10

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Simulating Crop Growth and Biogeochemical Fluxes in Response to Land Management Using the SALUS Model

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The Green Revolution, through the adoption of new crop varieties, irrigation, and agrochemicals, saved about 1 billion people from famine by increasing global food production (FAO 2011). We now recognize that these enormous gains in agricultural production were accompanied by harm to agriculture's natural resource base, jeopardizing our future ability to meet human food, fuel, and fiber needs for a growing population. Earth's population is projected to increase from ~7 billion in 2011 to ~9 billion in 2050. Given the future challenges to food production and environmental integrity, it is imperative that sustainable land management of agricultural production become an important priority for policy makers. Agricultural crop and soil management practices often cause degradation of the environment, especially the quality of ground and surface water and the fertility of agricultural soils. Clearly, a sustainable framework for developing and improving land use for crop production must be based on long-term and broad-based perspectives.

Sustainable land management is the focus of many research programs, ranging from socioeconomic to ecological, since sustainability is an integrated concept with associated challenges. A multiplicity of factors can prevent production systems from being sustainable; the goals set by a sustainable crop production system may be in conflict with one another, and solutions that work in one site or region with a particular soil, climatic, and socioeconomic setting may not be appropriate in others (Robertson and Harwood 2013). On the other hand, with sufficient attention to indicators of sustainability, a number of practices and policies could be implemented to accelerate the adoption of sustainable practices. Indicators to quantify

changes in crop production systems over time at different hierarchical levels are needed for evaluating the sustainability of different land management strategies. Indicators should encompass (1) crop productivity, (2) socioeconomic and ecological well-being, and (3) resource availability.

Approaches for improving land management for the sustainability of crop production should be based on reduced chemical inputs, as well as higher resource use efficiency, enhanced nutrient cycling, and integrated pest management. Modeling is necessary to identify the best approaches because field experiments cannot be conducted with sufficient detail in space and time to find the best land management practices for sustainable crop production across diverse environmental settings. Input from long-term crop and soil management experiments, including measurements of crop yields, soil properties, biogeochemical fluxes, and relevant socioeconomic indicators, is critical to develop and test the models.

Simulation models, when suitably tested in reasonably diverse locations over sufficient time periods, provide a useful tool for finding combinations of management strategies to reach the multiple goals required for sustainable crop production. Models can provide land managers and policy makers with ways to extrapolate experimental results from one location to others where soil, landscape, and climate information is available. When biophysical simulation model results are combined with socioeconomic information, a Decision Support System (DSS) can provide management options for maximizing sustainability goals. Decision Support Systems describe a wide range of computer software programs designed to make site-specific recommendations for pest management (Michalski et al. 1983, Beck et al. 1989), farm financial planning (Boggess et al. 1989), and general crop and land management (Plant 1989). Decision Support System software packages have been designed primarily for use by crop consultants and other specialists who work with farmers and policy makers, although some are used directly by farmers. Users provide site-specific information about soil properties, crop type and management, weather conditions, and other data specific to the software. Typically, a given DSS provides a variety of management options to reach desired sustainability goals.

Process-based models of crop growth and development are integral parts of the most effective DSS models and have been developed and used for more than 40 years, since the advent of high-speed computers. During this time, two scientific teams have integrated such models into DSSs, namely, DSSAT (Tsuji et al. 1998) and APSIM (McCown et al. 1996), and both have proven useful for many groups involved in agricultural research and decision making throughout the world. The International Consortium of Agricultural Systems Applications (ICASA) was formed from several modeling groups to promote the efficient and effective use of functional models for problem solving and decision making (Ritchie 1995). Crop models that simulate crop growth, the timing of critical growth stages, and grain yields have added soil and plant carbon and nitrogen dynamics for different climate, soil, and management conditions (e.g., Parton et al. 1988).

Here, we provide a general overview of crop simulation models followed by a concise description of the model Systems Approach for Land Use Sustainability (SALUS) for evaluating the impact of agronomic management on crop yields, carbon (C) and nitrogen (N) dynamics, and environmental performance. We describe

key model components and the minimum data required for simulating crop yields under different management practices. Research at the Kellogg Biological Station Long-Term Ecological Research Site (KBS LTER) provides the opportunity to test models of long-term changes in soil carbon, nitrogen leaching, crop yields, and gaseous emissions from soil. Data from KBS LTER also provide an excellent context for illustrating the utility and limitations of crop models, and we use these data to show two examples of model applications: (1) an evaluation of nitrate leaching as affected by nitrogen fertilizer management in a corn (*Zea mays* L.) and alfalfa (*Medicago sativa* L.) rotation and (2) soil carbon dynamics under various tillage systems. We also illustrate spatially connected processes by linking SALUS to digital terrain modeling.

Crop Models

Crop simulation models range from simple to complex. Simple models are often adopted to estimate yield across large land areas based on statistical information related to climate and historical yields and include little detail about the soil–plant system. The more sophisticated physically based models are capable of providing additional details on processes in the soil–plant–atmosphere system, but sophisticated models demand detailed initial environmental and agronomic information that may be unavailable in many situations.

Crop models may be either deterministic or stochastic. Deterministic models provide a specific outcome for a certain set of conditions, with all plants and soil within the simulation space assumed to be uniform. Stochastic models produce outcomes that incorporate uncertainty due to spatial variability of soil properties, temporal variability of weather conditions, abiotic and biotic factors not accounted for in a deterministic model, and uncertainties of model logic and functions. However, stochastic crop models are at an early stage of development and not used in DSSs to our knowledge.

To overcome some of the problems of using deterministic crop models, soils with known spatial variability can be grouped into small homogenous units and the results aggregated to model yield at the whole-field scale. Similarly, running simulations over multiple years with deterministic yields accounts for temporal variability (Basso et al. 2007).

Deterministic crop models can be statistical, mechanistic, or functional (Addiscott and Wagenet 1985, Ritchie and Alagarswamy 2002). Statistical models—fitting a function to observed weather variables and crop regional yield statistics to predict crop yield—were the first crop models used for large-scale yield estimations. Average regional yields were regressed on time to reveal a general trend in crop yields (Thompson 1969; Gage et al. 2015, Chapter 4 in this volume). An example is the upward trend in crop yield over the past several decades due to technological advancements in genetics and management, especially the increased use of fertilizers. Thompson (1986) quantified the impact of climate change and variability on corn yield in five U.S. states using a statistical model. In that study, preseason precipitation (September–June), June temperature, and temperature and

rainfall in July and August were closely correlated with corn yield variations from the trend. Recently, Gage et al. (2015, Chapter 4 in this volume) incorporated climate effects into regional yield trends with the use of a Crop Stress Index (CSI). This approach significantly improved predictions of historical yields of corn and soybean.

In general, the results of statistical models cannot be extrapolated to other places and time periods because of variation in soils, landscapes, and weather not included in the population of information from which the statistical relationship was derived. Furthermore, the impact of agricultural technology cannot be extrapolated over space and time. Despite these limitations, statistical models can provide many insights about past yields and historical influences (Gage et al. 2015, Chapter 4 in this volume) and can be used to inform the other kinds of models.

Mechanistic models are based on known physical, chemical, and biological processes occurring in the soil–plant–atmosphere continuum. Soon after computers became available, mechanistic models were developed to simulate photosynthetic processes such as light interception, uptake of carbon dioxide (CO_2), carbon allocation to different plant organs, and loss of CO_2 during respiration, as well as the dynamics of soil water including infiltration, evaporation, drainage, and root uptake.

Mechanistic models describe processes at fine time scales (e.g., photosynthesis and transpiration processes) but a large amount of input information is required to execute them. Uncertainties in some assumptions make mechanistic model outcomes less certain and often make them less useful to those outside of the model development group (Basso et al. 2012a). Mechanistic models are rarely adopted to solve problems; rather, they are often used for academic purposes to gain a better understanding of specific processes and interactions.

Functional models are based on empirical functions that approximate complex processes, such as a crop's interception of energy using plant leaf area (as an indicator of biomass) and radiation use efficiency (as a measure of biomass produced per unit of radiation intercepted). This type of function is relatively simple and usually produces reasonable results when compared to field measurements, although it has uncertainties related to the fraction of biomass partitioned to roots and nonlinear photosynthetic responses to light. Another example is the simulation of potential evapotranspiration using the well-known functional Penman or Priestley–Taylor equations, which have been used successfully for decades although they are highly simplified compared to mechanistic evapotranspiration models.

Functional crop models use simplified equations and logic to partition simulated biomass into various plant organs, which are integrated to estimate total biomass and yield. Functional models primarily use "capacity" concepts to describe the amount of water available to plants as compared to using "instantaneous rate" concepts from soil physics. The difference between the upper and lower limits of soil water-holding capacity determines the amount of water available to plants.

Functional models typically use daily time step inputs for weather and management variables such as precipitation, solar radiation, temperature, irrigation, and fertilizer use. Low data input requirements make these models attractive when detailed data on biophysical processes are lacking. These models, when properly

tested, can provide an appropriate level of detail needed for assessing many aspects of crop production. Functional type models are now routinely used in DSSs.

Examples of Models to Simulate Crop Ecosystems

Here, we provide a brief summary of the most widely adopted models to simulate soil organic matter, soil water, and biogeochemical fluxes and how these variables affect crop growth in response to land management.

Soil Organic Matter and Gas Emission Models

One of the most widely used soil organic matter (SOM) models is the CENTURY model developed by Parton et al. (1988) to simulate long-term (10–1000 years) patterns in surface SOM dynamics, plant production, and nutrient cycling (N, phosphorus [P], and sulfur [S]). The model uses a monthly time step with monthly average maximum air temperature (at 2 m height), monthly precipitation, soil texture (sand, silt, and clay content), nutrient and lignin content of dead plant material, and atmospheric and soil inputs of N. Plant material is divided into structural (difficult to decompose) and metabolic (readily decomposable) fractions. Soil organic matter is divided into active, slow, and passive pools. Decomposition of plant material and SOM is a function of soil water and temperature, and is influenced by soil type and the C/N ratio of decomposing material. A complete description of the N and soil C model is presented by Parton et al. (1987). The plant submodel is highly simplified, using only inputs of stored water at planting, precipitation during plant growth, a fixed water-use efficiency, and available soil N. Partitioning of C and N into various plant components is performed using fixed partitioning coefficients. While emphasizing long-term organic matter dynamics, the CENTURY model lacks details important for short-term soil water and crop growth dynamics as well as soil management other than N inputs.

A daily incrementing modification of CENTURY called NGAS-DAYCENT or simply DAYCENT (Parton et al. 1996, 1998, 2001; Del Grosso et al. 2000a, b) simulates trace gas fluxes of nitric oxide (NO), nitrous oxide (N_2O), and dinitrogen (N_2) from soils as well as methane (CH_4) formation and oxidation. The DAYCENT model has been used to simulate national N_2O emissions in the United States from major cropped soil regions (Del Grosso et al. 2006). Soil water calculations are performed at hourly time steps, which may not match other processes simulated at daily time steps (Basso et al. 2010, 2011).

Another mechanistic SOM and gas emission model is the DeNitrification–DeComposition (DNDC) model. The DNDC model has been used for estimating N_2O and CH_4 emissions from agricultural lands (Li 1995, 2000), but it requires substantially more input detail than other models.

While providing much detail about soil greenhouse gas emissions and carbon dynamics, these three models lack detail for estimating crop yield. Thus, they are useful for simulating SOM and soil greenhouse gas dynamics but have limited utility for evaluating the sustainable production of food, fuel, and fiber.

Crop and Soil Water Models

The Decision Support System for Agrotechnology Transfer (DSSAT) (Tsuji et al. 1998) contains a suite of crop models widely used to simulate crop biomass and yield as influenced by weather, soil, crop management, and crop genotype. The primary crop models contained in DSSAT are CROPGRO for major grain legumes, CERES for cereal crops, and SUBSTOR for crops with belowground storage organs. The models were developed with a goal of minimizing the data needed for prediction and control purposes. Simulations are executed on a daily time step using solar radiation, temperatures (maximum and minimum), and precipitation, thereby accounting for day-to-day variation that can be substantial. They are based on empirical functions to estimate the soil water balance (runoff, drainage, evapotranspiration, soil storage) and biomass production. Input needs include soil physical and chemical properties for several depth increments as available in soil surveys. Crop management input needs include date of sowing, plant population, dates and quantities of nutrient and irrigation water applications, photoperiod, and crop genotype. Air temperature and photoperiod during critical phases of development determine plant ontogeny and biomass partitioning, and are based on plant genotype. The DSSAT system has two options for simulating N balance and SOM: the original SOM model (Godwin and Singh 1998) and a modified CENTURY model that operates on a daily time increment and at soil depth increments that conform to DSSAT (Gijsman et al. 2002).

The Environmental Policy Integrated Climate (EPIC) model was originally designed to simulate soil erosion and its effects on soil fertility (Williams et al. 1984). EPIC has now evolved into a comprehensive agro-ecosystem model capable of simulating biomass and yields of crops grown in complex rotations and under diverse management practices such as tillage, irrigation, fertilization, and liming (Williams 1995). The SOM module in EPIC uses processes similar to CENTURY but with daily time increments and several soil depths. The soil water balance submodel is similar to that in DSSAT models.

The Agricultural Production Simulator (APSIM) model is another widely used model (Keating et al. 2003) similar in detail to DSSAT and EPIC. APSIM was developed with a modular structure to allow testing and use of various methods of simulating several components of the soil, plant, and atmosphere system.

Rivington and Koo (2010), in a recent comprehensive meta-analysis of crop modeling for climate change and food security, reported that DSSAT crop models were the models most commonly used by various groups surveyed throughout the world. The report revealed perceived model limitations and made suggestions for model improvements based on user feedback.

Simulation of Crop Yield

Yield simulation in crop models is based on two processes: crop growth and development. The fraction of total biomass partitioned into grain or other harvested biomass is termed the economic yield. Crop simulations thus involve the two-step

Table 10.1. Factors affecting crop growth and development and their sensitivity to water and nitrogen deficits.

	Growth Rate		Development (Duration)	
	Mass	Expansion	Phasic	Morphological
Principal environmental factor affecting the process	Solar radiation	Temperature	Temperature, photoperiod	Temperature
Degree of variation between genotypes	Low	Low	High	Low
Sensitivity to water deficit	Low–Stomata Moderate–Leaf wilting and rolling	High–Vegetative stage Low–Grain filling stage	Low–Delay in vegetative stage	Low–Main stem High–Tillers and branches
Sensitivity to nitrogen deficiency	Low	High	Low	Low–Main stem High–Tillers and branches

Source: Ritchie and Alagarswamy (2002).

process of estimating total biomass using crop growth rate and duration and partitioning that biomass into harvested components. Separating growth and development processes also allows a distinction between sources and sinks of assimilate (i.e., photosynthetically produced carbon) within the various plant organs. A plant can be exposed to source or sink limitation during its growth cycle, where "source" refers to the production of organic matter by photosynthesis, and "sink" refers to the assimilation of that organic matter in tissues. The assimilates are stored in roots or elsewhere if the sink demand is less than source supply, as the aboveground plant parts cannot grow faster than the sink demand. During seed development, stored assimilates become available to augment daily grain fill demand.

Table 10.1 summarizes the environmental factors that influence crop growth and development and the sensitivity of these processes to water and N deficits. In the next sections, we discuss the three major processes—growth, development, and yield and yield components—important in simulating crop yield.

Crop Growth

Net photosynthesis is simulated in functional models using radiation use efficiency (RUE), which assumes that daily biomass production is directly proportional to intercepted photosynthetically active radiation (IPAR), a concept introduced by Monteith (1977). Model simulations need to consider variations in the RUE proportionality constant over the time interval measured (hourly, weekly, or seasonal), the form of biomass measured (aboveground, belowground, or specific plant part), and the type of radiation measured (i.e., total solar or photosynthetically active radiation).

Accurate leaf area index (LAI) estimates are crucial for models based on IPAR. Since LAI is the ratio of plant leaf area to the average ground area covered, it can change dramatically over the growing season until a full plant canopy has developed.

Crop Development

Phasic development describes the duration of different growth phases and the biomass partitioning among different plant organs. Morphological development refers to organ development during the plant life cycle. Both are affected by temperature (Table 10.1), as calculated by growing degree-days. Phasic development is also affected by photoperiod and genetics (Table 10.1). Genetic diversity within a crop species enables plants to be adapted to diverse settings in different regions of the world. For example, wheat genotypes are grown from temperate Argentina (latitude 50° S) to Sweden (60° N) and in tropical regions between.

Plant growth rate and duration are equally important in determining potential crop yields; hence, the accuracy of yield simulation models. Record high yields of annual crops are always obtained in cooler environments where there is maximal duration of daylight for plant growth. Warmer climates can equal the total annual yields of the cooler region yields by growing more than one crop per year.

The principal functional approach used to estimate the duration of crop growth is based on thermal time calculation (Gallagher 1979). Thermal time (t_d) is the accumulation of degree-days (i.e., °C d) above a base temperature and is calculated as

$$t_d = \sum_{i=1}^{n} \left(T_a - T_b\right)$$

where T_a is 24-hour daily mean temperature; T_b is the base temperature below which the crop growth ceases; and n is the number of days. T_a is usually approximated by taking the mean of daily maximum and minimum temperatures (Ritchie and NeSmith 1991).

Thermal time to simulate development requires temperature to be measured close to the growing point of the plant. Ritchie and NeSmith (1991) showed that using air temperatures to calculate thermal time and to predict the number of leaf tips and leaf development overpredicted leaf numbers in the CERES corn model, and required correction using a higher phyllochron value (i.e., duration between leaf tip appearances) (Vinocur and Ritchie 2001).

Several crop species are sensitive to photoperiod. In general, plants adapted to grow in shorter day lengths (e.g., corn, sorghum, and soybean) develop more quickly when exposed to shorter days. Plants adapted to grow in longer day lengths (e.g., wheat and barley) grow more quickly when exposed to longer days. In addition to temperature, Ritchie and NeSmith (1991) showed that photoperiod in corn can significantly affect leaf number and the duration of vegetative stages.

Yield and Yield Components

Simulation procedures for yield estimates differ among crop models. One approach is to assume a constant fraction of biomass produced at maturity (i.e., the point of economic yield) or to assume a constant increment of biomass production each day after grain filling starts. Another approach is to separately estimate the yield components (ear number, kernels per ear, and kernel weight).

The simplest level of yield simulation assumes that economic yield is a constant fraction of total aboveground biomass at maturity, known as the harvest index (HI). This index can range from 0.40 to 0.55 for corn. Both the EPIC (Williams et al. 1989) and CROPSYS (Stockle et al. 1994) models are based on HI calculations. Some models estimate corn yields using a constant rate of change in HI after silking (Muchow et al. 1990, Muchow and Sinclair 1991, Sinclair and Muchow 1995). In this case, the rate of change of HI for corn is 0.015 d^{-1} during the entire period of kernel growth. The accuracy of yield simulations by models based on the HI concept depends on the accuracy of simulating total aboveground biomass as well as the stability of HI. Such models are of more limited value in situations where the crop yields are low because of water deficits that constrain HI.

Kernel number (KN) is an important predictor of yield in most cereal crops (Evans 1993), and reflects the irreversible effects of water deficit and nutrient deficiencies that occur around the time of anthesis. Crop models using the KN concept are based on two approaches. A simple approach calculates KN from biomass at anthesis, while a more complex one estimates KN from biomass production during a critical period (around silking in the case of corn). SALUS, for example, uses the simulated stem weight at anthesis to simulate grain number.

The Systems Approach to Land Use Sustainability Model

The Systems Approach to Land Use Sustainability (SALUS) (Basso et al. 2006, 2010) is similar to the DSSAT family of models but is designed to simulate not only yields of crops in rotation, but also soil, water and nutrient dynamics as a function of management strategies over multiple years (Fig. 10.1). SALUS accounts for the effects of rotations, planting dates, plant populations, irrigation and fertilizer applications, and tillage practices. The model simulates daily plant growth and soil processes on a daily time step during the growing season and fallow periods. SALUS contains (1) crop growth modules, (2) SOM and nutrient cycling modules, and (3) soil water balance and temperature modules. The model simulates the effects of climate and management on the water balance, SOM, N and P dynamics, heat balance, plant growth, and plant development. Within the water balance, surface runoff, infiltration, surface evaporation, saturated and unsaturated soil water flow, drainage, root water uptake, soil evaporation, and transpiration are simulated. Soil organic matter decomposition, along with N mineralization and formation of ammonium and nitrate, N immobilization, and gaseous N losses are also simulated.

Crop development in the SALUS model is based on thermal time calculations modified by day length and vernalization. Potential crop growth depends on intercepted light using solar radiation data and simulated LAI, and is reduced by water or nitrogen limitations. The crop growth modules in SALUS are derived from the CERES model originally developed for single-year and monoculture simulations (Ritchie 1998, Ritchie et al. 1998). Phasic development is controlled by temperature and photoperiod and is governed by variety-specific genetic coefficients. The main external inputs required for the crop growth simulations are the genetic coefficients and climate data (daily solar radiation, precipitation, and air temperature).

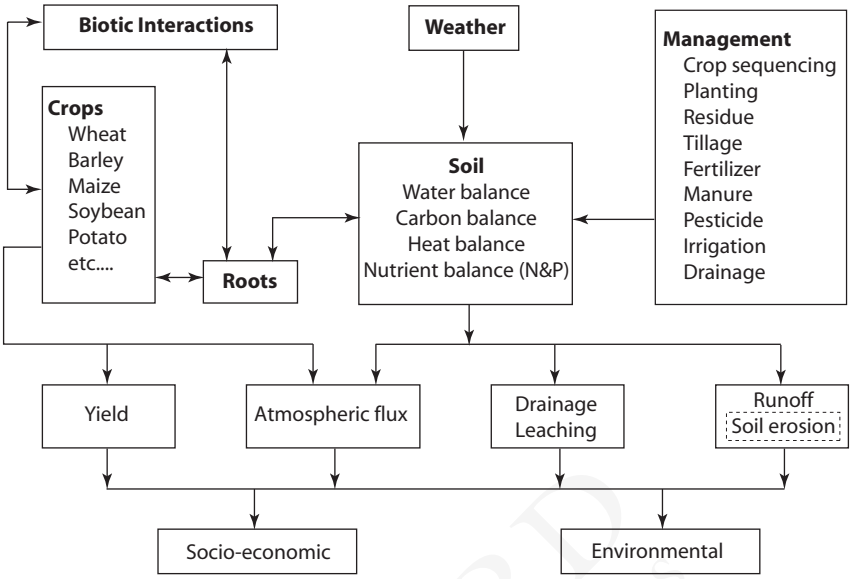

Figure 10.1. Components of the System Approach for Land Use Sustainability (SALUS) model.

The SALUS soil N and SOM modules are derived from CENTURY (Parton et al. 1988) with several new additions and modifications. The model simulates SOM and N mineralization/immobilization from three soil organic carbon pools (active, slow, and passive) that vary in their turnover rates and characteristic C:N ratios (see Paul et al. 2015, Chapter 5 in this volume). There are two crop residue/fresh organic matter pools (structural and metabolic) for representing recalcitrant and easily decomposable residues, based on residue lignin and N content. A surface active SOM pool associated with the surface residue pools was added to better represent conservation tillage systems and perennial crops. A soil P model incorporates inorganic and organic P dynamics. Inorganic P is divided into labile, active, and stable pools.

The soil water balance module has advanced from the DSSAT models with new improvements in calculating infiltration, drainage, evaporation, and runoff. The time-to-ponding (TP) concept (White and Sully 1989) replaces the previous runoff and infiltration calculations based on the USDA-NRCS runoff curve number. SALUS does not account for impacts of pests, disease, or extreme weather such as hail.

Input data required by SALUS consist of weather, soil and crop management, soil properties, genetic characteristics of the crop, and the site location. When models are to be used in new locations, plant data such as phenology, biomass, and economic yield are needed. To test the soil simulations, information on water content and nitrate concentrations is helpful.

Weather uncertainty is the major source of insecurity and risk in agricultural production. SALUS accounts for weather variability by using several decades of existing weather information. The minimum weather dataset required for SALUS is listed in Table 10.2. Daily totals of rainfall and solar radiation along with the

Table 10.2. The minimum and optional weather datasets required as inputs for crop simulation models.

Minimum	Optional
Daily solar radiation	Daily dewpoint temperature
Daily maximum temperature	Daily wind run
Daily minimum temperature	Daily net radiation
Daily precipitation	Precipitation intensity

Source: Ritchie and Alagarswamy (2002).

maximum and minimum temperature are considered the minimum needed for relatively accurate crop simulation. The main weather element of greatest concern in most agricultural regions is the temporal distribution of rainfall. Solar radiation is the main weather variable for describing the energy available for crop growth and evapotranspiration (ET). Temperature is necessary to simulate crop phenology and to modify growth and ET.

Ideally, weather data should be obtained at a site near the area where the model is to be applied, especially for daily rainfall. Temperature and radiation are more spatially uniform, so the weather station need not be on-site. Most weather stations record rainfall and temperature but not always solar radiation. Accurate solar radiation data can be obtained from NASA (http://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/agro.cgi), although the spatial resolution is given in 1° grid cells. This NASA site also provides all the daily weather data required by DSSAT and SALUS, but with the same spatial resolution issues as with solar radiation.

The minimum soil information required to run crop simulation models such as SALUS is listed in Table 10.3. On-site measurement of soil properties is recommended where possible to validate the model for a specific site. Not all soil input data may be available, in which case soil characteristics such as texture, bulk density, and organic matter content can serve as surrogate measures. However, the lower limit of available soil water and the field capacity or drained upper limit (DUL) water content are often more accurate when measured in the field than when using laboratory measurements of field soil samples. These measurements must be made when field conditions are at or near their lower and upper limits. In well-drained soil, the DUL can best be measured after the profile has been thoroughly wetted and allowed to drain without irrigation until drainage practically stops. The lower limit is best measured during a dry period in the growing season when water content ceases to decline in the root-zone because of a shortage of soil water.

The minimum crop management information required to run crop simulation models such as SALUS is listed in Table 10.4. When irrigation is used, the dates, amounts and mode of application are required. Information on the type, dates, and mode of fertilizer application is necessary to simulate nutrient dynamics, although often model assessments of crop yield assume that nutrient availability is not limiting.

Table 10.3. Soil datasets required as inputs for crop simulation models.

Minimum	Desirable for Specific Applications	Initial Conditions
Lower limit water content at 10- to 20-cm depths	Hydraulic conductivity and water retention curves at 10- to 20-cm depths	Water content at 10- to 20-cm depths
Field capacity soil water content at 10- to 20-cm depths	Runoff curve number	Soil nitrate concentration at 10- to 20-cm depths
Crop rooting depth	Surface albedo	Soil ammonium concentration at 10- to 20-cm depths
Hydraulic conductivity at soil depths that restrict water flow	Soil pH at 10- to 20-cm depths	Soil extractable phosphorus at 10- to 20-cm depths (if phosphorus subroutine is run)
	Soil organic carbon in upper depths	Fresh plant residues or manure amounts and depth of incorporation
	Soil textural characterization for 10- to 20-cm depths	
	Surface water ponding capacity	
	Soil bulk density at 10- to 20-cm depths	
	Groundwater depth bypass flow fraction	

Source: Ritchie and Alagarswamy (2002).

Table 10.4. Crop management datasets required as inputs for crop simulation models.

Minimum	Optional
Crop cultivar characteristics	Row spacing
Planting date and depth	Row direction
Plant population density	Pesticide inputs
Irrigation inputs (date, amount, depth)	Harvest date
Fertilizer inputs (date, amount, type)	
Crop residues or manure inputs (dates, quality, amount)	

Source: Ritchie and Alagarswamy (2002).

The crop variety, genotype, or cultivars also must be specified; cultivars may vary significantly in the duration of developmental phases and in the partitioning of assimilates within the plant. Wheat and corn cultivar information is generally expressed as genetic coefficients, which allow models to simulate crop phenology over a wide range of latitudes and planting times.

Assessment of Biogeochemical Fluxes under Different Management Strategies Using SALUS

Nitrate Leaching Following Manure Application

Organic sources of N are often considered superior to inorganic fertilizers because they decompose slower and promote better soil structure and overall soil quality. However, there has been little field-based research to quantify nitrate leaching when animal manure is applied as the primary source of nutrients in intensive crop production systems. It is possible that when organic sources of N fertilizer are used, nitrate leaching may be greater than when using inorganic N because organic N is converted to inorganic N only slowly, so large quantities of organic N are needed to provide enough N to rapidly growing crop plants during the relatively short time of intense N uptake. More surplus N may then be mineralized and available for leaching at the end of the growing season.

Basso and Ritchie (2005) quantified N leaching from KBS plots receiving large quantities of either animal manure (18 ton ha^{-1} yr^{-1}) or inorganic N fertilizer (120 kg N ha^{-1} yr^{-1}) from January 1994 to December 1999 in a corn–alfalfa rotation. The results were used to validate the ability of SALUS to simulate nitrate leaching. Most of the water drainage occurred early in the season or after harvest and was lower during the growing period of the crop. SALUS provided a reasonable simulation of the amount of water drained and nitrate leached for both manure and inorganic N fertilizer over the 6 years of the study (Table 10.5). The manure plots leached 33% more N as nitrate (NO_3^-) than did the plots treated with inorganic N, illustrating the trade-off between the organic matter benefits of manure and a greater N loss to the environment (Millar and Robertson 2015, Chapter 9 in this volume). Field studies and the validated model results showed that leaching can be substantial if a high quantity of manure is applied to soils in autumn (Basso and Ritchie 2005, Beckwith et al. 1998, Chambers et al. 2000).

Soil Carbon Changes in Cropped and Unmanaged Ecosystems

Soil tillage has contributed significantly to the increase in atmospheric CO_2 that has occurred over the last two centuries (Wilson 1978). Historically, intensive tillage of agricultural soils has led to substantial losses of soil C, ranging from 30 to 50% of preconversion levels (Davidson and Ackerman 1993). These CO_2 losses are related to soil fracturing and opening, which facilitates the movement of CO_2 out of—and oxygen into—the soil (Reicosky 1997, Lal 2004), and especially to the destruction of soil aggregates (e.g., Grandy and Robertson 2006; Paul et al. 2015, Chapter 5 in this volume), which exposes otherwise protected organic matter to microbial attack. Although conventional moldboard plowing buries nearly all plant residue, it leaves the soil in a rough, loose, and open condition, which maximizes CO_2 loss and results in a consistent reduction in SOM. Reduced tillage results in more soil C retention or sequestration, which reduces its atmospheric release (Cole 1996, Paustian et al. 1998, Rasmussen et al. 1998).

Table 10.5. Comparison of SALUS simulations to field measurements for cropping systems with either inorganic nitrogen (N) or manure additions.

Variable	Inorganic N (140 kg ha^{-1})	Manure (18 ton ha^{-1})
Biomass (kg ha^{-1})		
Measured[a]	20,893	21,015
Simulated[a]	21,450	21,932
(RMSE[b])	450	645
Cumulative Nitrate Leaching[c] (kg NO_3-N ha^{-1})		
Measured	279	367
Simulated	273	362
RMSE[b]	15.7	14.3
Cumulative Drainage[c] (mm)		
Measured	1904	1857
Simulated	1901	1862
RMSE[b]	24.4	54.5

[a]Corn dry biomass harvested for silage (1997).
[b]RMSE = Root Mean Square Error.
[c]Nitrate leaching and drainage were measured and modeled over a 6-year (1994–1999) corn–alfalfa rotation at the W.K. Kellogg Biological Station south of the KBS LTER Main Cropping System Experiment (selected data from Basso and Ritchie 2005).

A major concern among producers is the possibility of yield reductions associated with permanent no-till management compared to conventional tillage (Grandy et al. 2006). Residue cover on the soil surface reflects solar radiation and acts as an insulator, slowing warming of the soils in the spring. This effect is more noticeable in temperate climates with wet and cool springs because high soil water content maintained by residue cover is combined with low incoming energy (Allmaras et al. 1977). Reicosky et al. (1977) reported that on poorly drained soils, corn yields were decreased because poorly drained soils are usually colder in the growing season due to higher water content. When vegetative corn development is delayed by lower soil temperature because of residue cover, yield can be lost due to a shortened growth period. However, residue cover can improve soil water availability by increasing infiltration, protecting the soil surface from erosion, and reducing evaporative losses. Thus, residue cover can improve yields in lower rainfall years and in drier locations (Basso et al. 2006, Bertocco et al. 2008).

SALUS was recently used to simulate soil carbon changes in different land use management practices, including tillage, at the KBS LTER (Senthilkumar et al. 2009; Paul et al. 2015, Chapter 5 in this volume). The simulations of soil C changes obtained using SALUS were consistent with measurements in the Conventional and No-till systems of the KBS Main Cropping System Experiment (Fig. 10.2). The model also simulated the observed large loss of soil C in fertilized, conventionally tilled plots in an adjacent experiment.

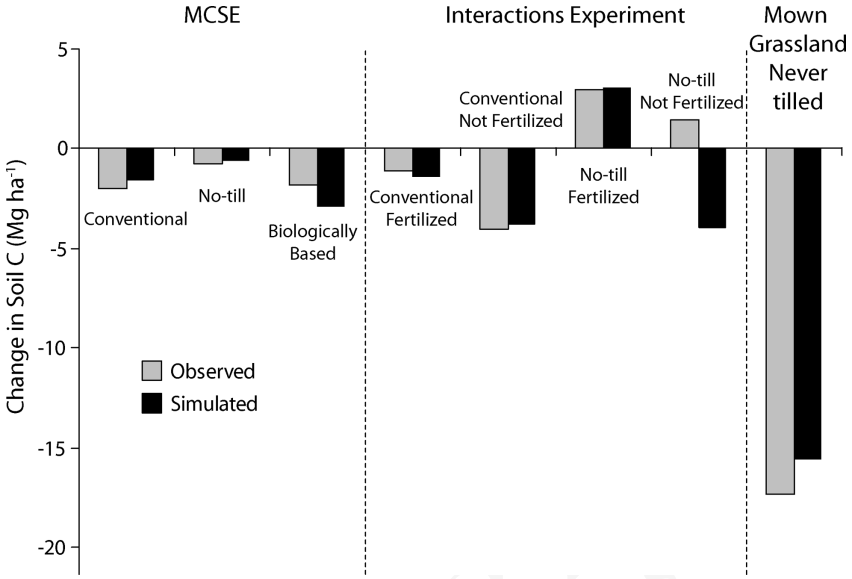

Figure 10.2. Measured and simulated changes in soil carbon after 18–21 years of different management systems at the KBS LTER Main Cropping System Experiment (MCSE) and at the Interactions Experiment, an adjacent continuous corn tillage (conventional vs. no-till) × nitrogen fertilizer (fertilized vs. not fertilized) experiment. Modified from Senthilkumar et al. (2009).

Linking Crop Models with Digital Terrain Analysis for Assessing Spatially Connected Processes

The assessment of soil water spatial patterns is crucial for understanding crop yield variation across the landscape. Soil water within a field is highly variable in space and time as a result of several processes that occur at different scales and because of complex interactions among weather, topography, soil, and vegetation. The effect of topographic convergence and divergence in natural landscapes has a major impact on soil water balance (Moore and Grayson 1991). Without consideration of the terrain characteristics, accurate simulation of soil water balance in entire, nonuniform fields is not possible. Spatial variability of soil water content is often the cause of yield variation over space and time. Accurate estimation of the spatial variability of soil water is also important for other applications including soil erosion, groundwater flow models, and precision agriculture.

The dynamics of soil water balance and crop growth have been extensively modeled to assess the risk associated with uncertainty in water availability (Jones et al. 1993). Soil–plant–atmosphere models often simulate vertical drainage but not lateral movement and water routing across the landscape (Basso 2000).

Existing digital terrain models are able to partition the landscape into a series of interconnected elements to spatially route water flow (Moore et al. 1993, Vertessy et al. 1993). Most digital terrain models fill the depressions in landscapes to provide

a continuous flow of water to streams, making their application for agricultural purposes limited. Basso (2000) created a spatial soil water balance model called SALUS-TERRAE that accounts for water pooling in depressions, surface and subsurface water movements, and the water runoff–runon mechanism occurring on the landscape. SALUS-TERRAE was developed by coupling the Ritchie vertical–soil–water balance model (Ritchie 1998) with TERRAE, a digital terrain model developed by Gallant and Basso (2013). SALUS-TERRAE is a spatial soil water balance model composed of vertical and lateral components of the water balance. The model requires a digital elevation map for partitioning the landscape into a series of interconnected irregular elements. Weather and soil information for the soil water balance simulation is also needed.

SALUS-TERRAE has been applied at a location in Michigan similar to the KBS LTER. Figure 10.3 shows the spatial variability of soil water content across the landscape the day after a rainfall event of 65 mm. SALUS-TERRAE was able to simulate the higher surface ponding capacities in the depression areas. The model performed well when compared to field measurements of soil water content for the entire growing season (Fig. 10.4): the root mean square error (RMSE) between measured and simulated results varied from 0.22 cm to 0.68 cm (Basso 2000, Batchelor et al. 2002). The net surface flow (Fig. 10.5) is the difference between the amount of water leaving each element (runoff) from that running onto the element (runon). The highest value (–5 cm) is observed at summit positions in the landscape since these elements do not have any water running into them. Application of the SALUS-TERRAE model can benefit precision agriculture by being able to select the appropriate management strategy for optimizing management practices across the landscape.

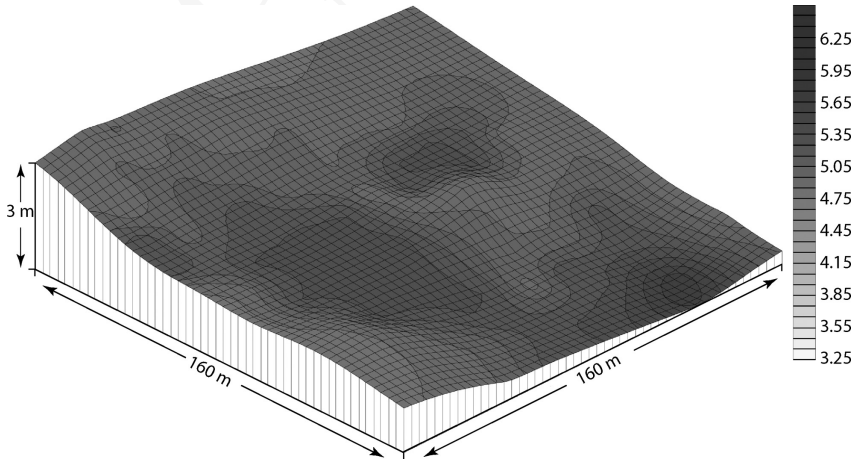

Figure 10.3. Simulated kriged map of soil water content (cm) for the surface (0–26 cm) soil layer using the digital terrain model SALUS-TERRAE in a sandy loam soil in Durand, Michigan. Redrawn from Basso (2000).

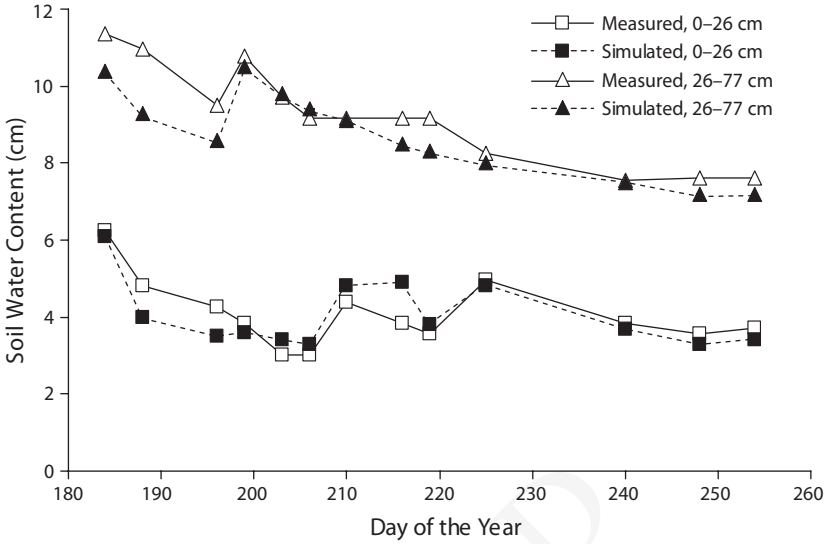

Figure 10.4. Measured and simulated water content for the soil profile (0–26 cm) and (26–77 cm) in the medium elevation zone (upper saddle) for the entire season in Durand, Michigan. Redrawn from Basso (2000).

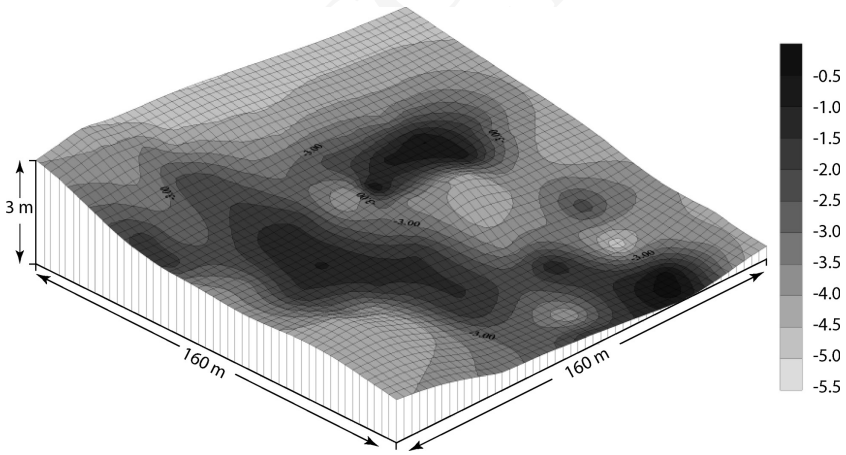

Figure 10.5. Simulated kriged map of net surface flow (cm) calculated as the difference between run-on and run-off using SALUS-TERRAE on a sandy loam soil in Durand, Michigan. Redrawn from Basso (2000).

A current limitation in most crop models is the assumption of uniform plant distribution. Yield variability at the field scale is the norm rather than the exception (Sadler et al. 1994; Basso et al. 2001, 2012b). Visual observations as well as measurements commonly indicate that crops are not uniformly distributed, and therefore assuming they are can be an unrealistic assumption and a significant source

of uncertainty in yield simulations. A correction procedure based on the extent of variation in plant stand uniformity or dominant plant density may be necessary. Correction also is required to compensate for yield loss from plants missing in a population; to some extent, neighboring plants can compensate for missing plants because they have more space to intercept light. Pommel and Bonhomme (1998) demonstrated the degree of compensation and losses from irregular stands in corn.

Summary

Simulation models are important for providing producers and policy makers with better decision-making capabilities. By predicting the response of different sustainability indicators to changes in crop management and climate, models can provide much needed information for designing sustainable cropping systems and landscapes. Functional models are particularly useful in that they integrate crop growth and yield with environmental responses such as nitrate leaching, carbon sequestration, erosion, and nitrous oxide emissions. It would be impossible for a single model to address all the issues regarding sustainable crop productivity or meet the goals of every researcher, planner, or policy maker. However, based on the successes of models like DSSAT, CENTURY, SALUS, and EPIC—along with continuing technological improvements—it is reasonable to expect development of more useful Decision Support System models to meet a growing range of demands. SALUS is promising because it has a crop model with several years of testing and is coupled with tested conservative simulations of soil C, N, and P models, allowing users to account for the impact of agronomic management on crop net primary productivity and on the environment. It also has tested capability to simulate climate change impact on production and the environment. The coupling with TERRAE makes SALUS a unique system with the capabilities of simulating the effects of topography and terrain attributes on water routing across the landscape.

References

Addiscott, T. M., and R. J. Wagenet. 1985. Concepts of solute leaching in soils: a review of modeling approaches. European Journal of Soil Science 36:411–424.

Allmaras, R. R., E. A. Hallauer, W. W. Nelson, and S. D. Evans. 1977. Surface energy balance and soil thermal property modifications by tillage induced soil structure. Technical Bulletin 306–1977, Minnesota Agricultural Experiment Station, University of Minnesota, Minneapolis, Minnesota, USA.

Basso, B. 2000. Digital terrain analysis and simulation modeling to assess spatial variability of soil water balance and crop production. Dissertation, Michigan State University, East Lansing, Michigan, USA.

Basso, B., M. Bertocco L. Sartori, and E. C. Martin. 2007. Analyzing the effects of climate variability on spatial pattern of yield in a maize-wheat-soybean rotation. European Journal of Agronomy 26:82–91.

Basso, B., D. Cammarano, A. Troccoli, D. Chen, and J. T. Ritchie. 2010. Long-term wheat response to nitrogen in a rainfed Mediterranean environment: field data and simulation analysis. European Journal of Agronomy 33:132–138.

Basso, B., and J. T. Ritchie. 2005. Impact of compost, manure and inorganic fertilizer on nitrate leaching and yield for a 6-year maize-alfalfa rotation in Michigan. Agriculture, Ecosystems & Environment 108:329–341.

Basso, B., J. T. Ritchie, D. Cammarano, and L. Sartori. 2011. A strategic and tactical management approach to select optimal N fertilizer rates for wheat in a spatially variable field. European Journal of Agronomy 35:215–222.

Basso, B., J. T. Ritchie, P. R. Grace, and L. Sartori. 2006. Simulation of tillage systems impacts on soil biophysical properties using the SALUS model. Italian Journal of Agronomy 4:677–688.

Basso, B., J. T. Ritchie, and J. W. Jones. 2012a. On modeling approaches for effective assessment of hydrology of bioenergy crops: comments on Le at al. (2011) Proc Natl Acad Sci USA 108:15085–15090. European Journal of Agronomy 38:64–65.

Basso, B., J. T. Ritchie, F. J. Pierce, R. P. Braga, and J. W. Jones. 2001. Spatial validation of crop models for precision agriculture. Agricultural Systems 68:97–112.

Basso, B., L. Sartori, D. Cammarano, P. Grace, C. Sorensen, and S. Fountas. 2012b. Environmental and economic evaluation of N fertilizer rates in a maize crop in Italy: a spatial and temporal analysis using crop models. Biosystems Engineering 113:103–111.

Batchelor, W. D., B. Basso, and J. O. Paz. 2002. Examples of strategies to analyze spatial and temporal yield variability using crop models. European Journal of Agronomy 18:141–158.

Beck, H. W., P. Jones, and J. W. Jones. 1989. SOYBUG: an expert system for soybean insect pest management. Agricultural Systems 30:269–286.

Beckwith, C. P., J. Cooper, K. A. Smith, and M. A. Shepherd. 1998. Nitrate leaching loss following application of organic manures to sandy soils in arable cropping. Soil Use and Management 14:123–130.

Bertocco, M., B. Basso, L. Sartori, and E. C. Martin. 2008. Evaluating energy efficiency of site-specific tillage in maize in NE Italy. Bioresource Technology 99:6957–6965.

Boggess, W. G., P. J. van Blokland, and S. D. Moss. 1989. FinARS: a financial analysis review expert systems. Agricultural Systems 31:19–34.

Chambers, B. J., K. A. Smith, and B. F. Pain 2000. Strategies to encourage better use of nitrogen in animal manures. Soil Use and Management 16:157–166.

Cole, C. V. K. 1996. Agricultural options for mitigation of greenhouse gas emissions. Pages 746–771 in R. T. Watson, M. C. Zinyowera, and R. H. Moss, editors. Climate change 1995: impacts, adaptations and mitigation of climate change. Scientific-technical analysis. Contribution of Working Group II to the Second Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK.

Davidson, E. A., and I. L. Ackerman. 1993. Changes in soil carbon inventories following cultivation of previously untilled soils. Biogeochemistry 20:161–193.

Del Grosso, S. J., W. J. Parton, A. R. Mosier, D. S. Ojima, A. E. Kulmala, and S. Phongpan. 2000a. General model for N2O and N2 gas emissions from soils due to denitrification. Global Biogeochemical Cycles 14:1045–1060.

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

Del Grosso, S. J., W. J. Parton, A. R. Mosier, D. S. Walsh, D. S. Ojima, and P. E. Thornton. 2006. DAYCENT national scale simulations of N_2O emissions from cropped soils in the USA. Journal of Environmental Quality 35:1451–1460.

Evans, L. T. 1993. Crop evolution, adaptation, and yield. Cambridge University Press, Cambridge, UK.

FAO (Food and Agriculture Organization of the United Nations). 2011. Save and grow: a policymaker's guide to the sustainable intensification of smallholder crop production. FAO, Rome, Italy.

Gage, S. H., J. E. Doll, and G. R. Safir. 2015. A crop stress index to predict climatic effects on row-crop agriculture in the U.S. North Central Region. Pages 77–103 in S. K. Hamilton, J. E. Doll, and G. P. Robertson, editors. The ecology of agricultural ecosystems: long-term research on the path to sustainability. Oxford University Press, New York, New York, USA.

Gallagher, J. N. 1979. Ear development: processes and prospects. Pages 3–9 in J. H. J. Spiertz and T. H. Kramer, editors. Crop physiology and cereal breeding. PUDOC, Wageningen, The Netherlands.

Gallant, J. C., and B. Basso. 2013. Creating a flow-oriented modeling mesh using the stream function. Page 346 in J. Piantadosi, R. S. Anderssen, and J. Boland, editors. Adapting to change: the multiple roles of modelling. 20th International Congress on Modelling and Simulation (MODSIM2013). Adelaide, Australia.

Gijsman, A. J., G. Hoogenboom, W. J. Parton, and P. C. Kerridge. 2002. Modifying DSSAT crop models for low-input agricultural systems using a soil organic matter-residue module from CENTURY. Agronomy Journal 94:462–474.

Godwin, D. C., and U. Singh. 1998. Nitrogen balance and crop response to nitrogen in upland and low-land cropping systems. Pages 55–78 in G. Y. Tsuji, G. Hoogenboom, and P. K. Thornton, editors. Understanding options for agricultural production. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Grandy, A. S., and G. P. Robertson. 2006. Initial cultivation of a temperate-region soil immediately accelerates aggregate turnover and CO_2 and N_2O fluxes. Global Change Biology 12:1507–1520.

Grandy, A. S., G. P. Robertson, and K. D. Thelen. 2006. Do productivity and environmental trade-offs justify periodically cultivating no-till cropping systems? Agronomy Journal 98:1377–1383.

Jones, J. W., W. T. Bowen, W. G. Boggess, and J. T. Ritchie. 1993. Decision support systems for sustainable agriculture. Pages 123–138 in Technologies for sustainable agriculture in the tropics. ASA Special Publication 56. ASA, CSSSA, and SSSA, Madison, Wisconsin, USA.

Keating, B. A., P. S. Carberry, G. L. Hammer, M. E. Probert, M. J. Robertson, D. Holzworth, N. I. Huth, J. N. G. Hargreaves, H. Meinke, Z. Hochman, G. McLean, K. Verburg, V. Snow, J. P. Dimes, M. Silburn, E. Wang, S. Brown, K. L. Bristow, S. Asseng, S. Chapman, R. L. McCown, D. M. Freebairn, and C. J. Smith. 2003. An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy 18:267–288.

Lal, R. 2004. Soil carbon sequestration impacts on global climate change and food security. Science 304:1623–1627.

Li, C. 1995. Impact of agricultural practices on soil C storage and N_2O emissions in 6 states in the US. Pages 101–112 in R. Lal, J. Kimble, E. Levine, and B. A. Stewart, editors. Soil management and greenhouse effect, Advances in soil science, CRC Press, Boca Raton, Florida, USA.

Li, C. 2000. Modeling trace gas emissions from agricultural ecosystems. Nutrient Cycling in Agroecosystems 58:259–276.

McCown, R. L., G. L. Hammer, J. N. G. Hargreaves, D. P. Holzworth, and D. M. Freebairn. 1996. APSIM: a novel software system for model development, model testing and simulation in agricultural system research. Agricultural Systems 50:255–271.

Michalski, R. S., J. H. Davis, V. S. Bisht and J. B. Sinclair. 1983. A computer-based advisory system for diagnosing soybean diseases in Illinois. Plant Disease 4:459–463.

Millar, N., and G. P. Robertson. 2015. Nitrogen transfers and transformations in row-crop ecosystems. Pages 213–251 in S. K. Hamilton, J. E. Doll, and G. P. Robertson, editors. The ecology of agricultural ecosystems: long-term research on the path to sustainability. Oxford University Press, New York, New York, USA.

Monteith, J. L. 1977. Climate and the efficiency of crop production in Britain. Philosophical Transactions of the Royal Society of London B 281:277–294.

Moore, I. D., P. E. Gessler, G. A. Nielsen, and G. A. Peterson. 1993. Soil attribute prediction using terrain analysis. Soil Science Society of America Journal 57:443–452.

Moore, I. D., and R. B. Grayson. 1991. Terrain-based catchment partitioning and runoff prediction using vector elevation data. Water Resources Research 27:1177–1191.

Muchow, R. C., and T. R. Sinclair. 1991. Water deficit effects on maize yields modeled under current and "greenhouse" climates. Agronomy Journal 83:1052–1059.

Muchow, R. C., T. R. Sinclair, and J. M. Bennett. 1990. Temperature and solar radiation effects on potential maize yield across locations. Agronomy Journal 82:338–343.

Parton, W. J., M. D. Hartman, D. S. Ojima, and D. S. Schimel. 1998. DAYCENT and its land surface submodel: description and testing. Global and Planetary Change 19:35–48.

Parton, W. J., E. A. Holland, S. J. Del Grosso, M. D. Hartman, R. E. Martin, A. R. Mosier, D. S. Ojima, and D. S. Schimel. 2001. Generalized model for NO_x and N_2O emissions from soils. Journal of Geophysical Research-Atmospheres 106:17403–17419.

Parton, W. J., A. R. Mosier, D. S. Ojima, D. W. Valentine, D. S. Schimel, and K. Weier. 1996. Generalized model for N_2 and N_2O production from nitrification and denitrification. Global Biogeochemical Cycles 10:401–412.

Parton, W. J., D. S. Schimel, C. V. Cole, and D. S. Ojima. 1987. Analysis of factors controlling soil organic matter levels in Great Plains Grasslands. Soil Science Society of America Journal 51:1173–1179.

Parton, W. J., J. W. B. Stewart, and C. V. Cole. 1988. Dynamics of C, N, P, and S in grassland soils: a model. Biogeochemistry 5:109–131.

Paul, E. A., A. Kravchenko, A. S. Grandy, and S. Morris. 2015. Soil organic matter dynamics: controls and management for sustainable ecosystem functioning. Pages 104–134 in S. K. Hamilton, J. E. Doll, and G. P. Robertson, editors. The ecology of agricultural ecosystems: long-term research on the path to sustainability. Oxford University Press, New York, New York, USA.

Paustian, K., E. T. Elliott, and K. Killian. 1998. Modeling soil carbon in relation to management and climate change in some agroecosystems in central North America. Pages 459–471 in R. Lal, J. M. Kimble, R. F. Follett, and B. A. Stewart, editors. Soil processes and the carbon cycle. Advances in Soil Science. CRC Press, Boca Raton, Florida, USA.

Plant, R. E. 1989. An integrated expert decision support system for agricultural management. Agricultural Systems 29:49–66.

Pommel, B., and R. Bonhomme. 1998. Variations in the vegetative and reproductive systems in individual plants of a heterogeneous maize crop. European Journal of Agronomy 8:39–49.

Rasmussen, P. E., K. W. T. Goulding, J. R. Brown, P. R. Grace, H. H. Janzen, and M. Korschens. 1998. Long-term agroecosystem experiments: assessing agricultural sustainability and global change. Science 282:893–896.

Reicosky, D. C. 1997. Tillage-induced CO_2 emission from soil. Nutrient Cycling in Agroecosystems 49:273–285.

Reicosky D. C., D. K. Cassel, R. L. Blevins, W. R. Gill, and G. C. Naderman. 1977. Conservation tillage in the southeast. Journal of Soil Water Conservation 32:13–20.

Ritchie, J. T. 1995. International consortium for agricultural systems applications (ICASA): establishment and purpose. Agricultural Systems 49:329–335.

Ritchie, J. T. 1998. Soil water and plant stress. Pages 41–54 in G. Y. Tsuji, G. Hoogenboom, and P. K. Thorton, editors. Understanding options for agricultural production. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Ritchie, J. T., and G. Alagarswamy. 2002. Overview of crop models for assessment of crop production. Pages 43–68 in O. C. Doering III, J. C. Randolph, J. Southworth, and R. A. Pfeifer, editors. Effects of climate change and variability on agricultural production systems. Kluwer Academic Publishing, Dordrecht, The Netherlands.

Ritchie, J. T., and D. S. NeSmith. 1991. Temperature and crop development. Pages 6–29 in J. T. Ritchie and H. J. Hanks, editors. Modeling plant and soil systems. American Society of Agronomy, Madison, Wisconsin, USA.

Ritchie, J. T., U. Singh, D. C. Godwin, and W. T. Bowen. 1998. Cereal growth, development and yield. Pages 79–98 in G. Y. Tsuji, G. Hoogenboom, and P. K. Thornton, editors. Understanding options for agricultural production. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Rivington, M., and J. Koo. 2010. Report on the meta-analysis of crop modelling for climate change and food security survey. CGIAR Research Program on Climate Change, Agriculture and Food Security, Copenhagen, Denmark. <http://cgspace.cgiar.org/handle/10568/10255>

Robertson, G. P., and R. R. Harwood. 2013. Sustainable agriculture. Pages 111–118 in S. A. Levin, editor. Encyclopedia of biodiversity. Second edition. Volume 1. Academic Press, Waltham, Massachusetts, USA.

Sadler, E. J., P. J. Bauer, and W. J. Busscher. 1994. Spatial corn yield during drought in the SE coastal plain. Pages 365–381 in P. C. Robert, R. H. Rust, and W. E. Larsen, editors. Site-specific management for agricultural systems. Proceedings of Second International Conference, ASA-SSA-CSSA, Minneapolis, Minnesota, USA.

Senthilkumar, S., B. Basso, A. N. Kravchenko, and G. P. Robertson. 2009. Contemporary evidence for soil carbon loss in the U.S. corn belt. Soil Science Society of America Journal 73:2078–2086.

Sinclair, T. R., and R. C. Muchow. 1995. Effects of nitrogen supply on maize yields: I. Modeling physiological responses. Agronomy Journal 87:632–641.

Stockle, C. O., S. A. Martin, and G. S. Campbell. 1994. CropSyst, a cropping systems model: water/nitrogen budgets and crop yield. Agricultural Systems 46:335–339.

Thompson, L. M. 1969. Weather and technology in production of corn in US corn belt. Agronomy Journal 61:453–456.

Thompson, L. M. 1986. Climate change, weather variability, and corn production. Agronomy Journal 78:649–653.

Tsuji, G. Y., G. Hoogenboom, and F. C. Thornton, editors. 1998. Understanding options for agricultural production. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Vertessy, R. A., J. T. Hatton, P. J. O'Shaughnessy, and M. D. A. Jayasuriya. 1993. Predicting water yield from a mountain ash forest catchment using a terrain analysis based catchment model. Journal of Hydrology 150:665–700.

Vinocur, M. G., and J. T. Ritchie. 2001. Maize leaf development biases caused by air-apex temperature differences. Agronomy Journal 93:767–772.

White, I., and M. J. Sully. 1989. Use of hydrological robustness of time-to-incipient-ponding. Soil Science Society of America Journal 53:1343–1346.

Williams, J. R. 1995. The EPIC model. Pages 909–1000 in V. P. Singh, editor. Computer models of watershed hydrology. Water Research Publications, Highlands Ranch, Colorado, USA.

Williams, J. R., C. A. Jones, and P. T. Dyke. 1984. A modeling approach to determining the relationship between erosion and soil productivity. Transactions of the ASAE 27:129–144.

Williams, J. R., C. A. Jones, J. R. Kiniry, and D. A. Spanel. 1989. The EPIC crop growth model. Transactions of the ASAE 32:479–511.

Wilson, A. T. 1978. The explosion of pioneer agriculture: contribution to the global CO_2 increase. Nature 273:40–41.