ELSEVIER

Geoderma 79 (1997) 227–260

GEODERMA

The use of models to integrate information and understanding of soil C at the regional scale

Keith Paustian [a,*], Elissa Levine [b], Wilfred M. Post [c], Irene M. Ryzhova [d]

[a] *Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, CO 80523, USA*
[b] *NASA's Goddard Space Flight Center, Biospheric Sciences Branch, Greenbelt, MD 20771, USA*
[c] *Environmental Sciences Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831, USA*
[d] *Department of Soil Sciences, Moscow State University, 119899, Moscow, Russia*

Revised 7 October 1996; accepted 9 April 1997

Abstract

Regional analysis of ecosystem properties, including soil C, is a rapidly developing area of research. Regional analyses are being used to quantify existing soil C stocks, predict changes in soil C as a function of changing landuse patterns, and assess possible responses to climate change. The tools necessary for such analyses are simulation models coupled with spatially-explicit databases of vegetation, soils, topography, landuse and climate. A general framework for regional analyses which integrates models with site-specific and spatially-resolved data is described. Two classes of models are currently being used for analyses at regional scales, ecosystem-level models, which were originally designed for local scale studies, and more aggregated 'macro-scale' models developed for continental and global scale applications. A consideration in applying both classes of models is the need to minimize errors associated with aggregating information to apply to coarser spatial and temporal scales. For model input data, aggregation bias is most severe for variables which enter into non-linear model functions, such as soil textural effects on organic matter decomposition and water balance or the temperature response of decomposer organisms. Aggregation of model structure also needs to be considered, particularly for macro-scale models. For example, representations of litter and soil organic matter by only one or two pools may be suitable for representing equilibrium conditions but rates of change will tend to be overestimated for transient-state conditions using highly aggregated models. Geographic soils data, derived from field surveys, are a key component for regional analyses. Issues of data quality and interpretation of soil survey data are discussed in the context of regional analyses of soil C. Areas for further

* Corresponding author. Fax: +1 970 491-1965; E-mail: keithp@nrel.colostate.edu

PII S0016-7061(97)00043-8

development of data and modeling capabilities, including refining soil C maps, developing spatial databases on landuse and management practices, using remotely sensed data in regional model applications, and linking terrestrial ecosystem models with global climate models, are discussed.

Keywords: simulation modelling; soil organic matter; scaling; spatial aggregation; climate change; remote sensing; GIS

1. Introduction

An understanding of the distribution and dynamics of soil C at the regional level is an important step in quantifying regional and global C balances and in assessing the responses and feedbacks of terrestrial ecosystems to climate change. Soils constitute the major land surface C reservoir, ~ 1600 Gt C, which is roughly three times the amount of C contained in the terrestrial biomass (Sundquist, 1993). Soil C levels are controlled by a variety of climatic and biogeophysical factors, but in addition, they are highly influenced by landuse practices, in particular by the conversion of native ecosystems to agricultural use (Post and Mann, 1990; Davidson and Ackerman, 1993; Paustian et al., 1997a). Thus, both environmental and human factors need to be incorporated into methodologies for predicting regional soil C changes.

In this paper we review current methodologies which are applicable for regional analyses of soil C, focusing on the use of simulation models linked to georeferenced databases. Over the past twenty years, a number of estimates of regional and global soil C stocks have been made based on extrapolations from measured data (Schlesinger, 1977; Post et al., 1982; Eswaran et al., 1993). While efforts to refine these estimates will continue, purely empirical approaches are limited in their ability to assess future changes in soil C which are likely to occur as a result of changes in climate, atmospheric CO_2 enrichment and the pattern and intensity of landuse. Thus, models which can integrate the principle mechanisms governing the turnover of soil C are needed for making projections of soil C change. Models can also be used to couple terrestrial processes with atmosphere and hydrosphere components of the global system.

Methodologies for regional scale analyses of soil C need not be specific to any particular region of the world. However, their application will be differentially constrained according to data availability and the degree of understanding of a particular system, as embodied in the model functions. There are still relatively few examples of regional-scale analyses of soil C using dynamic models and spatially-resolved input data, and nearly all such studies have dealt with temperate systems (Parton et al., 1987; Pastor and Post, 1988; Burke et al., 1994; Donigian et al., 1994; Paustian et al., 1997b). There have also been global- and continental-scale analyses (Esser, 1992; Potter et al., 1993; VEMAP, 1995; King et al., 1997), using conceptually similar approaches. Although many of the examples cited in this paper are from temperate zone studies, most of the concepts may apply equally to the tropics.

In this paper, we outline a general framework for making regional analyses of soil C change and we evaluate different modeling approaches. We consider questions of scale, data and model aggregation and the evaluation of error and uncertainty as they pertain to regional analyses of soil C. We address regional and global soils databases, primarily in the context of providing information to initialize and validate soil C models. Finally, we discuss several emerging issues concerning prediction of soil C responses to global change including (i) refining empirically-derived soil C maps, (ii) predicting the impacts of landuse change, (iii) using remotely sensed data in modeling studies, and (iv) interfacing terrestrial system models with global climate models.

2. A general framework for regional analyses of soil C

Regional analysis of soil C requires the integration of dynamic models, which represent the feedbacks and interactions between soil processes, with information about the biotic and abiotic variables which drive these soil processes. Empirical data on soil C dynamics, applicable to the region under study, is also needed to evaluate model performance. A general framework for the integration of these elements of regional analysis was proposed by Elliott and Cole (1989). In this approach, there are four main components (Fig. 1). Process studies (I) include experimental work and theory development about the processes (and their controls) which influence soil C dynamics. Such processes could include decomposition, nutrient mineralization/immobilization, soil heat and water flux, inorganic chemical equilibria and vegetation dynamics. This knowledge is embodied in a systems model (II) which integrates the processes controlling soil C and its changes over time. Controlling factors which are considered as being exogenous to the system are referred to as driving variables, and include such 'geographic' data (III) as climate, soil factors (e.g., soil texture, mineralogy), topography, land cover and landuse. Within a region, these factors vary spatially (and temporally) and thus geographic information system (GIS) technologies have emerged as a means of organizing such information. In addition to supplying driving variables, geographic information can provide validation data, such as regional maps of soil C distribution, which can be compared with model outputs. Geographic information can consist of empirical data or data generated from another model, e.g., climate station records versus climate model output. Several issues dealing with geographic information such as soil C maps and remotely-sensed data are discussed later in the paper. Finally, site-specific data from detailed field experiments on soil C dynamics provide high quality information for validating model behavior. When this information is organized into 'site networks' (IV) where different climate regimes, soil types and land

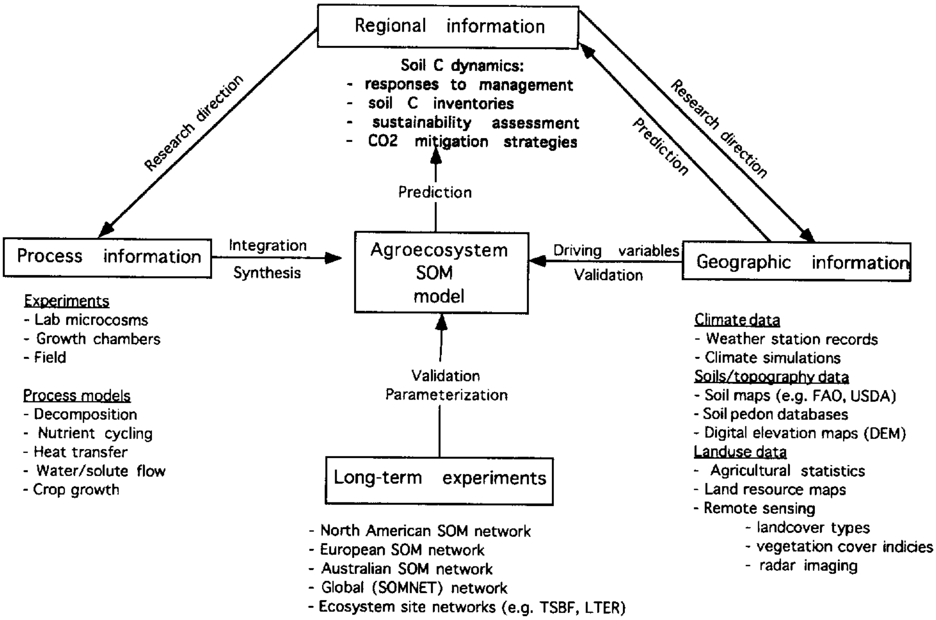

Fig. 1. A framework for regional analysis showing the integration of process information, site networks of long-term field experiments and spatially-resolved geographic information with system models to predict soil C dynamics. Derived from Elliott and Cole (1989) and Paustian et al. (1995).

management practices are represented, then the validity and generality of the model can be evaluated over the range of conditions existing within the region. Several such site networks of existing long-term experiments have recently been organized for North America (Paustian et al., 1995; Elliott and Paustian, 1996; Paul et al., 1997), Australia (Martin et al., 1995; Grace, 1996) and Europe (Smith et al., 1996a) and organization of a global field experiment network, SOMNET, is currently ongoing (Smith et al., 1996b). Other examples of networked research projects which can provide this kind of information include the Tropical Biology and Fertility Programme (TSBF) and the US Long-Term Ecological Research (LTER) Program.

In the remainder of this paper we discuss some different types of soil C models, implications of scale, aggregation and model resolution, and the use of spatially-resolved data which can be integrated with models to make regional projections of soil C dynamics.

3. Approaches to modeling soil C

Much of our current understanding of soil behavior, including organic matter dynamics, stems from the broad, regional-scale perspectives of pioneer pedologists such as Dokuchaev, Hilgard, Jenny and others. Their comparative studies of soil properties as determined by climate, parent material, biota, topography and time attempted to generalize patterns of soil properties from local to global scales. Ironically, it is only recently that quantitative models of soil organic matter and nutrient dynamics have begun to be applied to the kinds of regional-scale questions posed by the classical pedologists. For the most part, these models were originally developed to investigate questions of ecosystem behavior at the site or 'patch' level (e.g., a forest stand, a maize field, a pasture). Implicit in their formulation is the assumption that driving variables such as climate and soil properties are homogeneous across the land area of the patch.

The relatively recent interest in applying models to regional and global level questions of soil C dynamics has led to the emergence of two basic modeling approaches, which we refer to as 'ecosystem-level' models and 'macro-scale' models. The first category refers to models which were originally developed to simulate ecosystem processes at local scales but which are increasingly being applied at regional scales. The latter group refers to a class of models which have been developed primarily for global modeling in which the spatial scale is defined as a latitudinal–longitudinal grid cell. We recognize that spatial scales form a continuum, allowing for a potentially infinite number of model spatial resolutions. However, we maintain that the development and application of soil and ecosystem models have led to a more or less dichotomous grouping. To illustrate these two approaches, we have selected only a few of the many models which consider soil C dynamics.

3.1. Ecosystem-level models

Most existing soil C models are inherently fine-scale, on the order of square meters or hectares, in their original design concept. Most can be characterized as one-dimensional in that they consider only soil variability with depth, in order to account for differences between soil horizons. Many are structurally complex and consider multiple organic matter fractions to account for variability in the decomposability of different organic compounds. Most of the models assume that decomposition follows first-order kinetics, i.e., a constant fractional loss per unit time, of different organic matter fractions, with the potential rate being modified by a variety of soil environmental conditions (Paustian, 1994). In general, a relatively large number of rate controls representing soil environmental conditions are considered in these models, including soil temperature, soil moisture, pH, soil texture, nutrient concentrations, as well as other factors such as litter composition and disturbance regimes. The model time steps range from daily to annual.

The relatively detailed structure of these models are indicative of their original development for ecosystem-level investigations, with applications in relatively data-rich environments. Three models which fall into this grouping but which have been used extensively for regional level applications are described below (Table 1).

Table 1
Summary of structure and characteristics of some models used for regional analyses of soil C

Model	Soil C pools	MRT (year) [a]	Spatial scale [b]	Main drivingvariables
Century	Metabolic litter	0.07	m^2	Monthly temperature and precipitation, soil texture, litter lignin and N content
	Structural litter	0.7		
	Active SOM	0.4		
	Slow SOM	6.5		
	Passive SOM	200		
Rothamsted	Easily decomposable litter	0.05	m^2	Monthly temperature and precipitation, pan evaporation, CEC (clay), vegetation cover
	Resistant litter	2		
	Zymogenous soil biomass	0.9		
	Authochtonous biomass	0.9		
	Humus	29		
	Inert organic matter	not defined		
Linkages	Leaf litter cohorts	1.5–5	833 m^2	Temperature, precipitation, soil water capacity, tree species composition
	Woody litter-fine	5		
	Woody litter-medium	10		
	Woody litter-coarse	33		
	Well-decomposed wood	20		
	Humus	26–51		
TEM	Total soil C	8–21	0.5°×0.5°	Temperature, soil moisture, soil texture
Osnäbruck	Herbaceous litter	0.7	2.5°×2.5°	Temperature, precipitation, soil type
	Woody litter	2		
	SOM C	68		

We classify the first three as ecosystem-level models and the last two as macro-scale models.
[a] Mean residence time (under steady-state conditions) represents $1/k_i$ where k_i is the specific decomposition rate constant under optimal conditions (i.e., without temperature, moisture or other limitation).
[b] Represents the inherent spatial scale in the model design and initial applications.

The Century model (Parton et al., 1987, 1988, 1994) is an ecosystem model that simulates soil C, N, P and S dynamics, primary productivity and water balance at monthly time steps. It was originally designed to analyze soil organic matter dynamics in grassland soils over periods up to several thousand years (Parton et al., 1987). Subsequent model modifications have expanded its applicability to agricultural systems (Cole et al., 1989; Paustian et al., 1992; Metherell et al., 1995), forests (Sanford et al., 1991) and savanna systems (Seward and Woomer, 1993; Woomer, 1993). It includes two litter fractions (metabolic and structural) and three organic matter fractions (active, slow, passive) differing in inherent decomposability and in the degree to which soil texture effects turnover rates. The principle driving variables are monthly minimum and maximum temperature and monthly precipitation. Other important soil process rate controls are soil texture, litter lignin and N content and tillage disturbance.

The Rothamsted soil C model (Jenkinson and Rayner, 1977; Jenkinson et al., 1987; Jenkinson, 1990) simulates soil C dynamics, using C inputs from primary productivity as an external driving variable, with monthly time steps. The model was originally designed for use in agricultural soils, in particular for analysis and interpretation of soil C changes in the classical long-term plots at Rothamsted (Jenkinson and Rayner, 1977). The model (Jenkinson et al., 1987; Jenkinson, 1990) consists of two litter fractions (decomposable and resistant) and four soil organic matter fractions (zymogenous and autochthonous microbial biomass, humus and inert organic matter). The principle driving variables are mean monthly temperature, precipitation, and pan evaporation (for calculation of soil moisture). Soil texture influences C turnover, with the influence of texture defined by inorganic cation exchange capacity (CEC), which depends on clay content and mineralogy. Litter quality is defined as the proportion of decomposable versus resistant material, based on calibrations of short-term (e.g., 1–5 years) decomposition experiments of different plant materials. Decomposition is reduced under vegetated conditions, compared to bare soil conditions.

The Linkages model (Pastor and Post, 1986; Pastor and Post, 1988) is a forest growth–biogeochemical model which simulates C and N pools and fluxes over the course of forest succession. Because litter chemistry varies with vegetation composition, the decomposition of specific litter cohorts is modeled. This differs from the 'lumped' pool approach for litter decomposition in the two models described above. The decomposition rate of a specific litter cohort is a function of evapotranspiration, a canopy gap factor (for microclimate effects), lignin and N content and species-specific constants. At a certain stage of decomposition, defined by a critical $C:N$ ratio for each litter type, net N mineralization begins and the remaining mass in the litter cohort is then transferred into a single humus pool. Decomposition rate of the soil humus pool is controlled by the $C:N$ ratio of the humus, the gap/microclimate factor and a potential rate constant. The model operates on monthly and annual time steps. The driving variables are monthly temperature and precipitation and soil water holding capacity (i.e., field capacity and wilting point moisture).

3.2. Macro-scale models

The growth of global-level studies of biogeochemistry, vegetation dynamics and climate has led to the development of another class of models which address soil C change at very large spatial resolutions, typically thousands of square kilometers. The primary objective of most of these models has been to model global vegetation patterns and net C fluxes to and from terrestrial ecosystems. In most instances their spatial dimensions are defined by latitude–longitude grid cells. Compared to the ecosystem models described above, they have a simpler structure (i.e., fewer plant, litter and soil components) and they employ more general or 'lumped' rate controlling factors (e.g., precipitation, temperature, 'soil type'). Arguably, process rates tend to be more empirical (e.g., regression-like) in their formulation compared to ecosystem-level models. Attributes of two of these models, the Terrestrial Ecosystem model (TEM) and the Osnäbruck model are described in Table 1.

The TEM model (Raich et al., 1991; Melillo et al., 1993) is designed to simulate major C and N fluxes and pools at continental and global scales, based on $0.5 \times 0.5°$ latitude–longitude grid cells, with a monthly temporal resolution. It has been used to simulate patterns of net primary production (NPP) and net C flux for South America (Raich et al., 1991). It is designed to operate in conjunction with a global water balance model (Vörösmarty et al., 1989) which provides soil moisture and evapotranspiration rates as driving variables to TEM. A single detrital component (litter + SOM) is included and C levels and other variables are assumed to be uniform within the grid cell. The main external controls on decomposition rates are temperature and soil moisture, where moisture effects on decomposition are also a function of soil texture, for which five textural classes (sand, sandy loam, loam, clay loam and clay) are considered. The specific decomposition rate constant is determined by model calibration on each specific vegetation type.

The Osnäbruck model (Esser, 1987, 1989, 1992) was designed to model global vegetation patterns and C pools and fluxes of the biosphere. It has been used to model changes in global NPP and C flux associated with historical landuse patterns (Esser, 1989) and in response to global climate change and CO_2 fertilization (Esser, 1990, 1992). The basic spatial resolution is a $2.5 \times 2.5°$ grid cell, but with multiple types of land cover represented as fractional areas within each grid cell. The model operates on an annual time step. It includes herbaceous and woody litter pools and lignin derived from litter, which is used as a surrogate for soil organic matter. Litter lignin contents, 30% for wood and 11% for herbaceous litter, determine the C inputs to soil organic matter. Litter production (i.e., C inputs to detrital pools) are determined by the balance of NPP and the net change in standing biomass C, which are calculated in separate functions driven by temperature, precipitation, CO_2, a soil fertility factor and mean stand age. Specific decomposition rates for herbaceous and woody litter and lignin (SOM) are modified by the minimum of either temperature and precipitation limitations.

4. Implications of scale: model and data aggregation

The standard approach to regional analysis is to define a subdivision of geographic areas for which unique sets of driving variables (e.g., climate, soil properties and landuse) are derived and then supplied to the model. Most regional/global studies treat each spatial unit as independent, i.e., there are no interacting processes connecting them. An obvious limitation of this approach is that 'horizontal' fluxes such as water, soil (i.e., erosion) and gaseous element transfers between geographic areas cannot be explicitly represented. Models which incorporate such two-dimensional processes have been developed for ecosystem and landscape (e.g., watershed) level applications but to our knowledge these approaches have yet to be applied to regional modeling of soil C dynamics. While this represents an important future challenge, our focus in this paper will be on existing approaches to regional modeling which assume spatial independence.

The temporal and spatial resolutions of both model and data and how they are integrated have a major influence on the error and uncertainty of regional estimates. For ecosystem-level models, applications to areas larger than their inherent scale (Table 1) is necessary for practical application at regional scales. While macro-scale models, by definition, operate at regional scales, the data required to run them may or may not be obtained at a commensurate scale. In addition, the theory basis for coarse-scale models is generally derived from fine-scale knowledge (Rastetter et al., 1992). Thus, in either case, aggregation of data, models or both is necessary, although the main issues concerning aggregation are somewhat different for models operating at different scales. Aside from fundamental issues of data and model validity, the key question for applying ecosystem-level models to regional predictions is whether the degree of spatial and temporal aggregation of data is commensurate with model formulations. For macro-scale models, the fundamental questions concern both model aggregation (i.e., can the factors that control SOM dynamics be successfully captured at regional levels of resolution), as well as the acquisition and representation of data (for model inputs) at coarse spatial and temporal resolutions.

4.1. Ecosystem-level models

Soil C models have developed within the disciplines of ecosystem ecology and soil science, where the concepts, experimentation and data used to derive these models pertained to fine spatial scales (on the order of square meters or hectares), for which assumptions of spatial homogeneity in climate and soil conditions were considered defensible. As these models are applied at coarser spatial scales it is important to examine how the model responds to increasing departures from these assumptions of homogeneity. It is well recognized that the degree to which model relationships are non-linear has a large impact on the magnitude of error introduced by aggregation (O'Neill, 1979; King et al., 1991; Rastetter et al., 1992). For a non-linear function, the value of the function evaluated at the mean of two or more function arguments (i.e., aggregated variables) is not equal to the mean value of the function evaluated separately at the values of each of the arguments. Examples of non-linear relationships in some soil C models include the influence of soil texture on soil C stabilization (as in the Century and Rothamsted models) and the effect of temperature on decomposition, which is formulated as an exponential or Q_{10} type function in most models. The amount of error associated with aggregation will depend on the degree of non-linearity of the model and variability of the model variables (e.g., state variables, driving variables) which are being aggregated (O'Neill, 1979; King et al., 1991).

As an example, consider the relationship between soil texture, C input rates and soil C under steady-state conditions for Century and Rothamsted (Fig. 2). Because of the non-linearity in the response to soil texture (expressed either as sand content or inorganic CEC), an aggregation across two different soil textures (e.g., as an area-weighted mean) introduces an error in the prediction of the

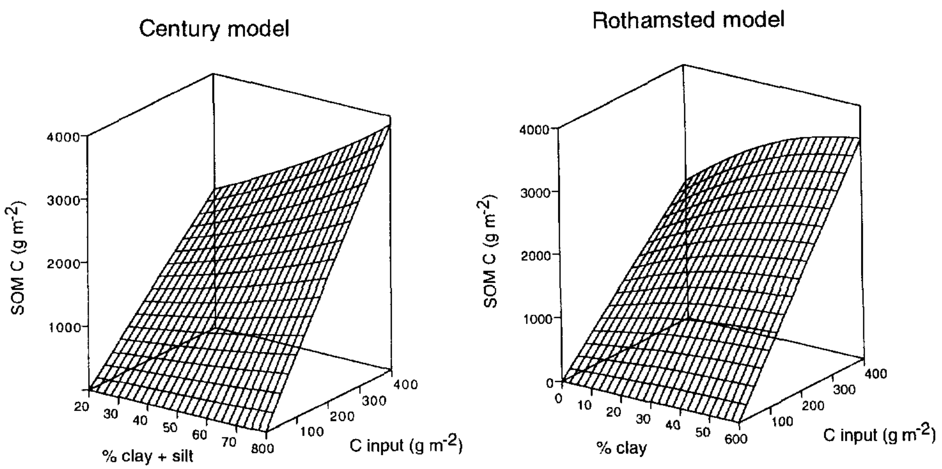

Fig. 2. Relationship of soil texture to steady-state soil C levels in two models, Century (Parton et al., 1987) and the Rothamsted model (Jenkinson et al., 1987). The relationship between texture and soil C is non-linear in both models but differs in form, i.e., concave (upward) in Century and convex (downward) in Rothamsted. See text for discussion on the degree of aggregation bias for averaging soil textures.

dependent variable, soil C. The severity of the aggregation error will increase with the degree of disparity between soil textures and with the evenness in distribution of different soil types (i.e., lack of dominance of a single soil type). For example, compare the estimates of mean C levels for two soils calculated by using an average of soil textural properties versus the amounts calculated for each soil separately and then averaged, under steady-state conditions. Averaging two soil texture types at the extremes of the ranges shown in Fig. 2. (i.e., 0 and 60% clay for Rothamsted or 20 and 80% clay + silt for Century) would give an underestimate of mean steady-state C levels of 6% for Century, and an overestimate of 9% for Rothamsted.

In contrast, aggregation errors are minimal when the relationship between the independent variable (to be aggregated) and dependent variable is inherently linear. For example, the relationship between C input rates and soil C is linear (Fig. 2), due to the first-order assumptions governing decomposition in both models (Paustian et al., 1997c). Thus, aggregation across levels of C input, if other variables were constant, could be made without biasing the aggregate results.

This interaction of aggregation level and the linearity (or non-linearity) of model relationships was well demonstrated in a simulation study by Burke et al. (1990) using the Century model (Table 2). They applied the model using inputs (e.g., precipitation, soil texture) compiled at three levels (soil association, county and multi-county) of spatial resolution. Both precipitation and soil texture were calculated for each spatial scale using linear-weighted averages. Simulated primary production, which responds in a strongly linear fashion to precipitation (Parton et al., 1987), was insensitive to increasing spatial aggregation. In contrast, soil organic matter levels were more sensitive to the scale of aggregation, primarily due to the effect of averaging soil texture (Burke et al., 1990). Their results suggest that aggregation of soil texture at the soil association level (~ 2.5 km^2) up to the county level (ca. 1000 km^2) did not introduce major

Table 2
Effects of differing spatial aggregation on model predictions of net primary production (NPP) and soil organic matter carbon (SOM C) for a 4000 km^2 area of Northeast Colorado

	Aggregation level		
	Soil association	County	Multi-county
Area resolution (km^2)	~ 2.5	1500	4000
Number of aggregations (n)	768	10	1
Mean simulated NPP (g m^{-2})	184	186 (1%)	184 (0%)
Mean simulated SOM C (g m^{-2})	3135	3273 (4%)	2710 (−14%)

Input variables were aggregated at three different spatial resolutions and then means of the model outputs for each aggregation (n) were summed for the region. Values in parentheses show the aggregation bias, relative to the finest scale used in the analysis (i.e., soil association). Adapted from Burke et al. (1990).

difference in model results, while a further aggregation to multi-county (ca. 4000 km^2) scales introduced a strong bias (Table 2). Thus, in the choice of an appropriate spatial scale consideration must be given to the degree of heterogeneity of different model inputs, and their respective effects on aggregation error, for the particular region being modeled.

One way to reduce aggregation bias in regional applications is to categorize soil data at a sub-regional level and then produce area-weighted results of a series of model runs. Kittel et al. (1995) developed a regional database for the United States, scaled at $0.5 \times 0.5°$, in which soil input variables were derived from a cluster analysis of the dominant soil types described in a more detailed, 10-km gridded, soils database. Using this approach, a set of 1–4 modal soil profiles were used in simulations for each 0.5° cell, rather than a set of averaged soil properties which might not correspond to any actual soil in the region.

To reduce bias in aggregating multiple types of input data, Monte Carlo procedures can be used to sample input data from joint probability distributions of, for example, landuse and soil type. A Monte Carlo procedure for regional analysis using 'local-scale' ecosystem models was devised by King (1993) and applied to northern taiga and tundra regional ecosystems. In this study, the Monte Carlo simulations used several sets of external driving variables (e.g., climate and other abiotic variables) selected from within-region probability distributions to calculate an 'expected value' of net CO_2 fluxes for each region.

Climate factors (i.e., temperature and precipitation), which affect decomposition rates and the seasonality of primary production, vary with both space and time. Thus, the effects of both spatial and temporal averaging of climate data need to be considered. Temperature response functions used in decomposition models are generally non-linear and thus are subject to aggregation error. In modeling climate change effects for regions with distinct seasons, the predicted response of primary producers and decomposers will be different depending on whether changes in temperature and precipitation are distributed uniformly through the year or with seasonal differences incorporated. In other words, temporal aggregation of input data is another potential source of error. Ojima et al. (1991) demonstrated the effect of using either monthly or annually averaged output from a general circulation model (GCM) to predict soil C change in the Great Plains of the United States (Fig. 3). The simulations show distinct differences in predicted patterns of soil C for the same mean annual temperature change, depending on whether temperature change was expressed on a monthly basis or if it was 'aggregated' over the year.

Ecosystem-level models contain 'chains' or sequences of interacting processes which can create complex non-linear behaviors that are highly sensitive to driving variables and initial conditions. This is illustrated by the interactions between soil texture, water holding capacity, vegetation development and soil C in a simulation study of global change impacts on forests using Linkages (Post et al., 1992). Simulations of forest stands in the boreal/northern hardwood

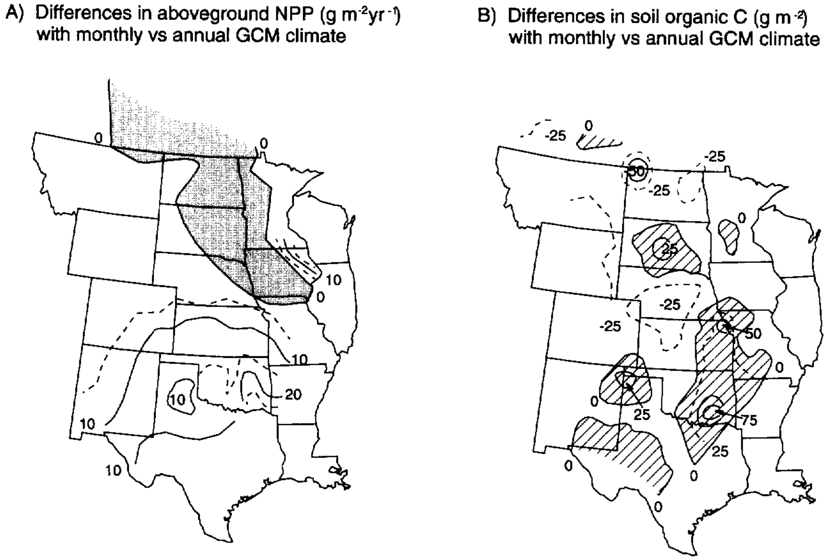

Fig. 3. Effect of aggregating across time scales in predicting effects of increased temperature on net primary production (NPP) and soil organic carbon (SOC) for the central United States. Maps show differences between model predictions for the same mean annual temperature increase, either distributed equally over the year (annual basis) or as monthly changes (monthly basis) as computed in GCM simulations. Temperature changes that were averaged monthly gave higher predictions of NPP in the southern United States (A) compared to using the aggregated mean annual temperature change. Differences in SOC responses for monthly versus annually average temperature change are shown in (B). From Ojima et al. (1991).

border in northeastern Minnesota were conducted, comparing changes for two contrasting soils, with sand and silty clay loam textures respectively. In the fine-textured soil, under increased temperature and CO_2, there was no decrease in available moisture while N availability increased, resulting in the replacement of the mixed pine/hardwood forest by a more productive hardwood forest vegetation (Fig. 4). In contrast, increased temperature and CO_2 sharply reduced water availability in the sandy soil, resulting in a replacement of the pine/hardwood forest by a stunted maple vegetation. These vegetational changes, in turn, resulted in a sharp divergence in nutrient availability and productivity levels, and thereby C input rates and long-term soil C storage. In such cases, the response of a system defined by an aggregated soil texture would be very different from the summed responses of the two systems.

In a whole systems context, the effects of aggregating driving variables can also be considered from the perspective of a sensitivity analysis. In a comparative analysis of zonal natural ecosystems of the Russian European region, Ryzhova (1993) showed that the sensitivity of podzolic soils in northern taiga to climate-dependent parameters was greater than the sensitivity of typical chernozems in meadow steppes. Therefore, the errors introduced by aggregation

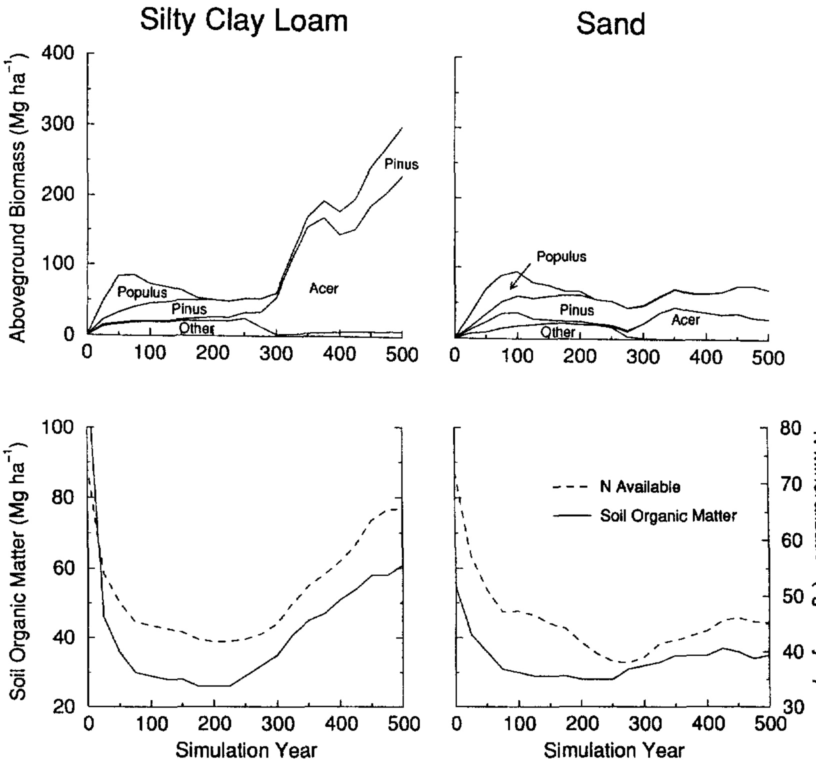

Fig. 4. Sensitivity of ecosystem properties to soil textural effects in the Linkages model (Pastor and Post, 1988). With warming and increased CO_2, forest succession and species composition are predicted to be different for coarse versus fine-textured soils, primarily due to differences in soil water balance (a). This leads to radically different ecosystem responses in soil variables such as N availability and litter + soil organic matter levels (b). Adapted from Post et al. (1992).

would be greater for the more sensitive system at a given degree of spatial aggregation, i.e., the aggregation errors for northern taiga should be larger than for meadow steppes. Moreover, aggregation errors would be larger if the area-averaging were made near the boundaries of soil–vegetation zones, where the sensitivity of the ecosystems to some climate parameters increased.

4.2. Macro-scale models

In principle, coarse scale models of regional soil C dynamics should be derived from the development of theory and experimental results that are commensurate with a coarse scale of resolution. In practice, however, most of our knowledge of ecosystem processes is fine-scale. Moreover, our ability to conduct measurements and experiments at coarse spatial scales, in order to derive new theory operative at such scales, is highly constrained. Consequently, one of the main issues confronting macro-scale models is how to aggregate and simplify fine-scale knowledge and information into a model configuration appropriate to coarser spatial scales.

Macro-scale C models have been simplified in comparison to ecosystem-level models in a variety of ways, including reduction of the number of detrital and soil C pools considered (Table 1), including fewer rate controls (e.g., excluding soil texture effects on C stabilization) and including aggregation of processes and rate controls (e.g., representing litter quality as woody and herbaceous material with fixed attributes versus considering a range of litter qualities).

Rastetter et al. (1992) identified several techniques by which fine-scaled relationships can be scaled-up, including rigorous statistical procedures to determine the error introduced through model aggregation. Of these techniques the most common is that of calibration, in which the 'derived' model is calibrated and parameterized to regional-level data. Ideally, calibration would be performed using regional-level measurements (e.g., from remote sensing) of model output variables. In practice, the quality and interpretation of remotely-sensed data are probably not yet suitable for model calibrations and to date most use of remotely-sensed data has been for purposes of model comparison and evaluation (e.g., Running et al., 1989; Burke et al., 1991). An alternative method is to use data from multiple sites across a region to parameterize and generalize the model. For calibration of the TEM model, NPP estimates from twelve sites, presumed to be representative of the seven vegetation types simulated for South America, were used (Raich et al., 1991). Cross-validation tests, using six different calibration sites yielded estimates of NPP within 20% of observed values for tropical evergreen forest sites, which was similar to the uncertainty in the measured productivity. While these and other results provide confidence that large scale patterns in productivity can be successfully modeled, analogous validations of simulated soil C patterns at these scales have not yet been reported.

There may be practical limits to aggregating soil C models to large scale applications, particularly under non-equilibrium conditions. Most macro-scale models represent soil organic matter by only one or two pools. While there is controversy as to the most appropriate model representation of soil organic fractions and how they can be measured or deduced (Paustian, 1994), there is a general consensus that several discrete fractions (Jenkinson et al., 1987; Parton et al., 1987) or a continuum of varying decomposability (Bosatta and Ågren, 1985) are needed to represent the kinetic heterogeneity of soil organic matter. Under steady-state conditions this is not a major concern since mean turnover rates and relationships between soil C levels and rate controlling factors (e.g., climate, soil texture, litter quality) can be made equivalent for single pool models and models which include multiple SOM fractions. However, under transient dynamics (e.g., following deforestation, changes in climate, new management practices) highly aggregated models with a single SOM pool are of limited value. For departures from steady-state, single pool models may severely

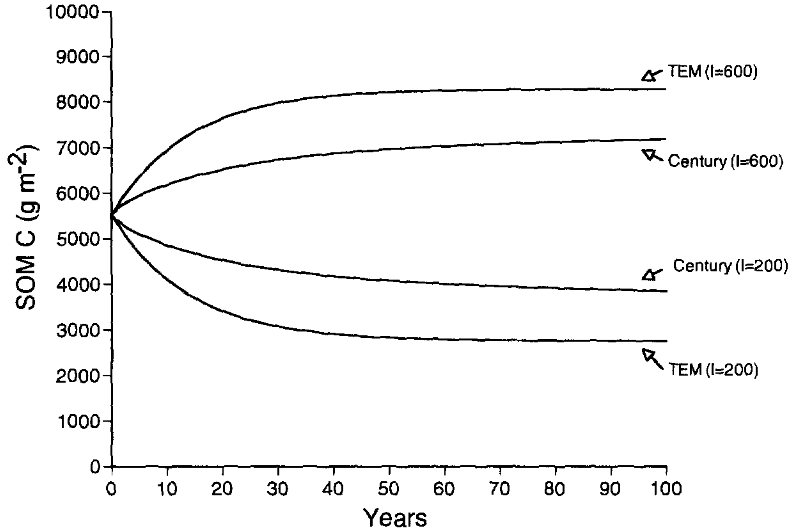

Fig. 5. Comparison of transient state dynamics of a highly aggregated decomposition model (TEM; Raich et al., 1991) and a disaggregated multi-compartment model (Century; Parton et al., 1987). The models were parameterized to yield identical soil C levels under steady-state conditions (e.g., 5500 g C m^{-2} with annual input of 400 g C m^{-2}). With a change in C input (I) of 200 g m^{-2} yr^{-1}, the time period to reach 90% of the new equilibrium value is 17 years for TEM and 220 years for Century.

overestimate soil C changes in the short-term, because the slower response times of older soil organic matter fractions cannot be adequately represented (Fig. 5). Thus, the use of models with multiple SOM pools is more appropriate for investigations of transient dynamics. Aggregating kinetically different SOM pools is equivalent to a series aggregation as defined by Gardner et al. (1982), who recommended against such aggregations where turnover times vary by more than a factor of three.

5. Use of spatially-resolved soils databases for regional C modeling

Models being used for regional analyses can make predictions of soil C based on a relatively small number of input variables. The information required includes climate variables, certain soil characteristics, vegetation attributes and, in the case of managed ecosystems, information on management and landuse practices. Of these requirements, climate data is the most readily available for regional analyses. This is not to say that model predictions could not be enhanced by more and higher quality climate information. However, relative to other data needs, the availability of climate information is probably not a limiting factor and will not be discussed further in this paper.

Vegetation type, distribution and productivity are key inputs to soil C models, both for specifying litter quality factors (e.g., lignin content) and for determining C input rates and location (i.e., above versus belowground). However, many models used for regional soil C predictions are coupled production–decomposition models which predict productivity on the basis of climate and soil parameters. Therefore, we will not address vegetation and land cover databases in detail. We will focus on issues dealing with the use of soils data, and to a lesser extent landuse and management databases with respect to their potentials and limitations for integration with models.

The primary function of spatially-referenced soils data is to provide initialization values, such as soil texture (e.g., Century, TEM), cation-exchange capacity (e.g., Rothamsted) and water holding capacity (e.g., Linkages) or the information necessary to derive these values (e.g., texture and mineralogy to estimate CEC). Secondly, soils databases can provide information to evaluate the performance of the models.

A variety of regional-level soils information is available including national soil surveys, the FAO global soils map, USDA's soil pedon database and others (Bouwman, 1990; Groenendijk, 1990; Eswaran et al., 1993; Bliss et al., 1995). Although these data sources differ in their characteristics, we will discuss some of the problems and limitations of regional soils databases for modeling applications, using as an example the soil survey data for the United States. This database is among the most extensive in existence and as such represents a 'best case' scenario for modeling; data sources from much of the tropics present additional problems and uncertainties.

A limitation of most soil characterization data is that the original purpose for sampling the soils was not to estimate or model soil C, but rather to characterize soil properties for agriculture and engineering applications (USDA, 1991). For example, soil information prepared by the United States Department of Agriculture–Natural Resources Conservation Service (USDA–NRCS) for distribution with their State Soil Geographic database (STATSGO) maps (USDA, 1991) report organic matter instead of organic C, available water holding capacity instead of values required to derive a water retention curve (i.e., water retained at 0.3 and 1.5 MPA), and information about bulk density or cation properties are often omitted. Thus, basic data for model algorithms may not be directly obtainable.

An additional purpose for soil survey is soil classification (Olsen, 1981), in which field measurements and laboratory analyses are used to describe soils as they exist in the field at sampling time (Smith, 1986). However, using soil characterization data to estimate C content in the soil would be misleading if changes in landuse, vegetative cover, climate, or other conditions that would affect C dynamics have occurred since sampling. Both organic and inorganic forms of C are part of the suite of analyses performed for soil classification purposes (Olsen, 1981). However, perusal of the soil characterization data shows that a laboratory measurement of C was not always made for each sample, and methods used to determine laboratory C content were not always consistent. In addition, soils which may represent a large sink of C such as forest soils, frozen soils, or organic (Histosols) soils were not always sampled since these are not generally used for agricultural purposes. In the case of Histosols, samples may not have been taken to sufficient depth to account for the large quantity of subsurface C they may contain. With these sampling problems, gross underestimates of soil organic C contents may occur. Thus, while the database does contain a great deal of information about soil properties, there are many missing or inconsistent pieces of information which constrain its use to estimate organic C amounts and interpret C dynamics.

Additional problems with the database are found in the data presentation and availability. A large data set of soil pedon data exists in digital form, but it is often difficult to use or has gaps in information. Not all samples are georeferenced, making sites difficult to locate or use in a geographic information system (GIS) format. Information is limited mostly to soils of the United States. Although there are data for international sites, many important areas are missing. Many additional data sets are available, but have not been put into digitized format for computer accessibility (Mielke et al., 1993).

Additional data sets are being developed which will improve some of the data quality issues mentioned above. These include the International Geosphere/Biosphere Programme (IGBP) soil data task group which is attempting to assemble a global database of profile descriptions and analytical measurements sufficient in quantity to characterize the range in major soil types (Scholes et al., 1995). The goal of this group is to provide quality controlled data with geographical and pedological gaps filled in from verifiable sources, provide tables of summary data, and spatially link data with the FAO/UNESCO Soil Map of the World (FAO/UNESCO, 1971).

The use of soil characterization data sampled at a county scale for agricultural purposes poses an additional problem when attempts are made to scale the information to larger areas. In these surveys, mapping units are aggregated for a minimum size based on map scale. Thus, some important features may be overlooked if they are smaller than minimal 'pixel size', e.g., wetland inclusions within a larger drier area can contain a large reservoir of carbon which may be overlooked. Underestimates of soil carbon, for example, were shown by Davidson and Lefebvre (1993) in a study of soils in Maine because small forested areas and organic soils had not been differentiated in the state STATSGO soil map as compared to the county soils data. Thus, understanding the purpose and sampling strategy for obtaining the data is critical before soils data can be used in a meaningful way.

Finally, there is no consistent data format which encompasses differences between horizons, profiles or landscapes. A general guideline for some data manipulation is given by the National Soil Survey Laboratory (1983), but this document is not readily available to the general scientific community, and again, does not include all 'ecology based' scenarios for scaling or aggregating purposes. Data aggregation remains a key issue as to how data should be treated (e.g., summed or averaged with various weighting factors), to what depth should measurements be aggregated (e.g., to common depth across profiles or for actual total depth for each profile), how missing data should be handled, how to compare data between profiles (e.g., by horizon, by depth, by master horizon, or with single value for the total soil). Each of these different methods has been used by researchers (Johnson and Kern, 1990; Webb et al., 1991, 1993; Levine et al., 1994) and thus understanding the dynamics of the soil system may become confounded by inconsistencies in methodology.

6. Future challenges and opportunities

6.1. Refinement of soil C maps

Soil maps at scales ranging from local to global are available in digital form, and can provide data for modeling soil carbon on a spatial basis. In the United States, the State Soil Geographic data base (STATSGO) (1:250,000) and National Soil Geographic Database (NATSGO) (1:1,000,000) produced by the USDA–NRCS can be used for meso-scale (areas approximately 1 million km^2), and can be generalized for global modeling of carbon. The Soil Survey Geographic Database (SSURGO) corresponds to the county level, and is presently being encoded (Bliss et al., 1995). Attribute data corresponding to mapping units for each of these products can provide the input required for carbon modeling at the appropriate scale (e.g., organic matter content, texture, slope, drainage class, erosion status).

On a global scale, the FAO/UNESCO Soil Map of the World (FAO/UNESCO, 1971) remains the best map of soil distribution, although attribute files containing information about carbon and variables required for carbon modeling are not linked with mapping units. To remedy this, other global products have been adapted from this map, or are being developed (Webb et al., 1991; Eswaran et al., 1993) from which global carbon inventories have been or can be estimated.

Estimates of soil organic carbon (SOC) have been made from these soil maps to provide inventories at varying scales (Kimble et al., 1990; Kern, 1994; Bliss et al., 1995). A general algorithm for deriving these estimates is described by Bliss et al. (1995) as: $CL = 5800 \times (ODRT)$, where CL is organic carbon for a layer ($g\ m^{-2}$), O is organic matter at the midpoint of the layer (g per 100 g soil), D is bulk density at midpoint of the layer ($g\ cm^{-3}$ fine soil fraction), R is rock fragment conversion factor, T is thickness of the layer (m), and 5800 is a constant that includes both unit conversions and relates organic matter to organic carbon.

Results vary when using this equation depending on the number and thickness of layers, and the types of soils included in the estimation. For example, Histosols were not included in the study of Kimble et al. (1990), and other studies are concerned with C contents to a constant depth, versus their total distribution in soils of varying depths (Eswaran et al., 1995). Also, the impact of missing data on C estimates is not known (Bliss et al., 1995). However, products which combine soil maps and information such as those with remotely sensed imagery, digital elevation data, other terrain maps and models using GIS, help fill in missing information.

For problems related to missing values and scale in soil data, neural networks may represent a useful modeling approach. Neural networks have the ability to learn patterns or relationships in data from a given set of inputs (including combinations of descriptive and quantitative data), they can generalize or abstract results from imperfect data, and they are insensitive to minor variations in input (such as noise in the data, missing data, or a few incorrect values). Thus, they are well suited for studies using soil characterization data. In a recent study, Levine and Kimes (1997) used neural networks to predict the amount of organic C in individual horizons for Mollisols in the midwestern United States using the USDA–NRCS Soil Pedon Database. Values were predicted for missing bulk density values using a neural net approach. Once the bulk density values were added to the data set, the best neural network estimates predicted percent organic carbon with 87% accuracy in individual horizons. Neural nets were able to discern subtle relationships between C and physical soil properties (e.g., density, depth, particle size) which control the rate of decomposition of organic matter, as well as chemical properties in the soil (e.g., nitrogen, base saturation), which can possibly be related to the type and amount of vegetation growth. With these results, neural networks show great potential for studies using existing soil pedon information.

6.2. Modeling landuse effects on soil C

Determining the impacts of landuse and management on amounts and distributions of C in tropical soils is an important area for applying regional scale analyses. When native vegetation is cleared and the land put into cultivation soil C can be substantially reduced (Greenland and Nye, 1959). Variability is high, but on average 20 to 30% of the C in the top meter of soil is lost (Mann, 1986; Post and Mann, 1990; Davidson and Ackerman, 1993), much of it in the first few years following conversion. Other disturbances such as conversion to pastures, shifting cultivation and logging followed by forest regrowth, generally have a smaller effect on the amount of soil organic matter (Lugo et al., 1986; Cerri et al., 1991; Van Noordwijk et al., 1997). Afforestation and reforestation may result in accumulation or loss of soil C depending on the C content of soils under newly established plantations, the productivity of the young vegetation, and other environmental factors (Billings, 1938; Schiffman and Johnson, 1989; Brown and Lugo, 1990; Harmon et al., 1990). While less dramatic, the use of different management practices in permanent agricultural lands can also substantially affect soil C levels (Lal, 1986; Paustian et al., 1997a). Thus, data on landuse and management are a critical component of regional analyses of soil C.

Until relatively recently, information on land cover and landuse has not been available in digital format and therefore has not been readily useable for regional modeling. Currently, the availability of digital land cover/landuse, based on existing vegetation maps (Matthews, 1983; Matthews, 1990) or derived from satellite imagery (Loveland et al., 1991), is growing. This information can be incorporated along with soil and climate data into a GIS format and interfaced with models, both to provide input data (Running et al., 1989; Potter et al., 1993) and for validation (Burke et al., 1991; VEMAP, 1995). Remote sensing can also be used to quantify gross changes in landuse over time. For example, deforestation rates in parts of the Brazilian Amazon have been estimated from time sequences of satellite data (Skole and Tucker, 1993; Moran et al., 1994). Analyses of the spatial patterns of forest clearing and subsequent changes in vegetation cover over time (i.e., maintained in crops versus abandoned to forest regrowth) has provided a better understanding of the dynamics of landuse change and the processes which control it (Skole et al., 1994).

Within a particular category of landuse, the specific management practices used can have a substantial effect on soil C dynamics. This kind of information is, however, not generally obtainable through remote sensing. Traditional agricultural statistics and survey data are the main source of information, but for subsistence agriculture in many areas of the tropics, data on management systems may be entirely lacking (P. Woomer, pers. commun.). Even more limited is information on the joint distribution of management systems and soil types. Surveys which have been conducted on management practices in subsistence agriculture reveal considerable variability in the frequency and type of practices used. For example, Table 3 shows the frequency of different management practices within a single landuse type (subsistence agriculture) in some agricultural districts in Uganda. Seward and Woomer (1993) modeled maize production and SOM changes in such systems to assess the effects of management. Their results suggest that erosion control, residue incorporation and manure application could greatly influence SOM levels and the long-term sustainability of the production system. For areas dominated by managed ecosystems, it is clear that our ability to make projections of changes in soil C at the regional level is highly dependent on type, distribution and dynamics of landuse systems.

Landuse and management systems are not static but change with the development of new technologies, climate trends, altered economic conditions, government policies and other socio-economic factors. A major challenge is to improve our understanding of the human factors which drive landuse change and how

Table 3
Frequency of different management practices employing organic matter or fertilizer additions for subsistence farmers in several agricultural districts in Uganda

District	Farmers practicing (%)				*n*
	Manuring [a]	Mulching [b]	Grass bunds	Fertilizers [c]	
Rukungiri	83	68	32	0	96
Kabale	49	7	45	0	101
Bushenyi	54	2	0	0	100
Mpigi	21	41	18	9	102
Iganga	8	11	30	4	115
Mbale	9	0	52	6	106
Gulu	1	5	64	0	92
Nebbi	0	0	14	0	94

After Tukahirwa (1992), as cited in Seward and Woomer (1993)
[a] Use of livestock manure.
[b] Does not include mulching of bananas.
[c] Use of inorganic fertilizers.

they interact with the biophysical environment. This includes understanding both past and future landuse changes as current trends in soil organic matter pools are influenced by previous landuse histories. Thus, information on soil organic matter status, landuse, and associated properties (i.e., amounts and types of organic matter inputs and climate) needs to be quantified for the previous several decades. Riebsame et al. (1994) developed a conceptual model which links the human environment (represented by economics, technological, policy and socio-cultural factors) with ecosystem processes and properties, in determining patterns of landuse and management for the United States Great Plains (Fig. 6). The development of such analytical strategies are urgently needed in the tropics to provide a framework for assessing future changes in soil C and other important ecosystem properties at the regional scale.

6.3. Linking soil C models with remote sensing

Measurements of ecosystem attributes at regional scales can be obtained directly through the use of remote sensing techniques, making remotely sensed data an important complement to simulation models. Satellite imagery in particular is being used increasingly in a variety of ecological applications (Roughgarden et al., 1991), especially for quantifying land cover and plant-driven processes (e.g., photosynthesis, evapotranspiration). Fung and Tucker (1986) indicated the need for understanding soil conditions (including nutrient and moisture content) and how these affect vegetation dynamics and effluxes of CO_2 and other trace gases for better interpretation of satellite imagery. With present technology, chemical and physical properties of soils (e.g., soil carbon, nutrient

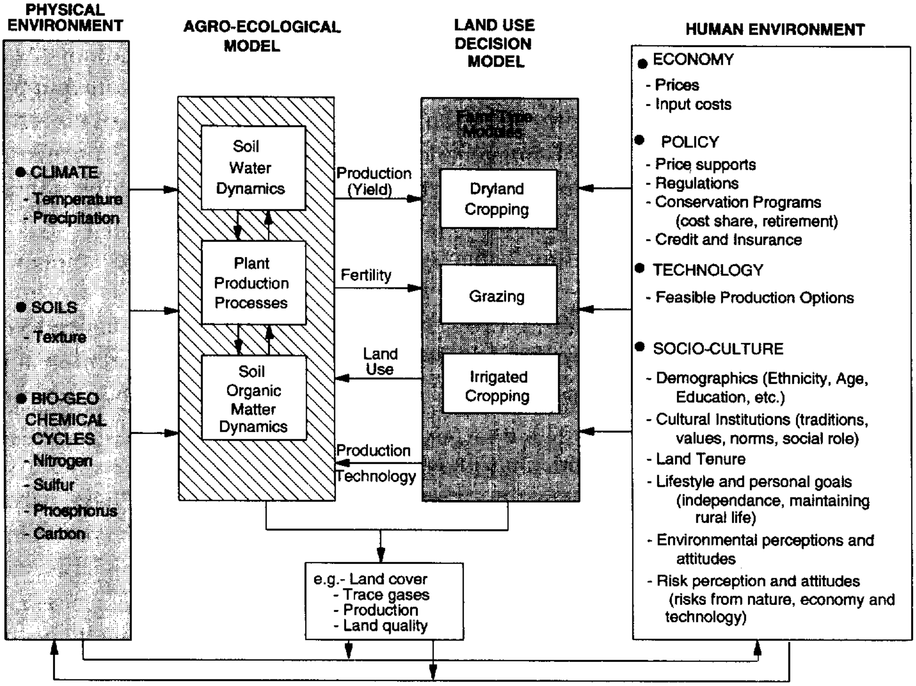

Fig. 6. A conceptual model of agricultural landuse in the Great Plains region of the United States. Driving variables associated with socio-economic and political systems ('human environment') and the biophysical factors affecting ecosystems interact to determine patterns of landuse and management and thus ecosystem properties and dynamics. Modified from Riebsame et al. (1994).

content, drainage class) cannot be directly observed by satellite. Thus, researchers attempting to draw inferences concerning soil characteristics must rely on surrogate indices, such as vegetation status or albedo, biomass estimates and surface soil moisture or temperature, combined with modeling techniques to assess soil properties. The long-term goal of such research is to identify and characterize satellite measurements that may be used to infer gross soil characteristics beneath a vegetation canopy (Merry and Levine, 1995).

An example of a surrogate for soils for remote sensing is the use of the normalized difference vegetation index (NDVI) (Gates et al., 1965; Tucker, 1979). NDVI has been linked with various aspects of vegetation dynamics which can then be indirectly related to the underlying soil properties. Correlations have been made between NDVI and properties such as leaf area index (Curran, 1983; Asrar et al., 1984), vegetational seasonal dynamics (Justice et al., 1985; Tucker et al., 1985), net primary productivity (Goward et al., 1987), and seasonal variations in atmospheric CO_2 (Tucker et al., 1986).

The relationship between soil and vegetation properties shown with NDVI was investigated for South America by Levine et al. (1987). A black and white rendition of a 3 year composite (1982–1985) NDVI image (Fig. 7, top) is compared with a digitized version of the FAO soil map of South America (Fig. 7, bottom). Visual comparison of these show many areas where soil mapping units are similar or identical to NDVI patterns. In their study, Levine et al. (1987) co-registered the NDVI image and soil map, and performed statistical analyses on a number of control points from each data source. Results showed low but positive correlations between NDVI and soil properties such as base saturation, acidity, water holding capacity, and bulk density when soils were clustered into climate groups.

A study by Lozano-Garcia et al. (1991) also used NDVI from advanced very high resolution radiometer (AVHRR) to determine soil/vegetation relationships, but over a smaller area (the state of Indiana). Their work showed clear relationships between soil 'associations' (a map unit used in soil survey made up of two or more soil series) and phytomass development. Land cover type, soil texture, and water holding capacity within soil associations all have strong effects on NDVI (Levine et al., 1994). In a study at the Northern Experimental Forest at Howland, Maine, Levine et al. (1994) found soil properties, and especially soil drainage class were well correlated with vegetative growth, as explained by NDVI. Soils falling within the moderately well to well drained class had the highest NDVI values, while very poorly drained organic soils, or those formed from recent alluvium, had the lowest NDVI values.

Ecosystem models can utilize NDVI or other indices of primary production to evaluate temporal and spatial patterns of primary production as simulated in models. In both native and agricultural ecosystems, soil organic matter levels are often closely related to the amount of C added to soil (Ågren et al., 1996; Paustian et al., 1997a). Carbon input rates are primarily a function of primary production and plant life histories (e.g., annual, herbaceous perennial, woody perennial). The use of remotely sensed production indices to evaluate simulated production rates can provide a measure of confidence for this important determinant of soil C distributions.

In a regional analysis of forest ecosystems in Montana, Running et al. (1989) found good correspondence between leaf area index (LAI) as estimated from AVHRR/NDVI data and field measures of LAI. Using the LAI values to initialize a simulation model, annual photosynthesis and evapotranspiration were computed and mapped for the 1500 km^2 region. Simulated photosynthesis using this approach was strongly correlated to field measures of forest stand growth. Similarly, Burke et al. (1991) used NDVI to evaluate simulated NPP for a three-state region in the central United States for a year with normal precipitation and a drought year. Comparison with the NDVI data and field measurements suggested that the model underestimated production in drought-stricken areas but that simulated NPP with normal precipitation was closely correlated to the regional pattern of NDVI. While the use of remote sensing data for model validation is not without problems, these examples illustrate the potential uses of

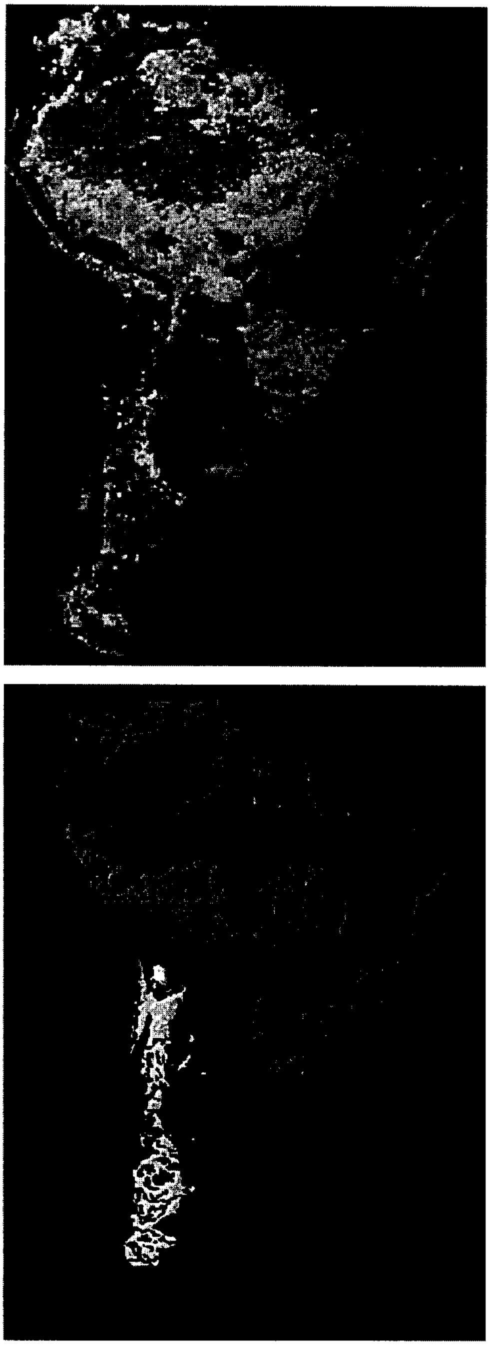

Fig. 7. Maps of South America showing: (top) normalized difference vegetation index (NDVI) from the advanced very high resolution radiometer (AVHRR) at a spatial resolution of about 15 km. Data are from 3 week periods of the NOAA global vegetation index product composited over a 3 year period (1982–1985), provided by the Global Inventory Mapping and Monitoring group (GIMMS) at NASA's Goddard Space Flight Center; (bottom) digitized version of soil map from FAO/UNESCO (1971) at a scale of 1:5,000,000.

such information to identify and help correct model weaknesses in regional applications.

Some NPP models, such as the Carnegie–Ames–Stanford Approach (CASA), use remotely sensed data as drivers (Potter et al., 1993). In CASA, NPP is driven by the fraction of photosynthetically active radiation (PAR) absorbed annually by green vegetation, where PAR is based on a linear function of NDVI (Potter et al., 1993; Field et al., 1995) and incident solar radiation.

Estimates of biomass and aboveground forest type, another possible surrogate for soil carbon, have been predicted using radar in combination with radar backscattering models. Biomass predictions using data from a 1991 overflight of AIRSAR over the Northern Experimental Forest at Howland, Maine gave an r^2 of 0.83 when compared with field measured biomass values (Ranson and Sun, 1994). Aboveground forest type was classified with 80% accuracy for a forest in Saskatchewan, Canada using spaceborne imaging radar-C (SIR-C) and X-band synthetic aperture radar (XSAR) data (Ranson et al., 1995). Image calibration and environmental conditions affect the accuracy of these techniques so that additional field work needs to be done for improved accuracy of first type classifications.

Other variables can act as drivers for models to predict carbon. Soil moisture and surface temperature, for example, can provide inputs to carbon models to predict rates of decomposition or plant growth on a land cover type or ecosystem basis. Active and passive microwave measurements have potential for producing values for soil moisture because of the great difference between the dielectric properties of liquid water and dry soil (Ulaby et al., 1986). These predictions are complicated by surface conditions, however, so that microwave measurements must be coupled with information on vegetation and surface roughness (Engman and Chauhan, 1995). Similar problems exist with thermal–infrared measurements of the surface temperature in which unknown surface emissivities, atmospheric corrections, and other variables affecting the relationship between thermal radiance and partitioning of surface energy fluxes complicate the data (Norman et al., 1995).

Thus, while remote sensing remains a powerful tool for providing surrogate measures of soil carbon, or driving variables for soil carbon models, much work needs to be done to provide accurate and dependable estimates from this source (Sellers et al., 1995).

6.4. Interfacing soil C models with climate models

Models have been used to evaluate potential climate change effects on soil C at local (Cole et al., 1993; Woomer, 1993; Paustian et al., 1996), regional (VEMAP, 1995) and global scales (Jenkinson et al., 1991; Ojima et al., 1993; King et al., 1997). For regional simulations of climate change effects, bridging the gap between spatial scales used in general circulation models (GCM) and the scales appropriate for ecosystem-level models remains a major challenge.

The problem of 'scaling down' the outputs from GCM simulations for regional applications have been addressed using both empirical and model-based approaches (Schimel, 1994). One empirical approach is to use local weather records or statistics to filter the output from GCMs. For example, the VEMAP database (Kittel et al., 1995) uses the difference between current and future climate GCM results and interpolates them using historical weather station averages of monthly climate variables. Another empirical approach is to use statistical weather generators to modify GCM outputs so that effects of topography and elevation can be incorporated (Schimel, 1994). Because empirical approaches rely on past history as part of their inference of future climate conditions, they are subject to criticism for extrapolation beyond the range of the data. Moreover such approaches cannot capture the indirect effects of ecosystem–climate interactions, such as climate-induced changes in vegetation feeding back on regional climate. However, because of their strong empirical basis they may provide the best estimates of near-future climate conditions at regional and sub-regional scales. A more mechanistic model-based approach is to use a regional/mesoscale meteorological model driven by GCM output to generate finer scale climate predictions (Kittel and Coughenour, 1988; Georgi, 1990). This technique is referred to as 'nesting' (Schimel, 1994) and it can incorporate some of the dynamic interactions between sub-regional features such as clouds, topography and vegetation. Improvements in the simulation of regional patterns of precipitation have been demonstrated using this technique (Georgi, 1990) provided the large scale boundary conditions simulated by the GCM are well represented.

Similarly, improvements are needed in 'scaling up' soils and vegetation information needed in GCMs. Previously, soils information used in general circulation models was highly simplified. Spatial distribution of soils was generally assumed to be uniform across the landscape, and averaged surface soil parameters such as a 'texture' or 'water holding capacity' were assumed, usually incorrectly, to be representative of the total soil profile (Hansen et al., 1983; Henderson-Sellers et al., 1986; Sellers et al., 1986; Fung, 1992). As models become more sophisticated (Abramopoulos et al., 1988; Levine et al., 1993) more realistic data for soil properties within profile horizons are required to simulate feedbacks between global change and soil processes.

Finally, regional models of climate change effects on soils and other ecosystem components will become more informative when the interactions between ecosystem and atmospheric processes are fully coupled. Most existing regional analyses can be characterized as incorporating one-way interactions, where atmospheric models provide inputs to ecosystem models or vice versus, but feedbacks between the two systems are not included (Pielke et al., 1993). Temperature and precipitation patterns are, however, affected by changes in vegetation and soil properties, which may either dampen or reinforce changes in these ecosystem properties. The development of coupled atmospheric–terrestrial ecosystem models will significantly enhance our abilities to evaluate and plan for future environmental change.

Acknowledgements

The authors thank Bob Scholes and John Kimble for reviewing an earlier draft of the manuscript and for two anonymous reviewer's comments on a revised version. Support for this work from the US Department of Energy's National Institute for Global Environmental Change, Great Plains Region, for the senior author (K. Paustian) is acknowledged.

References

Abramopoulos, F., Rosenzweig, C., Choudhury, B., 1988. Improved ground hydrology calculations for global climate models (GCMs): soil water movement and evaporation. J. Clim. 1, 921–941.

Ågren, G.I., Kirschbaum, M.U.F., Johnson, D.W., Bosatta, E., 1996. Ecosystem physiology—soil organic matter. In: Breymeyer, A., Hall, D.O., Melillo, J.M., Ågren, G.I. (Eds.), Global Change: Effects on Forests and Grasslands. Wiley, Chichester, pp. 207–228.

Asrar, G., Fuchs, M., Kanemasu, E.T., Hatfield, J.L., 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agron. J. 76, 300–306.

Billings, D., 1938. The structure and development of lod field shortleaf pine stands and certain associated physical properties of the soil. Ecol. Monogr. 8, 437–456.

Bliss, N.B., Waltman, S.W., Petersen, G.W., 1995. Preparing a soil carbon inventory for the United States using geographic information systems. In: Lal, R., Kimble, J., Levine, E., Stewart, B.A. (Eds.), Soils and Global Change. Adv. Soil Sci., CRC Press, Boca Raton, FL, pp. 275–295.

Bosatta, E., Ågren, G.I., 1985. Theoretical analysis of decomposition of heterogeneous substrates. Soil Biol. Biochem. 17, 601–610.

Bouwman, A.F., 1990. Global distribution of the major soils and land cover types. In: Bouwman, A.F. (Ed.), Soils and the Greenhouse Effect. Wiley, Chichester, pp. 33–59.

Brown, S., Lugo, A.E., 1990. Effects of forest clearing and succession on the carbon and nitrogen content of soils in Puerto Rico and US Virgin Islands. Plant Soil 124, 53–64.

Burke, I.C., Schimel, D.S., Yonker, C.M., Parton, W.J., Joyce, L.A., Lauenroth, W.K., 1990. Regional modeling of grassland biogeochemistry using GIS. Landscape Ecol. 4, 45–54.

Burke, I.C., Kittel, T.G.F., Lauenroth, W.K., Snook, P., Yonker, C.M., Parton, W.J., 1991. Regional analysis of the central Great Plains: sensitivity to climate variability. BioScience 41, 685–692.

Burke, I.C., Lauenroth, W.K., Parton, W.J., Cole, C.V., 1994. Interactions of landuse and ecosystem structure and function: a case study in the central Great Plains. In: Groffman, P.M., Likens, G.E. (Eds.), Integrated Regional Models. Interactions Between Humans and Their Environment. Chapman Hall, New York, pp. 79–95.

Cerri, C.C., Volkoff, B., Andreaux, F., 1991. Nature and behaviour of organic matter in soils under natural forest, and after deforestation, burning and cultivation, near Manaus. For. Ecol. Manage. 38, 247–257.

Cole, C.V., Stewart, J.W.B., Ojima, D.S., Parton, W.J., Schimel, D.S., 1989. Modelling land use effects of soil organic matter dynamics in the North American Great Plains. In: Clarholm, M., Bergstrom, L. (Eds.), Ecology of Arable Land. Kluwer, Dordrecht, pp. 89–98.

Cole, C.V., Paustian, K., Elliott, E.T., Metherell, A.K., Ojima, D.S., Parton, W.J., 1993. Analysis of agroecosystem carbon pools. Water Air Soil Pollut. 70, 357–371.

Curran, P.J., 1983. Multispectral remote sensing for the estimation of green leaf area index. Phil. Trans. R. Soc. Lond. B. Biol. Sci. 309, 257–270.

Davidson, E.A., Ackerman, I.L., 1993. Changes in soil carbon inventories following cultivation of previously untilled soils. Biogeochemistry 20, 117–129.

Davidson, E.A., Lefebvre, P.A., 1993. Estimating regional carbon stocks and spatially covarying edaphic factors using soil maps at three scales. Biogeochemistry 22, 107–131.

Donigian, A.S., Barnwell, Jr., T.O., Jackson, IV, R.B., Patwardhan, A.S., Weinrich, K.B., Rowel, A.L., Chinnaswamy, R.V., Cole, C.V., 1994. Assessment of Alternative Management Practices and Policies Affecting Soil Carbon in Agroecosystems of the Central United States. US EPA Report EPA/6004-94/067.

Elliott, E.T., Cole, C.V., 1989. A perspective on agroecosystem science. Ecology 70, 1597–1602.

Elliott, E.T., Paustian, K., 1996. Why site networks? In: Powlson, D.S., Smith, P., Smith, J.U. (Eds.), Evaluation of Soil Organic Matter Models. NATO ASI Series I, Global Environmental Change, vol. 38. Springer, Berlin, pp. 27–36.

Engman, E.T., Chauhan, N., 1995. Status of microwave soil moisture measurements with remote sensing. Remote Sens. Environ. 51, 189–198.

Esser, G., 1987. Sensitivity of global carbon pools and fluxes to human and potential climatic impacts. Tellus 39B, 245–260.

Esser, G., 1989. Global land-use changes from 1860 to 1980 and future projections to 2500. Ecol. Model. 44, 307–316.

Esser, G., 1990. Modelling global terrestrial sources and sinks of CO_2 with special reference to soil organic matter. In: Bouwman, A.F. (Ed.), Soils and the Greenhouse Effect. Wiley, Chichester, pp. 247–261.

Esser, G., 1992. Implications of climate change for production and decomposition in grasslands and coniferous forests. Ecol. Appl. 2, 47–54.

Eswaran, H., Van Den Berg, E., Reich, P.F., 1993. Organic carbon in soils of the world. Soil Sci. Soc. Am. J. 57, 192–194.

Eswaran, H., Van Den Berg, E., Reich, P., Kimble, J., 1995. Global soil carbon resources. In: Lal, R., Kimble, J., Levine, E. Stewart, B. (Eds.), Soils and Global Change. Adv. Soil Sci., CRC Press, Boca Raton, FL.

FAO/UNESCO, 1971. Soil Map of the World, 1:5,000,000, vols. I–X. Food and Agricultural Organization, Rome.

Field, C.B., Randerson, J.T., Malmstrom, C.M., 1995. Global net primary productivity: combining ecology and remote sensing. Remote Sens. Environ. 51, 74–88.

Fung, I.Y., Tucker, C.J., 1986. Remote sensing of the terrestrial biosphere. In: Rosenzweig, C., Dickinson, R. (Eds.), Climate–Vegetation Interactions. Report OIES-2. Univ. Corp for Atmos. Res., Boulder, CO.

Fung, I.Y., 1992. A toy model for estimating N_2O emissions from natural soils. In: Ojima, D. (Ed.), Modeling the Earth System. UCAR Office for Interdisciplinary Earth Studies, Boulder, CO.

Gardner, R.H., Cale, W.G., O'Neill, R.V., 1982. Robust analysis of aggregation error. Ecology 63, 1771–1779.

Gates, D.M., Keegan, H.J., Schleter, J.C., Weidner, V.R., 1965. Spectral properties of plants. Appl. Optics 4, 11–20.

Georgi, F., 1990. Simulation of regional climate using a limited area model nested in a global circulation model. J. Climate 3, 942–963.

Goward, S.N., Kerber, A., Dye, D., Kalb, V., 1987. Comparison of North and South American biomes from AVHRR observations. Geocarto Int. 2, 27–39.

Grace, P.R., 1996. The Australian site network. In: Powlson, D.S., Smith, P., Smith, J.U. (Eds.), Evaluation of Soil Organic Matter Models. NATO ASI Series I, Global Environmental Change, Vol. 38. Springer, Berlin, pp. 55–67.

Greenland, D.J., Nye, P.H., 1959. Increases in the carbon and nitrogen contents of tropical soils under natural fallow. J. Soil Sci. 10, 284–298.

Groenendijk, H., 1990. Compilation of a soil data set for Europe. In: Bouwman, A.F. (Ed.), Soils and the Greenhouse Effect. Wiley, Chichester, pp. 535–539.

Hansen, J., Russell, G., Rind, D., Stone, P., Lacis, A., Lebedeff, S., Reudy, R., Travis, L., 1983. Efficient three-dimensional global models for climate studies. Mon. Weather Rev. 111, 609–662.

Harmon, M.E., Ferrell, W.K., Franklin, J.F., 1990. Effects on carbon storage of conversion of old-growth forests to young forests. Science 247, 699–702.

Henderson-Sellers, A., Wilson, M.F., Thomas, R., Dickinson, R.E., 1986. Current global land-surface data sets for use in climate-related studies. Tech. Note TN-272 + STR. Nat. Center for Atmos. Res., Boulder, CO.

Jenkinson, D.S., Rayner, J.H., 1977. The turnover of soil organic matter in some of the Rothamsted classical experiments. Soil Sci. 123, 298–305.

Jenkinson, D.S., Hart, P.B.S., Rayner, J.H., Parry, L.C., 1987. Modelling the turnover of organic matter in long-term experiments at Rothamsted. Intecol Bull. 15, 1–8.

Jenkinson, D.S., 1990. The turnover of organic carbon and nitrogen in soil. Phil. Trans. R. Soc. Lond. B 329, 361–369.

Jenkinson, D.S., Adams, D.E., Wild, A., 1991. Model estimates of CO_2 emissions from soil in response to global warming. Nature 351, 304–306.

Johnson, M.G., Kern, J.S. (Eds.), 1990. Sequestering Carbon in Soils: A Workshop to Explore the Potential for Mitigating Global Climate Change. EPA/600/3-91/031, Environmental Research Laboratory, Corvallis, OR.

Justice, C.O., Townshend, J.R.G., Holben, B.N., Tucker, C.J., 1985. Analysis of the phenology of global vegetation using meteorological satellite data. Int. J. Remote Sens. 6, 1271–1318.

Kern, J.S., 1994. Spatial patterns of soil organic carbon in the continuous United States. Soil Sci. Soc. Am. J. 58, 439–455.

Kimble, J.M., Eswaran, H., Cook, T., 1990. Organic carbon on a volume basis in tropical and temperate soils. 14th Trans. Int. Congr. Soil Sci., Kyoto, Japan, pp. V248-V253.

King, A.W., Johnson, A.R., O'Neill, R.V., 1991. Transmutation and functional representation of heterogeneous landscapes. Landscape Ecol. 5, 239–253.

King, A.W., 1993. Quantifying regional changes in terrestrial carbon storage by extrapolation from local ecosystem models. In: Vinson, T.S., Kolchugina, T.P. (Eds.), Carbon Cycling in Boreal Forests and Sub-Arctic Ecosystems, EPA Report 600/R-93/084. US EPA, Washington, DC, pp. 221–234.

King, A.W., Post, W.M., Wullschleger, S.D., 1997. The potential response of terrestrial carbon storage to changes in climate and atmospheric CO_2. Clim. Change 35, 199–228.

Kittel, T.G.F., Coughenour, M.B., 1988. Prediction of regional and local ecological change from global climate model results: A hierarchial modeling approach. In: Pielke, R.A., Kittel, T.G.F. (Eds.), Monitoring Climate for the Effects of Increasing Greenhouse Gas Concentrations. Cooperative Institute for Research in the Atmosphere (CIRA). Colorado State Univ., Fort Collins, CO.

Kittel, T.G.F., Rosenbloom, N.A., Painter, T.H., Schimel, D.S., VEMAP modeling participants, 1995. The VEMAP integrated database for modelling United States ecosystem/vegetation sensitivity to climate change. J. Biogeogr., 22: 857–862.

Lal, R., 1986. Soil surface management in the tropics for intensive land use and high and sustained production. Adv. Soil Sci, vol. 5. Springer, Berlin.

Levine, E.R., Kerber, A.G., Cook, T., Kimble, J., 1987. Relationships of soils and vegetative growth in South America using satellite imagery. Agronomy Abstracts. American Society of Agronomy 1987 Annual Meetings, Atlanta, Georgia.

Levine, E.R., Ranson, K.J., Smith, J., Williams, D., Knox, R.G., Shugart, H., Urban, D., Lawrence, W., 1993. Forest ecosystem dynamics: linking forest succession, soil process, and radiation models. Ecol. Model. 65, 199–219.

Levine, E.R., Knox, R.G., Lawrence, W.T., 1994. Relationships between soil properties and vegetation at the Northern Experimental Forest, Howland, Maine. Remote Sens. Environ. 47, 231–241.

Levine, E., Kimes, D., 1997. Predicting soil carbon in mollisols using neural networks. Adv. Soil Sci., (in press).

Loveland, T.R., Merchant, J.W., Ohlen, D.O., Brown, J.F., 1991. Development of a land-cover characteristics database for the conterminous US. Photogramm. Eng. Remote Sen. 57, 1453–1463.

Lozano-Garcia, D.F., Fernandez, R.N., Johannsen, C., 1991. Assessment of regional biomass–soil relationships using vegetation indexes. IEEE Trans. Geosci. Remote Sen. 29, 331–339.

Lugo, A.E., Sanchez, M.J., Brown, S., 1986. Land use and organic carbon content of some subtropical soils. Plant Soil 96, 185–196.

Mann, L.K., 1986. Changes in soil carbon storage after cultivation. Soil Sci. 142, 279–288.

Martin, R.J., Grace, P.R., Anderson, C.A., Fegent, J.C. (Eds.), 1995. Long-Term Agronomic Experiments for Productive and Sustainable Farming Systems. Aust. J. Exp. Agric., 35: 825–1062.

Matthews, E., 1983. Global vegetation and land use: New high-resolution data bases for climate studies. J. of Climate and Appl. Meteorol. 22, 474–487.

Matthews, E., 1990. Global data bases for evaluating trace gas sources and sinks. In: Bouwman, A.F. (Ed.), Soils and the Greenhouse Effect. Wiley, Chichester, pp. 311–325.

Melillo, J.M., McGuire, A.D., Kicklighter, D.W., Moore III, B., Vörösmarty, C.J., Schloss, A.L., 1993. Global climate change and terrestrial net primary production. Nature 363, 234–240.

Merry, C.J., Levine, E.R., 1995. Methods to assess soil carbon using ground-based techniques and remote sensing. In: Lal, R., Kimble, J., Levine, E., Stewart, B.A. (Eds.), Soils and Global Change. Adv. Soil Sci., CRC Press, FL, USA, pp. 265–274.

Metherell, A.K., Cambardella, C.A., Parton, W.J., Peterson, G.A., Harding, L.A., Cole, C.V., 1995. Simulation of soil organic matter dynamics in dryland wheat-fallow cropping systems. In: Lal, R., Kimble, J., Levine, E., Stewart, B.A. (Eds.), Soil Management and Greenhouse Effect. Adv. Soil Sci., CRC/Lewis Publishers, Boca Raton, FL, pp. 259–270.

Mielke, L.N., Lytle, D.J., Levine, E.R., 1993. Research databases for soil—using history for the future. Agronomy Abstracts. American Society of Agronomy 85th Annual Meeting, Cincinnati, OH.

Moran, E.F., Brondizio, E., Mausel, P., Wu, A.Y., 1994. Integrating Amazonian vegetation, land-use and satellite data. Bioscience 44, 329–339.

National Soil Survey Laboratory, 1983. Principles and Procedures for Using Soil Survey Laboratory Data. National Soil Survey Laboratory, USDA-SCS, Lincoln, NE.

Norman, J.M., Divakarla, M., Goel, N.S., 1995. Algorithms for extracting information from remote Thermal–IR observations of the Earth's surface. Remote Sens. Environ. 51, 157–168.

Ojima, D.S., Kittel, T.G.F., Rosswall, T., Walker, B.H., 1991. Critical issues for understanding global change effects on terrestrial ecosystems. Ecol. Appl. 1, 316–325.

Ojima, D.S., Parton, W.J., Schimel, D.S., Scurlock, J.M.O., Kittel, T.G.F., 1993. Modeling the effects of climatic and CO_2 changes on grassland storage of soil C. Water Air Soil Pollut. 70, 643–657.

Olsen, G.W., 1981. Soils and the Environment: A Guide to Soil Surveys and their Application. Chapman and Hall, New York, NY.

O'Neill, R.V., 1979. Natural variability as a source of error in model predictions. In: Innis, G.S., O'Neill, R.V. (Eds.), Systems Analysis of Ecosystems. Int. Coop. Publ. House, Fairland, MD, pp. 23–32.

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

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

Parton, W.J., Ojima, D.S., Cole, C.V., Schimel, D.S., 1994. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. In: Quantitative Modeling of Soil Forming Processes. SSSA Spec. Publ. 39, Madison, WI, pp. 147–167.

Pastor, J., Post, W.M., 1986. Influence of climate, soil moisture, and succession on forest carbon and nitrogen cycles. Biogeochemistry 2, 3–27.

Pastor, J., Post, W.M., 1988. Response of northern forests to CO_2-induced climate change. Nature 334, 55–58.

Paul, E.A., Paustian, K., Elliott, E.T., Cole, C.V. (Eds.), 1997. Soil Organic Matter in Temperate Agroecosystems: Long-Term Experiments in North America. CRC Press, Boca Raton, FL, 414 pp.

Paustian, K., Parton, W.J., Persson, J., 1992. Modeling soil organic matter in organic-amended and nitrogen-fertilized long-term plots. Soil Sci. Soc. Am. J. 56, 476–488.

Paustian, K., 1994. Modelling soil biology and biogeochemical processes for sustainable agriculture research. In: Pankhurst, C., Doube, B.M., Gupta V.V.S.R., Grace, P.R. (Eds.), Management of Soil Biota in Sustainable Farming Systems. CSIRO Publ., Melbourne, pp. 182–196.

Paustian, K., Elliott, E.T., Collins, H.P., Cole, C.V., Paul, E.A., 1995. Use of a network of long-term experiments for analysis of soil carbon dynamics and global change: the North American model. Aust. J. Exp. Agric. 35, 929–939.

Paustian, K., Elliott, E.T., Peterson, G.A., Killian, K., 1996. Modelling climate, CO_2 and management impacts on soil carbon in semi-arid ecosystems. Plant Soil 187, 351–365.

Paustian, K., Collins, H.P., Paul, E.A., 1997a. Management controls on soil carbon. In: Paul, E.A., Paustian, K., Elliott, E.T., Cole, C.V. (Eds.), Soil Organic Matter in Temperate Agroecosystems: Long-Term Experiments in North America. CRC Press, Boca Raton, FL, 414 pp.

Paustian, K., Cipra, J., Cole, C.V., Elliott, E.T., Killian, K., Bluhm, G., 1997b. The contribution of grassland CRP lands to C sequestration and CO_2 mitigation. J. Prod. Agric., (in press).

Paustian, K., Ågren, G.I., Bosatta, E., 1997c. Modelling litter quality effects on decomposition and soil organic matter dynamics. In: Cadisch, G., Giller, K. (Eds.), Driven by Nature: Plant Litter Quality and Decomposition. CAB International, UK, pp. 313–333.

Pielke, R.A., Schimel, D.S., Lee, T.J., Kittel, T.G.F., Zeng, X., 1993. Atmosphere–terrestrial ecosystem interactions: implications for coupled modeling. Ecol. Model. 67, 5–18.

Post, W.M., Emanuel, W.R., Zinke, P.J., Stangenberger, A.G., 1982. Soil carbon pools and world life zones. Nature 298, 156–159.

Post, W.M., Mann, L.K., 1990. Changes in soil organic carbon and nitrogen as a result of cultivation. In: Bouwman, A.F. (Ed.), Soils and the Greenhouse Effect. Wiley, Chichester, pp. 401–406.

Post, W.M., Pastor, J., King, A.W., Emanuel, W.R., 1992. Aspects of the interaction between vegetation and soil under global change. Water Air Soil Pollut. 64, 345–363.

Potter, C.S., Randerson, J.T., Field, C.B., Matson, P.A., Vitousek, P.M., Mooney, H.A., Klooster, S.A., 1993. Terrestrial ecosystem production: a process model based on global satellite and surface data. Global Biogeochem. Cycles 7, 811–842.

Raich, J.W., Rastetter, E.B., Melillo, J.M., Kicklighter, D.W., Steudler, P.A., Peterson, B.J.,

Grace, A.L., Moore III, B., Vörösmarty, C.J., 1991. Potential net primary production in South America: application of a global model. Ecol. Appl. 1, 399–429.
Ranson, K.J., Sun, G., 1994. Mapping biomass for a northern forest using multi-frequency SAR data. IEEE Trans. Geosci. Remote Sen. 32, 388–396.
Ranson, K.J., Saatchi, S., Sun, G., 1995. Boreal Forest Ecosystem Characterization with SIR-C/XSAR. IEEE Trans. Geosci. Remote Sen. 33, 867–876.
Rastetter, E.B., King, A.W., Cosby, B.J., Hornberger, G.M., O'Neill, R.V., Hobbie, J.E., 1992. Aggregating fine-scale ecological knowledge to model coarser-scale attributes of ecosystems. Ecol. Appl. 2, 55–70.
Riebsame, W.E., Parton, W.J., Galvin, K.A., Burke, I.C., Bohren, L., Young, R., Knop, E., 1994. Integrated modeling of land use and cover change. Bioscience 44, 350–356.
Roughgarden, J., Running, S.W., Matson, P.A., 1991. What does remote sensing do for ecology?. Ecology 72, 1918–1922.
Running, S.W., Nemani, R.R., Peterson, D.L., Band, L.E., Potts, D.F., Pierce, L.L., Spanner, M.A., 1989. Mapping regional forest evapotranspiration and photosynthesis by coupling satellite data with ecosystem simulation. Ecology 70, 1090–1101.
Ryzhova, I.M., 1993. Analysis of sensitivity of soil–vegetation systems to variations in carbon turnover parameters based on a mathematical model. Eurasian Soil Sci. 25, 43–50.
Sanford, R.L. Jr., Parton, W.K., Ojima, D.S., Lodge, D.J., 1991. Hurricane effects on soil organic matter dynamics and forest production in Luquillo Experimental Forest, Puerto Rico: results of simulation modeling. . Biotropica 23, 364–372.
Schiffman, P.M., Johnson, W.C., 1989. Phytomass and detrital carbon storage during forest regrowth in the southeastern United States Piedmont. Can. J. For. Res. 19, 69–78.
Schimel, D.S., 1994. Introduction. In: Groffman, P.M., Likens, G.E. (Eds.), Integrated Regional Models. Interactions Between Humans and Their Environment. Chapman Hall, New York, pp. 3–10.
Schlesinger, W.H., 1977. Carbon balance in terrestrial detritus. Annu. Rev. Ecol. Syst. 8, 51–81.
Scholes, R.J., Skole, D., Ingram, J.S., 1995. A Global Database of Soil Properties: Proposal for Implementation. IGBP-DIS Working Paper #10. IGBP-DIS, Paris, France.
Sellers, P., Meeson, B.W., Hall, F.G., Asrar, G., Murphy, R.E., Schiffer, R.A., Bretherton, F.P., Dickinson, R.E., Ellingson, R.G., Field, C.B., Huemmrich, K.F., Justice, C.O., Melack, J.M., Roulet, N.T., Schimel, D.S., Try, P.D., 1995. Remote sensing of the land surface for studies of global change: Models–Algorithms–Experiments. Remote Sen. Environ. 51, 3–26.
Sellers, P.J., Mintz, Y., Sud, Y.C., Dalcher, A., 1986. A simple biosphere model (SIB) for use with General Circulation Models. J. Atmosph. Sci. 43, 305–331.
Seward, P.D., Woomer, P.L., 1993. Use of the CENTURY model to simulate the effects of erosion control, stover management and manuring on field maize at Kabanyolo, Uganda. Tropical Soil Biology and Fertility Programme, Nairobi, Kenya.
Skole, D.L., Tucker, C.J., 1993. Tropical deforestation and habitat fragmentation in the Amazon: satellite data from 1978 to 1988. Science 260, 1905–1910.
Skole, D.L., Chomentowski, W.H., Salas, W.A., Nobre, A.D., 1994. Physical and human dimensions of deforestation in Amazonia. Bioscience 44, 314–322.
Smith, G.D., 1986. Rationale for Concepts in Soil Taxonomy. SMSS Tech. Monograph # 11. Soil Conservation Service, Washington, DC.
Smith, P., Powlson, D.S., Glendining, M.J., 1996a. Establishing a European soil organic matter network (SOMNET). In: Powlson, D.S., Smith, P., Smith, J.U. (Eds.), Evaluation of Soil Organic Matter Models. NATO ASI Series I, Global Environmental Change, vol. 38. Springer, Berlin, pp. 81–98.
Smith, P., Smith, J.U., Powlson, D.S. (Eds.), 1996b. GCTE Task 3.3.1 — Soil Organic Matter

Network (SOMNET): 1996 Model and experimental metadata. GCTE Report No. 7, GCTE Focus 3 Office, Wallingford, UK, 255 pp.

Sundquist, E., 1993. The global carbon dioxide budget. Science 259, 934–941.

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitored vegetation. Remote Sens. Environ. 11, 171–189.

Tucker, C.J., Townshend, J.R.G., Goff, T.E., 1985. African land cover classification using satellite data. Science 227, 369–375.

Tucker, C.J., Fung, I.Y., Keeling, C.D., Gammon, R.H., 1986. Relationship between atmospheric CO_2 variations and a satellite derived vegetation index. Nature 319, 195–199.

Tukahirwa, E.M., 1992. Uganda—Environmental and Natural Resource Management Policy and Law: Issues and Options. II. Documentation. The Institute of Environment and Natural Resources, Makerere University, Kampala, Uganda.

Ulaby, F.T., Moore, R.K., Fung, A.K., 1986. Microwave remote sensing: Active and passive, vol. III: From Theory to Applications. Artech House, Norwood, MA, pp. 1065–2162.

USDA, 1991. State Soil Geographic (STATSGO) Data Base: Data use information. US Dept. of Agric., Natural Resources Conservation Service, National Soil Survey Center, Misc. Publ. 1492, US Government Printing Office, Washington, DC.

Van Noordwijk, M., Cerri, C., Woomer, P.L., Nugroho, K., Bernoux, M., 1997. Soil carbon dynamics in the humid tropical forest zone. In: Elliott, E.T., Kimble, J.M., Swift, M.J. (Eds.), The Management of Carbon in Tropical Soils Under Global Change: Science, Practice and Policy. Geoderma 79, 187–225, this issue.

VEMAP, 1995. Vegetation/ecosystem modeling and analysis project (VEMAP): comparing biogeography and biogeochemistry models in a continental-scale study of terrestrial ecosystem responses to climate change and CO_2 doubling. Global Biogeochem. Cycles, 9: 407–437.

Vörösmarty, C.J., Moore III, B., Grace, A.L., Gildea, M.P., Melillo, J.M., Peterson, B.J., Rastetter, E.B., Steudler, P.A., 1989. Continental scale models of water balance and fluvial transport: an application to South America. Global Biogeochem. Cycles 3, 241–265.

Webb, R.S., Rosenzweig, C.E., Levine, E.R., 1991. A Global Data Set of Soil Particle Size Properties. NASA Tech. Memo. 4286. NASA Office of Management, Washington, DC.

Webb, R.S., Rosenzweig, C.E., Levine, E.R., 1993. Specifying land surface characteristics in general circulation models: soil profile data set and derived water-holding capacities. Global Biogeochem. Cycles 7, 97–108.

Woomer, P.L., 1993. Modelling soil organic matter dynamics in tropical ecosystems: Model adoption, uses and limitations. In: Mulongoy, K., Merckx, R. (Eds.), Soil Organic Matter Dynamics and Sustainability of Tropical Agriculture. Wiley-Sayce, pp. 279–294.