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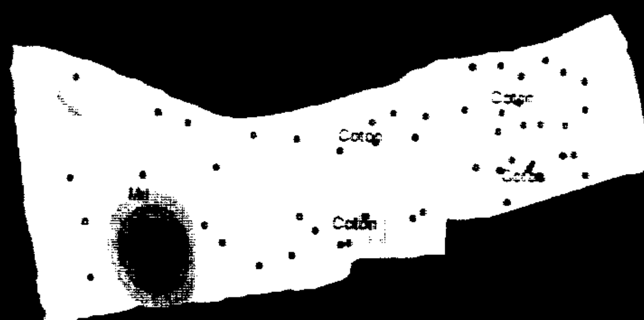
Soil Management C♦R♦S♦P

A Soil Carbon Accounting and Management System for Emissions Trading

Special Publication



Soil Management Collaborative Research Support Program

A SOIL CARBON ACCOUNTING AND MANAGEMENT SYSTEM FOR EMISSIONS TRADING

SOIL MANAGEMENT COLLABORATIVE
RESEARCH SUPPORT PROGRAM

SPECIAL PUBLICATION
HONOLULU, HI

Cover credits: The graphic was generated from soil samples and field boundaries provided by Abdou Ballo of the l'Institut de Economie Rurale, Bamako, Mali. It represents the variation in soil organic carbon in the farm of Mr. Mory Konate near the village of Oumarbougou, Mali. The red points are sample sites collected in December 2000 and the green points were taken in March 2002. The contours were formed from a geo-statistical estimation (Kriging) of soil organic carbon and vary from 0.2 (yellow) to 0.5 %C (brown) and extrapolated to the field boundaries using ArcGIS 8.2 (ESRI, Redlands, California).

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CHAPTER ONE

CREATING INCENTIVES FOR SUSTAINABLE AGRICULTURE: DEFINING, ESTIMATING POTENTIAL AND VERIFYING COMPLIANCE WITH CARBON CONTRACTS FOR SOIL CARBON PROJECTS IN DEVELOPING COUNTRIES

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INTRODUCTION

The purpose of this monograph is to propose procedures needed to support the creation of carbon contracts and projects for farmers. While these procedures are general, our goal is to address the particular needs of farmers in developing countries where incentives to adopt sustainable farming practices are needed most. We have identified three steps to creating carbon contracts: 1) define the contract or project areas for soil carbon sequestration; 2) estimate the potential for soil C sequestration; and 3) verify compliance with contracts.

While storing carbon in soils can counter rising CO_2 levels in the atmosphere, this public good will very likely be far outweighed by the positive benefits that increased soil organic matter content will bring: raising agricultural productivity, alleviating poverty and combating desertification, especially in the world's poorest countries. Linking carbon trading to carbon sequestration will be critical because the war against desertification and poverty requires levels of financing that traditional donors alone cannot provide.

Carbon is a resource, and like income, can be spent or saved to earn more income. Subsistence farmers have no option but to "spend" their carbon supply for fuel, fodder or fertilizer. They plow their fields, not only to loosen the soil, but also to expose buried humus to the elements so that microorganisms can mineralize and release nutrients locked in the humus. In essence, subsistence farmers mine their soils for carbon and nutrients and in the process convert humus to CO_2. This unsustainable practice provides immediate, short-term benefits to farmers who cannot afford fertilizers, but is a major cause of land degradation.

Farmers in the rich, industrialized countries, on the other hand, have no need to use crop residue for fuel, fodder or fertilizer, or even to till their soils. They instead use crop residue to protect their soil from the elements, practice no-till conservation agriculture and replace nutrients removed from the field in the harvested crop with chemical fertilizers. Rich farmers not only protect their carbon reserves, but keep adding to what they already have, not so much to increase, as to sustain their already high yields and to protect the environment.

Poor farmers can also benefit from joining the ranks of conservation agriculturalists, but lack the price of admission. Carbon credit can serve this purpose. At a minimum, farmers need fertilizers, no-till planters and access to markets for farm inputs and produce. Governments, indifferent to the needs of poor farmers now, may view them differently when they see farmers receiving credit for protecting and improving their land, and generating income from the nation's natural resource base. This may convince governments that agriculture can indeed be an engine for economic growth and begin to develop infrastructure and formulate policies that favor agricultural development. It is for this reason that we need to explain more explicitly to a larger audience how sustainable agriculture in particular, and sustainable development in general, could be linked to carbon sequestration.

CARBON'S LINK TO SUSTAINABILITY

Organic carbon is the glue that binds sand, silt and clay into large compound soil aggregates. The bulk of healthy topsoil is mainly composed of organically-cemented aggregates rather than individual sand, silt and clay particles, interspersed with humus. If the aggregates are large and stable, the pores between them will also be large and stable, enabling water, during heavy rains, to seep into the soil for storage and subsequent use by plants rather than to flow over and erode the land. Thus, the capacity of sloping land to withstand the erosive forces of wind and rain depends on the ability of organic carbon to cement dust into stable aggregates.

Organic carbon is also the sponge that absorbs and stores water and nutrients and releases them to plants for photosynthesizing fresh organic matter. Soil microorganisms consume and transform litter and dead root into more glue and sponge. This recycling of carbon, water and nutrients through the soil-biota-atmosphere continuum, if protected from cultivation, results in a net annual storage of carbon until the soil's carbon storage capacity is reached. This capacity to store carbon varies locally and globally and is influenced by the characteristics of the soil-biota-atmosphere continuum. A soil high in clay content, for example, can store more organic carbon than a sandy soil, and all things being equal, a degraded soil depleted of carbon from decades of carbon and nutrient mining has a higher potential to store carbon than its uncultivated, virgin counterpart. For once, poor farmers with the greatest need have the most to gain and the best opportunity to benefit from carbon trading. The benefits subsistence farmers can expect from carbon sequestration are shown in Figure 1. Many food-deficient regions can benefit immediately from the use of fertilizers alone, because carbon credits would enable farm households to purchase fertilizers without fear of crop failure and debt payment. Freedom from fear of risk can be a decisive factor in insuring carbon sequestration in regions with variable rainfall, while simultaneously impacting positively on climate change, desertification and poverty.

The most visible change carbon credits can bring about, however, may be in the reduction of cultivated area. Most agronomists believe that in developing countries crop yields, because they are so low, can be doubled and even tripled, and it is difficult to imagine yields not doubling after a decade of practicing conservation agriculture. If this expectation is realized, marginal lands can be returned to their natural state to serve as habitat and refuge for endangered wildlife.

STEP 1: DEFINING CONTRACT OR PROJECT AREAS

In order to create economic incentives for farmers to adopt more sustainable farming practices, some form of agreement will have to be reached between the parties to the agreement. We shall refer to this agreement as a contract. A key issue is whether these contracts are intended to be traded in an emissions credit market to meet GHG emissions standards (similar to the market for SO_2 emissions in the United States), or whether they are an agreement between the seller and an entity such as a government that does not trade the contracts. We assume that to be a traded asset, a contract would have to specify the amount of C being produced and methods for verification. In contrast, a contract meeting the terms of a single buyer (either a government agency, or a non-governmental organization) would not have to specify the quantity of C produced, e.g., it could instead specify what land use or management practices the seller agreed to adopt. Thus, this situation is more suited to the

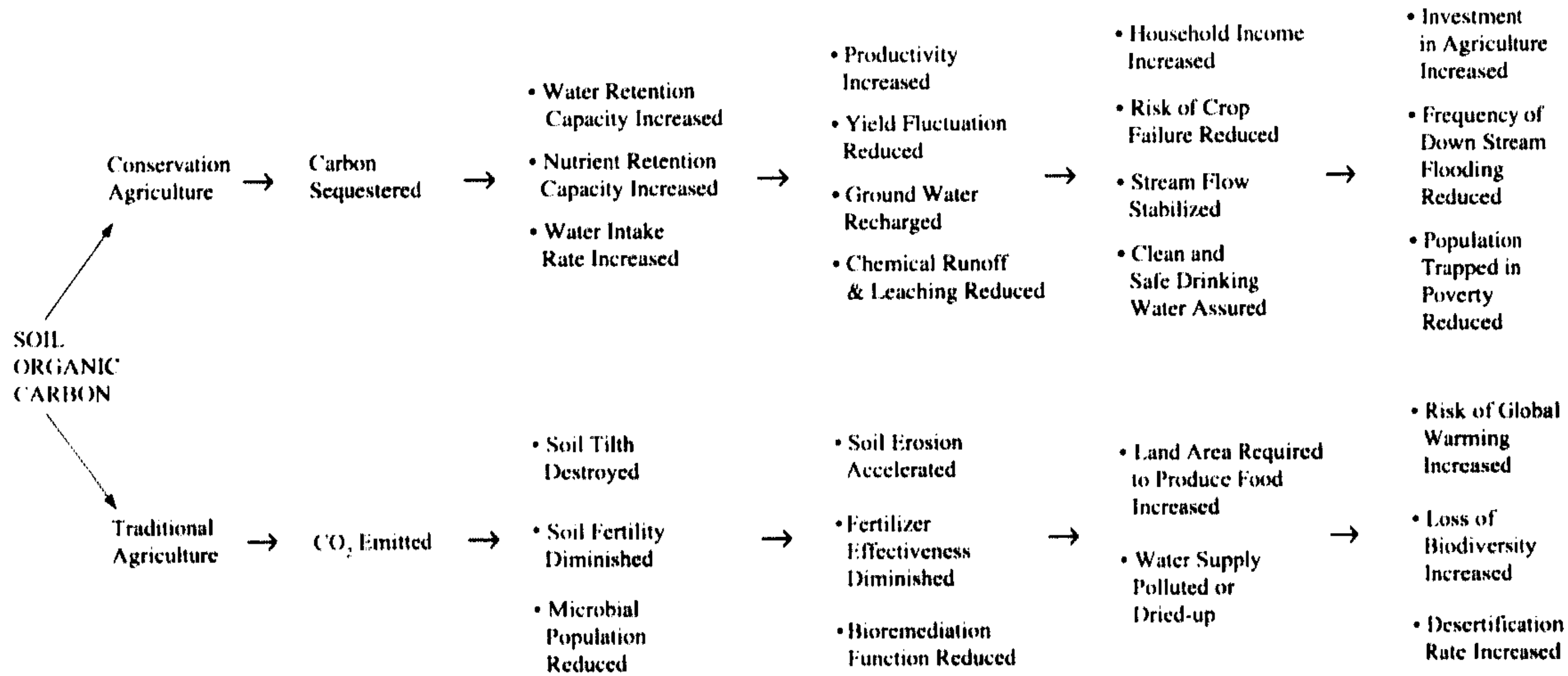

Figure 1. Carbon is the master variable for managing natural resources and combating poverty.

use of a per-hectare contract similar to the ones used in existing U.S. government conservation programs. For example, in the Conservation Reserve Program, participation is established by technical eligibility criteria based on potential soil erosion, and management practices are specified, but changes in environmental outcomes (actual reductions in erosion) are not required to be verified as part of the contract.

A key consideration in defining a region for a carbon contract is the transaction costs associated with the contract. Since these transactions costs are in part fixed per contract, the larger the amount of carbon transacted, the lower will be the cost per tonne as the size of the contract increases. A large number of farms will be needed to participate in a single contract if carbon is traded in units of say 100,000 metric tonnes. A key question in defining the area for a carbon project is therefore on what scale farmers can be efficiently organized into a group that can then be efficiently monitored for compliance with the contract as discussed below.

It would be a simple matter to design contracts for carbon sequestration if soil organic matter were easy to measure, uniformly distributed throughout the landscape and sequestered each year in amounts sufficiently high to be measured and verified. If that were the case, a few measurements over space and time would suffice to quantify gains or losses of sequestered carbon in a parcel of land over a specified period. It turns out, however, that soil carbon, like other soil properties, varies spatially, and changes too slowly in amount with time to be measured with any degree of confidence on time steps of less than five years. This slow, nearly imperceptible change in carbon content, even under the most favorable conditions, simply reflects, however, the huge size of the sink. Most soil laboratories present carbon analysis to the second decimal place. Annual carbon gains from conservation agricultural practices will cause the carbon content to change at the second decimal place. For example, an increase in 1.0 Mg carbon per hectare per year, which is more than the highest reported carbon sequestration rate, will raise carbon levels by only 0.05 percent each year, if the increase occurred in the surface 20 cm.

Fortunately, soil science has dealt with these issues throughout its history. The fact that soils vary spatially, often over short distances, is a fact of nature. Two types of spatial variability are recognizable in the landscape. The first type is called *systematic variability* and is created by differences in the underlying rock from which soils form, differences in the time the rock has been subjected to weathering and differences in climate, vegetation and drainage. It would be unusual indeed if two adjacent sites, one limestone and the other granite, did not produce soils with very different textures, vegetation and carbon contents. These differences are easy to see and therefore are delineated and mapped in soil surveys. In developing countries, where detailed soil surveys are rarely available, remote-sensing technology can be used to stratify lands into reasonably homogenous soil groups.

A second type of soil-spatial variability, which soil surveys and remote-sensing technology cannot take into account, is *random variability*. This type of variability originates from soil processes, many of which are not fully understood. However, one can imagine variability in the particle-size distribution of soils stemming from the way sediment was deposited in an ancient flood plain. Today, the landscape, no longer recognizable as a flood plain, still retains the mark of ancient depositional processes. The sand, silt and clay contents still vary from point to point in the field. This variability in texture affects air and water permeability, drainage, water and nutrient retention, shrinkage and swelling. Clays have greater surface area than sands or silts and therefore absorb and protect organic matter from microbial decomposition. In the end, organic carbon covaries with clay content, and along with texture, becomes a random variable.

An important feature of random soil variables is that their values tend to be more alike between closely-spaced samples than between samples separated by great distances. For this reason, a spatial dependence among values of a particular variable often exists. This tendency of random variables to be spatially dependent is the key that reduces the cost of carbon accounting in spatially-variable soils. Unlike conventional statistics, in which the mean is the best estimate of a variable at unsampled locations, geostatistics, one type of spatial statistic, takes advantage of the existence of spatial dependence or structure in the variance to estimate data at unsampled locations.

Without the aid of geostatistics or some other form of spatial statistics, the cost, time and effort required to obtain baseline-carbon levels could render carbon trading impractical. Another technology that simplifies the use of geostatistics is the low cost and ready availability of global positioning systems (GPS). Geostatistics requires georeferenced data, and in a large project covering thousands of hectares, GPS will be an invaluable tool for sample collection and record keeping. Finally, geographic information systems (GIS) provide the means to display carbon stocks over space and time. The application of remote-sensing technology and geostatistics for carbon trading is more fully described the chapter by Yost et al. in this monograph.

STEP 2: ESTIMATING TECHNICAL AND ECONOMIC POTENTIAL FOR SOIL C SEQUESTRATION

Another requirement of a carbon-accounting system is the capacity to assess the carbon-sequestration potential of a project area and to forecast the rate of carbon sequestration over space and time. Since farmers will have the final say in what practices they will adopt, the projected rate of carbon sequestration must be based on farmers' choice of crops, inputs and practices. It is easy to deduce that the on-farm cost of producing a metric tonne of carbon depends on the ratio of two critical pieces of information: the farmer's opportunity cost of changing management practices, and this cost divided by the increase in soil C per hectare over the relevant time period. For a project to compete in a market for carbon, it must have either a sufficiently-low opportunity cost to farmers or a sufficiently high biophysical potential for storing carbon. It is clear that information about biophysical and economic potentials cannot be obtained experimentally and can only be predicted by using dynamic biophysical simulation models that closely mimic key processes in the soil-biota-atmosphere continuum, and economic models that simulate the land use and management decisions of farmers.

Models can only be as accurate as the knowledge of processes used to construct models, and since our knowledge of processes is incomplete, our models will necessarily be imperfect. The question, therefore, is not about perfection, but whether the models are sufficiently accurate to meet the accounting requirement for carbon trading. To meet this requirement, two well tested biophysical models, the CENTURY and DSSAT models have been combined to produce a model that links processes in the soil-biota-atmosphere continuum in a systems mode. The CENTURY model was developed to simulate the biogeochemical cycle of carbon in soils, whereas the DSSAT (Decision Support System for Agrotechnology Transfer) model was developed to simulate the effects of soil, weather, and crop genetics on crop growth and development. The combined model allows the user to simulate, for example, the effect of soil characteristics, climate, and crop type and farm management, including crop residue management, tillage practices, and fertilizer application on carbon sequestration. The role of biophysical modeling is fully discussed in the chapter by Jones *et al.* in this monograph.

If the below ground carbon sequestration rate can only be estimated, the aboveground biomass can, in addition be observed, and measured. Good agreement between measured and estimated biomass production is necessary to give carbon traders the confidence they need to rely on models to forecast the probable success or failure of a project. An important role of models is to simulate outcomes of farming practices farmers are willing to adopt. This means that model users will need to simulate many types of practices and outcomes from which farmers can choose. Enabling farmers to exercise choice will be a key requirement for project success, but the options available to farmers will obviously depend on the price of carbon. Fortunately, economists have developed models that can realistically simulate farmers' land use and management decisions. Thus, it is possible to link the outputs of the biophysical models and economic models, so that model outputs appear not only as biomass and grain yield, but also as profit or loss in local currency so that farm-opportunity cost can be estimated. The economics of carbon sequestration and trading is covered in the chapter by Antle in this monograph.

STEP 3: VERIFYING COMPLIANCE WITH CONTRACTS

Carbon has often been mistakenly described as a commodity that can be produced by farmers like wheat and other crops. This description is inaccurate because soil C is stored in the soil, and thus is an asset owned by the owner of the land. The buyer of a C contract *cannot take delivery of the carbon* (note the similarity to a futures contract: the buyer does not want or intend to take delivery of the commodity). A more accurate description is that farmers provide a *service* in the form of accumulating and storing soil C. As soon as we recognize that farmers are providing a service, not selling a commodity, many of the issues about carbon sequestration that have been debated recently in the context of the Kyoto agreement can be resolved. For example, soil scientists know that soil C can be either accumulated or released from soils, and this has led to a debate about whether C sequestered in soils would be *permanent*. The resolution of this debate is very simple: farmers will maintain carbon in soils as long as they are being compensated for providing that service.

Recognizing that contracts for soil C are service contracts, not commodity contracts, also provides insight into the types of procedures that could be used to verify compliance with the terms of the contracts. If the contracts specify services to be performed, such as utilizing specified management practices on a specified land unit over a specified time period, then it is these activities that must be monitored. If the contract also specifies the amount of carbon that is to be accumulated and stored, then soil C measurements also must be made. Note, however, that if the contract is defined over a large number of land units, then verification need not occur on every land unit; rather a statistical sampling scheme can be used to obtain a representative estimate of the accumulation of soil C. The determination of the appropriate sample size is a standard statistical problem that has well-known solutions.

PROTOCOL FOR ASSESSMENT OF C ACCRETION POTENTIAL

We assume for the purposes of this exercise that a country has been identified and several potential sites have been located therein.

Introduction. Project team meets with in-country scientists and jointly reviews site selection criteria and collectively agrees on sites that appear to directly relate to project objectives. This will require consideration of existing maps and data as well as possibly including remotely sensed data. Issues to consider might be that systems there are likely to sequester, reasonably representative of large areas. This should include a visual inspection of the site with cooperators. This and subsequent activities will be conducted on a collaborative basis with the in-country scientist taking increasing responsibility as appropriate.

Survey. A large area survey and quantification, using remotely sensed and GIS coverage, of major agricultural and natural systems in the region (likely an area of 50,000 to 100,000 hectares) will be carried out in order to identify landuse/cropping systems for detailed study. Specific fields with example landuse/cropping systems and comparable control fields will be selected representing various periods of time under the selected landuse/cropping systems to develop 1 to 3 to 10 year calibration curves of soil and biomass carbon. These fields will be key for initial intensive measurements that will lead to characterization of the soils and C pools used in model prediction and characterization of C sequestration potential.

Planning Workshop. A regional workshop may be useful wherein collaborators present the results of the initial survey and identification of their sites. The subsequent methods and steps of the project will be discussed and project sampling, analysis, simulation, scaling up and monitoring will each be discussed and detailed.

Sampling. A two phase-sampling procedure may be required. The first stage sampling will take place in a manner that will permit characterization of major trends in variability—likely on the order if 40 to 80 samples per landuse/cropping system will comprise the initial sampling phase (see Procedure for Sampling).

Laboratory Analysis. Samples of soil and biomass will be analyzed in order to characterize the landuse/cropping system. Procedures to analyze soil organic carbon for carbon sequestration purposes may be different from the traditional Walkley-Black methods. The traditional method does not measure total soil organic carbon, may not measure some fractions, and releases the environmentally toxic chromic acid. Methods based on total carbon combustion are now recognized as the best estimate of soil organic carbon. Initial statistical analyses of these samples will include 1) determination of means, medians, and standard deviations, and 2) semi-variograms will be constructed in order to determine the presence of spatial dependence for developing efficient sampling.

Statistical Analysis and Local Workshops. Analysis and interpretation of the phase one biomass and soil analytical data will be carried out jointly with the in-country scientists with local knowledge together with the land managers and farmers in an effort to establish the long term record of cropping patterns and fallow periods. It is expected that the selection or rejection of fields could take place at this step. A local workshop in each country will be conducted to assist in the analysis and interpretation of phase one biomass and soil data and in preparation for the Regional workshop.

Regional Workshops. Regional workshop to summarize results of the phase one sampling, design of phase two sampling, and preparation for simulation studies.

Year Two Sampling. The year two sampling will correspond to the second-phase sampling, which will be based on the low-cost preliminary soil analysis and the resulting spatial dependence, if present. With such information in hand, an efficient sampling scheme can be designed and carried out. It is expected that no more than 200–500 samples will be needed on the average, of a region that is a good candidate for carbon sequestration to a specified precision. The second sampling will serve as the primary input for point estimation of crop yield, biomass, and soil organic carbon and will include the same measurements as indicated above plus the measurement of crop residue (using remote-sensing) during the period immediately before the typical onset of rains and generation of new biomass.

Simulation Modeling. Using simulation models, the data will be used to estimate 5, 10, 15, 20 and 100 year status of C with accompanying uncertainty analysis. Analysis with the aid of simulation models will be undertaken in order to estimate the 'steady state' C levels in biomass and soil organic carbon will provide an estimate of carbon sequestration potential.

Scaling Up. After completion of the initial estimation of biomass and soil organic C at point locations, these estimates will be scaled up to the geographical extent of the initial stratification of landuse/cropping system at the larger land area scale. Remote sensing will be used in order to assess the variation in crop residue remaining after the end of the dry season among fields within the 5,000 to 10,000 ha region. Where systems are too complex for meaningful simulation yet accumulation patterns seem significant, estimation of large area accretion will be carried out by means of kriging and co-kriging.

Year Four Samples. Sampling of soils to assess measured change in soil organic C using the sample configuration developed for phase two sampling.

Monitoring. A monitoring evaluation of landuse/cropping systems will be conducted in two ways: (1) comparing measured soil and biomass C accretion measured at 24 months with that measured at 48 months, and (2) comparing predictions of soil and biomass C using remotely sensed imagery taken at 48 months (near the time of max. seasonal biomass) with that measured at 48 months. In the former case, the results give an indication of the change in C per unit time and the latter gives an estimate of accuracy of the use of remotely sensed imagery in predicting soil and biomass C change.

Synthesis and Reporting. A synthesis/reporting workshop of project outputs is recommended to present summary results and preliminary conclusions.

Training and Capacity Building. Another anticipated barrier to soil carbon trading will be a shortage of individuals and organizations, particularly in developing countries, able to estimate carbon tonnage in large tracts of spatially variable lands. This constraint can be removed with a training program based on a standardized carbon accounting system approved and certified by the international carbon trading community. It should be possible for buyers to use this same system for verification of carbon tonnage in the field.

CHAPTER TWO

DEFINING THE CONTRACT AREA: USING SPATIAL VARIATION IN LAND, CROPPING SYSTEMS AND SOIL ORGANIC CARBON

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INTRODUCTION

In the chapter by Antle and Uehara, a protocol for developing a carbon accounting system is introduced, which is comprised of defining the contract area, estimating sequestration potential and verifying compliance. In this chapter, we describe methods of physically defining a contract area. Though other concerns are important in defining a contract area, such as the administrative, political, and social aspects, these are not the focus of this chapter. One of the challenges in defining a contract area is identifying a sufficiently large, uniform area such that large quantities of soil carbon can be sequestered with confidence. To meet this challenge, we propose using remote sensing imagery. Initially, we will discuss aspects of remote sensing that can assist in this task, and at the end of this chapter, we will describe other aspects of remote sensing that can be useful for modeling and model validation, as well as for verification that an accepted contract is being followed.

USING REMOTE SENSING FOR LAND USE CLASSIFICATION AND MEASUREMENT

To develop a common vision of the carbon trading/sequestration possibilities, goals and objectives, study and consideration of the land-use inventory is needed by all parties involved in the sequestration project. In defining potential carbon sequestration areas, it is usually necessary to determine whether an area is sufficiently large and uniform to support the measurement and trading of units of carbon as large as 100,000 tonnes.

Remote sensing methods (see Table 1 for some example satellite imagery) can be an efficient way of inventorying and classifying a large region into land uses, cropping systems, topography, transportation, infrastructure and other features that contribute to defining a contract area. A reconnaissance inventory of a region may be a first step in a regional soil carbon assessment. Such an inventory gives an estimate of the area within the region that is a candidate for carbon sequestration by identifying cropping systems, landuses, topography all of which provide the broad view and set the bounds for potential carbon sequestration.

Landuse Classification

A landuse classification and definition of the specific land covers can be achieved through image classification. Classification of large areas can be improved based on some prior information of the local landscape and a general landuse map. Stratification into management units can be based on Digital Elevation Models (DEMs) and derived products (e.g., a slope map), landuse and topographical maps, and soil maps or even historical imagery data sets that are grouped based on spectral features. The availability of the above information can be limited in most regions of the world. A minimum dataset of the DEM and some ancillary image products can help define the area. Surface-soil physical features usually follow the patterns in the DEM. High-resolution DEMs are more likely to be available than high-resolution digital-soil classification maps. Combining the available DEM and derived products from spectral imagery, processed adequately and developed in geographic information layers, can be very effective in stratification of management units for sampling and assessment of soil carbon.

Table 1. Satellite and image data for landuse classification and stratification of a region into homogenous areas for sampling and analysis.

Acronym	Name	Resolution	Information/Advantages
MSS	Landsat Multispectral	60 meters V-NIR*	Identifies land cover
ETM	Landsat Enhanced Thematic Mapper	30 m, 6 visible NIR bands 15 m (Panchromatic) Pan	Represent vegetation, plant stress, and plant greenness very well. Soil and Vegetation classification.
SPOT	SPOT Image	20meters, 4 V-NIR bands 10m Pan	Soil and Vegetation classification
IKONOS	Product of 'Space Imaging, Inc.'	4 m- 4 V-NIR band 1m Pan	Extremely detailed imagery, some of the highest resolution commercially available. Very costly. Acquired from NASA day-buy program.
ASTER	New satellite, part of the Terra Platform	15 m, 3 V- NIR bands 30 m, 6 Mid-infrared 90 m, 5 Thermal	Mapping vegetation and soils. There are 6 thermal bands useful for emissivity and surface residue.
ALI	Advanced Land Imager	30 m, 9 V-NIR bands 10 m Pan	Landuse mapping, soil and vegetation cover.
Hyperion	Hyperspectral Imager EO-1 Platform with ALI	30 m, 220 V-NIR bands	One of the first examples of 'hyperspectral' data. Large no. of bands should increase specificity of detection.
DEM	Digital Elevation Model	60-600 m elevation contours	Represents the change in land scape elevation. The data availability is dependant on location
Ground data:			
Soil surface	ASD, Analytical Spectral Devices, Inc.	1 nm band resolution between 350-2500 nm	Permits precise reflectance measurements on the ground for use in calibration satellite imagery
DGPS	Differential Geographical Positioning System	1m resolution	Permits precise location of ground-based ancillary data to calibrate with satellite imagery. Provide verification for DEM data.

* V-NIR – Visible and Near Infrared spectral bands

Landuse classification can be accomplished by a standard procedure known as *supervised classification.* A supervised classification uses statistics derived from 'training datasets' to identify image areas as 'homogeneous' and then to group similar areas as spectral classes. Ground data are collected to identify the different types of vegetation and bare soil from training sites. The training sites identified in the imagery provide 'signatures' for the various classes of land cover. These are combined into signature files and a supervised classification is then performed by matching each pixel of the image with the signature file using the Mahalanobis Distance as the criteria for similarity (Stern *et al.*, 2001). One-third of the training data set is not included in developing the signature files used in the supervised classification. These remaining data are used to validate the classification accuracy, which is important for estimation of vegetation biophysical parameters such as leaf area index (LAI) and biomass. A complex terrain with a mixture of land covers requires the development of training sites at various locations (Area of Interest-AOI) within the study area.

Imagery acquired through the period of active vegetative growth is necessary to accurately separate the various land cover and landuse types, while prior knowledge of the vegetation phenology permits the selection of the best window for acquiring the imagery. The size of the study area dictates the type of imagery that can be used for the classification. In general, Landsat and SPOT are used for areas between 300-3000 km^2. However, for regions 100 km^2 or smaller, the newer satellite imagery such as IKONOS (Space Imaging Inc.) can provide the required resolution, and an option using imagery collected from aircraft for smaller areas also exists. Table 1 shows the available satellite imagery, based on the size and extent of the study area. Note that ground data are required for accurate landuse classification.

As a result of landuse classification, zones of similar carbon sequestration potential can be identified as well as the approximate uniformity of them. This provides information for the definition of the contract area. Once the landuses of a region have been classified, the representative and candidate cropping/landuse systems can proceed..

Development of Management Units for Soil Carbon Sampling

After completing a landuse classification, land management units can be delineated to guide soil sampling and carbon measurement. Soil physical properties including texture and surface organic carbon has been correlated to specific spectral responses (Dalal and Henry, 1986; Shonk *et al.*, 1991; Leone *et al.*, 1995) but with some conditions. Barnes and Baker (2000) showed that surface soil textural classes could be delineated only when fields have uniform tillage conditions. Salisbury and D'Aria (1992), however, showed that some of the interferences caused by variation in soil moisture, organic matter, minerals other than quartz can be minimized by combining the reflectance in the visible, near infrared and thermal infrared bands.

The delineation of management units serves as a guide to soil sampling. With the characterization of the spatial dependence one can minimize the number of samples needed to represent a given area. The reversal of this process, using geospatial methods described later in this chapter, provides a mechanism for scaling-up soil organic carbon estimates and predictions as to the management units and the landuse classifications. Figure 1 is a schematic of the landscape classification procedures for developing land management units.

Development of land management units for agricultural lands would be most suitable during bare soil conditions. However, this may be more challenging in the tropics than at higher latitudes where the vegetation phenology is more defined for cultivated lands and natural vegetation. The availability of multi-spectral imagery during specific periods for bare soil classifications and separation of vegetation classes is most critical for developing suitable landuse and sampling management units. A combination of high-spatial resolution imagery with high-spectral resolution is optimum for developing spectral indices that can separate the soil

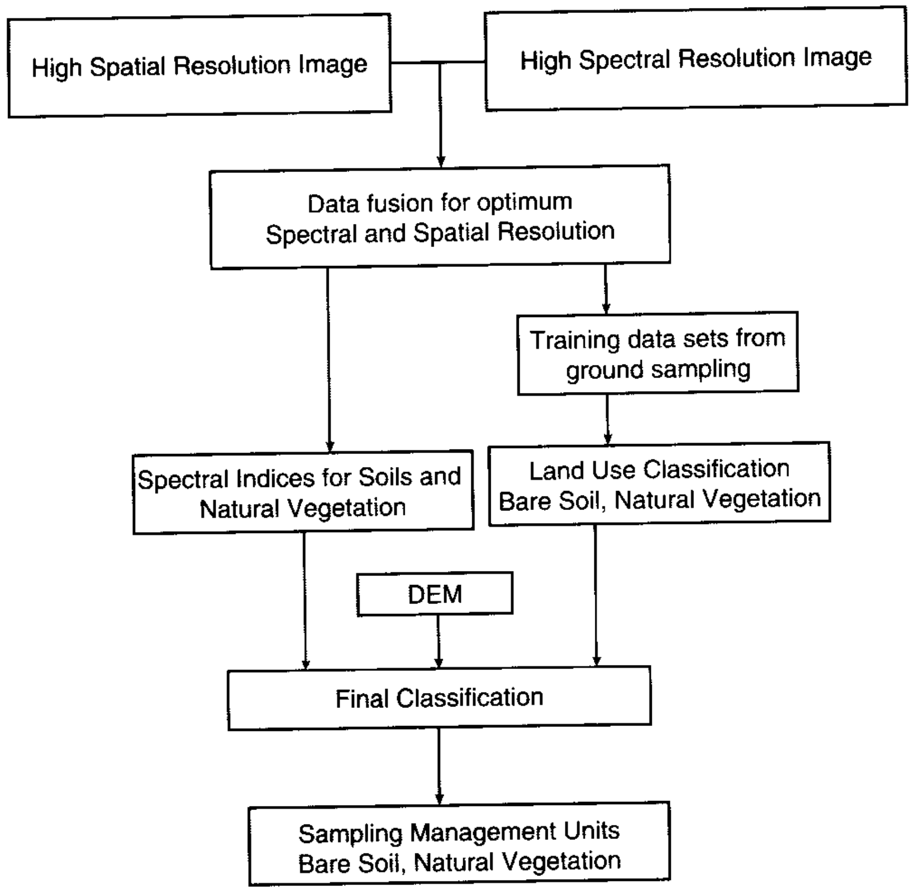


Figure 1. Use of remotely sensed data to define soil carbon contract areas through landuse classification and management unit delineation.

classes as well as vegetation type (Figure 1). The natural vegetation classes could be further stratified into smaller sampling management units based on the vegetation condition, which may be in response to the differences in soil conditions.

Measurement of soil carbon and nutrient properties based on management zones can be developed using geospatial technology that integrates ground measurements with information derived from satellite remotely sensed imagery. Soil physical properties including texture and surface organic carbon have been correlated to specific spectral responses (Dalal and Henry, 1986; Shonk *et al.*, 1991; Leone *et al.*, 1995). Multi-spectral images have shown potential for developing soil classification mapping units. Barnes *et al.* (1996) studied the sand and clay content of soils using remotely sensed data to complement and enhance spatial assessment of the samples.

Estimating Soil and Crop Properties with Remote Sensing

We emphasize the use of remotely sensed data for defining contract areas, but with technology improvements it is increasingly used for direct measurement of soil and crop properties. These direct measurements are useful in assessing and modeling soil organic carbon. In this section we describe some of those techniques and point out the importance of monitoring developments in the field for new methods that can improve carbon sequestration measurement.

Soil Surface Texture. Stoner and Baumgardner (1981) conducted one of the earliest investigations on the use of spectral reflectance to infer soil surface characteristics. The spectral reflectance in the visible and near infrared (0.3-2.8 nm) was related to differences in organic matter content, iron content and texture. Others have related surface reflectance spectra with fractions of sand, silt and clay with varying degrees of success (Suliman and Post, 1988). Barnes and Baker (2000) showed that surface soil textural classes could be delineated only when fields have uniform tillage conditions. The effects of soil moisture, organic matter, and minerals other than quartz interfere with textural classification and can be minimized by combining the reflectance in the visible, near infrared and thermal infrared (Salisbury and D'Aria, 1992). The determination of soil surface texture may be useful in stratifying soils' carbon sequestration potential.

Soil Organic Carbon. As a general rule, a dark colored soil will have a higher organic carbon content than a light colored soil. This rule of thumb holds for soils with light colored minerals such as silica sand and silicate clay minerals. In the dry, warm tropics, however, rock weathering results in an accumulation of dark colored iron and manganese oxides which also add to dark soil colors. In the humid tropics, more intense weathering produces a residue of brown and yellow hydrated iron oxides, which interacts with and neutralizes the dark color of organic carbon to lighten the color of high organic carbon soils.

Examples of the dark, low organic carbon soils include the black cotton soils of India, the tropical black earths of Australia, the Houston black clay and the dark magnesium clay of Hawaii. These soils, now all classified as Vertisols in the US Soil Taxonomy (Staff, USDA, 1999), are noted for their dark colors but are generally low in organic carbon content (Buol *et al.*, 1989). Another group of soils with dark colors not unrelated to organic carbon are the manganiferous Oxisols of Hawaii. The Wahiawa series in Central Oahu, Hawaii is red when freshly plowed, but turns purplish-black after several weeks of exposure owing to accumulation and oxidation of manganese on the soil surface. These dark colored Vertisols and Oxisols occur in regions with extremely dry and dry, soil moisture regimes.

Several studies conducted over agricultural fields have related soil reflectance data with organic carbon (Henderson *et al.*, 1992; Chen *et al.*, 2000). The visible wavelengths (0.425- 0.695 nm) were found to have a strong correlation with soil organic carbon for soils with the same parent material. The relationship was, however, sensitive to Fe- and Mn-oxides for soils from different parent materials. For soils from the same parent material, the middle infrared wavelengths were sensitive to organic carbon content of soils. Chen *et al.* (2000) accurately predicted soil organic carbon using area-specific regression relationships from true color imagery. The challenge of correctly estimating organic carbon in soils of the Tropics using spectral reflectance data is that the black Vertisols may have the least soil organic carbon, while the red, highly weathered Ultisols and Oxisols often contain large amounts of soil organic carbon.

Most of the relationships developed in the past have focused on selecting specific spectral bands and, collectively or individually, correlating them to soil properties such as soil texture and organic carbon. Development of algorithms or indices with a combination of specific bands would be a more stable and consistent method for assessment of soil properties and should be transferable to other locations with the same Soil Taxonomy.

With continued development of geospatial technologies (instrumentation and software) and high-resolution spectral and spatial sensors, a revisit to this topic of accurately mapping soil organic carbon is encouraging. Surface reflectance measurements of bare soils from remotely sensed platforms should provide a less labor-intensive grid sampling and more accurate assessment of soil organic carbon maps.

SAMPLING AND STATISTICALLY ANALYZING SOIL ORGANIC CARBON IN LAND MANAGEMENT UNITS

In this chapter, the use of remote sensing to define the contract area has been described, as well as landuse classification and the delineation of land management units. In this section, we describe statistical aspects of optimal sample design, the estimation of spatial dependence in soil organic carbon data and the scaling up of measurements to land management units and contract areas.

As indicated in the introductory section, measurements of soil properties usually include a component of estimating the spatial dependence of soil properties, which is the tendency of most soil measurements to become alike as samples are taken more closely together. We illustrate the use of spatial dependence, using the methods of geostatistics, to extract information and economize sampling in ways not previously available in classic experimental statistics.

First thoughts on spatial variability of soil organic carbon are often negative, as in the case of experiments where high variability dilutes significance of results. We will illustrate, however, that spatial variability, or rather the measurement and analysis of spatial variability, can give insight and understanding in most cases, or at a minimum quantify, soil carbon for modeling, summation or comparison.

Using Systematic and Random Variability to Improve Estimates of Soil Organic Carbon

Continuing the discussion of systematic and random variability of soil properties such as soil organic carbon, we give examples of such variability and of the property of spatial dependence, which describes how samples tend to be similar the closer they are taken together. We also give examples of how to use geostatistics to improve the sampling, interpolating and extrapolating of point measurements or simulations, described in succeeding sections. We describe how these geospatial techniques can assist in the daunting task of quantifying and predicting change in soil organic carbon—a critical necessity in developing a soil carbon accounting system.

Another way of looking at systematic and random variability is to express it in equation form using statistical terms such as the following:

(1) $Y = \mu_i + \varepsilon$

where:

- Y = an observed biophysical variable such as above ground biomass,
- μ_i = what, in the simplest form, can be considered systematic variability and represented either as categories, such as soil types, landuse systems and cropping systems, or as a continuum, such as gradients in soil pH, soil carbon or clay content. In a somewhat more complex form these systematic values could be the prediction results of a multiyear simulation model (see Jones *et al.* chapter).
- ε = the random variation representing the fact that samples differ from each other according to some statistical distribution. In geology and soils, however, ε is often not random and contains a further systematic component beside that already specified in μ_i. The analysis of this systematic component has been important in practical mining and geologic studies leading to geostatistical science. Cressie (1991) provides an extensive discussion of the often-stormy relationship between geostatistics and classic statistics. The introduction of geostatistics into American soil science, however, owes a lot to Dr. D. Nielsen, University of California at Davis.

In the earlier discussion on using remote sensing for landuse classification, we related one way of identifying the systematic variation μ_i of Equation 1. We shall now analyze the data for the spatial dependence contained therein. Spatial dependence is the property by which sample values tend to become similar the closer samples are to each other. Classical statistics requires that samples be independent of each other for the probability statements of significance to hold. The presence of spatial dependence invalidates this necessary assumption for classical statistical methods. Geostatistics, however, includes the realization of such lack of independence and, in fact, quantifies and uses spatial dependence in measures called variograms. An example variogram of soil organic carbon is illustrated in Figure 2. The spatial dependence illustrated in Figure 2 is described by the following equation:

$$(2)\quad \gamma = C0 + C*1.5(x/a) - 0.5(x/a)^3 \quad \text{for } x < a$$
$$= C0 + C \quad \text{for } x \geq a$$

where:

- γ = the semivariance,
- C0 = the Y intercept,
- C0 + C = the "sill," or the sample variance (ε of equation 1),
- x = distance between samples,
- a = "range," or the point where the semivariance increases to become equal to the sample variance (ε).

Three features of the variogram are important: the *sill*, the *nugget variance*, and the *range*. These terms were coined by early geostatisticians and represented new concepts to statistical science. The *sill* refers to the maximum semivariance, which is often similar to the sample variance that represents the variability of a number of samples taken in a field (Figure 2). The sill is important because, as shown in Figure 2, it usually is the upper boundary of semivariance shown in the variogram. When the sill is exceeded it might indicate that there is a consistent trend in values across the field. The *nugget variance* represents the variance among samples taken at the same location. Because it is physically impossible to take more than one sample at a point, the nugget variance is extrapolated from samples taken closest together. The nugget variance in Figure 2 was estimated in this

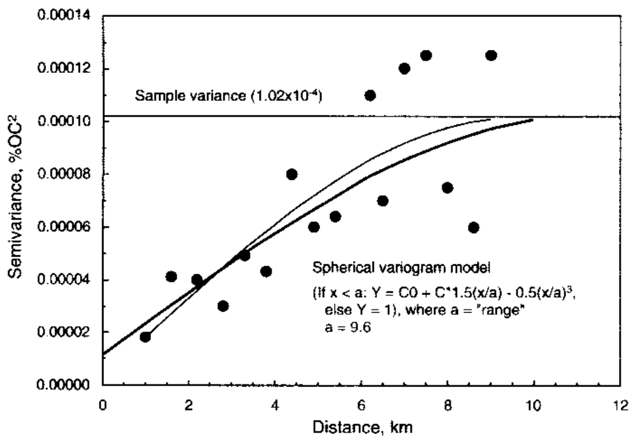


Figure 2. Variogram of soil organic carbon, Pearl Harbor Watershed, Oahu, Hawaii.

way. No samples were taken at exactly zero distance apart, so the fitted curve was extrapolated to zero distance for an estimate of nugget variance. The nugget variance is important in the measurement of spatial variability because when it is equal to the sill, often the sample variance, it indicates that samples are behaving independently with distance; that is the spatial dependence is zero. The term *nugget variance*, derived from the mining industry, reflects the variogram of gold when the gold is randomly distributed as nuggets—one either hits a nugget or not; rather than finding a smooth trend of gold content in the deposit.

The third term, the *range* of a variogram, differs from the range used in classic statistics. It is the minimum distance between samples at which they behave independently. This is represented in the variogram as the distance at which the semivariance approximates the sample variance. For example, the range in Figure 2 was about 9.6 kilometers. The range of the variogram is important in the measurement of spatial variability because it gives an indication how far apart samples should be from each other in order to provide the maximum information.

Sample Design. Geostatistics considers the effect of distance and location on the statistical properties of measured phenomena. In effect, it indicates that not only does it matter how variable a measurement is but also where the samples were taken for the measurement. For example, taking two samples side by side is somewhat wasteful if another part of the field is not sampled. The importance of this additional information becomes apparent when we open classic texts of statistics and learn that we need to take the following number of samples in order to obtain a desired precision. This is given by the following equation or variants of it:

(3) $n = t_1{}^2 s^2/d^2$

where:

- t_1 = the tabulated t value for the desired confidence level and the degree of freedom of the initial sample, and
- d = the half-width of the desired confidence interval (Steel and Torrie, 1960).

We see that in these cases, the authors of the classic texts have recognized neither the spatial dependence nor the fact that location of the sample strongly affects how much independent information is obtained. McBratney and Webster (1981a, b) have discussed these issues, and computer routines were developed to assist in the estimation of sample requirements where there is spatial dependence.

The spatial dependence—the *range* of the semivariance, in particular—gives the distance at which samples give the maximum information. At sample distances less than the *range*, sample values, as indicated by the semivariance, become dependent and provide less information than at greater distances. Thus, estimating the *range* gives a suggested grid size for efficient sampling. In practice, when samples have strong spatial dependence, fewer samples are needed to characterize the variation. The semivariance provides the data needed to develop curves that relate number of samples (and costs) to target sample variances. These curves give a comparative estimate of how many samples are needed for a specified variance and thus an estimate of samples costs. In the chapter by Antle, sample costs are described further.

Kriging. So far, the quantification of spatial dependence through the estimation of the variogram has been illustrated. Geostatistics offers still more concepts and methods in the quantification of spatial variability—the prediction of spatially-variable properties across the landscape. To develop and discuss the principles of kriging is beyond the purposes of this paper so we refer the readers to several texts that present this methodology (Gooverts, 1997; Isaacs and Srivastava, 1989; Journel and Huijbregts, 1978; David, 1977).

Kriging uses information about a property's location and spatial dependence to best estimate that property at unsampled locations. As such, it is an ideal method of taking point data to estimate spatial distribution of soil properties, or, when extended to three dimensions, it can be used to estimate quantities of ore, mineral deposits or concentrations of contaminants (Gooverts, 1997). The geostatistics texts listed in the cited literature section at the end of this chapter are good references for the details of the procedures. Perhaps more importantly, modern software now includes variograms and kriging as part of the mainstream statistical methods for spatial measurement and estimation (Surfer, 2001; IDRISI32, 2001; ArcGIS, Geostatistics Extensions, 2001). Geostatistics was recognized as necessary and was developed by gold miners in South Africa when they tried to predict the value of ore from samples, as a tool to guide the costly process of prospecting the most valuable deposits, and Matheron (1955) later developed the statistical basis for the technique. Adoption in the US has been surprisingly slow, but recent texts by Cressie (1991) and papers in the American Statistical Journals indicate a gradual penetration into American practice. Geostatistical methods have proven to be of great value in quantifying and managing other spatially distributed phenomena in environmental monitoring and measuring of contaminants, geography, geology, soil science and other biological sciences.

Following is an illustration of how geostatistical concepts can assist in the daunting task of quantifying and predicting change in soil organic carbon using some examples of studies of soil organic carbon from Indonesia, Hawaii and West Africa.

Soil Organic Carbon in Indonesia. In this example, the presence of spatial dependence over large distances, as large as several kilometers, is illustrated, and in this case is probably related to distance from an active volcano. The detection of spatial dependence helps define a potential soil carbon contract area.

Soil organic carbon was measured in land clearing operations in West Sumatra, Indonesia as one of many properties often adversely affected by the clearing of land

(Trangmar *et al.*, 1987). The initial, regional study covered an area of about 106,000 ha (ibid, 1984). The first activity identified five geomorphic features of the area, which included: a dissected peneplain, a transition peneplain-terrace, subrecent terraces, recent floodplain and granite. While there were no differences among the geomorphic units in mean soil organic carbon (it varied from 3.1 to 3.9 percent), the study indicated extreme acidity on the upland, peneplain surfaces (pH 4.3), while the recent floodplain pH was still acid (pH 5.1, ibid, 1984). Analysis of the variograms of soil organic carbon at the resolution indicated that there was some spatial dependence even at the regional level (Figure 3). The *range* of spatial dependence was almost 3 km, with substantial differences between the nugget variance and the sill. Such range values suggest a pattern among the regional units of a recurring distance of 3 km, possibly related to regional differences in soil organic carbon. This variogram illustrates a case where the sill or maximum value of the semivariance was less than the sample variance, a somewhat unusual occurrence.

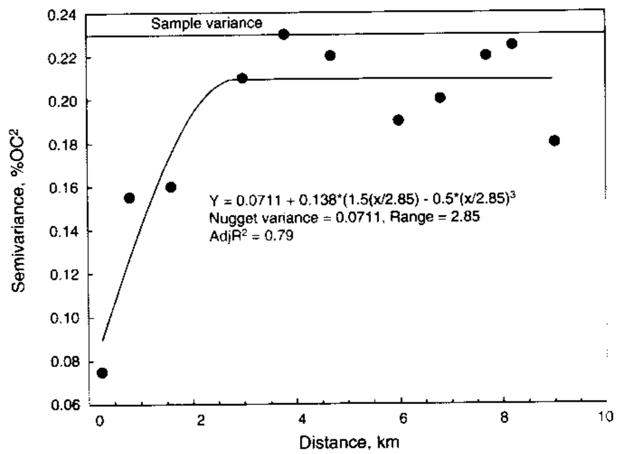


Figure 3. Variogram of soil organic carbon, regional study, Sitiung, West Sumatra, Indonesia (Trangmar, 1984).

One of the issues in the region was the extreme soil variability at the research plot level. In many cases strong differences in the research treatments occurred yet the experimental variability was extreme and the experiments were unable to detect differences among treatments. Consequently, a study of soil variability at high resolution was also conducted. A representative section of recently cleared land was selected that measured 28 meters x 28 meters (Trangmar *et al.*, 1987). Samples were collected on transects of 1 to 1.4 meter intervals for a total of 137 samples in the square of 784 m^2. Interestingly the soil organic carbon varied from 0.2 to 7.2 percent, with a sample variance of 0.17 percent OC^2, only slightly less than the variance of the 88 samples collected in the same province but over 106,000 ha (106,000,000 m^2). As shown in Figure 4, spatial dependence was also observed in the high resolution data with the range at about 10 meters and a sill not greatly less than the sample variance (Figure 4).

Taken together these two studies illustrate *nested variability*. This should not be surprising because clearly different processes are operating at the different resolutions. At the regional level, large-scale differences in geology, volcanic activity and river erosion influence properties and can result in spatial dependence. At the detailed resolution level, landuse changes, effects of a bulldozer in clearing land and exposing subsoil and burning, as part of land clearing, may predominate.

Such distinctions between causes of variability lead to better understanding of the underlying processes and give clues to grouping and stratifying fields and regions. These facilitate modeling by predicting changes in soil organic carbon, a topic to be taken up later in this chapter.

This example shows that spatial dependence in soil organic carbon can exist at both large distances (several kilometers) and at small distances (several meters). These results quantify the number and spacing of samples needed in order to estimate soil organic carbon with a specified precision or variance.

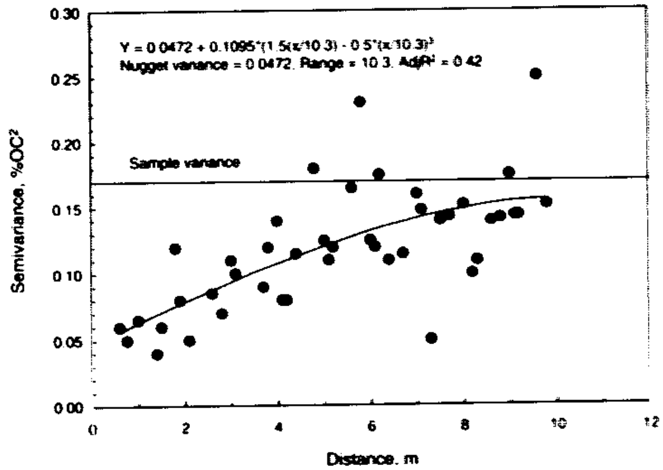


Figure 4. Variogram of soil organic carbon, detailed 28 x 28 field study, Sitiung, West Sumatra, Indonesia (Trangmar *et al.*, 1987).

Soil Organic Carbon in Hawaii. Variability in soil organic carbon was the object of a study in Hawaii. In this case, however, the study was prompted by the need to evaluate soil organic carbon for its role in pesticide leaching – a severe problem that risks contamination of the drinking water supply in the islands only aquifer (Yost *et al.*, 1993). For this study, Equation 1 was expanded to quantify variation in soil organic carbon by considering the systematic variability represented by the mapping units identified during the soil survey and the associated soil taxonomy (Equation 4).

(4) $Y_{ijklmno} = Order_i + Suborder_j + GreatGroup_k + Subgroup_l + Family_m + Series_n + MappingUnit_o + \varepsilon$

where:

- $Y_{ijklmno}$ = the measured phenomena on each Mapping Unit,
- $Order_i$ = the variability partitioned by the Order level of Soil Taxonomy
- $Suborder_j$ = the variability partitioned by the Suborder level of Soil Taxonomy
- $GreatGroup_k$ = the variability partitioned by the Great Group of Soil Taxonomy
- $Subgroup_l$ = the variability partitioned by the Subgroup of Soil Taxonomy
- $Family_m$ = the variability partitioned by the Family level of Soil Taxonomy
- $Series_n$ = the variability partitioned by the Series level of Soil Taxonomy
- $MappingUnit_o$ = the variability partitioned by the designated Mapping Unit
- ε = the remaining variability not accounted for by any of the preceding criteria.

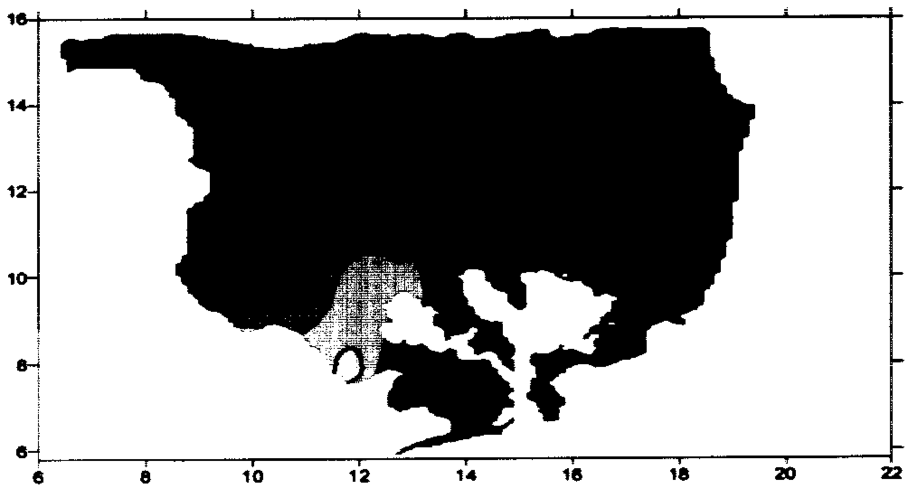
In this way, the criteria of Soil Taxonomy were shown to effectively stratify variability in soil organic carbon (Yost and Fox, 1983).

Equation 4 can be of use where soils have been mapped and classified. Unfortunately, this approach is not useful unless there has been a detailed soil survey, which is usually the exception rather than rule in the Tropics. The equation illustrates that systematic variability can be removed from regional variation in natural resource measurements such as soil organic carbon. As we will illustrate in the case of soil organic carbon in Mali, the categorical variables are helpful in removing effects related to cropping, landuse systems and geomorphic position.

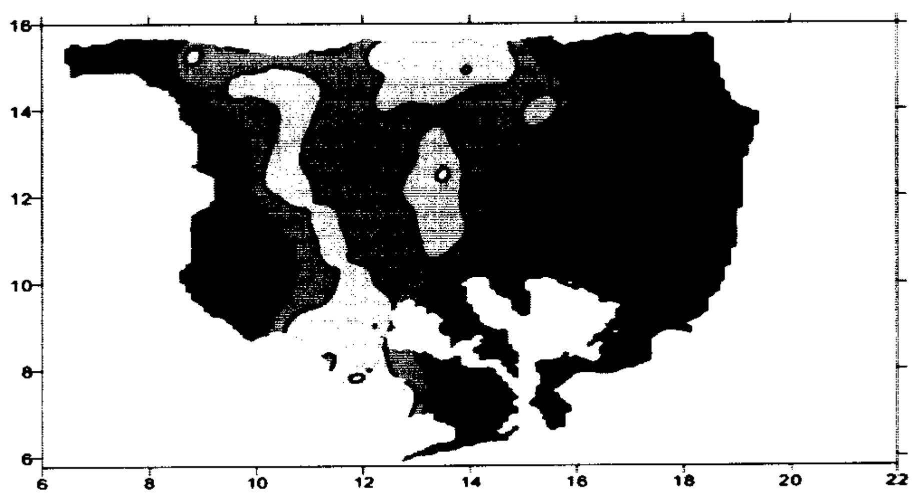
The estimation of soil organic carbon in Hawaii began with the georeferenced soil profiles that were part of the original soil survey (Foote *et al.*, 1972). These numbered only 14 for the approximately 736,000-hectare region. The data from the original 14 samples was modeled with a variogram (Figure 2), which was far less than the usual 50 to 75 samples minimum for a variogram (Journel and Huijbregts, 1978). Nonetheless, with this reduced number of samples, considerable spatial dependence was detected and the information was used to select an additional 39 samples at approximately 1 km distances along roads in the watershed. With this additional set of samples, a revised variogram was estimated and the minimum variance was estimated from the nugget variance. This value was compared with the minimum variance estimated from the use of Soil Taxonomy to stratify levels of soil organic carbon in the watershed. The variances were very similar, indicating that Soil Taxonomy had nicely stratified variability in soil organic carbon (Equation 4), but also that the use of geostatistics gave relatively similar results. These results suggest that sampling with the guidance of an initial variogram permits an efficient sampling of the long distance variability in the watershed. The variogram also indicates that by selecting approximately 511 samples, the variance in estimating soil organic carbon can be reduced to a value 1/5 of the original. The study also suggests that the further collection of 4,600 samples or even 7.36 million would not substantially reduce the variance of soil organic carbon measurements. Of importance to the estimation of soil organic carbon was the relatively good performance of additional sampling based on the spatial dependence of the initial samples. The costs of estimating soil organic carbon using the spatial dependence information provided by geostatistical means would have been substantially less than the costs of sampling without spatial dependence information. Without knowing the spatial dependence of soil organic carbon, one may select too few or too many samples relative to the relationship between sample numbers and sample cost.

Estimating regional soil carbon levels from point samples. Kriging was used to interpolate and extrapolate the 53-point measurements of soil organic carbon in order to estimate the levels of soil organic carbon throughout the region (Figure 5, top). This approach to scaling up of point measurements provides a smooth surface and illustrates the regional variation of properties such as soil organic carbon. A map of the variance in the estimates of soil organic carbon is shown in Figure 5, bottom. Notice, for example, that the variance increases at distances further from the center of the map, where the majority of the samples were taken (Figure 5, bottom).

Said another way, we demonstrate the extrapolation of soil organic carbon measurements from point locations to unsampled locations (Figure 6) using geospatial methods that have been incorporated into the IDRISI32 software. As illustrated in Figure 5, the variances of extrapolation become large at distances away from the sample points, reflecting considerable spatial dependence (Figure 7).



Soil organic carbon, kriged estimates.



Soil organic carbon, estimation variances indicating zones of high uncertainty.

Figure 5. Geostatistical extrapolation from 53 point samples to over 700,000 ha and associated errors. Surfer® version 7.0 software. Values are g organic C g^{-1}.

An alternative, perhaps more realistic method of extrapolating point data, is illustrated in Figure 8 (using the IDRISI32 software). This method, Gaussian simulation, gives predictions at unsampled locations based on existing data plus random variates generated from the statistical distribution of the data together with the modeled spatial dependence from the variograms. Comparing Figures 6 and 8, it is clear that the kriging operation, while providing an optimal estimate, tends to smooth the predictions perhaps unrealistically. Gaussian simulation may thus be a preferable method of extrapolating and estimating values at unsampled locations, as shown by the comparable variance of estimation provided in Figure 8 as an output from the Gaussian

Figure 6. Kriged soil organic carbon (% C) and original data points, Pearl Harbor Watershed, Hawaii. Output from IDRISI32®, Version 2, Geostatistics module (implementation of the Gstat software).

Figure 7. Contours of estimation variance, kriged soil organic carbon, Pearl Harbor Watershed, Hawaii. Output from IDRISI32® Version 2.

simulation. Figure 7, showing the estimation resulting from the kriging operation, indicates the estimation variance remains quite low although the measured values vary from approximately 0.14 percent to 1 percent. This illustrates the importance of location and uniformity on the prediction uncertainty.

Sampling soil organic carbon in Mali, West Africa. In the third case, soil organic carbon was, in fact, the objective of a reconnaissance sampling in improved cropping systems in Mali, West Africa. This sampling study is in progress; consequently, only partial results are available.

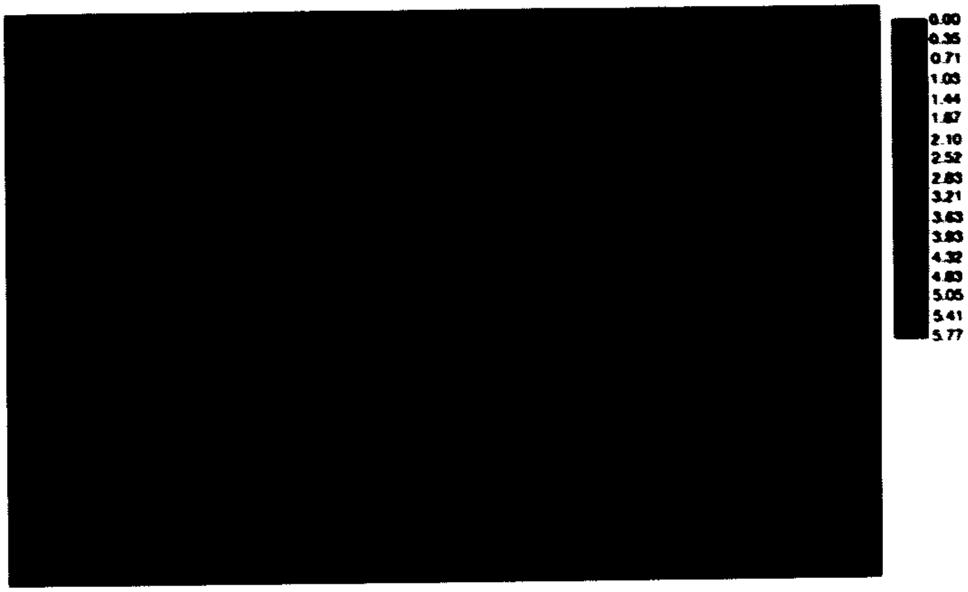


Figure 8. Gaussian simulation of soil organic carbon, based on existing data (points), spatial dependence and the statistical distribution of original data. Pearl Harbor Watershed, Hawaii. Output from IDRISI32® version 2, Geostatistics module, which is an implementation of the Gstat software.

The protocol being tested is to use remotely sensed data to identify landuse and land management units and remove this variability using Equation 1 with standard statistical software for example. A two-stage sampling of the *random* variability is then carried out. The first stage is a minimum sampling, designed to estimate spatial dependence, while the second stage is designed to use the optimal sampling design based on spatial dependence, estimated from the first sampling, to estimate soil organic carbon. This comprises a hierarchical or stratified sampling design with remotely sensed data as the first step and then the use of geostatistical methods to quantify the spatial dependence in preparation for the second, detailed sampling.

With the assistance of scientists from IER/Mali, a selection of farmers' fields were mapped using DGPS (Figures 9 and 10) and sampled for soil organic carbon to make a comparative study of the traditional Walkley-Black, combustion and mid-infrared methods of measuring soil organic carbon. The preliminary statistical analysis of the different landuse systems, using Equation 1, shows that the various locations and cropping systems, with the last crop in the rotation indicated in the table, differed strongly in soil organic carbon content. Also note that cropping systems at similar levels of soil clay differed in soil organic carbon (Tables 2 and 3). This suggests that percent clay was not the lone factor affecting soil organic carbon levels. The sample variance of soil organic carbon, containing both systematic and random variation, was 0.155 percent OC^2. After the removal of the systematic variability, expressed as location, cropping systems and the interaction of location by cropping systems, it was significant with a probability level of 0.0186, indicating that a

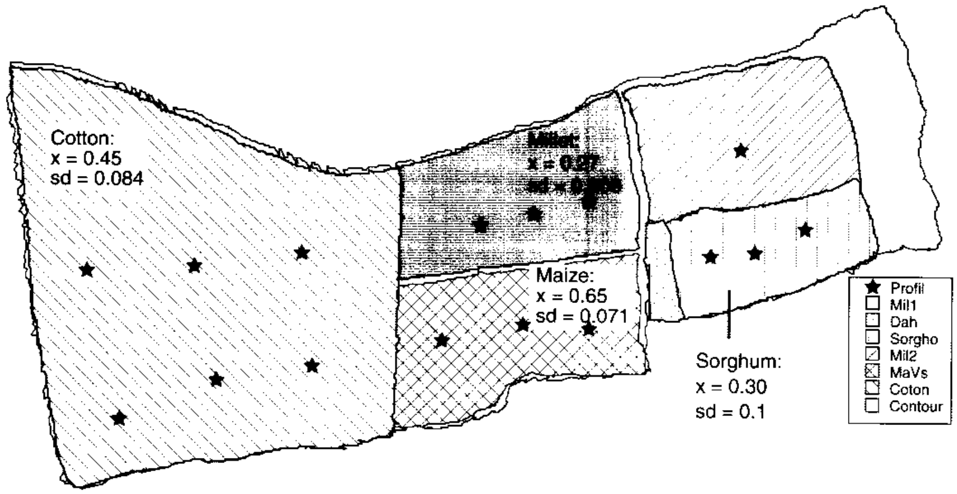


Figure 9. The soil carbon content and variability in the 0-20 cm soil depth of fields of Mory Konate, Koutiala, Mali. Total area: 20.17ha. Fields were traced with DGPS, courtesy IER/Mali. Map by Abdou Bello, IER/Mali.

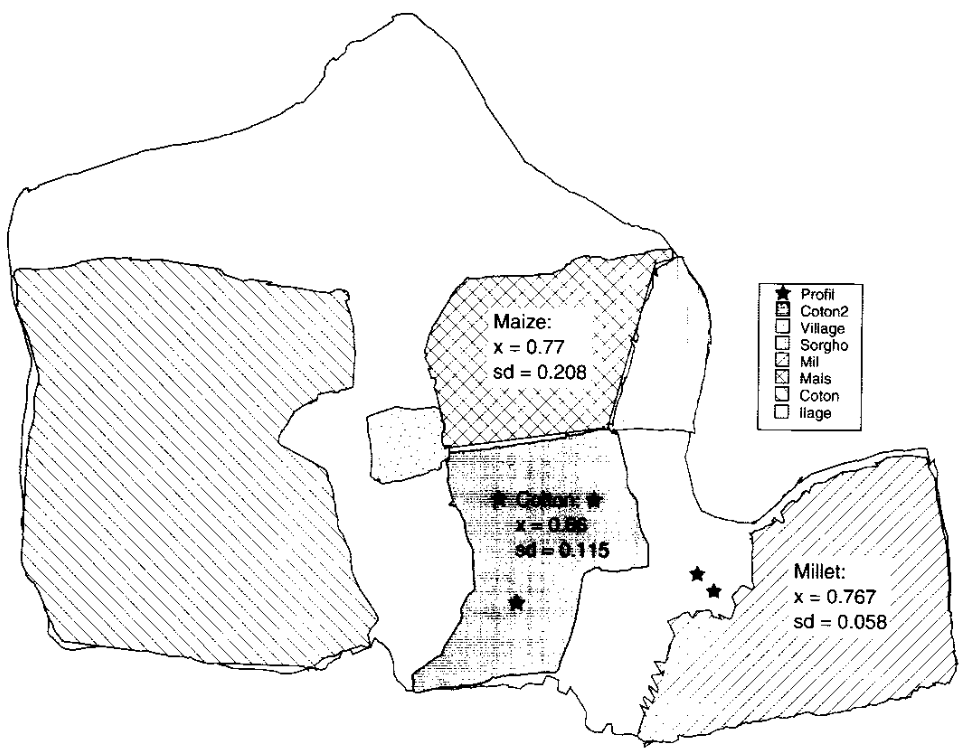


Figure 10. Fields of Lassine Dembele, Koutiala, Mali. Total area: 16.9ha.

Table 2. Preliminary estimates of soil organic carbon levels in Mali, West Africa, (Doumbia *et al.*, unpublished data, 2001).

Location, rainfall, mm	No. samples	Soil organic carbon, %	Soil clay, %
Konobougou (800 mm)	14	0.269	4.9
Koutiala (1000 mm)	27	0.566	6.2
Sikasso (1200 mm)	17	0.426	6.2
$LSD_{.05}$		0.085	1.2

Table 3. Preliminary estimates of soil organic carbon levels for selected crops at three locations in Mali, West Africa, (Doumbia *et al.*, unpublished data, 2001.

Location	Crop	No. samples	Soil organic C, %	Soil clay, %
Konobougou	Cotton	5	0.24	5.0
	Fallow	3	0.31	5.5
	Millet	3	0.28	3.9
Koutiala	Cotton	9	0.55	4.8
	Fallow	2	1.0	10.3
	Maize	6	0.68	5.2
	Millet	7	0.48	8.0
Sikasso	Cotton	3	0.34	4.9
	Maize	4	0.45	7.0
	Millet	3	0.22	5.5
	Rice, flooded	3	0.66	10.3
$LSD_{.05}$			0.22	2.7

substantial amount of the variability was due to the cropping systems and location effects. Initial samples were insufficient to estimate the spatial dependence and subsequent sampling will be necessary.

In general, systematic variability (Equation 1) is that which can be identified and associated with a known cause. It thus becomes clear that the more known about a particular region and the processes operating therein, the greater a proportion of the variability is viewed as systematic and the less as random. In nearly all cases, however, significant amounts of variability remain as random and need spatial analysis to detect spatial dependence. For continuous variables, such as soil pH and soil organic carbon, considerable spatial dependency often occurs (see examples above). This means that the processes that have led to the variation in soil organic carbon often apply over an area of a few meters in the case of local vegetation to several kilometers in the case of annual rainfall patterns, varying in these examples in nearly every situation. A challenge to carbon measurement is identifying the major causes of systematic variability, such as landuse, geologic formation and soil forming factors of vegetation, topography, parent material, time and human management systems. As illustrated in Figure 11 and detailed in the SAS analyses of the landuse variation, significant variation among landuses and cropping systems exists. Locations also differed from each other. This ongoing experiment is now ready for geospatial analysis in order to determine spatial dependence of soil organic carbon in the *random* areas of cropping systems and locations in the region.

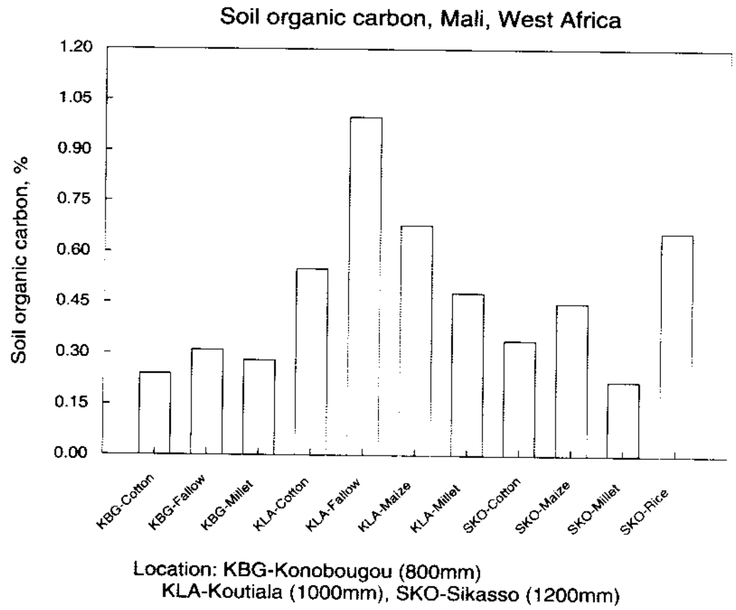


Figure 11. Soil organic carbon across a gradient of rainfall, Mali, West Africa.

that illustrated in Figures 9 and 10, where the DGPS is put into streaming mode and the technician walks around the field. Figures 9 and 10 also illustrate the variation in duplicate tracing of the field boundaries by separate technicians. As suggested below, such an instrument can also be useful in obtaining elevation data for fields of high relief.

Calculating Carbon Sequestration from Maps of Carbon Distribution

Calculating total carbon for a portion of the landscape from point measurements is fraught with problems similar to those of spatial variability, described in this chapter. Geospatial methods to estimate maps, or coverages, of soil organic carbon have been suggested. This approach provides maps of both the estimated carbon and the estimated errors of the map. The next steps in calculating the amounts of carbon are not as simple as multiplying the carbon concentration by the sample depth, for several reasons.

Field Area. Firstly, one must calculate the actual area of the study fields. One of the easiest approaches is the use of high-resolution remote sensing data such as that described in Table 1 (IKONOS, for example). A less efficient alternative is the measurement of the field using DGPS, such as that illustrated in Figures 9 and 10 (see above).

Field Topography. If a field has some relief, the actual surface area is greater than that assumed from simple distance measures. To illustrate: if a field has a 30 percent slope, then the actual surface area is more than 15 percent greater than if it were flat. This can be determined by a simple trigonometric calculation, available in software such as Surfer or ArcGIS Spatial Analyst. Given such a problem, how can the actual surface over a variable landscape be calculated? Our suggestion follows. Several software packages mentioned in this section do this calculation automatically. However, in order to perform the calculation, some elevation data from the field is needed; i.e., the Z direction for each of the X and Y measure points. This is called the Digital Elevation Model (DEM) for the surface. The Surfer® software simplifies the calculation of an interpolated surface given the X, Y, and Z data. Published DEMs, however, are rarely sufficiently accurate for small fields, and while the ideal would be surveyed elevation data obtained by transit, the reality is that other means are usually needed. Obtaining the elevation from differentially corrected GPS data is a recent technology option, but undifferentiated GPS measurements are rarely sufficiently accurate for this purpose.

Given an elevation map of the field, the calculation of surface volume based on the actual surface area of the field is again challenging because of the irregular surface. Volume-estimating techniques, however, have long been available for geoprospecting and the most-used alternatives are also available in the Surfer software. These techniques involve the mathematical integration of the volume over the irregular surface, defined by the map coverage representing elevation.

Still on the issue of the varying topography of fields for which C accretion is to be estimated, the elevation data can also provide some useful calculations based on *terrain analysis*, which is a new field for analyzing regional properties of surfaces with varying topography (Moore *et al.*, 1993). Some variables expressing amount of land area above a particular point in the landscape (CTI, the compound topographic index) may be useful in providing covariates for the co-kriging as described elsewhere in this chapter (see section, "Scaling Up of Point Measurements...").

A Possible Protocol for C Measurement

Throughout the examples given above, a certain pattern suggests a protocol for estimating soil organic carbon on such a large scale, which is necessary to provide inventories of sequestered carbon in quantities of interest to international traders. The protocol, also summarized in the chapter by Antle and Uehara, includes the following elements:

1. Identify the Systematic Variability

Background information. Initially survey the region to be assessed for carbon sequestration potential. This includes a search of existing, background information published in soil survey reports, project reports, and consultant reports and other databases and maps. In addition, sometimes the persons involved in such reports may still be accessible and they often have useful insights for the measurement exercise.

Search to obtain all the available remotely sensed imagery, aerial photography, property maps. This is usually one of the most cost-effective inventories of a region and even ground surveys may provide information and data that can be quantitatively related to mapped features, usually in building or updating a map database.

Use of remotely sensed imagery for the hierarchical stratification. In the event that local institutions do not have sufficient remotely sensed imagery, international sources of imagery may be used. Often imagery is available from institutions such as EOSAT, SPOT and others. All the efforts of the steps discussed so far should be focused on the most informed category designations of landuse, geology or land shape, since these are usually key to stratifying the systematic variability in soil organic carbon.

2. Detection of Spatial Dependence in the "Random" Variability in Measured Data

Initial sample collection. Collect initial samples in the various stratified categories identified in the previous step. The samples should be from the plow or tilled layer on cultivated soil and from the 0 - 5cm and the 5 - 20cm layer in perennial or natural landuse systems without tillage. The 50-75 samples are needed in order to adequately detect and quantify spatial dependence in a specific region. The accurate laboratory measurement of soil organic carbon is difficult and time-consuming and, depending on the method, can produce hazardous waste. New methods based on near/mid infrared hold promise.

Analysis of systematic variability. Analyze the systematic variability in the sample data using methods that consider the categories as classes and compare the results of the stratification (e.g., SAS PROC GLM or MIXED or equivalent). If the differences among categories are significant, continue with the categories: however if not, pool them and proceed with the spatial analysis of the random variability. This can proceed by analysis of the residuals resulting from removal of the systematic variability from the original data.

Additional sampling? If, as a result of the analysis, there appears to be spatial dependence but the sampling density is too sparse to delineate the variogram, a further sampling may be needed.

Once the categories of landuse/stratification are identified as a result of the remotely sensed data, they can be selected for modeling (see Jones *et al.* chapter). The subsequent steps will help scientists to use the simulation models to better understand and quantify the dynamics associated with the farmer's selection of landuse categories. Results of the simulation exercise will be useful in identifying the landuse systems with high potential for reliable C accretion.

Scaling up. After the potential of selected landuse systems has been clarified by the simulation activity, the predicted accretion rates can be scaled up to the selected landuse areas, identified by remote-sensed imagery, using techniques such as block or point kriging. The mean accretion rates of land categories can be determined as well as the precision with which the estimates are obtained (the estimation variances produced by block or point kriging).

Scaling Up of Point Measurements and Simulation Results to Regional Estimates

Scaling up of measurements and simulation results is necessary for presentation of a logical, well-characterized contract area. Extrapolation must be done carefully so that errors do not jeopardize predictions and result in faulty contracts. Extrapolations can be almost mechanical when carbon gain per hectare in a millet field, for example, is multiplied by the hectares of millet in the region under consideration. At another extreme, extrapolations can include auxiliary information from DEMs and derived parameters from terrain analysis, such as slope curvature, wetness index, upslope distance and other information. Somewhat intermediate among this range of options, time and expertise, is the use of kriging, where the extrapolation is conditioned by measured data, but spatial dependence is used to guide the estimates in unsampled regions. This combination provides an optimal use of the stratified landuse and the measured point data.

In our view the first step in the extrapolation from point measurements or simulations should be the ordinary kriging of the fields representing the various locations. This type of extrapolation or scaling up is illustrated in our example of the Pearl Harbor Watershed (Figures 4 to 6). As already indicated, this type of extrapolation provides both a map of extrapolated values and a map of the estimation variances (Figures 5 and 7). For example, in Figure 7, we can see that the variance remains low (around 0.15) in the vicinity of the samples, but only increases to about 0.35 between clusters of samples. In contrast, on the edges the variance increases at similar distances to 0.75 or more (Figure 7), reflecting a lack of samples and the tenuous nature of any extrapolation in that region. We recommend this approach for obtaining estimates of amounts of soil organic carbon in fields and over large regions necessary for carbon trading.

Additional options for extrapolation may be possible or more appropriate depending on the local conditions. One of these is the use of co-kriging, which builds on ordinary kriging by including the relationship between the primary variable, likely soil organic carbon in our case, and an auxiliary variable that is easily and cheaply or accurately measured, but which correlates very highly with the primary variable. There are numerous examples of using co-kriging (Trangmar *et al.*, 1986). One example use of co-kriging would be to employ remotely sensed data as compiled in a vegetation or soil carbon index as the covariate to estimate soil organic carbon over a region.

CONCLUSIONS

In summary, there is an emerging protocol for measuring soil organic carbon that initially requires an inventory of landuse and cropping systems. Based on this inventory, selected systems and regions can be sampled and the status and variability of soil organic carbon determined. If still favorable, either further sampling can be carried out or the data can be analyzed using geospatial methods and extrapolated or scaled up to areas or volumes in the region. The scaling up requires a quantitative inventory. The result is an inventory and estimate of the amount of soil carbon that can be fixed if a particular cropping system remains in place.

As described in the chapter by Jones *et al.* in this monograph, existing cropping systems and landuses may or may not have carbon accumulation potential, a factor that relies on the simulation of the carbon balance and steady state levels.

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APPENDIX 1. SOFTWARE TO ESTIMATE SPATIAL DEPENDENCE AND USE IT IN OPTIMAL INTERPOLATION

The sampling protocol for estimating soil organic carbon can be found in the chapter by Antle and Uehara. Identification and preliminary comments on some of the software that is available for dealing with the spatial variability of soil organic carbon are provided in this appendix. Software which might be considered in dealing with the sampling protocol for estimating soil organic carbon are described here: 1) After identifying the major geomorphic units or landuse systems, whichever is likely to best stratify soil organic carbon, a standard statistical analysis can be performed with dummy variables for the different geomorphic units or land uses. Software such as SAS is useful to estimate these large-scale effects. 2) With the residuals from the removal of large systematic variation, such as the observable, discrete units, estimation of the spatial dependence using typical geostatistics software can be made. First the variograms must be estimated. This can be done with a variety of software, such as Variowin, Geo-Eas or Geo-Pack (DOS environment), or one of the integrated packages such as Surfer 7 & 8 (which includes both variogram and kriging estimations of a grid of new points), the ArcGIS 8.1 Geostatistics Analyst and the IDRISI32 Geostatistics modules. The kriging-estimation procedure provides a quality interpolation method together with an estimate of the reliability of the estimates. This is also available in the Surfer 7 & 8, ArcGIS 8.1 and later versions, the IDRISI32 Geostatistics modules, as well as in the Geo-Eas and Geo-Pack software mentioned above. The recent GIS software such as ArcGIS Geostatistics Analyst and IDRISI32 Geostatistics powerful modules: 1) Spatial Dependence Modeler; 2) Model Fitting; and 3) Kriging and Simulation. These modules provide a new level of flexibility, insight and ease of use for exploring and quantifying spatial dependence, in modeling semivariograms, and in providing a range of options of kriging (simple, ordinary, universal and co-kriging, ArcGIS and IDRISI32) as well as Gaussian and indicator simulations (IDRISI32). These packages, integrated with the GIS software, are some of the most powerful and easy to use modules available today.

In addition, many years ago, a very simple DOS version of the variogram and kriging software was developed at the University of Hawaii. In the event that such highly simplified software is useful, we can be contacted.

The websites/locations of this software are given below.

ArcGIS 8.1 & 8.2 Geostatistics Analyst
http://www.esri.com/

Geo-Eas
http://www-sst.unil.ch/research/variowin/index.html

Geostatistical Toolbox
Froidevaux, R., "Geostatistical Toolbox Primer, version 1.30," FSS International chemin de Drize 10, 1256 Troinex Switzerland, 1990.
http://www-sst.unil.ch/research/variowin/index.html

GSLIB
Deutsch and Journel, GSLIB-A geostatistical toolbox
http://www.gslib.com/

Gstat
Stand alone software and choice of IDRISI32 Geostatistics module
http://www.geog.uu.nl/gstat/

IDRISI32
Clark Labs, Clark University
950 Main Street
Worcester, MA
01610
(508)-793-7526
idrisi@clarku.edu
http://www.clarklabs.org/01home.htm

SAS, SAS Institute
Academic Software Sales
SAS Worldwide Headquarters
SAS Campus Drive
Cary, NC 27513-2414
USA

SigmaPlot
SPSS Science
233 S. Wacker Drive, 11th floor
Chicago, IL 60606-6307
http://www.spssscience.com/corpinfo/index.cfm

Surfer 7 or 8, Golden Software, Inc.
809 14th Street,
Golden, Colorado
80401-1866
303-279-1021
www.goldensoftware.com

VAR5, AKRIGE, COKRIGE
(DOS versions only)
University of Hawaii at Manoa
3190 Maile Way
Honolulu, HI
96822
rsyost@hawaii.edu

Variowin
http://www-sst.unil.ch/research/variowin/index.html
Pannatier, Y., "VARIOWIN: Software for Spatial Data Analysis in 2D," Springer-Verlag, New York, NY, 1996. ISBN 0-387-94679-9 (out of print)

APPENDIX 2. SOME EXAMPLE CODE FOR MODELING VARIOGRAMS WITH SAS AND SIGMAPLOT

Modeling variograms with SAS: MODJP.CNTL

```
*Program for modeling of isotropic semivariograms;
*Written by B. Trangmar;
Title weighted Spherical, Mitscherlich and Linear models;
data vsemk;
infile data;
   input y x n dir dtol;
*Spherical and Mitscherlich models for 90+/-90 semivariogram;
data one; set vsemk;
   if dir=90 and dtol=180;
   if y > 0.129072 Then delete;
   if x < 25;
proc nlin best=10;
   parms c0=0.062311 C=0.066761 A=25;
   _weight_=n;
   if x<a then do;
   model y=c0+c*(1.5*(X/a)-0.5*(X**3/a**3));
   end;
   else do;
   model y=c0+c;
   end;
output out=e p=yhat r=yresid;
proc plot data=e;
   plot y*x='*' yhat*x='p'/overlay;
   plot yresid*x/vref=0;
proc nlin best=10;
   parms b0=0.129072 b1=0.062311 b2=0.3;
   _weight_=n;
   model y=b0-b1*exp(-b2*x);
   output out=f p=yhat r=yresid;
proc plot data=f;
   plot y*x='*' yhat*x='p'/overlay;
   plot yresid*x/vref=0;
*linear model for 90+/-90 semivariogram;
data two; set vsemk;
   if dir=90 and dtol=180;
   if x < 35 and y < 0.129072;
proc print;
proc glm;
   weight n;
   model y=x;
   output out=d p=yhat r=yresid;
proc plot data=d;
   plot y*x='*' yhat*x='p'/overlay;
   plot yresid*x/vref=0;
```

Statistical Analysis System (SAS) instructions for fitting semivariograms to output from the variograms programs.

Sigmaplot code for fitting spherical variograms models (version 5 and later)

Nonlinear Regression (user defined equation)

```
[Variables]
x = col(2)
y = col(1)
[Parameters]
a = 1/3*max(x) "Auto {{previous: 10.298}}
c0 = stddev(y) ' {{previous: 0.047238}}
c = stddev(y) ' {{previous: 0.109503}}
[Equation]
f=if(x<=a,line(x),c0c)
line(x) = c0 + c*(1.5*(x/a) - 0.5*(x/a)^3)
c0c=c0 + c
fit f to y
[Options]
tolerance=0.000100
stepsize=100
iterations=100
```

CHAPTER THREE

PREDICTING SOIL-CARBON ACCRETION: THE ROLE OF BIOPHYSICAL MODELS IN MONITORING AND VERIFYING SOIL CARBON

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ABSTRACT

Increasing the amount of carbon in soils could help counter the rising atmospheric CO_2 concentration as well as reduce soil degradation and improve crop productivity in many areas of the world. Participating in carbon markets could provide farmers in developing countries the incentives they need to improve land management. Carbon traders, however, need assurances that contract levels of carbon are being achieved. Thus, methods are needed to monitor and verify soil carbon changes over time and space to determine whether target levels of carbon storage are being met. Because measurement of soil carbon changes over the large areas needed to sequester contract amounts of carbon is not possible, other approaches are necessary. An integrated approach is described in which biophysical models are combined with soil sampling and remote sensing to achieve reliable and verifiable estimates of soil carbon over time and space. Although there are uncertainties associated with data and models, reliability in estimates is realized by using observations to adjust inputs and model parameters for target areas. An overall framework is suggested for providing information on potential soil carbon sequestration rates before a project area is selected and also for producing reliable estimates of soil carbon accretion during a contract.

INTRODUCTION

Carbon sequestration as a means to mitigate the increasing atmospheric carbon dioxide (CO_2) concentration is gaining interest worldwide. Furthermore, there is increasing interest in compensating land managers for removing carbon from the atmosphere through land management practices that will store carbon for long periods of time in trees or soils. While storing carbon in soils can counter rising CO_2 levels in the atmosphere, this public benefit will likely be far outweighed by positive benefits that increased soil organic matter content could produce for many of the degraded soils of the world, by raising agricultural productivity, reducing poverty and combating desertification. But to achieve these benefits, farmers must have economic incentives to adopt land improvement practices. Due to a lack of such incentives, current agricultural practices are causing depletion of soil carbon and concomitant reductions in soil fertility and food production. Farmers typically respond by expanding the area of land cultivated or grazed, thus mining soil organic matter and continuing along an unsustainable pathway. Participation in carbon markets could provide farmers with much needed incentives if carbon traders can be confident that contracts with farmers in developing countries will result in removal of an agreed-upon amount of atmospheric carbon over an agreed-upon time period. Before committing to a contract, carbon traders need information on the carbon sequestration potential of agricultural soils, and they need information during a contract to assure them that the agreed-upon carbon amounts are being stored. Unfortunately, however, this information is not easy to obtain, especially in low input agricultural systems in developing countries.

If potential carbon sequestration rates could be predicted accurately for a specific area under proposed land use and management practices, this would provide a basis for developing contracts. The potential of soils to sequester carbon depends on many factors, including soil physical and chemical attributes, weather, land use and land management practices. These factors vary considerably over space and time and they interact with each other in highly complex ways. Biophysical models integrate crop, soil, weather and management practice information and predict the consequent biomass and yield components as well as changes in soil nutrients and carbon (Cole *et al.*, 1987; Moulin and Beckie, 1993; Singh *et al.*, 1993; Probert *et al.*, 1995). Although these models predict biophysical responses for uniform areas for which soil properties, weather and management practices are known, they can also be used to predict these responses over large, nonuniform areas if the models are provided information on spatial variability of soil, weather and management inputs, using geographic information systems (GIS) (Calixte *et al.*, 1992; Hartkamp *et al.*, 1999). By simulating responses for a number of years, it is possible to estimate the potential changes in productivity as well as changes in soil carbon. Thus, tools are available for predicting potential soil carbon sequestration. We emphasize "potential" soil carbon sequestration because such predictions would be based on assumptions about future weather conditions (usually by using historical weather patterns for a number of years), and they would be based on assumptions regarding socioeconomic conditions as well as land management over space and time.

After a contract between a carbon trader and land managers is made, mechanisms are needed for monitoring compliance. Regardless of whether the contract calls for land managers to adopt specific practices or for specified amounts of carbon storage, assessments of changes in soil carbon storage are needed to confirm that the desired impact of the contract is being achieved. Direct measurements of soil carbon over time and space are needed to quantify carbon accretion rates and to confirm that contract amounts are being met. Due to the costs associated with these measurements, however, it is necessary to complement direct measurements with indirect methods for estimating soil carbon accretion. This can be done by monitoring actual management practices over space and time, using remote sensing to complement ground observations, then using biophysical models to provide estimates of soil carbon sequestration. By combining direct measurements of soil carbon with spatial statistics and biophysical models, one can obtain measures of soil carbon sequestration over space and time in an operational program.

The use of biophysical models must be combined with direct measurements, remote sensing and socioeconomic information in an overall approach for measuring and assessing soil carbon sequestration for use in carbon trading. In this paper, we describe concepts of soil carbon cycling in agricultural production systems and give example predictions using the DSSAT-CENTURY model (Gijsman *et al.*, 2002) showing how changes in soils, weather, and management practices affect potential soil carbon sequestration. In addition we describe how the models are integrated into an overall framework for assessing and monitoring soil carbon changes.

CARBON CYCLING IN THE SOIL, PLANT AND ATMOSPHERE

Organic carbon exists in many forms in terrestrial ecosystems. Figure 1 is a schematic showing the major forms in which carbon is stored in managed or unmanaged parcels of land. Inorganic carbonates are not

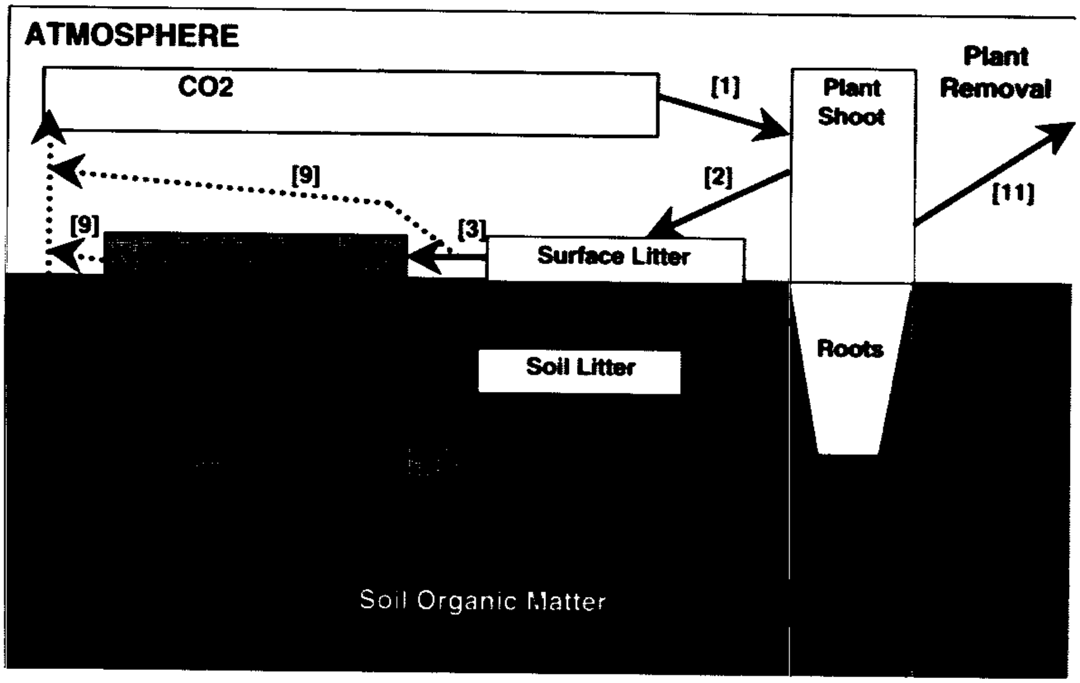

Figure 1. Simplified schematic diagram of carbon flows (denoted by arrows) in the soil-plant-atmosphere system.

included in Figure 1, although they may be significant for some soils, because they are not easy to manipulate in soils. Total carbon on the land unit is the sum of the C in all of the components (plants and their roots, surface and soil litter, soil organic matter (SOM), and microorganisms). Carbon sequestration can occur if this total carbon of the parcel of land increases. Carbon sequestration in forests, for example, occurs as trees assimilate CO_2 from the atmosphere, convert it into biomass and store large amounts of woody tissue that accumulates over a number of years; with a forest fire, this carbon is returned to the atmosphere. Soil carbon sequestration in agricultural systems occurs when plant material is returned to the soil through natural or anthropogenic processes and accumulates over time as soil organic matter.

The arrows in the figure depict the transformations and flows of carbon among the different components. Arrow 1 between the atmospheric CO_2 and the plant represents the photosynthesis process. Dead shoot material is added to the litter on top of the soil surface (arrow 2) and dead roots add to the soil litter (arrow 5). Surface litter may be incorporated to become soil litter (arrow 4). Both the surface and soil litter are assimilated by microbes (arrow 3 and 6), which transform the litter into soil organic matter (arrow 7 and 8). All these transformation processes are accompanied by a release of CO_2 back into the atmosphere (arrow 9). The SOM, finally, is also decomposed to CO_2 (arrow 10). Arrow 11 depicts removal of plant material by humans or animals. If animals graze the land, their manure would also be a source of organic matter for the soil (not shown in Figure 1). During a specified time period, such as a year, the net change of carbon on the land unit is the sum of flows among all compartments. Positive net flows mean that carbon has increased, whereas negative net flows indicate that carbon is lost from the system. This carbon cycling and the balance sheet that accounts for carbon are fundamental concepts underlying the process of soil carbon sequestration.

Figure 1 is also useful to discuss factors that lead to soil carbon accretion or mining. The processes (arrows) in the figure include combinations of natural and human actions. Thus, soil carbon will be increased or decreased (mined) depending on interactions of natural processes and human interventions. In agricultural systems in which all above-ground plant material is removed from the land for consumption or fuel wood, the net change in the soil carbon more likely will be negative as microorganisms continue to break down litter and soil organic matter; root biomass is usually a small fraction of total plant biomass. Rapid rates of soil organic matter transformations are associated with tillage (exposing more organic matter to microorganisms), soil texture (more rapid in sandy soils), soil water content (less decomposition in very dry or very wet soils) and temperature (decomposition rate decreases under cold and very hot conditions), and availability of nutrients in the soil (transformation rates decrease when soil nitrogen or phosphorus are low). In most land units, these conditions change over time due to weather variations as well as land management.

If crops are grown for grain, the yield will be removed from the field, but the residue may be returned to the soil or removed and used for animal feed or other purposes. In pasture systems, overgrazing would reduce grass productivity and thus limit soil carbon sequestration even though some C would be returned to the soil in animal manure. If farmers harvest only the edible yield and practice limited or no tillage (thus reducing SOM decomposition rate), the return of residue to the soil could lead to accretion of soil carbon, especially under management practices that lead to high biomass production (such as application of nitrogen or other nutrients that may be limiting).

Predicting soil carbon accretion over time for a particular land management unit requires that an accounting of the carbon flows and storage be made. This accounting must allow for natural processes of photosynthesis and growth of the crop and transformation rates and respiration associated with organic matter decomposition. These processes depend on soil characteristics and weather, which also must be taken into account. In addition, carbon accounting must take into account management of the land (tillage, fertilizer inputs, residue management, irrigation), as these human interventions affect carbon assimilation by the crop, how much is removed for human or animal uses, and carbon losses by decomposition of SOM. Biophysical models incorporate all of these factors and account for the day-to-day crop growth and organic matter transformations and the long-term net changes of soil carbon and other nutrients.

BIOPHYSICAL MODELS FOR PREDICTING SOIL CARBON SEQUESTRATION

Biophysical models have been developed to compute the flows and transformations depicted in Figure 1 and the resulting changes in vegetative biomass and soil carbon. However, not all have proven capabilities for predicting productivity and soil carbon changes under a wide range of soils, climate and management systems.

Recently, the most widely used and tested package of crop production models (Decision Support System for Agrotechnology Transfer, DSSAT, Tsuji *et al.*, 1994; Jones *et al.*, 1998) was combined with one of the most widely used and tested models of soil carbon dynamics (CENTURY, Parton *et al.*, 1988, 1994) for predicting soil carbon sequestration under widely varying soils, weather and crop management systems (Gijsman *et al.*, 2002). This model version, referred to as the DSSAT-CENTURY model, can simulate a wide range of crop rotation systems over long time periods to estimate biomass production and yield as well as changes in soil organic matter.

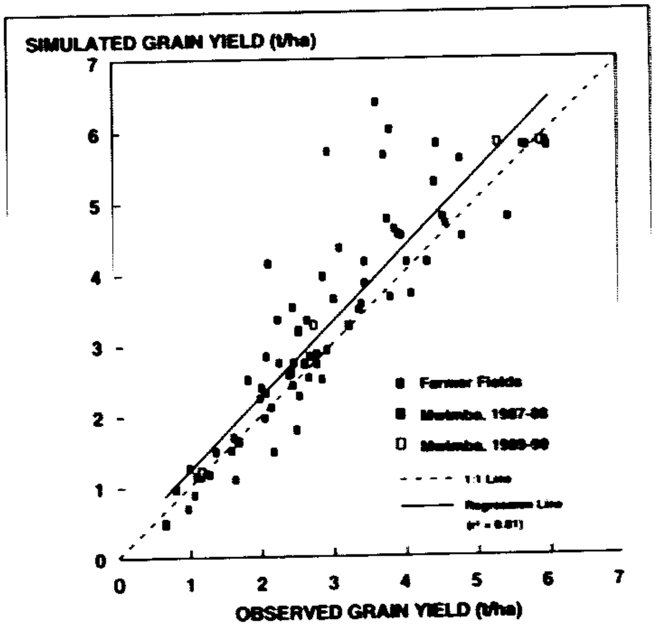

Figure 2. Comparison of simulated maize grain yield with grain yield observed in Mwimba experiment station (1987-88 were calibration years and 1989-90 validation years) and farmer fields in central Malawi, 1990-1992 (from Thornton and Wilkens, 1998). Crops were grown using a wide range of fertilizer nitrogen levels, including non-fertilized treatments.

DSSAT-CENTURY Model

The DSSAT forms a comprehensive model-based decision support system for assessing agricultural management options. It is widely used in both developed and developing countries (Algozin *et al.*, 1988; Bowen *et al.*, 1993; Bowen and Wilkens, 1998; Jagtap *et al.*, 1993; Lal *et al.*, 1993; Singh *et al.*, 1993; Thornton and Wilkens, 1998; Paz *et al.*, 1998; Paz, 2000; Mavromatis *et al.*, 2001). For example, Figure 2 shows results from Thornton and Wilkens (1998) of testing one of the DSSAT models (maize) in Africa. The present version 3.5 incorporates 16 crops (maize, wheat, rice, sorghum, millet, barley, bean, soybean, peanut, chickpea, cassava, potato, sugarcane, tomato, grass and sunflower), with several more being implemented. The models in DSSAT handle management strategies that involve crop rotations, irrigation, nitrogen fertilization and organic matter applications. Although crops (or cultivars) and crop management (e.g., mechanization) may differ from country to country and even from village to village, the effect of fertilizer or irrigation on crop production follows similar biophysical and biochemical pathways. An important difference, however, between high-input and low-input agricultural systems is that, in the former, deficits of nutrients required by crops are supplied by chemical fertilizers, whereas in the latter, nutrients become available through decomposition of soil organic matter (SOM) and plant residues. This means that the soil organic matter component of crop simulation models is more important for accurate simulations of crop productivity in low-input systems, as well as for accurate simulations of changes in soil carbon.

CENTURY Model

The CENTURY model (Parton *et al.*, 1988, 1994) has proven its value in both temperate and tropical systems (Carter *et al.*, 1993; Cole *et al.*, 1989; Kelly *et al.*, 1997; Metherell *et al.*, 1995; Parton *et al.*, 1989, 1993, 1994; Paustian *et al.*, 1992; Seastedt *et al.*, 1992; Woomer, 1992, 1994). In a special issue of Geoderma 81 (1997), nine SOM models were evaluated with twelve long-term datasets, including inorganic fertilizer, organic manures and different rotations. Measured and simulated data were compared, using an array of statistical-analysis tools. Among the models that performed best, the CENTURY model produced consistently low errors for all datasets but one, showed the lowest overall bias, and was able to simulate both low- and high-N treatments (Smith *et al.*, 1997). Figure 3 demonstrates the ability of the combined DSSAT-CENTURY model to accurately simulate measured depletion of soil carbon under a long-term experiment where periodic measurements of soil carbon were made in a bare-fallow treatment (Gijsman *et al.*, 2002).

Potential options for increasing soil carbon in Africa include rotations of crops with natural vegetation fallow or converting degraded land back into natural ecosystems. The dominant natural ecosystems in Africa are savanna systems where both trees and grasses contribute to the system-level plant production, aboveground carbon levels and soil carbon storage (Scholes and Walker, 1993). African savanna systems include a substantial amount of wood with up to 2000 g [C] m^{-2} contained in aboveground woody biomass. Total carbon levels are greatly influenced by human management of savanna systems. For example, intense grazing of tree and grass biomass by goats and cattle, increased fire frequency and fire wood collection can greatly reduce both wood biomass and soil carbon levels. Data from Kruger National Park in South Africa (Jones *et al.*, 1990) showed that 50 years of annual burning reduced soil carbon levels by 300 g m^{-2} and reduced wood biomass levels. Eliminating fire for a 50-year period

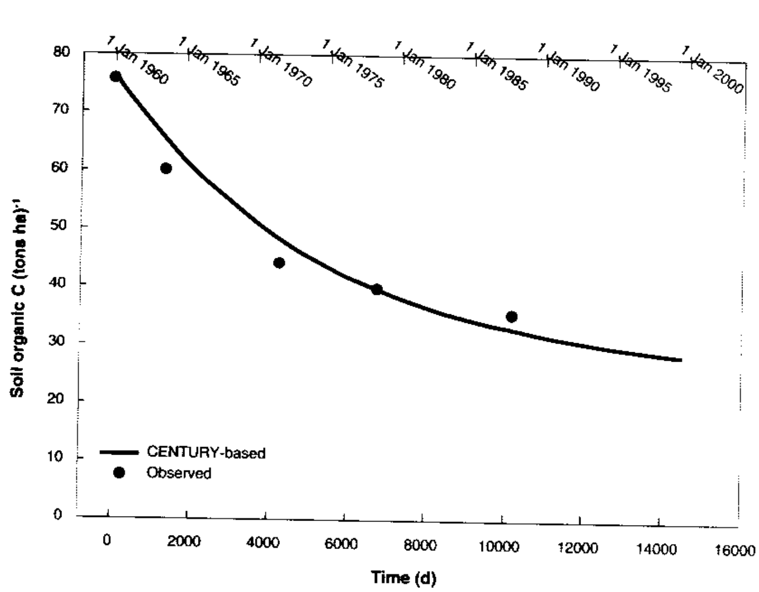

Figure 3. Comparison of simulated and measured soil organic carbon for a long-term bare fallow treatment in Rothamsted (Gijsman *et al.*, 2002).

in Kruger National Park increased soil carbon levels by 800 g m^{-2} and increased live wood carbon by 500 g m^{-2}. The CENTURY soil organic matter model (Parton *et al.*, 1988, 1994; Metherell *et al.*, 1993, 1995) can simulate the impact of management practices on the soil carbon levels and storage of carbon in the woody biomass. The CENTURY model simulates the carbon and nutrient dynamics of both trees and grasses and the cycling of soil nutrients and organic matter. The model has been tested extensively for grassland systems in Africa (Parton *et al.*, 1993) and is currently being tested using observed wood growth, grass plant production and soil carbon and nitrogen data from savanna systems in Africa and Australia (Beale, 1973, Jones *et al.*, 1990, Dye and Spear, 1982 and Scholes, 1987). Comparison of the model dynamics with observed data shows that the model correctly predicts the growth of wood biomass, the impact of fire on soil and wood carbon levels and the influence of wood biomass on grassland plant growth. Recent CENTURY model results from a Senegal Carbon Sequestration workshop (Woomer *et al.*, 2001) show that one of the most promising ways to increase carbon storage in the Sahel region is to re-establish natural savanna systems on degraded cropland.

Information Needs for Predicting Potential Soil Carbon Sequestration

The DSSAT-CENTURY and CENTURY biophysical models operate at a land management unit or field scale. They simulate crop productivity and changes in soil carbon over many years for individual land management units in which management practices are known or assumed. In a forward-looking approach to estimate soil carbon sequestration, the models are used to simulate each land management unit using historical weather data over a number of years. This approach, demonstrated in the next section, assumes that future weather conditions will be statistically the same as those in the past. These estimates could also be made using other future weather conditions, such as those produced for climate change scenarios. In order to make these forward-looking estimates, a minimum set of information is needed. Input requirements for the DSSAT models are well defined for each land management unit at which predictions are to be made (Jones, 1984; Hunt and Boote, 1998). These same inputs, summarized in Table 1, are also necessary for backward-looking simulations performed for calibrating and evaluating the models for local soil and cropping system situations and for obtaining area-wide estimates of soil C sequestration. However, additional inputs are necessary for these later uses; they will be described in later sections. Weather, soil and management characteristics described briefly below are the absolute minimum requirements for using the biophysical models to simulate soil C sequestration potential of different land management options for selected land management units in a carbon contract area.

Weather Data. Daily weather data required are maximum and minimum temperatures, rainfall, and solar radiation. For estimating soil carbon sequestration potential, historical daily data are needed for a number of years (i.e., 20 or more) to provide an assessment of climate and its variability for the locations under consideration. Using these data in the model will allow one to evaluate the annual variability in crop production and carbon sequestration as well as to assess uncertainty due to weather patterns over different periods of time (i.e., 5, 10 or 20 years). In most countries, historical rainfall and temperature data are available for this

Table 1. Minimum information required to simulate productivity and soil carbon sequestration for a land management unit.

Daily Weather Data:	**Management**
Precipitation (mm)	Crops grown in Rotation
Temperature Maximum (°C)	For each crop:
Temperature Minimum (°C)	Cultivar (length of season)
Solar Radiation (MJ $m^{-2}d^{-1}$	Planting date or window
	Planting method
Soil Data:[1]	Plant density
Texture (each soil horizon)	Fertilizer (kg ha^{-1} N, P, K)
Initial soil C (each soil horizon)	Crop residue management
Initial inorganic nutrients (kg ha^{-1} N)	Tillage
Slope	Harvest

[1]The models require much more soil information as direct inputs (Jones and Ritchie, 1990; Gijsman *et al.*, 2002). However, the list in this table are the absolute minimum information required for estimating the additional inputs for simulations, such as soil water holding limits (lower limit, drained upper limit, and saturation), bulk density, pH, albedo, soil water evaporation, drainage and runoff parameters. Published relationships are used to estimate more detailed inputs if necessary.

use, although solar radiation data are rarely available in less-developed countries. Methods have been developed to approximate daily solar radiation from hours of sunshine, which is sometimes available, or from latitude, altitude and daily values of rainfall and maximum and minimum temperature (Donatelli and Marletto, 1994).

Soil Data. Soil data inputs to the models are basic profile characteristics for the surface, such as color and slope, and for each soil layer, such as texture, water holding characteristics (wilting point, field capacity, saturation), SOM content and its N concentrations, bulk density and pH. For predicting potential soil carbon sequestration, at minimum, soil texture information is needed for a land management unit (Table 1), so that the required soil properties can be estimated using pedotransfer functions (e.g., Pachepsky *et al.*, 1999; Saxton *et al.*, 1986; Rawls *et al.*, 1982). However, these estimates will introduce uncertainty in the simulations (Gijsman *et al.*, *in press*) and should be used only if field samples cannot be taken for evaluating the model or if estimating parameters from data measured in the past is not possible. For those cases, the use of soil texture information to parameterize the water-retention estimation method is recommended. Information is also needed on initial soil water, C, and N conditions of the soil in the land management unit where predictions are to be made. Geostatistical methods will be essential for providing inputs to models at the land management unit for such uses (see chapter by Yost *et al.*).

Land Management. For estimating potential soil carbon sequestration, descriptions of the main farming systems in use in the region, as well as optional systems aimed at maintaining productivity while increasing soil C sequestration are essential to properly define the systems to be analyzed with the model. Crop or fallow rotations should be known (Table 1). Crop management practices, such as the cultivars used, the planting window, planting method (broadcast/in rows/ridge planting), planting density and depth are all needed. Also, harvesting and residue management must be defined for each system. For example, which part of the crops is harvested and removed from the field, which part is added to the soil as residues (left on top of the soil or incorporated), and how much residue is eaten by animals? If fertilizers are applied, their application dates, application method (broadcast/banded, application depth), types and amounts need to be known. For organic residues (crop residues, manure) a similar set of characteristics is needed, supplemented by the lignin, and N concentration of the residue.

SENSITIVITY OF SOIL CARBON SEQUESTRATION TO CLIMATE, SOIL AND MANAGEMENT FACTORS

Simulations were done to illustrate the importance of various factors and their interactions on the amount of carbon retained in the soil as soil organic matter (SOM). Factors that affect the SOM level include soil type, climate, cropping system, residue management and soil disturbance (tillage). The results presented here are from a provisional series of calculations. The predictive models must be calibrated for local conditions and used with field observations in projects for measuring and assessing soil carbon sequestration.

Methods and Procedures

For the climate data, existing long-term measured data sets were used, combined with "generated" daily weather data that were based on the limited set of measured data. The data were taken from a relatively dry area, *low-rainfall*, (Maradi, Niger, 616 mm) and a somewhat wetter *medium-rainfall* site (Samaru, Nigeria, 989 mm/yr). All simulations were done for a 25-year period.

The soil types were 1) a 97-cm deep Chromi-Epiferric Luvisol from Nigeria, which varied in texture across the vertical profile from 40 to 60 percent sand and in SOM content, from 0.30 to 0.01 percent, and 2) an unclassified sandy soil from Zambia of 167 cm deep, with about 90 percent sand across the entire profile and a SOM content declining from 0.84 percent in the topsoil to 0.09 percent at depth. To get a sufficiently wide range of soil-weather combinations for the analysis, the Nigeria and Niger weather were combined with both soil types. Although the combination of these soil and weather conditions do not represent a real location, it is likely that a similar combination of soil and weather conditions can be found at several locations in Africa.

For the medium-rainfall site, two crops were grown in the wet season, followed by bare fallow during the remaining part of the year. For the low-rainfall site, only one crop could be grown per season. By default (unless indicated otherwise) the soil type was the Nigerian Luvisol. The following simulation treatments were applied.

For the Medium-rainfall Weather:

1. Bare soil fallow. In this case, no vegetation was allowed to grow. This treatment is needed to determine the baseline decomposition of SOM in a soil with no new C additions.
2. A rotation of bean-bean-bare fallow each year, in which the beans are harvested and the harvest residues returned to the soil (not plowed in). The bean crop fixes nitrogen if N is limiting (no fertilizer was added). This would be similar to growing cowpea for grain.
3. As No. 2, but with the harvest residues removed from the field, as is common in Africa. This would be similar to growing cowpea for grain and fodder.
4. As No. 2, but with the complete bean crop returned to the soil as a green manure.
5. Permanent pasture *Brachiaria decumbens*, with 10, 25, 50 or 100 kg N per hectare per year.
6. The same as No. 1 through 4, but with the soil from Zambia.
7. The same as No. 1 through 4, with the Nigerian soil, but with its texture replaced by either 10% sand 50%

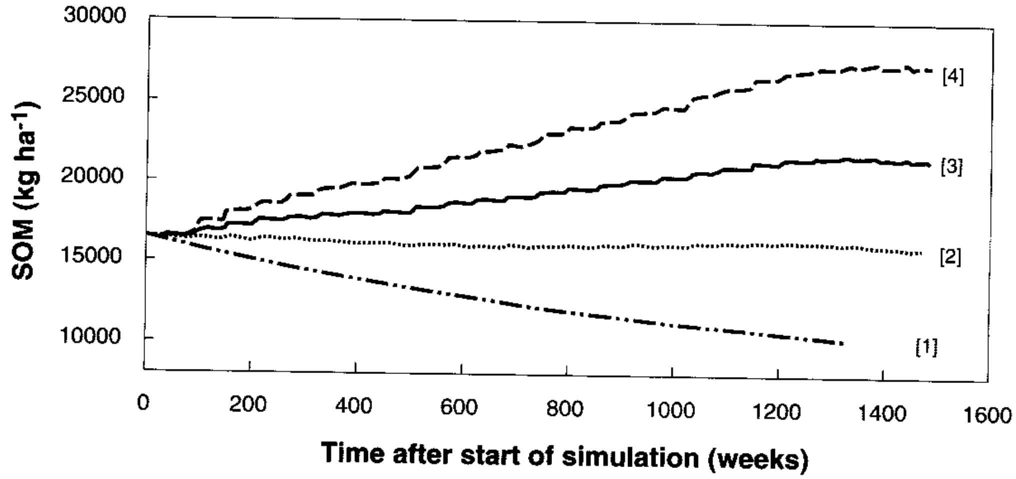

Figure 4. Time pattern of SOM for the legume crop treatments 1-4 of the medium-rainfall weather from Nigeria with the default soil (Luvisol). [1] bare fallow; [2] Complete shoot harvested; [3] Only beans harvested; [4] Bean crop as green manure.

clay/40% silt, or 95% sand/5% clay/0% silt across the whole profile. The water-retention data (wilting point, field capacity, saturation) belonging to these textures were calculated using the method of Saxton *et al.* (1986).

For the Low-rainfall Weather:

8. The same as No. 1 through 4, but with a bean-bare fallow rotation each year instead of a rotation with two bean crops per year.
9. The same as No. 5.

Effects of Soil Properties

The default soil (Luvisol) with the medium-rain regime showed a decline in SOM from 16.5 to 10.3 tonnes[C]/ha if it were maintained under bare fallow for 25 years (Figure 4). Cropping the field with a bean-bean-bare fallow rotation resulted in an increase of the SOM level to 21.5 tonnes[C]/ha, if only the bean grains were harvested and the harvest residues were returned to the soil. The harvest residues plus the roots were enough to result in an increased SOM level. A greater increase may be expected with crops, such as maize, that leave larger amounts of residues.

If the complete shoot of the bean was removed from the field (no crop residues were returned to the soil besides roots and shoot parts that senesced during the season), the soil C was near a steady state level; it dropped by only 0.6 tonnes[C]/ha over the 25 year time period (Table 2; Figure 4). At the other extreme, if the complete shoot was left in the field (including the grain)—thus with the bean crop as a green manure—the SOM increase was considerably larger (to 27.4 tons[C]/ha). Though a common bean may not be used as a green manure, other legumes are widely used to enhance soil-fertility (e.g., *Mucuna pruriens* in Central America and parts of Africa). In the beans-as-green-manure case presented here, organic N increased by about 450 kg[N]/ha (1582 to 2030 kg[N]/ha), which is a 30 percent increase in this soil's fertility factor.

Table 2: Initial and final (after 25 years) SOM level of the various treatments.

Initial SOM content	Nigerian Luvisol				*Zambian deep-sandy soil, ca. 90% sand*		*Zambian deep soil, but 10% sand, 60% clay*	
	Medium rain 16473		*Low rain 16473*		*Medium rain 37087*		*Medium rain 37087*	
	Final SOM content	*Increase or decrease*	*Final SOM content*	*Increase or decrease*	*Final SOM content*	*Increase or decrease*	*Final SOM content*	*Increase or decrease*
Bare fallow	10262	*-6211*	10168	*-6305*	17708	*-19379*	25481	*-11606*
Only beans harvested	21482	*5009*	17685	*1212*	24002	*-13085*	29588	*-7499*
Complete shoot harvested	15918	*-555*	14391	*-2082*	20932	*-16155*	28082	*-9005*
Beans as green manure	27353	*10880*	19817	*3344*	27160	*-9927*	31175	*-5912*
Pasture + 10 kg[N]/ha	12781	*-3692*	13628	*-2845*	19324	*-17763*	*	*
Pasture + 25 kg[N]/ha	15388	*-1085*	16038	*-435*	20585	*-16502*	*	*
Pasture + 50 kg[N]/ha	20371	*3898*	19940	*3467*	23222	*-13865*	*	*
Pasture + 100 kg[N]/ha	26676	*10203*	23960	*7487*	29971	*-7116*	*	*

* Simulations were not made for these cases

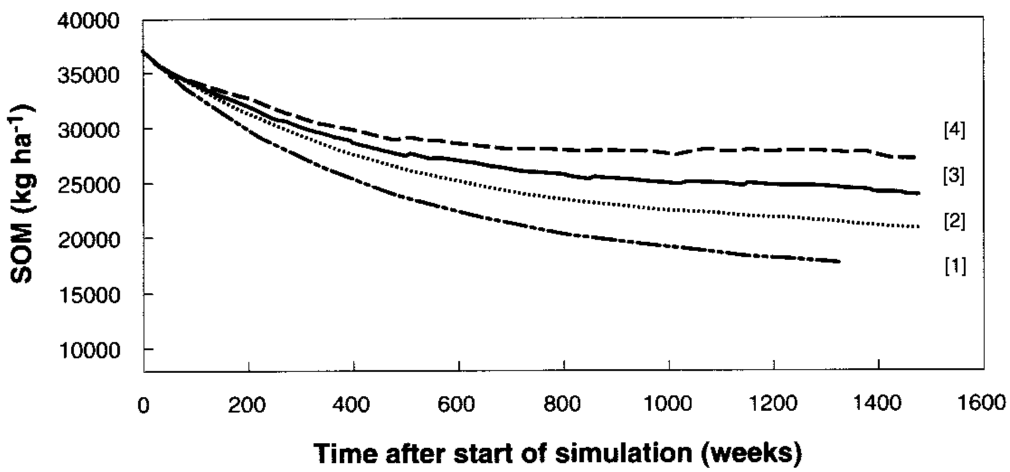

Figure 5. Time pattern of SOM for the legume treatments 1-4 of the medium-rainfall (Nigerian) weather with the deep sandy soil (about 90% sand across the profile) from Zambia. Treatments are: [1] bare fallow; [2] Complete shoot harvested; [3]Only beans harvested; [4] Bean crop as green manure.

Using the deep sandy soil from Zambia with the same weather resulted in a decline of SOM in all treatments (Figure 5). Several factors are involved in why this may be so different, though not all favor a stronger SOM decline in the sandy soil:

1. The initial SOM level was higher (0.84% vs. 0.30% in the topsoil) and may have been recently taken out of forest. If so, its SOM may have been above the steady state level for this soil type/management system combination.
2. This soil is much deeper (167 cm) than the Luvisol (97 cm), but the root input is mainly in the topsoil; SOM at depth will decompose, but probably at a lower rate than in the topsoil and with little replacement by new material.
3. On the other hand, the sandy soil is much drier, particularly in the topsoil, which favors a slowing down of the SOM decomposition.
4. SOM decomposition is generally slower in a clayey soil, because clay offers organic particles protection from decomposer microbes. This deep sandy soil is very low in clay and silt, and SOM decomposition is thus expected to go relatively fast.

To gain insight on which factors may have been most important, we used the Zambian deep sandy soil, but changed its texture and related water-retention parameters to 60% clay and 10% sand. Of course this results in an artificial soil, but it illustrates the importance of different factors. In this 'artificial' soil, factors *1* and *2* were unaffected compared to the original deep sand; thus, differences in SOM level would relate to factors *3* and *4*. Table 2 shows the results of these simulations. One notices that decreasing the sand fraction and increasing the clay fraction leads to a greater conservation of SOM in all treatments. The fact, though, that there still was no build-up of SOM in any of the treatments shows that initial SOM level (factor 1) and deep soil (factor 2) are important in determining whether soil C will increase or decrease if all other factors are constant. The SOM level per soil layer (data not shown) suggests that both factors 1 and 2

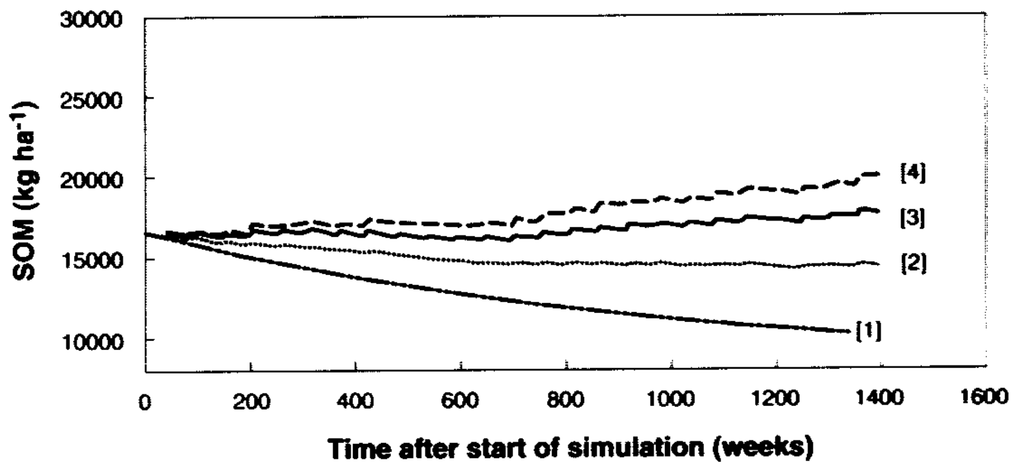

Figure 6. Time pattern of SOM for the legume treatments 1-4 of the low-rainfall weather from Niger with the default soil (Luvisol). [1] bare fallow; [2] Complete shoot harvested; [3] Only beans harvested; [4] Bean crop as green manure.

contributed to decreases in soil C under all combinations tested. Whereas the 0-5-cm layer, which is affected by the surface-deposited shoot, increased in SOM from 6.7 to 7.1 tonnes[C]/ha in the beans-as-green manure treatment, the remaining layers together decreased from 30.4 to 22.2 tonnes[C]/ha.

Climate Effect Simulations

A comparison of the SOM level after 25 years of medium-rainfall weather (Figure 4) with that after an equal period of low-rainfall weather (Figure 6) also shows a clear difference. The drier weather resulted in a smaller build-up of SOM in the grain-only harvests and beans-as-green manure treatments. This is easily understood because in the low-rainfall weather, the production of dry matter by a bean crop in the grain-only harvested treatment was about half of what it was in the medium-rainfall regime. Since the medium-rainfall regime can have two crops per season, the annual dry matter production differs considerably between the two rainfall regimes: 2.9 vs. 6.6 kg[DM]/ha for the low-rainfall versus the medium-rainfall weather.

With the low-rainfall weather, the SOM decrease under bare fallow was similar to that under medium-rainfall conditions (respectively, 6.3 vs. 6.2 tonnes[C]/ha) (Table 2). This is remarkable, as one would expect that SOM decomposition rate to be lower under dry conditions. However, with the imposed bare soil condition, soil moisture is conserved in both soils in the model because there was no water loss by a crop, resulting in favorable conditions for SOM decomposition most of the year in both rainfall types.

Crop Management

Figure 4 suggests that it makes a big difference when part of the crop is harvested. A slight decrease (0.6-tonnes[C]/ha) in SOM occurred if the complete shoot was harvested, a 5-tonnes[C]/ha increase if only the grains were harvested, and an almost 11-tonnes[C]/ha increase if all of the bean crop

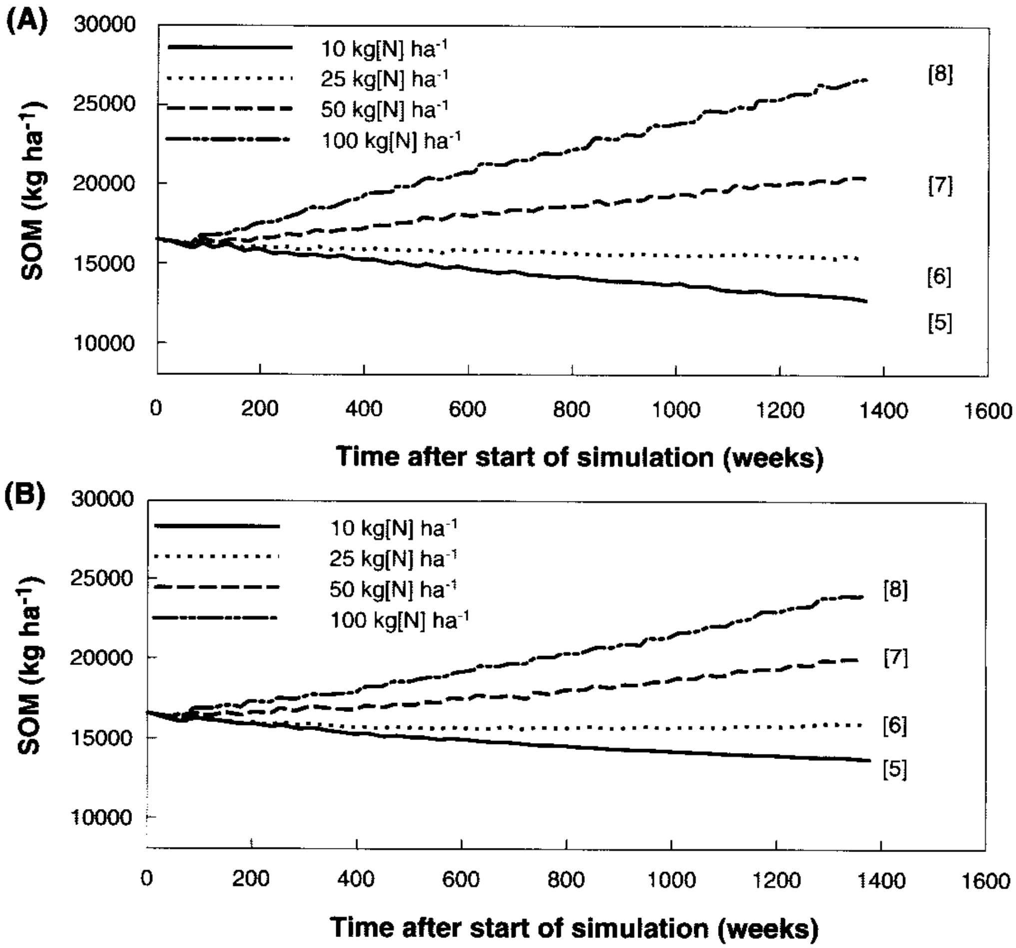

Figure 7. Time pattern of SOM for the Brachiaria pasture treatments of (A) the medium-rainfall weather, and (B) the low-rainfall weather, both with the default soil (Luvisol). Treatments are [5] 10 kg[N]/ha; [6] 25 kg[N]/ha; [7] 50 kg[N]/ha; [8] 100 kg[N]/ha.

were incorporated into the soil as if it were a green manure (Table 2).

Two primary examples of the many other possibilities of how crop management may affect SOM content are fertilization and irrigation. We show here an example of fertilization, a practice that is within reach for many small farmers. The grass *Brachiaria decumbens* is a popular species for improved pastures in the tropics. It originates from Africa and could potentially be of interest for building up the SOM level across the soil profile, as it is a deep-rooting grass. Since this grass does not fix nitrogen (like the bean crops), it has to be fertilized. This was simulated at four levels: 10, 25, 50 and 100 kg[N]/(ha.yr). The highest two fertilization levels resulted in SOM increases to, respectively, 20.4 and 26.7 tonnes[C]/ha for the medium-rainfall location (Table 2). The 25-kg[N]/ha treatment resulted in almost no change in SOM (a decrease of 1.1 tonnes[C]/ha) and the lowest N application resulted in a large decline in SOM (to 12.8 tonnes[C]/ha).

Figure 7 shows simulated changes on soil carbon over time for these pasture simulations in the two rainfall locations.

The shoot weight for the 10-kg[N]/ha application treatment peaked at about 4 tonnes[dry matter]/ha for the medium rainfall case, but it went down soon after reaching its peak (results not shown). The highest N level reached 10.0 tonnes[DM]/ha and was able to maintain a high shoot mass for several weeks during each season. A fine-tuning of the fertilization during the season when maximum growth occurs is likely to result in a higher production and, possibly, a steeper SOM increase.

UNCERTAINTIES IN BIOPHYSICAL MODEL PREDICTIONS

Estimating soil C sequestration for a land management unit is complicated by many factors. The use of biophysical models is necessary, but great care must be taken in making these estimates and interpreting results from the analyses. There are a number of uncertainties associated with this approach, and procedures must be implemented to help one understand these uncertainties in order to produce reliable and credible estimates. We first give an overview of sources of uncertainty and then suggest procedures for combining measurements with biophysical model simulations to make reliable predictions of soil C sequestration.

Uncertainties in Inputs

The above example simulations illustrate the large effects of soil properties, initial SOM, weather and management factors in the soil C balance. Thus, it should be clear that uncertainties in the input data representing these factors would lead to uncertainties in predictions of soil C sequestration. This implies that measurements are needed to provide accurate inputs of these factors so that accurate predictions of soil C sequestration can be made for each selected location. Since these soil, weather and management inputs vary considerably over space and time, measurement of these inputs for each land management unit in an area is not possible. The use of the so-called pedotransfer functions (Gijsman *et al.*, *in press*) to estimate soil inputs from texture information introduces uncertainties, as do assumptions about uniformity of rainfall in an area. Historical weather data and soil properties measured in the past can be used for estimating potential soil C sequestration, but initial soil carbon measurements are needed to establish baseline levels. Uncertainty also exists in management, since decisions are made by individual farmers. For example, uncertainties in how much crop residue is put back into the soil will lead to large variations in soil C sequestration estimates. Therefore, uncertainties in estimates depend on uncertainties in soil properties over space as well as uncertainties in future weather conditions and land management.

Uncertainties in Models

There are also uncertainties due to the imperfect models that are used in the predictions. For example, increasing soil C requires that crop residues be returned to the soil. Uncertainties in predicting crop biomass cause uncertainties in fresh organic matter input to the soil and thus in soil C sequestration. In addition, the soil models have empirical relationships that modify the rates of mineralization of SOM under different temperatures, soil water conditions, and soil texture. Inherent uncertainty is present in each of these relationships, which may lead to variations in accuracy depending on environmental conditions.

There are also simplifications for representing SOM in the models. For example, SOM is often divided into several fractions of different decomposability. The most-easily-decomposable is generally a microbial fraction, followed by a fraction of intermediate decomposability, and lastly a recalcitrant fraction. In reality, there is a continuum of fractions, but the three-pool concept is widely used (e.g., the CENTURY model; Parton *et al.*, 1988, 1994). An important question is how to distribute the SOM over the three pools. The microbial pool is very small (only a few percent of the total SOM), while the intermediate pool and recalcitrant pool together make up the large majority. It makes a big difference, though, in how these pools are set up at initialization of the simulations. It is likely that in a highly degraded soil in a warm climate, much of the intermediate pool has been decomposed and most SOM would thus be recalcitrant. In the simulation results shown, the SOM pool fractions were assumed to be 0.02: 0.54: 0.44 for microbial: intermediate: recalcitrant pools. To illustrate the effect of this uncertainty on predictions, we also initialized the SOM with a higher fraction of recalcitrant SOM (i.e., 0.64 or 0.74); the microbial fractions stayed the same (0.02). Increases in soil C over 25 years in the only-beans-harvested treatment changed from 1212 kg[C]/ha for the 0.44 recalcitrant fraction to 3269 and 4299 kg[C]/ha for the 0.64 and 0.74 recalcitrant fractions, respectively, because less of the original SOM decomposed.

Dealing with Uncertainties: Combining Measurements with Predictions

Uncertainties will always exist in any procedures for monitoring and predicting soil C sequestration. The best way to deal with these uncertainties is to combine measurements with models, taking advantage of the strengths of each. There are two steps in our recommended procedures: 1) calibrating the biophysical models to simulate data already collected from on-station experiments and on-farm trials, and 2) feedback adjustment of model parameters using data monitored during the course of a C sequestration project. These adjustments would be done initially so that potential predictions are realistic and credible, and done during the contract to verify that estimates of soil carbon are reliable. The quality of the verification process will be enhanced by integrating direct measurements of soil carbon at selected sites with model predictions, which use weather, soil properties and management information in this complementary approach.

Adapt Models to Soil, Climate, Crops and Management of the Area. Existing data from experiments on research stations and from on-farm trials should be assembled and used to adapt the biophysical models for soil, weather, crop and management systems that are to be considered in the soil C sequestration project. The minimum weather, soil and management information must be available for each of these experiments (Table 1. Also, measurements of crop productivity and season length are necessary for calibrating the models for local uses. For calibrating model parameters, measurements of crop growth and yield are needed for traditional as well as target production systems. At minimum, data are needed on grain yield, above ground biomass and crop maturity. Ideally, one would have access to some experiments in which detailed soil measurements were made and in which in-season samples of biomass are available. Because of the differences that exist between on-station and on-farm management and levels of productivity, data from both are needed to make sure that predictions of biomass and yield represent on-farm levels. Protocols for in-field sampling are provided in the DSSAT documentation (Tsuji *et al.*, 1994). Procedures for calibrating models using data from on-station research plots are described by Boote *et al.* (2001), from on-station yield trials in a region by Mavromatis *et al.* (2001), from on-farm trials by Welch *et al.* (2002), and from county records of farmer yields (Jagtap and Jones, 2002). These procedures adjust soil and crop parameters so that the models predict biomass, grain yield and crop development (flowering and maturity dates) across all trials with minimum root mean square errors between simulated and observed. Parameters adjusted usually include genetic coefficients for the crop and soil parameters (soil water holding limits, root depth, runoff characteristics and soil fertility factor). Our recent experience has demonstrated good accuracy when more than 15 field-year combinations are used (Mavromatis *et al.*, 2002).

Long-term experiments in which changes in soil C vs. time were measured should be used to evaluate the ability of the biophysical models to simulate soil C accurately for climate, soil and management systems in the region of study. These data may be useful for adjusting parameters in the soil C module to achieve greater accuracy.

Feedback Adjustment of Model Predictions over Time. During the course of a carbon contract, one must have reliable estimates of soil carbon changes for whatever weather and land management practices occurred up to any point in time. Reliable estimates can best be obtained by combining information on land management practices and weather with measurements of biomass production and soil carbon at selected land management units in the contract area. Direct measurements of soil carbon at sample sites and geostatistical procedures can be used to obtain estimates of total soil carbon sequestration for selected land management units (see chapter by Yost *et al.*). The biophysical models, calibrated to local climate, soil and management systems, can estimate soil carbon sequestration at the same sites where direct measurements are made. Model predictions will provide a consistency check for measurements and thus help ensure that quality measurements are being made. Measurement procedures may be improved over time through this process.

A number of fields (e.g., 30-40) should be selected in a contract area for monitoring management, productivity and soil C changes over time. Soil, rainfall and management data from these fields would be used as model inputs to models. An evaluation of model predictions of biomass, grain yield and soil C changes would be used first to estimate errors of prediction, and then to adjust parameters in the models to reduce prediction errors. Adjustments over time may be essential, as the models may not accurately predict dry matter production or soil organic matter transformations for the conditions in the contract area. Direct measurements of dry matter productivity and soil carbon at selected sites can be used in a feedback loop to fine tune crop and soil model parameters in order to reduce errors of prediction. Improved predictions, verified at measurement sites, can then be used for new forward-looking predictions for the selected land management units. New predictions of soil carbon changes over the remaining term of the contract will thus also be improved. Such feedback adjustments to biophysical models have been shown to greatly improve predictions in a number of studies (Swaney *et al.*, 1986; Hansen and Jones, 2000; Jagtap and Jones, 2001; Paz *et al.*, 1998; Irmak *et al.*, 2001).

It is this combination of direct measurements and model predictions that will provide the greatest confidence in verifying soil carbon sequestration. Neither direct sampling of soil carbon at selected sites (which has its own uncertainties and problems, see chapter by Yost *et al.*) nor model predictions alone (based on observed practices, weather and soil inputs) are adequate by themselves. However, the combination of the measurements and model predictions, using site measurements, remote sensing and spatial statistics for model inputs, provide the necessary quality control, consistency checks, and feedback adjustments needed for successfully verifying soil carbon sequestration relative to target levels.

SCALING UP PREDICTIONS OVER SPACE

Crop-soil biophysical models predict biomass production, yield and soil carbon changes over time for a uniform land management unit, subjected to specific weather, soil and management practices. Soil carbon sequestration predictions are needed for large areas under contract. Applications of crop models at scales greater than a homogeneous plot require spatial aggregation. Aggregation error, model imperfections and limitations of data quality and coverage complicate the task of obtaining good predictions of spatially-aggregated crop and soil responses. Hansen and Jones (2000) presented two different approaches for scaling up crop model results for providing aggregated predictions over space. The most rigorous, referred to as geographic space integration, is to characterize the spatial distribution of all model inputs, then simulate over each small increment of space and sum up or average the results. This approach may work well for areas where intense sampling is done in a geo-referenced way, such as in precision agriculture. This approach, however, is not practical for large areas because it would require soil, weather and management information for perhaps thousands of land units. A second approach described by Hansen and Jones (2000) was to incorporate heterogeneity of inputs using the relative frequencies of combinations of soils, management systems and weather. For example, one can obtain detailed information on management practices for each land management unit and, through the use of remote sensing, identify similar land management units using supervised classification procedures (e.g., Barnes and Baker, 2000; Seidl *et al.*, 2000; Jones and Barnes, 2000).

Scaling up is needed to estimate potential soil C sequestration (i.e., before a contract is made) and to estimate area-wide amounts of C sequestered by soil during a contract period. Before the contract, predictions of potential soil C sequestration can be made for a number of land management units. Aggregate estimates can be obtained by determining the area of each land management unit and multiplying it by the soil C estimates for each unit. Similarly, during a contract, area-wide estimates will be needed annually. The problem becomes one of identifying land management units and the area of each in the contract area. We propose the use of remote sensing to identify land management units based on crops, tillage systems, topography and productivity levels. A number of these land management units will be selected for monitoring over time (i.e., about 8-10 of each type of 4 or 5 land management units to be considered in the contract program). Data from these locations will be used for comparison with model estimates of productivity and soil C changes, and possibly for feedback adjustments to the models (see above, "Feedback Adjustments of Model Predictions over Time"). It may not be practical to monitor each combination of land management unit identified, but the locations selected for sampling should represent the range of variability that exists in the area. Scaling up predictions of soil C sequestration will be done by estimating soil C for each of the land management units and multiplying that estimate by the area identified for each via remote sensing. Estimates of soil C sequestration for each land management unit will include variations in management practices based on variations observed in the selected locations by running the models for each management combination within the observed variability.

BIOPHYSICAL MODELS IN OVERALL INTEGRATED APPROACH

For biophysical models, such as DSSAT-CENTURY, there are two major uses in assessing and monitoring soil carbon sequestration. The first use is in determining whether an area and candidate management systems have sufficient potential for sequestering soil C, and the second use is for integration with direct measurements for computing soil C sequestration in an active program. The sampling, input data and modeling procedures to meet each of these needs differ, as noted in the summary below.

Predicting Potential Soil Carbon Sequestration for an Area

1. Initial survey to identify candidate areas and management systems for soil C sequestration. Identify land management units using remote sensing and surveys.
2. Select subset of selected land management units for sampling and monitoring (e.g., 30-50). Measure baseline soil carbon for the fields under consideration. Procedures include stratified sampling and the use of geostatistics to interpolate soil carbon levels for all land management units of interest. (See chapter by Yost *et al.*)
3. Collect information on crop productivity, soils, weather, farming practices and socio-economic conditions for the area under consideration. Identify candidate land management systems for soil C sequestration.
4. Estimate the biophysical potential for soil carbon sequestration for each soil type and weather conditions in the selected area. The biophysical potential soil carbon sequestration level is based on soil properties, weather, and current soil carbon levels as well as the growth and yield of candidate cropping systems. For this step, the DSSAT-CENTURY crop-soil models are used to simulate rainfed crop biomass and grain production for a period of 20 to 50 years. The CENTURY soil organic matter model will be used for simulating natural systems, if they are to be considered in a C contract.
5. Scale up estimates using the remote sensing classification of existing land

management units. Assumptions will be necessary for levels of adoption and compliance with agreed-upon practices. Maps and summary statistics are prepared to provide upper limit estimates of soil carbon sequestration without considering socioeconomic limitations or actual land management. The potential for soil carbon sequestration is then computed by subtracting from these projected levels of soil carbon the simulated estimates of soil carbon over the 20 to 50 years, assuming that current practices are continued.

6. Estimate economic potential for soil carbon sequestration under most-likely, optimistic and pessimistic scenarios of biophysical and economic conditions. Key economic parameters include the prospective price of carbon, and prices for principal crops and inputs used in the baseline and more sustainable systems (see chapter by Antle for more details). This procedure integrates models of land use and management decisions of the farmers (considering their capabilities and limitations) with DSSAT-CENTURY and CENTURY models and data on soils, weather and baseline soil-carbon levels. This integrated analysis simulates the potential impacts of farmers changing land use and crop management practices in response to economic incentives provided by soil C contracts. The analysis assesses the impacts of these changes on the economic well being of farmers, on the long-term sustainability of farming systems and the impacts of these more sustainable systems on soil carbon. These analyses are done with different assumptions regarding compliance to produce optimistic, likely and pessimistic scenarios. Maps are produced with statistics that summarize soil carbon sequestration over the selected area at any selected year. A critical analysis of assumptions and risks is made. One should also analyze the possible increases in soil productivity levels, brought about by increased soil-carbon levels, a critical issue relative to acceptance of practices aimed at increasing soil carbon levels in low input agricultural systems.

Procedures for Monitoring and Verifying Compliance

1. Prepare target soil carbon levels vs. time for the overall contract area. This step implicitly assumes that specific land management practices have been agreed upon between agricultural community leaders/farmers and carbon traders. These practices will be used to estimate the most likely amounts of soil carbon sequestration vs. time, using historical weather data. This analysis will provide estimates of uncertainty in the most likely trajectory of soil carbon sequestration associated with uncertainty in weather. Since it is essential that any agreements will allow for changes in production technology as improvements are made, these targets will be updated over time as agreed upon by both parties. This step requires all of the information collected previously for assessing potential soil carbon sequestration, such as initial soil carbon levels, soil and weather data.
2. Monitor compliance. During some agreed-upon time interval, compliance to a contract is determined by monitoring compliance to agreed-upon land use and land management practices. Verification of practices is accomplished by remote sensing combined with visits to selected sites. Remote sensing will be used to observe aboveground biomass at critical periods of time, and images

taken at other times of the year will confirm land preparation and residue management practices.

3. Measure crop productivity in selected fields annually (e.g., 8-10 fields for each land management unit). Verify that predicted dry matter levels are reached for the agreed-upon practices. Adjust crop model parameters if needed to ensure correct predictions of dry matter production in all calculations.
4. Measure soil carbon. Every two years or other agreed-upon time interval (see above), soil carbon is measured in a selected sample of fields in the area based on geospatial and biophysical simulation considerations, stratified across soils and weather conditions. These measurements should be carried out in a manner to provide accurate estimates of soil carbon changes at these locations over the agreed-upon time period.
5. Estimate changes in soil carbon for the measurement sites, using the soil-crop models, soil, weather and management data for the sites and time period that actually occurred. These estimated changes in soil carbon are compared with measured changes to determine if model adjustments are needed for accurate prediction. Soil model parameters are adjusted based on feedback information on dry matter productivity and residue remaining on the fields being monitored.
6. Extrapolate estimates of soil carbon changes as well as changes in biomass production and grain yield over the entire area, using the biophysical models with adjustments that were necessary for accurately predicting the land management unit responses. This step will require information on distributions of land management units from remote sensing as well as spatial analyses of soil carbon and other properties (see chapter by Yost *et al.*). Compare these estimates with target levels; readjust target levels for future years as needed.
7. Estimate impacts of changes in land management practices on both subsistence and commercial crop production and socioeconomic conditions in addition to soil carbon sequestration. Summarize results in maps and tables for farmers, contractors and others.
8. Continue these procedures until the end of the contract, at which time an overall assessment will be made for the contractor, farmers, and government agencies.

Practical Issues

It is important to recognize that in addition to these procedures, significant institutional support (either private or public) will be needed to implement carbon contracts in developing country agriculture. Farmers will require information about the opportunity to participate in carbon contracts, yet many extension services are ineffective and local researchers often lack the resources to work directly with farmers. In addition, some institutional mechanism will be needed to reduce transaction costs between the large numbers of small land units that will be required to produce carbon in quantities that are commercially tradable. A point of entry could be through commercial crop production and the related private extension agents, scouts or traders that provide information and resources to farmers producing these commercial crops. An additional challenge in many developing countries is political risk and lack of legal institutions to enforce contracts and property rights. All of these factors present an enormous challenge to those who wish to provide opportunities to poor farmers in developing countries.

However, the risks of not investing in more sustainable agriculture are also enormous for these farmers and for the global community.

Methods are needed to help guide those who wish to make carbon trading available to developing countries that address the social, institutional and political issues related to large-scale carbon trading contracts. In our opinion, this can best be done by having or developing technology and methods that clearly have short-term benefits to farmers (e.g., by increasing production, decreasing risks, increasing quality of life, reducing hunger, etc.), while sequestering soil carbon. This strategy will provide long-term benefits as well, such as increased soil fertility and possible reversal of desertification.

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CHAPTER FOUR

ECONOMIC ANALYSIS OF CARBON SEQUESTRATION IN AGRICULTURAL SOILS: AN INTEGRATED ASSESSMENT APPROACH

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INTRODUCTION

A meaningful assessment of the potential for soil carbon sequestration requires the integration of the technical and economic information that is needed by two types of decision makers: those government or private entities that would like to sequester soil C to offset green-house gas emissions (demanders of C emissions credits or offsets), and farmers who would take actions to increase soil C (suppliers of C emissions credits or offsets).

Farmers will be willing to enter into agreements or contracts to sequester soil C if they believe the benefits of doing so justify the costs of the actions that they must take. To illustrate, suppose either a government agency or a private entity offered a farmer \$P for each tonne of carbon the farmer could sequester. Suppose further the farmer knew that if he changed from a crop-fallow rotation to a continuous-crop rotation, he would earn on average \$L less each year but would sequester C tonnes of carbon each year. It follows that to produce these C tonnes of carbon each year, it costs the farmer \$L/C per tonne. Clearly, if $PC - L > 0$ or equivalently $P > L/C$, the farmer is better off in economic terms by entering into a contract to change practices and thus earn an additional income of \$(PC-L).

This same information is likewise relevant to the potential buyer of the soil C agreement or contract. If the best alternative way is to reduce C emissions costs \$P per tonne, then the buyer wishing to minimize the cost of the carbon would only offer contracts to farmers if $P > L/C$. If $P < L/C$, the entity then would rather buy reductions in emissions from the alternative sources.

Thus, potential buyers and sellers of soil C need both technical information (how much C can be sequestered) and economic information (how much C sequestration costs) integrated to support decision-making. Broader economic, environmental or social consequences of carbon sequestration activities—such as the impacts on the long-term sustainability of agricultural systems, or impacts on regional economic development—are also considered relevant to the assessment of agricultural production systems by many private and public interests. Therefore, information about those impacts also needs to be incorporated into the analysis of a production system to support informed decision-making. In short, both private and public decision makers need the type of information that is provided by integrated assessment of agricultural production systems to evaluate soil C sequestration potential.

The first section of this chapter describes the economic basis for analysis of the benefits and costs of sequestering C in agricultural soils. The next section describes site-specific economic simulation models that can be linked to the DSSAT/CENTURY crop models (described in the chapter by Jones *et al.* in this monograph) for integrated assessment of the potential for agricultural production systems to sequester carbon in soil. The third section describes the Tradeoff Analysis Model software that can be used to implement an integrated assessment of agricultural production systems in order to assess the potential economic and environmental implications of soil C sequestration.

ECONOMIC ANALYSIS OF AGRICULTURAL SOIL CARBON SEQUESTRATION[1]

The atmosphere is a public good—everyone benefits from it without having to "pay" for it. This fact means that private individuals and firms, and even individual countries, have little incentive to take actions to prevent the accumulation of greenhouse gases (GHGs) in the atmosphere. Therefore, the demand for individuals to reduce emissions must derive primarily from collective action, i.e., from government policies aiming to limit GHG emissions. One policy mechanism to reduce GHG emissions is direct government intervention. Several examples of government policies exist which are designed to reduce environmental impacts of human activity through direct regulation. Many governments have tried, and largely failed, to mandate adoption of soil and other conservation practices in agriculture, whereas policies based on economic incentives have achieved considerable success. In the United States, for example, the Conservation Reserve Program provides payments to farmers who take actions that reduce soil erosion. In a similar way, policies could be designed to sequester soil carbon. Indeed, the U.S. Congress and other governments around the world are considering a number of such proposals.

An alternative mechanism to reduce pollution is for governments to limit emissions through a tradable emissions allowance system. Under a carbon cap and trade system, firms would be allocated the rights to emit GHGs in the form of emissions allowances, and these allowances could be traded. This system provides an incentive for firms that emit a relatively high rate of CO_2 per dollar of output to sell their emissions allowances to firms that emit a relatively low rate of CO_2 per dollar of output. Thus, because it creates incentives for inefficient firms (ones that emit a high rate of CO_2 unit of output) to reduce production and for efficient firms (ones that emit a low rate of CO_2 per unit of output) to increase production, the emissions allowance market provides an efficient mechanism to meet a given total emissions target. Another way for emitting firms to obtain emissions allowances or offsets would be for them to enter into agreements with landowners to manage their land as carbon sinks. These contracts would guarantee that landowners would sequester a specified quantity of carbon in soils or in biomass such as trees over a specified period of time.

Even without government policies to limit GHG emissions, private entities also may be motivated to take individual or collective actions to mitigate GHG emissions. Interest groups might organize concerned individuals to raise funds to purchase carbon credits or to enter directly into contracts with individuals or groups to sequester carbon. Business firms wanting to demonstrate environmental concern also may be motivated to buy carbon, whether or not their emissions are constrained by government policy. Further, business firms might buy carbon contracts in anticipation of emissions standards or to preempt the possibility of emission standards being imposed. This type of behavior may explain why there have already been some C sequestration agreements even though most countries do not have policies regulating GHG emissions (CAST, 2000). However, it would be surprising to see large-scale investment in carbon sinks

[1]This section is based on Antle and McCarl (2001).

without a government policy requiring firms to limit emissions.

From an economic perspective, soil C provides value in three dimensions: first, as an essential component of soil that affects agricultural productivity; second, as a way to offset CO_2 emissions from other sources; and third, as an indirect source of benefits involving improved environmental quality. Research shows that many farmers do not manage their soils so as to maximize its productivity. Using economic principles, we can explain why farmers are also not likely to manage soils to maximize the public benefits of increasing soil C levels.

The first component of soil C value is the private benefit to the farmer in the form of increased agricultural productivity (see the chapter by Jones *et al.* for a discussion of these agronomic benefits). An economically-rational farmer who understands the productive value of soil C can be expected to make management decisions that optimize the value of the soil C stock in economic terms. Yet it is evident that many farmers—particularly farmers in developing countries who lack an understanding of basic agronomy and soil science—do not understand the role of soil C in production, and lack the tools to measure it and manage it. The result is that farmers often use practices that deplete soil organic matter and result in a level of soil C that is sub-optimal for sustaining agricultural productivity and maximizing economic returns over time. Even when farmers in developing countries do understand the adverse effects of their management decisions on soil C, they often lack the resources and incentives needed to implement better practices.

The second dimension of soil C—the mitigation of GHG emissions—involves a benefit that is external to the farmer's own economic well-being. Therefore, we cannot expect farmers to optimally manage soil C to mitigate GHGs unless some mechanism exists to provide farmers with appropriate incentives to do so. Likewise, farmers cannot be expected to manage their soils to maximize other environmental benefits that accrue off-farm. Again, an incentive mechanism is needed to induce farmers to take account of the value of environmental quality improvement in their decision-making.

To analyze soil C from an economic perspective, we shall assume as a first-order approximation that agricultural producers are economically rational and thus utilize those land and management practices that they believe yield the highest economic returns, *subject to the limitations created by the available technology and farmers' knowledge of efficient soil management practices*. The analysis can be generalized in a straightforward manner to account for non-economic objectives. Experience shows, however, that maximization of economic returns provides a good approximation to behavior in most cases (an important exception may be when farmers are producing solely for their own subsistence). Thus, economically motivated producers are likely to adopt alternative practices that increase soil C when there is a perceived economic incentive to do so. If indeed farmers are under-investing in the stock of soil C from either a private or public perspective, then a policy that provides additional incentive to increase the stock of soil C should move them towards a more efficient resource allocation.

Incentives and Contract Design

Farmers could be provided economic incentives to sequester C in soil through direct government payments or through incentives provided by private markets. Direct government programs would include efforts such as the Conservation Reserve Program in the United States and various other government conservation programs throughout the world where government provides farmers incentives to change management practices. Alternatively, private markets could arise if the government imposes GHG emissions standards on industry and permits trading of emission credits (however, see the discussion below about the viability of emissions markets in developing countries). In the latter case, industry could buy emissions credits from farmers. In either case, contracts between firms emitting GHGs (buyers of emissions credits) and the farmers (sellers of emissions credits) would specify the payment mechanism and other terms for a government program or for sales in a market for carbon credits.

Two classes of costs exist that are associated with implementing contracts for the provision of an environmental amenity through changes in agricultural practices: *farm opportunity costs* and *contract costs.* The first is the opportunity cost of resources expended on the farm to produce the amenity, including the returns forgone from more profitable activities. The second is the costs associated with negotiating and implementing contracts and involves brokerage fees and monitoring compliance with the terms of the contract (in terms of changing practices or carbon accumulation), and any other transaction costs. Below we discuss how these costs can be measured and incorporated into analysis of soil C sequestration potential.

Contracts for soil C could be designed in several ways. A *per-hectare payment mechanism* would give producers a fixed payment per hectare of land switched from a cropping system with a relatively low equilibrium level of soil C to a system that produces a higher equilibrium level of soil C, similar to existing conservation programs such as the Conservation Reserve Program (below we discuss whether this is an efficient way to design contracts). Per-hectare contracts would specify management practices that the farmer agrees to follow, and the farmer would receive this payment regardless of the amount of C that is sequestered on the contracted land unit as long as the specified practices are followed. A *per-tonne payment mechanism* would pay farmers for each tonne of C sequestered when they change land use or management practices, so the payments per land area would vary according to how much C was sequestered. A per-tonne contract would be based on the agreed-upon price per tonne of C, and on an annual carbon rate that would be established for each agroecozone and each type of practice. Both types of contract would involve similar conventional transaction costs for contract negotiation, legal fees, etc.

Because the per-hectare contract is based on practices rather than the amount of C accumulated, this type of contract is most likely to be used for government programs where the actual amount of C stored does not necessarily need to be determined for government purposes, at least not to a high degree of accuracy (note that in other conservation programs such as the Conservation Reserve Program, site-specific measurements of erosion reduction and other benefits are not a required part of the program). The per-tonne contract would require establishing the soil C rates for each type of contract and monitoring C accumulation to a degree of accuracy specified in the contract. These contracts would be more suitable for the creation of an emissions credit that was to be a traded asset. Thus, as long as monitoring practices are less costly than measuring carbon, per-hectare contracts have the advantage that contract costs may be lower than per–tonne contacts. However, per-hectare contracts have the disadvantage of not targeting incentives to those land units where soil C can be produced most efficiently. Therefore, determining the most suitable type of contract depends on whether the goal is to create a tradable asset, and it also involves trading off the two components of cost.

Designing Contracts for Farmers in Developing Countries

Recent experience with attempts to create market economies in former Soviet states has demonstrated clearly what economists have long known: namely, that markets function well only when suitable institutions exist. The most fundamental institutions are the rule of law and private property rights. Transportation and communications infrastructure are also critical in order to reduce transaction costs (transportation costs, costs of acquiring market information) to the level that buyers and sellers can profitably interact over space and time, as are financial institutions to lower the cost of financial transactions and provide financial capital to facilitate transactions. We know that the lack of suitable institutions and infrastructure in developing countries hinders the effective operation of markets for conventional agricultural commodities, and this will also be true for attempts to create markets for C emissions allowances. The market for SO_2 emissions in the United States—the first such market to exist in the world—operates with the support of longstanding legal and financial institutions. In any country lacking such institutions, it is unlikely that a market for emissions credits will be able to operate effectively.

These considerations suggest two likely scenarios for C sequestration programs in developing countries. The first scenario is for C sequestration to be promoted through government institutions such as a ministry of agriculture, as part of existing agricultural research, extension and development programs. In this case, there would not be any necessary link to a market for C emissions, either nation or international. A second scenario is for C sequestration to operate through projects that would coordinate activities with enough farmers to create a marketable C contract. If a national emissions credit market did not exist, these contracts could be marketed directly to buyers in other countries, either through individual negotiations with buyers or through an international C emissions market.

Farm-Level Decision Making

We now consider the farmer's decision regarding the participation in a contract (either with a government agency or a private entity) to sequester C in soil. In order to increase the stock of C in the soil on a land unit, the farmer must make a change from production system i (e.g., a specified crop rotation) that had been followed over some previous period (the historical land-use baseline), to some alternative system s. As illustrated in Figure 1, we can assume that utilization of management practice i up to time 0 results in a soil C level of C^i, and adoption of practice s at time 0 causes the level to increase to C^s at time T. At time T, the soil reaches a new level (that has been referred to as a *steady state level* or *saturation point* by different researchers) at which the level of soil C stabilizes until further changes in management occur. The solid curve represents a possible logistic-shaped trajectory for soil C, whereas the dashed line represents the annual average change from time 0 to T. The data in Watson *et al.* (2000) and in the Jones *et al.* chapter suggest that these curves may have a nearly linear shape, so that the linear path is in fact a good approximation. Note that before time 0, the soil C level could have been on a positive or negative trajectory as well.

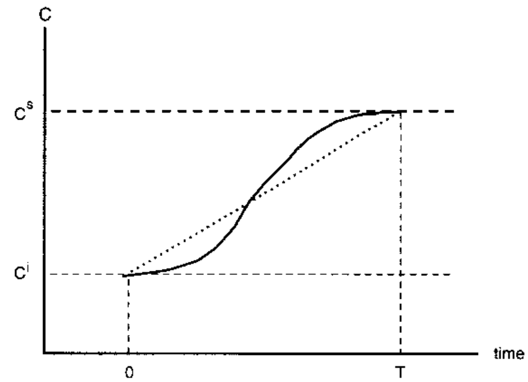

Figure 1. Time path and saturation point for soil C in response to a change in land use or management practices.

Changes in management practices may involve both fixed costs (e.g., for the construction of a terrace, or acquisition of new machinery or tools) and variable costs (terrace maintenance, changes in input use, etc.). In addition, the farmer receives a financial payment for participation in the contract. In the case of a per-hectare contract, the farmer receives g_t dollars per hectare per period. In the case of a per-tonne contract, the farmer receives a payment of \$$P_t$ per tonne of C sequestered each time period, so if the farmer changes from practice i to practice s and soil C increases by $\Delta c_t(i,s)$ tonnes per hectare per period, the farmer receives a payment of $P_t \Delta c_t(i,s)$ per hectare per period. The net present value (NPV) of changing from system i to system s for T periods is given by:

$$\text{(1) } NPV(i,s) = \sum_{t=1}^{T} D_t[NR(p_t, w_t, z_t, s) + g_t(i,s) - M_t(i,s)] - I(i,s)$$

where:

- $D_t = (1/(1+r))^t$ and r is the interest rate per unit time
- $NR(p_t, w_t, z_t, s)$ = net returns for system *s* in period t, given product price p_t, input prices w_t and capital services z_t (\$/ha/yr)
- $g_t(i,s) = g_t$ if a per-hectare contract , or $P_t \Delta c_t(i,s)$ if a per-tonne contract (\$/ha/yr)
- $M_t(i,s)$ = maintenance cost per period for changing from system i to s (\$/ha/yr)
- $I(i,s)$ = fixed cost for changing from system *i* to system *s* (\$/ha).

If the farmer does not participate in the contract and continues producing with system *i*, then $g_t(i,s) = M_t(i,s) = I(i,s) = 0$ and the farmer earns NPV(*i*). The farmer enters the contract if and only if $NPV(i,s) > NPV(i)$, and does not enter the contract otherwise.

In the special case where NR(p, w, z, *s*), P, $\Delta c(i,s)$, and $M(i,s)$ are constant over time, the above analysis can be simplified significantly. Let the fixed investment be converted into an equivalent annuity of $fc(i,s)$ dollars per period. With these assumptions the expression $NPV(i,s) > NPV(i)$ is equivalent to $NR(p, w, z, s) + g(i,s) - M(i,s) - fc(i,s) > NR(p, w, z, i)$. Rearranging, this equation becomes

$$\text{(2) } g(i,s) > NR(p, w, z, i) - NR(p, w, z, s) + M(i,s) + fc(i,s)$$

The expression on the right-hand side is the *farm opportunity cost* for switching to system *s* from system *i*. The farmer will switch practices when the farm opportunity cost is less than the payment per period. In the case of a per-tonne contract, $g(i,s) = P\Delta c(i,s)$ and therefore the condition for participation in the contract can be expressed as $P > (NR(p, w, z, i) - NR(p, w, z, s) + M(i,s) + fc(i,s))/\Delta c(i,s)$. The term on the right-hand side is now the *farm opportunity cost per tonne C*, and thus the farmer will participate when the price per tonne C is greater than the farm opportunity cost per tonne.

As we shall discuss further below, the contracts are expected to require certain monitoring and measurement activities and associated costs. If the farmer is required to pay these costs, then they can be incorporated into the terms $M(i,s)$ and $I(i,s)$. These costs would increase the per-tonne price of carbon that farmers would have to receive in order to be willing to participate in a carbon contract. Alternatively, if the buyer has to pay these costs, then they will reduce the net price the buyer would be willing to pay to the farmer, in the same way that transportation costs reduce the net farm-gate price farmers receive for other products they sell.

The Marginal Cost of Soil C and Spatial Heterogeneity

Agricultural land is spatially heterogeneous with respect to physical, climatic and economic characteristics. To account for spatial land and climatic heterogeneity, we introduce a site-specific vector of environmental characteristics e_j, for $j = 1,\ldots,J$ land units in the region. To account for economic heterogeneity we index prices and capital services by land unit. The net returns for each land unit can be written as $NR_j = NR(p_j, w_j, z_j, e_j, s)$ to indicate that returns vary spatially for system *s*. The equilibrium soil C per hectare can be expressed as a function $C_j = C(x_j, e_j, z_j, s)$, where x_j is a vector of the quantity of inputs used. The average rate of C sequestration for a change from practice *i* to practice s over T years is

$$(3)\quad \Delta cj(i,s) = [C(x_j, e_j, z_j, s) - C(x_j, e_j, z_j, i)]/T.$$

Thus, in a spatially heterogeneous region, the farm opportunity cost and the carbon rates both vary across land units, hence the opportunity cost per tonne of C varies spatially.

At the level of the individual land unit (the field), farmers make discrete land use decisions involving tillage system choices, land retirement choices, etc. The marginal cost curve for soil C can be constructed by ordering all land units according to their opportunity cost, and then aggregating the quantity of soil C produced at each marginal opportunity cost. Antle *et al.* (2001a) showed that the regional marginal cost curve is upward sloping because some land units can produce soil C at a lower marginal opportunity cost than other land units. Figure 2 shows marginal cost curves derived from recent studies of soil C sequestration in the United States.

Antle *et al.* (2001b) showed that for each quantity of C sequestered, the marginal opportunity cost of the per-hectare payment mechanism (MC_H) is greater than or equal to the marginal opportunity cost of the per-tonne mechanism (MC_T), i.e., $MC_H \geq MC_T$, with equality holding at the saturation point where the maximum amount of C is being produced (as illustrated in Figure 3). In addition, they showed that the efficiency of the per-hectare payment mechanism relative

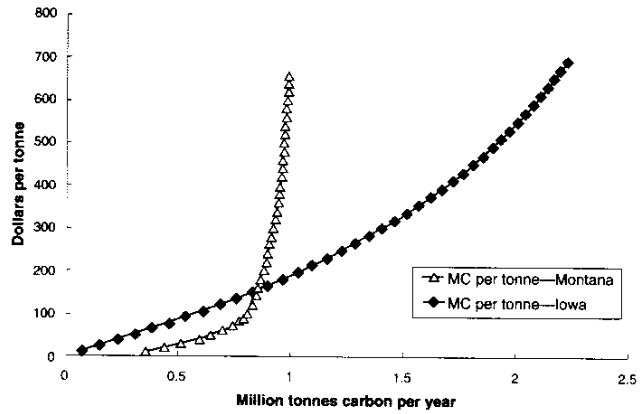

Figure 2. Marginal cost of soil C sequestration under a per tonne payment scheme for conservation tillage in Iowa and for crop intensification in Montana (Source: Antle *et al.*, 2001c).

to the per-tonne mechanism, as measured by the quantity MC_T/MC_H, is a decreasing function of a region's spatial heterogeneity of economic and environmental conditions. This result derives from the fact that the opportunity cost per tonne is equal to the ratio of the opportunity cost divided by the C rate. When spatial heterogeneity is high, farmers with very low C rates can participate under a per-hectare payment contract, yielding higher cost for each amount of C sequestered than with a per-tonne payment contract. In their analysis of the marginal cost of soil C sequestration in Montana, Antle *et al.* (2001b) found that a per-hectare payment scheme is as much as four times more costly than the per-tonne payment mechanism. They concluded that there could be high payoffs to implementing carbon contracts that account for spatial variability in biophysical and economic conditions.

Saturation, Permanence and Contract Duration

Soil science has established that there is a steady state level or saturation point for the amount of soil C that can be stored in the soil for a given soil, climate and set of management practices (Watson *et al.*, 2000; West *et al.*, 2000). In addition, soil research has shown that sequestered carbon is volatile and it has been found that if practices sequestering soil C are discontinued the C stored in the soil can be released back in to the atmosphere in a short period of time. For example, if a farmer practicing reduced tillage reverts to conventional plowing, the accumulated soil C may be released over a few years, and the soil C level can return to the level before the reduced tillage was adopted.

One way to address the permanence issue is to view farmers who enter into soil C contracts as providing a *service* in the form of accumulating and storing soil C. During the time period in which C is being accumulated, the farmer is providing *both* accumulation and storage services. Once the soil C level reaches the saturation point, the farmer is providing only storage services.

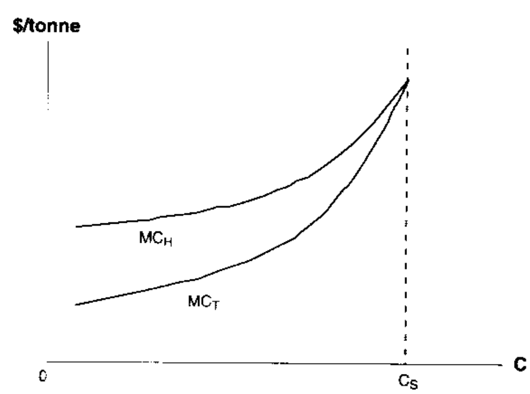

Figure 3. Marginal cost functions for soil C contracts that pay farmers per hectare of land (MC_H) and that pay farmers per tonne of soil C sequestered (MC_T).

The key point, however, is that both accumulation and storage services depend on the farmer continuing to maintain the land use or management practices that make the accumulation possible. This means that if saturation is reached in N_S years but society wants to store the carbon for $N_D > N_S$ years, the duration of the contract will have to be for N_D years. Clearly, if society wants to sequester soil C and this takes $N_S = 20$ years, but wants this C to remain in the soil for $N_D = 50$ years, farmers will have to be paid for 50 years. This implies a much higher cost than if farmers only have to be paid during the accumulation period. For example, a payment of $1 per acre over 20 years has a present value (at 5 percent interest) of about $12.50, whereas the present value of $1 for 50 years is about $18.30, about 50 percent higher.

Another way to approach the permanence issue in designing contracts is to impose a penalty for failure to comply with the terms of the contract, including penalties for subsequent release of the C after the contract expires. But since this would increase the cost to the farmer of complying with the contract and farmers would demand greater compensation, this contract provision would also have the effect of raising the cost of the contract.

Some have referred to soil C as a 'commodity' that farmers can produce and sell like conventional agricultural commodities (USDA and others, undated). The issues of saturation and permanence show that contracts between buyers and sellers of environmental services are different from contracts for conventional agricultural commodities. The buyer never actually takes delivery of the commodity; rather the commodity is stored in the soil that belongs to the landowner. The discussion above shows it is more accurate to describe the farmer as providing a service for a specified period of time.

Other Greenhouse Gases: Global Warming Potential

Agriculture is both a sink for C as well as a major emitter of carbon dioxide and two other potent greenhouse gases, nitrous oxide and methane (Watson *et al.*, 2000). Ideally, policies to mitigate GHG emissions would reward sinks and tax sources according to their 100 year global warming potential (GWP), wherein methane is estimated to be about 21 times more potent than a unit of CO_2, and nitrous oxide is estimated to be about 310 times more potent (IPCC, 1996). Both methane and nitrous oxide are also likely to be influenced by land use and other management practices. An efficient GHG policy would provide farmers with incentives not only to sequester C but more generally to reduce the net GWP of agriculture. To incorporate GWP into the economic analysis presented above, one simply replaces the carbon rate with a measure of GWP. The payment mechanism would provide a positive payment for a reduction in GWP and would impose a tax on an increase in GWP. While this generalization is straightforward in principle, implementing it poses additional measurement problems because methods and models to quantify nitrous oxide and methane emissions are not as well developed as those for carbon. Nevertheless, this does appear to be the direction that policy will move as the needed science and data are developed.

Co-Benefits and Costs

Many soil conservation practices and other management practices that would increase soil C have not been developed and promoted to increase soil C per se but rather to increase agricultural productivity, reduce soil erosion and reduce off-farm impacts of soil erosion on water quality. In the context of agricultural development, particularly in regions with predominantly subsistence or semi-subsistence agriculture, the various soil management practices that contribute to C sequestration also will likely have important impacts on the level and stability of farm production and food consumption. These impacts translate into improvements in health and nutrition of rural households and ultimately to improvements in rural economic development. Measuring these impacts requires analysis that goes beyond the models of agricultural production considered in this discussion. For example, additional data would be needed to characterize the farm and non-farm rural households, and to analyze market and non-market effects of improvements in agricultural production. Partial or general equilibrium economic models would be needed to fully assess rural development impacts in economic terms.

However, the integrated assessment framework that will be presented below can address the on-farm and immediate off-farm environmental consequences of adoption of management practices that sequester soil C, with the caveat that the broader economic and rural development impacts will require the use of additional data and analytical tools.

Program Eligibility and Perverse Incentives

A critical issue in designing any policy that provides subsidies to farmers is determining which producers are eligible for payments. A program that pays farmers to increase soil C on land that has been degraded can be viewed as penalizing those farmers who had adopted environmentally beneficial land use and management practices before the program began. This issue is particularly relevant where government or non-governmental organizations have previously promoted adoption of soil conservation and related practices without subsidies, if those who did adopt conserving practices would not be able to receive soil C payments to the extent that their soil was already saturated with C. Likewise, under a per-tonne soil C contract, farmers whose soil was saturated with C would not be able to receive payments for sequestering additional soil C. Some observers have argued that programs with this type of design would create the perverse incentive for producers using soil conservation practices, such as reduced tillage, to plow their land, release the carbon, and then enter the program.

A solution to this problem in the case of a government program would be to give credit for those who could document that they had changed practices previously. In a developing country setting, this solution would be of limited value because most farmers would lack such documentation. Alternatively, following the earlier discussion of contract duration, a government could justify providing payments to farmers both to adopt conserving practices and to continue using them. In the case of a private market for C that was driven by an international agreement requiring increases in soil C from a fixed baseline, it would be necessary to include provisions that would allow credit to be given for prior actions or for actions that would prevent the loss of soil C. If this type of provision were not included in international agreements, an individual government could still prevent the perverse incentive problem by purchasing credits from those farmers who had already adopted soil C-increasing practices (although the government itself might not be able to take credit internationally for this soil C as additions to its net emissions reductions).[2]

Transaction and Measurement Costs of Implementing Soil C Contracts

The chapter by Jones *et al.* in this monograph provides an outline of procedures that could be used to measure soil C to implement contracts. In this section we consider issues related to the costs of implementing soil C contracts.

Few data are available to estimate transaction costs associated with soil C contracts, and these costs are likely to vary widely depending on the type of contract and location. In established financial markets, transaction costs are typically a few percent of the value of the transaction. In the case of soil C contracts with farmers, however, intermediaries will need to aggregate agreements from large numbers of individuals to construct a commercial contract of, for example, 100,000 tonnes. If a practice is expected to sequester 10 tonnes C per hectare over the life of a twenty-year contract (as would be the case for a practice that yields 0.5 tonnes C per hectare per year on average over twenty years), and if the average farm size were 5 hectares, then it would take 2000 farms to make up a 100,000 tonnes contract. While C contracts would not necessarily have to be in units of 100,000 tonnes, it is clear that large groups of farmers would be needed to create commercially tradable contracts. An important question is how large numbers of farmers could be organized to participate in soil C contracts. It seems likely that existing government institutions could play the role of intermediary, as they already do to implement other agricultural policies. Another possibility would be for non-governmental agricultural institutions, such as agricultural cooperative organizations or banks, to act as intermediaries and coordinate farmers' participation in soil C contracts.

A key feature of transaction costs is that they are fixed costs in the sense that they do not vary with the amount of C sequestered. Some activities, such as contract negotiation between an intermediary and a buyer, may be independent of both the amount of C in the contract and the number of farmers participating on the seller side. However, because soil-C contracts would involve many individual farmers as sellers, the cost of negotiations between the intermediary and farmers would be likely to increase with the number of farmers participating in the contract, and we would expect this component of cost to increase at an increasing rate. Thus, we can assume that transaction costs take the form $TRAN = \tau_0 + \tau_1 N^\gamma$ where $\tau_0 > 0$ is the cost of negotiation with buyers, and $(\tau_1 N^\gamma)$ is the cost of negotiation with farmers, where $\tau_1 > 0$ and $\gamma > 1$. It follows that the average transaction cost per tonne of carbon sequestered is $TRAN/C = \tau_0/C + \tau_1 N^\gamma/C$. Following the discussion above, the number of tonnes sequestered is approximately proportional to the number of sellers, i.e., $C = chN$, where c is the average number of tonnes sequestered per hectare, h is the average number of hectares per farm participating in the contract, and N is the number of farms. It follows that the average cost of negotiation with farmers is likely to increase with N and C, whereas the average cost of negotiation with buyers

[2]Another solution that has been suggested by economists is a subsidy payment for soil C increases combined with a tax on losses. This is a way to prevent the perverse incentive problem but does not address the equity issue of penalizing those farmers who previously adopted conservation practices.

will decrease with C. The optimal size of the contract, from the point of view of minimizing transaction costs, will depend on the relative importance of these two terms.

The parameters of the transaction cost function (t_0, t_1, and γ) are likely to depend significantly on the location where the soil C is being sequestered and the institutional factors discussed above, and will be known with some confidence only after pilot projects have been implemented and data have been gathered on these two cost components.

We assume that to implement either per-hectare or per-tonne contracts, relatively homogeneous agroecozones, $m = 1,\ldots,A$, are identified using baseline bio-physical data, as discussed in the chapter by Jones *et al.* These data are combined with existing estimates of soil C from the literature and simulation models such as the DSSAT/CENTURY models to obtain *ex ante* estimates of baseline carbon levels $E[C_j(i)] = C(x_j, e_j, z_j, i)$ (we recognize that variable input decisions x_j and fixed factor z_j also may vary with production system). The *ex ante* average annual rate of C sequestration for a change from system *i* to system *s* over T years is then estimated to be $E[\Delta c_j(i,s)] = \{C(x_j, e_j, z_j, s) - C(x_j, e_j, z_j, i)\}/T$. This is the carbon rate used to establish a per-hectare or per-tonne contract and is the basis for estimation of the value of the contract and payments to farmers.

In the case of a per-hectare contract, we assume that the practices specified in the contract are monitored to assure compliance with the contract. These monitoring costs will depend on the type of monitoring used (e.g., use of remotely sensed data versus on-the-ground observation), but that additional measurements of carbon in the field are not made (this assumption can be modified as discussed below). These monitoring costs will be a function of the cost per observation, c_o, and the number of observations over the life of the contract, n_o, so $MON = Nc_on_o$.

For per-tonne contracts, we assume that statistical methods are used to measure carbon levels, to validate the model estimates, and to verify compliance with the contracts within each agroecozone. Let the measured baseline carbon stock for a hectare under the i[th] system be $C_j^i = C(x_j, e_j, z_j, i) + v^i$ where v^i is a random measurement error. The estimated carbon rate for changing from system *i* to system *s* over T years is therefore a random variable $\Delta c_j(i,s) = (C_j(x_j, e_j, z_j, s) - C_j(x_j, e_j, z_j, i))/T$ with mean $E[\Delta c_j(i,s)]$ and a variance that is a function of the variances and covariances of the v^i. Following Mooney *et al.* (2002), these measurement costs in a given region under a per-tonne contract are calculated as $MEA = n_sn_mc_mf_m$ where n_s is the number of different types of practices or systems that farmers can adopt to increase soil C, n_m denotes the sample size needed to estimate C to the accuracy specified in the contract for each practice or system, c_m denotes the cost of each sample, and f_m is the frequency of sampling during the contract. The sample size is determined using conventional statistical procedures for stratified random sampling (Mooney *et al.*, 2002) and depends on the estimated measurement error variances discussed above. The cost per sample can be estimated based on the time and materials costs associated with the measurement methods used. As discussed in the chapter by Yost *et al.*, the number of observations required to achieve a desired sampling error is a function of the spatial variability of environmental conditions.

In summary, the transaction, measurement, and monitoring costs can be represented as:

$$(4)\ \ TCOST = TRAN + MON + MEA = \tau_0 + \tau_1 N^{\gamma} + Nc_o n_o + n_s n_m c_m f_m.$$

where:

- τ_0 = fixed transaction costs per contract ($)
- τ_1 = transaction costs associated with number of participants ($/farm)
- N = number of farms participating in contract
- γ = transaction costs parameter (greater than 1)
- c_o = cost per monitoring observation ($)
- n_o = number of monitoring observations per contract
- n_s = number of practices or systems that farmers can adopt to sequester C
- n_m = sample size for carbon measurements
- c_m = measurement cost per sample
- f_m = frequency of measurements.

ECONOMIC MODELS FOR INTEGRATED ASSESSMENT OF SOIL C

Farmer decision-making is a central organizing concept of the integrated assessment of agricultural production systems. In the approach described here, farm decision-making is represented as a sequence of decisions about land use (or crop choice), and associated management decisions (e.g., land preparation, tillage, fertilization, pest management, harvest). In the application of this approach, an econometric production model for each production activity is estimated and used to simulate expected returns to crop and livestock production, the quantity and timing of management decisions, pesticide applications, and the value of production realized at the end of the growing season. The econometric production models are estimated using farm-level data, and these models are used to parameterize an econometric-process simulation model that represents short-run land use and management decisions on a site-specific basis. This type of model is described as an *econometric-process simulation model* and is discussed in detail in Antle and Capalbo (2001).

The econometric-process models introduce an explicit link between econometric production models and the biophysical production models for crop and livestock production (such as the DSSAT/CENTURY models). The biophysical models are used to represent the effects of spatial variations in biophysical conditions (soils and climate) on what is defined as the *inherent productivity* of a management unit (a farmer's field). The econometric models incorporate this inherent productivity into the estimation of behavioral relationships that are utilized in the simulation model to represent the spatial variation in land use and management decisions.

In an econometric-process simulation model, land use decisions are based on the comparison of expected returns across alternative activities. Econometric production models are used to simulate expected returns for the land use decision. These econometric production models can be formulated in several equivalent ways. For example, the revenue component of expected returns can be represented with the supply function derived from the restricted profit function, and the cost component can be represented by the restricted cost function. These two relationships can be used to compute expected returns as the difference between expected revenue and expected cost.

In applying this approach, the total quantity of a crop produced, for example, is specified as log-linear function of field size, input and output prices (with linear homogeneity in prices imposed), and other variables representing effects such as the previous crop (a rotation effect). This supply function is estimated jointly with a log-linear cost function that is a function of quantity supplied, input prices, previous crop, and field size. The system is estimated jointly with the first-order conditions for cost minimization to increase estimation efficiency.

Note that in the approach described here, a single output is produced on each field. In some cases, however, multiple crops are grown on a single field, i.e., the farmer uses inter-cropping. Another multiple-output case is created when farmers use crop residues for livestock feed. In these cases, the approach described above which utilizes a supply function and cost function is complicated by the existence of the jointly produced outputs. An alternative approach that can be used in this case is to specify and estimate a revenue function jointly with a system of factor demand functions.

Static factor demand functions can be derived from a cost function or can be represented explicitly in the system of equations representing production decisions. In some cases, a static representation of input use is adequate, e.g., in low-input systems few purchased inputs are used and there may be little variation across farmers in the timing of input use. In other cases, particularly in systems with intensive management of pests, a large number of applications may be made and the timing of applications may be critical. In such cases, the input demand functions can be estimated as a dynamic system representing the quantity applied and the time intervals between applications (Antle, Capalbo and Crissman, 1994). For example, for each type of pesticide used in a system, a two-equation reduced-form model can be estimated representing quantity and timing of pesticide applications. These functions depend on input and output prices, field size, fertilizer, application time and lagged quantity and timing variables to incorporate the dynamics of the sequential applications. This type of dynamic-factor demand model requires highly detailed data on the quantity and timing of individual input applications.

The value of production realized at the end of the season is estimated using a revenue function specified in terms of quantities of inputs applied during the season, previous crop, and field size. To simulate the realized value of output, the estimated models are used to predict the mean value of output and estimated error variances for the models are used to construct random components of the output value.

Incorporating Spatial Soils and Climate Data into Production Models

A problem facing empirical production economics research is how to incorporate effects of soils and climate on productivity into economic production models. Production economists have long specified production functions in the general form $q_i = f(\mathbf{v}_i, \mathbf{z}_i, \mathbf{e}_i)$, where output on the i^{th} field (q_i) is a function of a vector of: variable input quantities $(\mathbf{v}_i)$ such as fertilizer applications, pesticide applications and labor; a vector of services from capital inputs and other fixed factors $(\mathbf{z}_i)$; and a vector of biophysical factors such as soils and climate $(\mathbf{e}_i)$. In practice, the biophysical factors $\mathbf{e}_i$ are represented in models by using ad hoc indicators of soil quality and climate (e.g., dummy variables for soil types, or measures of weather such as average rainfall during the growing season). This approach ignores the systematic knowledge embedded in crop growth models about the relationships between management, biophysical conditions and crop growth. We can describe the knowledge embedded in crop growth models as implying a relationship in the general form $q_i = g(\mathbf{v}_i, \mathbf{z}_i, \mathbf{e}_i)$. We know that farmers base their management decisions on their knowledge of soil and climate conditions in each field as it relates to the expected or inherent productivity of each field. Crop growth models can be used as a tool to represent this inherent productivity. To do this, we can specify a typical or average input use, $\mathbf{v}$ and $\mathbf{z}$, and then define the inherent productivity as $q_i = g(\mathbf{v}_i, \mathbf{z}_i, \mathbf{e}_i)$. Now we can redefine the production process as $q_i = f(\mathbf{v}_i, \mathbf{z}_i, \mathbf{e}_i) = h(\mathbf{v}_i, \mathbf{z}_i, q_i) = h(\mathbf{v}_i, \mathbf{z}_i, g(\mathbf{v}, \mathbf{z}, \mathbf{e}_i))$. This result shows how the crop growth model's estimate of yield with representative management (what we call inherent productivity) can be used to formulate a production function model used in economic analysis.

Econometric-Process Simulation Models for Analysis of Soil C Sequestration

Figure 4 presents the linkages among data and models used to estimate and simulate an econometric-process simulation model (Antle and Capalbo, 2001). In the estimation component, crop (and/or livestock) models are used to estimate the inherent productivity of each activity on each land unit in the available data being used for model estimation. The econometric models for each activity are then estimated. In the simulation step, a field is sampled from the population of fields in the region being analyzed, and characteristics of the field are assigned (size, inherent productivity, etc.). Each sampled field is then simulated through time. Each production period, prices and other input variables are sampled from distributions, and the econometric production models (supply and demand functions) are simulated to estimate expected returns for each activity. Expected returns are compared, and the activity with the highest expected returns is selected. For the activity selected, a sequence of management decisions is then simulated using the system of static- or dynamic-factor demand equations. At the end of the input decisions, a harvest date is selected and the value of production is generated using the revenue function.

The econometric-process model approach is well suited for analysis of C sequestration in agricultural soils (see Antle *et al.*, 2001a,b for applications to U.S. agriculture). The standard econometric-process model reads a file containing the characteristics of the fields to be simulated (e.g., field size, inherent productivity). To analyze soil C sequestration, the DSSAT/CENTURY model can be used to estimate inherent productivity on each field and also the C level associated with the types of crops and management practices used. The DSSAT/CENTURY model can be executed for each management alternative to produce estimates of the carbon levels $C(i)$ associated with each practice, and these values can be stored in the data file describing each field to be simulated. The econometric-process model reads this field file and calculates the average annual change in soil C, $\Delta c(i,s) = \{C(s) - C(i)\}/T$, associated with changing management practices over a time horizon of T years. The econometric-process model then uses this information to simulate the land use decision, based on equation (2), taking into account both the

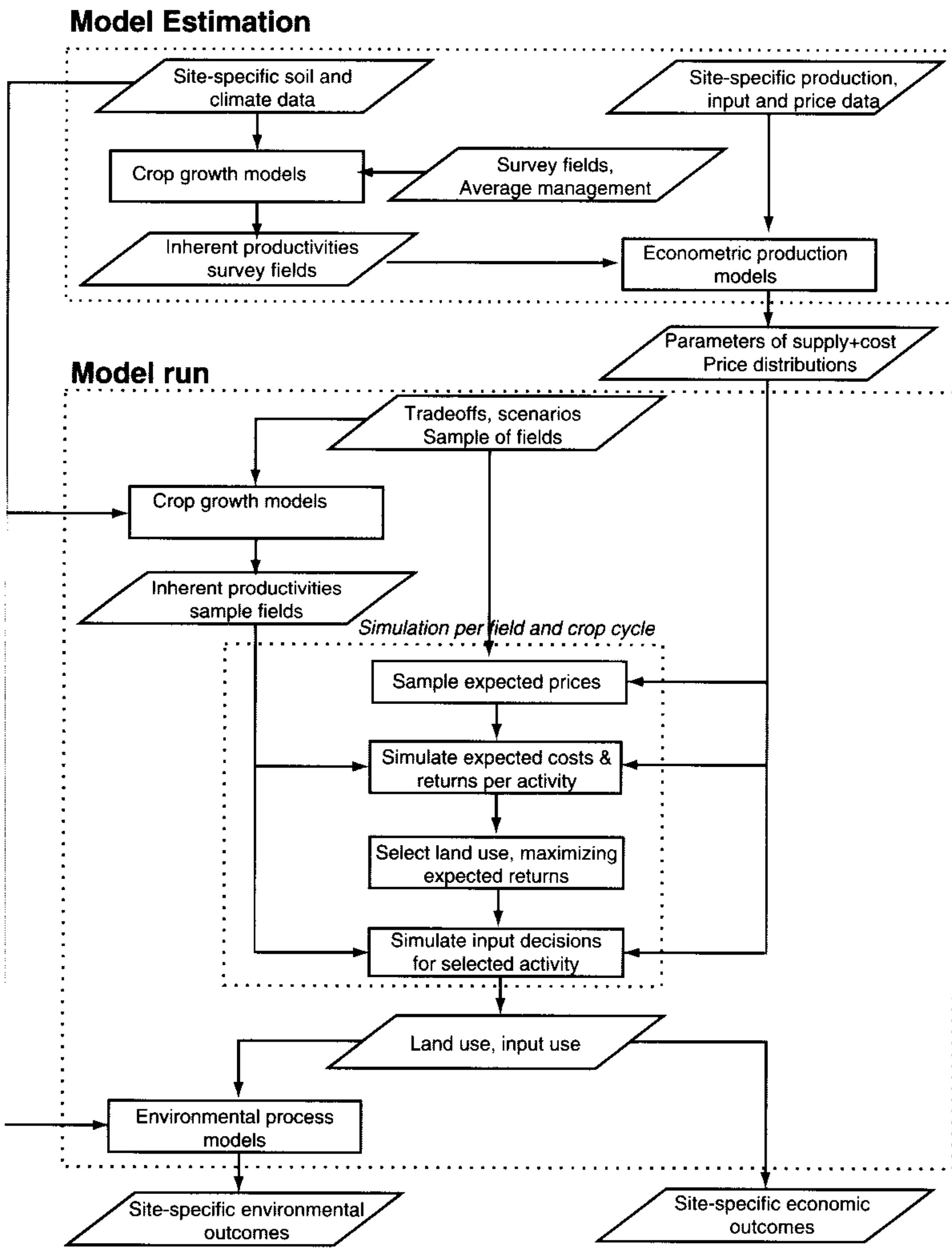

Figure 4. Structure of an econometric-process simulation model.

payments that the farmer would receive for participating in the specified soil C contract and the opportunity costs of changing practices. If the farmer chooses to participate in the contract, the model uses $\Delta c(i,s)$ to calculate the soil C sequestered, and includes that information in the model's output.

THE TRADEOFF ANALYSIS MODEL: A TOOL FOR INTEGRATED ASSESSMENT OF SOIL C

In this section we describe a software tool, the Tradeoff Analysis Model, which was developed as a decision support tool for agricultural and environmental policy analysis and policy decision-making (Stoorvogel *et al.*, 2001). This software allows an interdisciplinary research team to integrate GIS-based data, bio-physical models of production, models of other environmental processes such as soil C dynamics, and economic models of farmer decision-making. To incorporate the spatial heterogeneity of soil conditions, climate, and farmer behavior, these data and models are linked on a site-specific basis. By replicating the simulations for a statistically representative sample of land units in a region, the outcomes of this analysis can be aggregated to represent a larger spatial unit such as an agro-ecozone or other spatially-defined unit. In the case of an analysis for soil C sequestration, the simulations can represent a group of land units participating in a soil-C contract.

Tradeoff Analysis is a process designed to integrate public-policy decision makers and other stakeholders with a scientific team that provides quantitative information to support policy decision making (Crissman, Antle and Capalbo, 1998). In this process, input from stakeholders (the general public, policy makers, other interested groups) and scientists is used to identify the critical dimensions of social concern, i.e., criteria for assessment of the sustainability of the system. As we noted in the introductory section of this chapter, the stakeholders for analysis of soil-C sequestration range from the farmers who would sequester C in their soils, to buyers of soil-C contracts, to governmental and non-governmental organizations and the general public who have an interest in soil management. Research teams can use the Tradeoff Analysis process and the software to implement the soil C sequestration protocols described in this monograph.

Overview of the Tradeoff Analysis Model Structure

The Tradeoff Analysis Model can be broken down into several components (Stoorvogel *et al.*, 2001):

Data. The model begins with three types of data: environmental data, farm survey data and experimental data. Environmental data describe the spatial variation in soils and climate and is organized in a GIS format. It is used as input to the bio-physical models and to stratify the study area. Farm survey data describe the way farmers take decisions about land management. This decision-making process is described in the econometric production models. The Tradeoff Analysis uses crop models to describe the inherent productivity of farmers' fields (as an important factor in their decision-making process) and environmental impact models to estimate the impact on soil and water resources. These mechanistic models need to be calibrated to local conditions using experimental data.

Crop Models. Crop (and if appropriate, livestock) models in the DSSAT format (including the DSSAT/CENTURY model discussed in the chapter by Jones *et al.*) can be used to estimate the spatial and temporal variation in inherent productivity of the land that is driven by soil and climate variations. These measures of inherent productivity are inputs into the economic models to explain variation in management decisions of farmers. In the use of the DSSAT/CENTURY model, soil-C values are also are passed to the economic analysis.

Economic Models. Econometric production models are estimated using the farm survey data and the inherent productivity indexes derived from the crop models. Parameters for distributions of prices and other exogenous variables in the production models are estimated using the survey data. These parameters are input into an econometric-process simulation model, with the indexes of inherent productivity from the crop models.

Environmental Process Models. As appropriate to the analysis, the management decisions from the economic simulation model (e.g., land use, pesticide applications) can be used as inputs into environmental process models to estimate impacts on soil quality, pesticide fate, and other environmental processes of interest.

Scenario Definition, Model Execution and Analysis of Outcomes. For each policy or technology scenario of interest to policy decision makers, the simulation model is executed for a series of price or other parameter settings. Changes in prices and other parameters can be used to induce changes in management that in turn induce tradeoffs between economic and environmental outcomes. In the analysis of soil-C sequestration, key parameters are the payments made to farmers who enter into soil-C programs or contracts. Economic outcomes from the econometric-process simulation model (e.g., value of crop and livestock production) and environmental outcomes from the environmental process models (e.g., pesticide loadings to the environment, soil erosion) can be aggregated to represent a spatial unit made up of many fields. For analysis of soil-C sequestration, results can be aggregated to represent agroecozones used for setting up soil-C contracts.

Application of the Tradeoff Analysis Model to Analysis of Soil-C Sequestration

The Tradeoff Analysis Model can be used to analyze the potential for soil-C sequestration contracts as shown in Figure 5. The first step is to assemble the needed data, including the data for implementation of the DSSAT/CENTURY models and the econometric-process simulation model for the region to be analyzed. In addition, any relevant scenarios regarding alternative production technologies that could be used to sequester soil C and the types of contracts that would be used would need to be assembled. The DSSAT/CENTURY models would be executed for the set of fields that was being used in the analysis (this could be a set of fields randomly sampled from the region being analyzed, or a set of fields for which data were available from a production survey). Crop yields and soil-C values would be saved in a file that would then become an input into the econometric-process simulation model. This economic model would simulate farmer's land use and management decisions for the baseline case of no carbon contracts, and

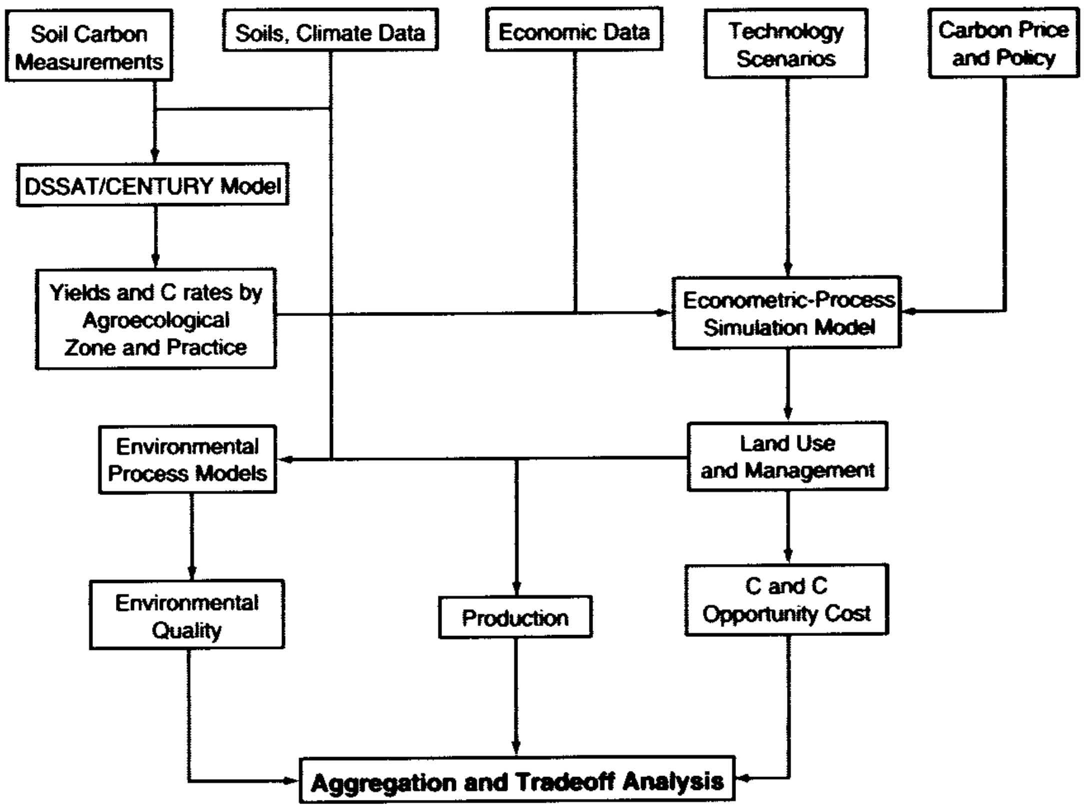

Figure 5. Key steps in use of the Tradeoff Analysis Model for analysis of soil C sequestration.

for the types of contracts that farmers could be offered. For example, an analysis could consider a per-hectare contract for adoption of specific sets of practices and a range of payment levels that might be offered to farmers. Alternatively, an analysis could consider a per-tonne contract (see Antle *et al.*, 2001a,b for examples of this type of analysis). The economic model would create an output file containing the farmer's land use and management decisions, and the changes in soil C associated with those decisions. This information could be passed to other environmental process models to analyze other environmental impacts such as soil erosion or fate of pesticides. Finally, the results of the various models are combined into an output file that can be aggregated to represent the region and used for various types of analysis. For the analysis of soil-C sequestration, a principal use of this output would be to construct a supply curve for soil C (see Figures 2 and 3) corresponding to each type of contract that was simulated. These supply curves show the amount of C that would be sequestered for each type of contract, given the available management options. If other environmental process models were included in the analysis, it would also be possible to assess tradeoffs with other environmental impacts, such as soil erosion, water quality, and future soil productivity.

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