widely depending on the approach and assumptions that are used. The comparison of changes in forest carbon stocks over decades for three sites in the Northeast demonstrated that the FVS modeling system could sometimes predict stock changes well, but in other cases could not because of decline of major species or lack of inclusion of fast-growing species after harvest (Fahey et al., 2010). Discrepancies can occur even when models are used by research scientists familiar with the ecosystems and models themselves, implying that greater deviations can be expected when these models are employed by less experienced individuals or when biases toward economically desirable outcomes might influence modeling procedures. Of course, model simulations cannot represent events that are not anticipated, such as the decline of a dominant species or effects of exotic earthworm invasion. For this reason, compliance programs require third-party verification and periodic sampling of the site. Additionally, none of the models discussed herein include non-GHG effects, such as changes in albedo that might promote local and regional warming (Whitehead, 2011).

For carbon credit markets such as CAR and RGGI, the requirements for high-precision measurement of multiple pools, even those such as soil carbon that change very slowly, and requirements for frequent resampling may increase transactions costs so much as to discourage participation in such markets. In addition, requirements for permanent legal conservation easements and maintaining the land in forest in perpetuity after the project period may also discourage participation.

Model and Policy Synthesis

Advantages and Limitations of Mitigation Options

To assess the potential for agriculture and forestry to mitigate climate change, scientists focused first on carbon storage in trees and soil (Campbell et al., 1991; Rasmussen and Collins, 1991; Davidson and Ackerman 1993; Donigian et al., 1994; Hamburg, 2000; Intergovernmental Panel on Climate Change, 2000a,b; Lewandrowski et al., 2004). Carbon storage is a particularly attractive approach because it affords the possibility of reducing current atmospheric CO_2 stocks through carbon fixation, whereas strategies available to most sectors of the economy focus on lowering GHG emissions, but do not remove existing atmospheric CO_2. In addition, building soil carbon, growing trees, and conserving forests confer numerous benefits to agriculture and society (Magdoff and Van Es, 2010). At first glance, it is easy to imagine strong support for tools that incentivize growers to build soil carbon or that encourage forest managers and governments to reduce rates of deforestation in biologically diverse ecosystems.

Biomass Carbon Storage

Policy initiatives' early focus on carbon storage in forest biomass (e.g., REDD) reflects the availability of reliable tools for estimating aboveground biomass, and the certainty that tree growth transfers carbon out of the atmosphere into organic matter. Allometric equations have long been used to estimate potential timber productivity (i.e., harvestable tree volume) for specific species on the basis of measurable tree attributes such as diameter at breast height and total tree height. To develop these relationships, researchers collected detailed destructive measurements of individual trees. These equations perform well for species and regions for which they were developed. The challenge is extrapolating the limited set of measurements to all species and regions of interest. Furthermore, data are generally scarce for tropical forests. Though allometric equations generally work well, there can be differences in predicted biomass from different equations (Ahmed et al., 2013). This variation in estimates among equations motivated efforts to develop a standardized set of equations for the conterminous United States (Jenkins et al., 2003). While variation in estimates of biomass using different allometric equations for individual trees can be substantial, a recent study found only modest errors in forest C stocks at the hectare scale of 1 to 5 Mg for two well-studied sites in Massachusetts and Maine (Ahmed et al., 2013).

Forest carbon storage as an approach to climate change mitigation faces a number of challenges. Chief among them has been concern about leakage, i.e., the circumstance under which conservation of a forest in one location simply shifts demand for forest products and associated tree harvest to a different location (Murray et al., 2002). Others include the very long time commitments (typically 100 yr) required of landowners to ensure that climate benefits accrue and persist.

Soil Carbon Storage

Soil carbon storage as an approach to mitigate climate change also faces several challenges. First, in most cases, soil carbon storage is reversible. Just as soil carbon can accumulate in response to management changes, it can decompose in the absence of continued management or in response to unexpected temperature or precipitation patterns or fire.

Second, because plowing previously uncultivated land initiates a period of rapid decomposition of SOM, some changes in management during that period might only slow the rate of carbon loss rather than result in soil carbon gains (Rasmussen and Collins, 1991). Slowing the rate of soil carbon decomposition confers a climate benefit relative to the business-as-usual case, but soil is still releasing more carbon to the atmosphere than is being stored. Stabilizing the climate will require near-zero emissions (Matthews and Caldeira, 2008). Therefore, using practices that reduce the C loss rate takes us in the right direction, but the remaining emissions ultimately need to be mitigated.

Third, there are limits to the rate and amount of soil carbon storage that a management change can yield. Long-term experiments have revealed that inflows and outflows of carbon in agricultural fields reach equilibrium, often within a few decades (Jenkinson and Rayner, 1977; Paustian et al., 1997). The practical consequence is that changing management to increase carbon inputs (or decrease carbon losses) will lead the amount of soil carbon to increase for a period of time and then to stabilize at a new level. After that time, we expect no additional climate benefit absent *additional* management changes that further increase carbon inputs.

Fourth, estimates of soil carbon stocks and conclusions about the response of SOC to management changes depend on the depth of sampling (Baker et al., 2007; Kravchenko and Robertson, 2011). Most studies of soil carbon have been restricted to the top 20 cm of the soil profile, where SOC content tends to be highest. However, carbon below 20 cm constitutes a very large proportion of total C in the profile and observations suggest that management changes influence carbon down to 1 m. For example, adding deep-rooted perennials to a rotation would be expected to increase SOC to at least 1-m depth (Kell, 2011), and shallow soil samples would fail to capture this change.

The case of reduced tillage illustrates the challenges that field scientists and modelers face as a result of questions about sampling depth. Hundreds of studies support the hypothesis that no-till management leads to higher soil carbon content, but very few of these studies sampled below 20 cm. However, in fields where investigators sampled to greater depths, SOC content tended to be greater in conventionally plowed fields compared with fields managed with conservation tillage (Baker et al., 2007, and references therein). These results suggest that SOC accumulation at depth is greater in conventionally plowed fields than in fields managed with conservation tillage, although the results are not statistically different in part because studies that sample deeply are relatively rare (Baker et al., 2007). One school of thought maintains that because agricultural management influences the soil profile at depth, comparisons among management practices require investigations of the entire profile (Baker et al., 2007). A finding of "no difference" in SOC from 0 to 100 cm between tillage practices precludes assigning climate benefits to conservation tillage. In contrast, Kravchenko and Robertson (2011) argue that no-till practices increase SOC in the top 20 of cm of the profile and not in the 20 to 100 cm segment. The absence of a detectable difference in the lower part of the profile results from the high variability among locations deeper in the profile. An unrealistically large number of samples would be needed to detect a difference given the known variability. According to this view, comparing the entire profile (0–100 cm) between tillage practices masks the clear signal from the upper part of the profile with the high variability in the lower part of the profile, and the correct conclusion would be that conservation tillage increases SOC because that is the finding in the part of the profile where a power analysis shows that we can detect a difference with the number of available samples.

Tillage practices vary across regions and cropping system, raising questions about whether the necessary sampling depth also varies systematically with geography. In a national-scale review of tillage effect on SOC in Canada, VandenBygaart et al. (2003, 2008, 2011) conclude sampling below 30 cm is often necessary to detect SOC change in eastern Canada, because of the extensive use of deeper moldboard plowing. Even for fields with shallower tillage management in western Canada, the authors found that increasing sampling from 15 to 30 cm revealed SOC differences across tilled and no-till fields. These results suggest that in many agroecosystems the sampling depth of currently available measurements comparing SOC accumulation between till and no-till systems is insufficient to accurately describe the effects of tillage in ecosystem models.

Mechanistic understanding about how tillage influences SOC has also played into the debate about sampling depth and whether meta-analyses comprised mainly of studies that used shallow samples provide robust findings that can be used to address climate change mitigation. The finding that no-till management increases soil C in shallow horizons is consistent with the idea that breaking up soil aggregates exposes more surface area to microbial attack. However, considering a more complete picture of how tillage influences the plant–soil ecosystem yields a less conclusive picture. For example, compared with conventional tillage, conservation tillage leaves more plant residue on the surface after harvest, and the insulated soils stay cooler longer into the spring. Because soil temperature controls root growth rate, fields managed with conservation tillage may have slower root growth and therefore add less carbon to the soil (Baker et al., 2007). On the other hand, conservation tillage increases the amount of plant residue on the soil surface, which can increase soil moisture retention and hence root growth, especially in drier soils. Because the relationship between tillage practices and SOC sequestration is mediated by a variety of factors such as these, the net influence of changing tillage practice on SOC is not intuitively obvious.

Despite these limitations, soil carbon storage has been broadly studied as an option in cap-and-trade policies, as occurred in HR2454, the American Clean Energy and Security Act of 2009. Soil carbon storage can, on the basis of some key assumptions, be accomplished fairly cheaply—US$27 or less per ton CO_2e—relative to other strategies for climate change mitigation (Creyts et al., 2007). There is a strong need to identify the most appropriate policy tools to take advantage of soil carbon storage, in light of these limitations and the large proportion of the landscape occupied by farms and forests.

Questions about how conservation tillage influences SOC sequestration illuminate the interplay of data availability, model projections, and policy. Although hundreds of studies support the relationship between no-till management and increased SOC, very few of these studies sampled below 20 cm. The mechanistic relationship between tillage and SOC is more complex than it might at first appear, and both tillage practices and the ecology of crop fields vary with geography and climate. A compilation by T-AGG of studies comparing tillage practices and SOC reinforced the "stamp of legitimacy" that no-till agriculture has received from the research community as an effective and quantifiable practice to increase soil carbon storage (Eagle et al., 2012; Eagle and Olander, 2012). Syntheses of available data and statements of consensus about policy-relevant science play a vital role at the science-policy nexus. However, what we can reasonably measure—hence what we have measured—and what we want to know are not necessarily the same thing. And given large investments in data collection, analysis, and interpretation, there is of course a desire to make use of those data to answer key questions (including policy questions) and to drive models. Many of these issues that influence technical recommendations for policy do not receive attention at the science-policy interface even though they bear directly on debates such as whether no-till agriculture reliably increases SOC sequestration.

Nitrous Oxide Emissions and Nitrogen Management

Issues of reversal and permanence that surround soil carbon storage, and leakage and permanence with forest carbon storage, are generally of less concern for reduced N_2O emissions. It is possible that reduced fertilizer application rates in 1 yr (with associated lower N_2O emissions) would be followed by proportionally higher fertilizer application (and higher N_2O rates) in a following year. But such temporal "catch-up" is not considered likely. In this respect, reduced N_2O emissions are significantly more straightforward to handle in a policy context, compared with soil carbon storage. Nevertheless, there are significant challenges in data availability and data quality related to developing robust policy tools.

Sound interpretation of N_2O flux measurements requires several years of data or more because the response of N_2O to particular management factors often depends on environmental variables such as rainfall and temperature, which vary from year to year (Groffman et al., 2000; Sistani et al., 2010). Data collected for less than one full year is particularly difficult to interpret with confidence because N_2O emissions can occur throughout the year, including under snow, and can exhibit peaks during brief warm and wet periods during winter and early spring (e.g., Johnson et al., 2010; Wagner-Riddle et al., 2007; Wolf et al., 2010; Kim et al., 2012). In addition, the amount of plant growth, which also varies across years, supplies carbon to microbes and therefore affects N cycling and N_2O emissions (Woldendorp, 1962). Therefore, to establish general relationships between management choices and N_2O emissions, it is necessary to capture the N_2O response to management under a range of conditions (Mosier et al., 2006).

In the case of practices such as manure addition, the continued accumulation of organic matter over many years can lead to changes in N_2O emissions (Chang et al., 1998), suggesting that projections of future N_2O emissions need to take into account expectations about how soil conditions will evolve in response to management as well as to changes in climate. So although N_2O emissions do not pose the same challenge for detection as soil carbon storage, we nevertheless need measurements of N_2O emission rates over multiple years following change in management, particularly where management changes influence soil characteristics (Six et al., 2004).

A major challenge to characterizing the response of N_2O emissions to agricultural management is that N_2O emissions are notoriously variable in both space and time, with the majority of emissions occurring in short bursts from particular (and difficult-to-predict) locations (Ambus and Christensen, 1994; Ambus and Robertson, 1998; Smith and Dobbie, 2001; Ellert and Janzen, 2008). For example, Ellert and Janzen routinely observed N_2O emissions at one sampling location 12 to 23 times larger than at 5 other sampling locations within the same treatment. Similarly, N_2O emissions commonly shift by orders of magnitude within short time periods (hours to days) depending on soil moisture (related to rain or irrigation), temperature, and the supply of carbon and nitrogen available to microbes (Parkin, 2008). Therefore, to estimate N_2O emissions accurately, experiments need to use sufficient replication at a site to capture spatial variation and measure emissions at key times of year (e.g., immediately after applying fertilizer) when we expect emissions to be well above background. In addition, to avoid missing the highest emissions—which in the case of N_2O can constitute the majority of total emissions—investigators need to characterize the daily pattern of N_2O fluxes at a site (Parkin, 2008).

Policies designed to reduce N_2O emissions from agricultural soil focus primarily on N management, and this approach raises questions about the appropriate spatial scale of analysis. First, considerable amounts of nitrogen leave the farm field, raising the challenge of how to account for N_2O that may result from its eventual processing. N lost from croplands escapes not only as N_2O but also as N_2 gas, NH_3^+, or NO_3^-. With the exception of N_2 gas, all other forms of N remain subject to microbial conversion to N_2O, so all management options that influence the rate of N loss from the field could influence rates of N_2O production. Associated accounting methods have so far remained rudimentary, usually using global Intergovernmental Panel on Climate Change default values and failing to differentiate between, for example, fields that use cover crops to trap N during the fallow season and fields that do not.

Available data suggest that the scale of analysis could have dramatic influence on estimates of potential reductions in N_2O loss. Blesh and Drinkwater (2013) compared N budgets for farm fields in the Mississippi River Basin that use common fertilizer management practices with farms that use legumes as the primary N source. Fields using conventional fertilizer typically have an N surplus of 30 to 38 kg ha^{-1} yr^{-1} N while fields managed with a legume N source have an N surplus of less than 4 kg ha^{-1} yr^{-1} N. Similarly, Tonitto et al. (2006) conducted a meta-analysis of nitrate losses from fields managed with and without cover crops and found that using cover crops reduced nitrate loss 40 to 70%. Surplus available N can be lost as N_2O or lost as NO_3^- and denitrified elsewhere in the watershed. Therefore differences in the N saturation of agroecosystem management directly impacts net N_2O loss potential. Models that consider only in-field N_2O emissions and do not represent the difference in N leakiness across management practices would be expected to underestimate total N_2O losses, and consequently to underestimate the benefits of farm management systems that minimize N surplus.

In addition, different sources of fertilizer N have radically different embodied emissions, raising questions about whether "upstream" CO_2 emissions should be coupled to policies designed to reduce N_2O emissions. As discussed in the section entitled "Reducing Agricultural GHG Emissions through Management of Agricultural Systems," on the "upstream" end of N management, synthetic N fertilizer production is an energy-intensive process driven by fossil fuel, with associated CO_2 emissions. Substituting legume-derived N or manure for synthetic N should drive reduced fertilizer production and hence reduced CO_2 emissions. An LCA approach would suggest granting growers credit for these CO_2 savings, but in practice who (if anyone) receives this credit is a matter of debate. Broad policy decisions to treat the fertilizer industry as a regulated entity have precluded carbon offset protocols from awarding credit for these emission savings to growers, despite the fact that growers' decisions drive (or diminish) fertilizer production.

Direct measurements of N_2O emissions have shown that nitrification inhibitors (NIs) and slow-release (SL) fertilizers reduce emissions from crop fields by approximately 38 and 21%, respectively, compared with conventional fertilizers that do not incorporate these technologies (Akiyama et al., 2010; Halvorson et al., 2013). The NI estimate represents a meta-analysis of 113 data sets from 35 field studies, and the data represent one of the few cases where we have a substantial number of studies and a consistent response of N_2O flux to a management practice despite the high inherent variability in N_2O emissions from soil. The estimate for SL is based on extensive research on irrigated corn fields at the USDA experiment station in Fort Collins, Colorado. These experiments found strong interactions between fertilizer technology and tillage; SL fertilizer led to reduced N_2O emissions in no-till and strip-till treatments, but not under conventional tillage. These findings underscore the limitations of data that show how N_2O emissions respond to management. Even these unusually robust data represent a narrow geography, and the relationships are restricted to a relatively specific cropping system and management context. In USDA's newly developed method for estimating N_2O emissions from agricultural fields in the United States, the Agency used both of these data sets (NI, SL) as a basis for adjusting estimates of N_2O emissions based on growers' use of NIs (Biggar et al., 2013).

Scientists and managers have devoted considerable attention to questions of scale for managing nitrogen losses from farm fields and their impacts on water quality (Lund et al., 2013, Giri et al., 2012; Jha et al., 2010). David et al. (2010) modeled riverine nitrate losses from counties in the Mississippi River Basin and identified 259 counties with predicted nitrate N yields >7.5 kg ha^{-1} N and 1135 counties with predicted nitrate yields <3 kg ha^{-1} N. They recommended using improved practices in the 259 counties with high nitrate loss rates. Resource conservation professionals have applied targeting at finer scales. For example, riparian zones have long been considered hot spots of nitrogen removal from shallow groundwater and are therefore targeted locations in the landscape to control nitrogen pollution of streams (Gurwick et al., 2008, and references therein; Vidon et al., 2010). Analogous targeting approaches could be applied to reduce N_2O losses from agricultural landscapes. Applying existing knowledge about N_2O losses could help focus the location of management practices, and identification of relevant knowledge gaps could help focus future research.

Consequences of Science Base for Protocol Development

If offsets are required to be permanent, progress developing offset protocols appears to reflect the relative strengths and limitations of soil carbon storage, forest carbon storage, and N_2O emission reductions. Although no systematic or in-depth study of this area has yet been published to our knowledge, we offer the following observations. In 2011, CAR embarked on development of two agricultural carbon offset protocols: one (termed "cropland management") intended to grant credits for soil carbon storage and the other ("nitrogen management") to grant credits for reduced N_2O emissions. In the first case the Reserve's decision not to adopt a cropland management project protocol (CMPP) highlights the multi-faceted challenge of SOC management. While Eagle et al. (2012) identify agricultural practices that support increased SOC, defining management practices that would qualify for offsets is not straightforward (Climate Action Reserve, 2011a). For instance, the suite of available long-term data sets imposes some limitations on model validation, particularly when the full soil profile is considered. Technical reports considered by the Reserve during the CMPP process identified cover cropping (Gershenson et al., 2011) and grassland management (Diaz et al., 2012) as promising techniques for increasing SOC storage. However, defining these management practices in a policy setting is challenging. Additionality was a major concern for protocol implementation, especially since no-till, reduced-till, and cover crops are supported by other conservation policy initiatives (Climate Action Reserve, 2011b). Permanence was also a major concern (Climate Action Reserve, 2011a). The workgroup was concerned about the ability of land owners to guarantee adherence to a given management practice for a long duration, given both the short timescale nature of agricultural management and the frequency of agricultural land renting.

In the second case ("nitrogen management"), CAR's process for developing a protocol began with a relatively extensive list of practices that might qualify for carbon credits but ended with only one practice—reduced N fertilizer application rates on maize in 12 midwestern states (Climate Action Reserve, 2011c, 2012a). The narrow scope of the N management protocol reflects the guidance Reserve staff received from a panel of expert scientists as well as technical experts on an advisory multistakeholder workgroup, all of whom argued that evaluations of other practices were not yet possible owing to a dearth of necessary data—N_2O emissions collected with appropriate spatial and temporal intensity from side-by-side experiments differing only in management (Climate Action Reserve, 2011d, 2011e). The breadth of the initial proposal indicates the kind of expectations and hopes that have been generated in the policy arena. Subsequent steps taken by the Reserve to refine this protocol, and to establish mechanisms for including additional practices as additional data become available, further demonstrate the extent to which data availability and advice from the research community have shaped this protocol.

Summary

Here we highlight the most important lessons learned for each topic in this chapter as bullet points under the following three themes: (i) model structure and scale of application, (ii) data limitations and nonlinearity, and (iii) applications to GHG offset projects.

Model Structure and Scale of Application

Even though models may perform well across large regions over long time periods, there are almost always major uncertainties in estimates for specific locations and management practices.

- Process models share basic approaches to representing ecosystem processes (e.g., controls on decomposition; which environmental conditions affect C and N cycling). However, apparently subtle differences in the way models represent ecosystem complexity lead to variation in strengths and weaknesses of different models.
- Our ability to test the mechanisms that underlie model estimates of net ecosystem GHG fluxes is constrained by the availability of data for specific processes such as shoot, root, or heterotrophic soil respiration. Therefore, even if model estimates of an integrative variable like soil carbon storage or net CO_2 flux reasonably match results of several experiments, there remains substantial uncertainty about whether the model will provide accurate estimates under different environmental conditions.
- Both process and empirical models tend to smooth out variation in GHG fluxes and estimate average values over time and space. For example, models of N_2O flux perform much better at the annual scale than at the daily scale. Similarly, at very large spatial and temporal scales such as the conterminous

United States over a decade, estimates of total GHG flux from complex process models and simple empirical models often converge. The utility of modeling average values for integrative variables like N_2O flux is limited if management recommendations require estimates that apply to specific localities.

- Even at large scales, where values of ecosystem-scale variables converge among models, the extent to which different processes contribute to these values can vary substantially among models. For example, CO_2 fluxes can originate mainly from litter decomposition in one model and more from woody debris and soil respiration in another. The source of GHG emissions is relevant for designing best management practices; therefore, discrepancies in model outcomes regarding GHG source affects the suitability of models for broad application to management questions.
- Because different models identify different underlying mechanisms for overall GHG flux, modelers and policymakers should exercise caution in concluding that any particular model accurately estimates GHG emissions.

Outstanding Questions

- Why do models converge and diverge?
- How important are the differences in representation of processes that control integrative variables?
- How much do different model representations of factors such as plant growth and soil water content account for variation in model performance under different environmental conditions?
- What should the next set of model comparisons look like to maximize understanding of underlying ecosystem processes as well as to accelerate our ability to apply models for management at more local and regional scales?

Data Limitations and Nonlinearity

Models are only as good as the data used to develop, parameterize, and validate them, and relevant data are scarce for many agricultural and forest ecosystems. Data scarcity is a major limitation for modeling all but the most common agricultural systems in the industrialized world and for nearly all ecosystems in less-developed countries. Thus, it is important for model developers and model users to understand and communicate clearly about which model estimates are most robust and which require further validation for specific processes, pools, management practices, soil types, etc.

- Agriculture and forest ecosystems are responding to shifting environmental and ecological conditions, and models often do not reflect such changing conditions. Changes include species invasions, changes in fire regimes, use of new management practices, and climate change. Models often omit such processes because starting with a simpler set of conditions is tractable and because data for many topics is very limited. Simple models are quite useful for research because they teach us how much variability in ecosystem processes can be explained by a small number of key factors. But when processes or practices not included in a model are influential, estimates of GHG emissions are unlikely to be correct.

- Despite increases in data availability, few data sets include concurrent measurements of key processes, pools, and GHGs (e.g., plant growth, CO_2, N_2O, NO_3^-, SOC, soil nutrient status). For example, there are hundreds of data sets that report N_2O measurements in agricultural systems, but few are adequate to support robust understanding of how management practices influence N_2O emissions. To assess the influence of different management practices on N_2O emissions, we need side-by-side trials of different management systems. We also need measurements of fluxes from these side-by-side comparisons over entire years, not just growing seasons; over multiple years; and with sufficient temporal and spatial frequency to capture both hot spots and hot moments.
- Estimating N_2O flux is inherently challenging as flux often exhibits a nonlinear response to controlling factors. Even when a model performs well after calibration at an annual scale, the seasonal pattern of flux may not be accurate, suggesting that simpler empirical models operating at an annual scale may be just as useful for some purposes.

Outstanding Questions

- Are data needs for model development and testing (to further our understanding of ecosystem dynamics) different from needs driven by existing policy and management frameworks? If so, what would be an appropriate process for balancing investments in data collection and model research to meet both objectives?

Applications to GHG Offset Projects

The application of models to estimate GHG emission reductions raises several issues that might not have been immediately apparent when agricultural offsets were first proposed for inclusion in environmental markets. These include (i) trade-offs between the cost of implementing an offset project—and hence the cost of carbon credits—and the precision and accuracy of estimates of GHG fluxes; (ii) the availability of tools to estimate agriculture-related GHG emissions at different scales; (iii) the likelihood of different kinds of crop fields being enrolled in carbon offsets programs; and (iv) the level of understanding about models within different policy institutions.

- Models have increasingly been used to quantify GHG budgets associated with carbon offset projects, supplementing measurements to estimate carbon in aboveground biomass of trees, or predicting N_2O fluxes that are too difficult and expensive to measure directly. But even well-validated models are unlikely to make accurate predictions across all combinations of soils, climate, species, and management practices, especially with limited site-specific measurements. Collecting sufficient site-specific data to accurately parameterize a model can be very costly and may still miss factors or practices that are not included in the model.

- During the last decade, there have been many applications and modifications of some models to enhance their use for GHG offset projects. However, there will always be a tension between the need for models to evolve and improve and the need for tractable and stable rules for assessing compliance with GHG offset projects.
- We can be confident that there is huge variation in the potential for N_2O emission reductions and soil carbon storage among agricultural fields. This variation has implications that merit more attention than they sometimes receive in the agricultural GHG offset arena.
- The understanding that ecosystem models do not produce robust estimates of GHG budgets at individual sites has led to a focus on average performance over large spatial scales. This approach assumes that the fields over which a protocol is applied are representative of the population of fields for which the model has been validated. If, for example, fields enrolled under a GHG offset protocol tend to have high baseline soil C or low baseline N_2O emissions compared with most fields, then they are not "average," and the average GHG benefit estimated by the model may not be realized. Institutions that apply an "average" approach should provide some assurance that the distribution of enrolled fields represents average conditions.
- In the context of water quality protection, recognition of variability in N loss from crop fields has resulted in efforts to target areas of the landscape with the highest losses and the greatest potential for reducing N pollution. This targeting approach has not yet been applied in the context of agricultural GHG offsets. Such targeting could potentially enable much greater returns on investment in agricultural GHG emission reductions, underscoring the benefits of developing the research base that enables site-specific estimation.
- For carbon offset projects, the desired accuracy often exceeds scientific capacity. For example, the effect of reduced tillage in sequestering carbon was modeled for many years, but then questions were raised about whether estimates were at all accurate when deeper soil horizons were included (Baker et al., 2007). Additionally, only a single agricultural practice was included in the CAR N management protocol- reduced N fertilizer rate on corn in 12 states because scientists said tools were not adequate to quantify the benefit of other management practices.
- Institutions like CAR that are charged with policy development have demonstrated an impressive capacity to assimilate relevant technical knowledge and craft policies that reflect an appreciation for the abilities and limitations of models. In the case of CAR's nitrogen management protocol, the

perspective of CAR staff shifted radically over the course of several months, illustrating the initial absence of a clear appreciation for many of the issues raised in this paper and also the Reserve's ability to learn quickly.

- When a model has become visible to the policy and management community, the interaction with the modeling community can be critical in establishing realistic expectations about the model's capability and limitations.
- Regardless of model accuracy, there remain issues with permanence for carbon sequestration in soil and vegetation.

Outstanding Questions

- Once a model has been published and accepted for certain uses in certain places, does it acquire legitimacy and credibility for application beyond those situations or processes for which it has been validated?
- How many policy institutions related to agriculture and greenhouse gas emissions have a sufficiently strong understanding of model capabilities and limitations to instill confidence that these institutions will use them appropriately and encourage investment in model development in the most useful ways?

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Appendix—Publications Reviewed for Simulation Model Comparison

Publication†

APEX
- Anomaa Senavirante et al. (2013)
- Cavero et al. (2012)
- Gassman et al. (2010)
- Kumar et al. (2011)
- Meki et al. (2011)
- Mudgal et al. (2010)
- Mugdal et al. (2012)
- Osei et al. (2008)
- Powers et al. (2011)
- Saleh et al. (2011)
- Tuppad et al. (2010)
- Wang et al. (2008b)
- Wang et al. (2009)
- Wang et al. (2011a)
- Wang et al. (2012c)

DAYCENT
- Adler et al. (2007)
- Chamberlain et al. (2011)
- Chianese et al. (2009)
- David et al. (2009)
- Davis et al. (2009)
- Davis et al. (2012)
- De Gryze et al. (2010)
- De Gryze et al. (2011)
- Del Grosso et al. (2005)
- Del Grosso et al. (2006)
- Del Grosso et al. (2008)
- Del Grosso et al. (2009a)
- Del Grosso et al. (2009b)
- Delgado et al. (2009)
- Foereid et al. (2012)
- Gao et al. (2013)
- Gramig et al. (2013)
- Hartman et al. (2011)
- Kim et al. (2009)
- Lee et al. (2011)
- Lee et al. (2012)
- Li et al. (2005)
- Miner et al. (2013)
- Paul et al. (2006)
- Reeling and Gramig (2012)
- Sendich et al. (2008)
- Smith et al. (2008a)
- Smith et al. (2012)
- Stehfest et al. (2007)
- Weiss et al. (2009)
- Xing et al. (2011)

DNDC
- Abdalla et al. (2011)
- Abdalla et al. (2012)
- Beheydt et al. (2007)
- Britz et al. (2009)
- Chirinda et al. (2011)
- David et al. (2009)
- Deng et al. (2011)
- Deng et al. (2011)
- Desjardins (2005)
- Desjardins et al. (2010)
- Dietiker et al. (2010)
- Farahbakhshazad et al. (2008)
- Follador et al. (2011)
- Fumoto et al. (2008)
- Giltrap et al. (2010)
- Giltrap et al. (2011)
- Gopalakrishnan et al. (2012)
- Guo et al. (2012)
- Hastings et al. (2010)
- Jagadeesh Babu et al. (2006)
- Kang et al. (2011)
- Kariyapperuma et al. (2011)
- Katayanagi et al. (2012)
- Kröbel et al. (2011)
- Leip et al. (2011)
- Li et al. (2005)
- Li et al. (2006)
- Li et al. (2010)
- Li et al. (2011)
- Li et al. (2012)
- Li et al. (2012)
- Liu et al. (2006)
- Ludwig et al. (2011a)
- Ludwig et al. (2011b)
- Nakawaga et al. (2008)
- Neufeldt et al. (2006)
- Ouyang et al. (2013)
- Pathak et al. (2005)
- Pathak et al. (2006)
- Qin et al. (2013)
- Qiu et al. (2009a)
- Qiu et al. (2009b)
- Qiu et al. (2011)
- Rafique et al. (2011)
- Shirato (2005)
- Sleutel et al. (2006)
- Smakgahn et al. (2009)
- Smith et al. (2008a)
- Smith et al. (2012)

Appendix continued.

DNDC continued.
- Syp et al. (2011)
- Tang et al. (2006)
- Terhoeven-Ureselmans et al. (2009)
- Tonitto et al. (2007a)
- Tonitto et al. (2007b)
- Wang et al. (2008a)
- Wang et al. (2011b)
- Wang et al. (2012a)
- Wang et al. (2012b)
- Wolf et al. (2012)
- Xu et al. (2011a)
- Xu et al. (2011b)
- Xu et al. (2011c)
- Xu et al. (2012)
- Xu et al. (2013)
- Yu et al. (2011)
- Zhang et al. (2006)
- Zhang et al. (2009)
- Zhang et al. (2011b)
- Zhang et al. (2012a)
- Zhang et al. (2012b)

ECOSYS
- Grant (1994a)
- Grant (1994b)
- Grant (1995)
- Grant (1997)
- Grant (1998)
- Grant (1999)
- Grant and Flanagan (2007)
- Grant and Heaney (1997)
- Grant and Pattey (1999)
- Grant and Pattey (2003)
- Grant and Pattey (2008)
- Grant and Rochette (1994)
- Grant et al. (1995)
- Grant et al. (1997)
- Grant et al. (2001a)
- Grant et al. (2001b)
- Grant et al. (2004a)
- Grant et al. (2004b)
- Grant et al. (2006)
- Grant et al. (2007)
- Grant et al. (2011)
- Grant et al. (2012a)
- Grant et al. (2012b)
- Li et al. (2004)
- Metivier et al. (2009)
- Parsinejad and Feng (2003)

RZWQM2
- Ahuja et al. (2010)
- Deb et al. (2012)
- Fang et al. (2010)
- Fang et al. (2012)
- Islam et al. (2012)
- Ko et al. (2010)
- Ko et al. (2012)
- Ma et al. (2009)
- Ma et al. (2012)
- Nielsen et al. (2012)
- Nolan et al. (2010)
- Qi et al. (2011)
- Qi et al. (2012)
- Qi et al. (2013)
- Saseendran et al. (2009)
- Saseendran et al. (2010)
- Saseendran et al. (2013)

† APEX, Agricultural Policy/Environmental eXtender; DAYCENT, Daily CENTURY; DNDC, Denitrification–Decomposition; EPIC, Environmental Policy Integrated Climate; RZWQM2, Root Zone Water Quality Model 2.