Quantifying Carbon Dynamics and Greenhouse Gas Emissions in Agricultural Soils of California: A Scoping Study

PIER Final Project Report

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Preface

The Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

The PIER Program, managed by the California Energy Commission (Energy Commission), annually awards up to $62 million to conduct the most promising public interest energy research by partnering with Research, Development, and Demonstration (RD&D) organizations, including individuals, businesses, utilities, and public or private research institutions.

PIER funding efforts are focused on the following six RD&D program areas:

- Buildings End-Use Energy Efficiency
- Industrial / Agricultural / Water End-Use Energy Efficiency
- Renewable Energy
- Environmentally Preferred Advanced Generation
- Energy-Related Environmental Research
- Strategic Energy Research

What follows is the final report for Assessment of Carbon Sequestration Potential in California Agricultural Soil, , 500-02-004, Work Authorization MR-005, conducted by the Complex Systems Research Center at the University of New Hampshire; Applied Geosolutions, LLC; and the Center for Agroecology and Sustainable Food Systems at the University of California at Santa Cruz. The report is entitled *Quantifying Carbon Dynamics and Greenhouse Gas Emissions in Agricultural Soils of California: A Scoping Study*. This project contributes to the PIER program objectives of improving the environmental costs and risks of California's electricity.

For more information on the PIER Program, please visit the Energy Commission's Web site at: http://energy.ca.gov/research/index.html or contact the Energy Commission's Publications Unit at 916-654-5200. For more information on this research, please contact Dr. William Salas, Applied Geosolutions, LLC at 603-868-2369.

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Executive Summary

Agriculture represents a significant opportunity for greenhouse gas (GHG) mitigation projects through soil carbon sequestration and reductions of methane (CH_4) and nitrous oxide (N_2O) emissions. Recently, significant investments are being made in assessing carbon sequestration projects in agricultural soils, due to the potential for trading carbon credits coupled with significant environmental benefits through improved soil quality, soil fertility, and reduced erosion potential. Changes in farming management practices, such as tillage, fertilization, irrigation, manure amendment, rotation with cover crops, and others are being evaluated for their potential in mitigating GHGs emitted from the agricultural sector. Because the cycles of water, carbon (C) and nitrogen (N) in the agroecosystems are tightly linked, any change in farming management could simultaneously alter crop yields, soil fertility, N leaching, soil C storage, and trace gas emissions. New methodologies linking GIS databases with process-based models are being used to bring complex agroecosystems into a computable framework for assessing the impact of alternative management practices on soil C storage and GHG emissions.

Process-based models have been developed to examine the complex interactions of agricultural management practices, soil C dynamics, and N_2O emissions. An agroecosystem biogeochemistry model—Denitrification-Decomposition (DNDC)—was adopted for this project. It was constructed based on four basic biogeochemical concepts: (1) biogeochemical abundance, (2) field, (3) coupling, and (4) cycling. It consists of the six submodels for soil climate, crop growth, decomposition, nitrification, denitrification, and fermentation. The six interacting submodels have included the fundamental factors and reactions, which integrate C and N cycles into a computing system. DNDC has been validated and tested by researchers in many countries and applied for their national C sequestration and N_2O and CH_4 inventory studies. By tracking crop biomass production and soil organic carbon (SOC) decomposition rates, DNDC captures short- and long-term SOC dynamics. It predicts N_2O emissions by tracking the reaction kinetics of nitrification and denitrification across climatic zones, soil types, and management regimes. With its prediction capacity of SOC, N_2O, and CH_4, DNDC is ready to serve offset analysis between C sequestration and non-CO_2 greenhouse gas (N_2O and CH_4) emissions for agroecosystems.

Objectives

In this project, DNDC is being used to estimate recent SOC dynamics and N_2O emissions at the county scale for all of the counties in California and to make recommendations for more detailed studies on carbon sequestration and N_2O emissions under a wide scope of alternative management scenarios. DNDC is also being used to evaluate the impact of several management alternatives (e.g., changing irrigation practices, use of reduced tillage or no-till, use of cover crops, and other alternative farming practices) on county-scale estimates of SOC dynamics and CH_4 and N_2O emissions. These management alternatives are being assessed to evaluate their potential in helping to mitigate GHG emissions from agriculture in California.

Outcomes

County summary data on soils, crop acreage, and climate have been compiled in a geographic information system (GIS) database. Daily climate data on precipitation and maximum and minimum temperature were obtained from the DAYMET and National Climate Data Center station data from 1980 through 1997. County crop acreages were derived from a GIS coverage based on the California Department of Water Resources (DWR) analyses of aerial photos and field surveys taken in the mid 1990s. Soils were derived from the statewide State Soil Geographic (STATSGO) database. The major crop types, such as strawberry, artichoke, tomatoes, truck crops, and others have been parameterized in DNDC based on communications with the local experts. For each county, we calculated the minimum, maximum, area-weighted minimum, and area-weighted maximum values of clay fraction, bulk density, organic matter, and pH. Because soil properties are one of the major sources of the uncertainties produced during the upscaling processes, soil range values are included, to enable the use of Monte Carlo or other statistical approaches to bring the uncertainties under control. Agricultural management practices (e.g., fertilizer use, residue incorporation, tillage practices, and planting and harvesting dates) were compiled based on discussions with the California Department of Food and Agriculture (CDFA) and the California Air Resources Board (CARB), and also on the University of California Cooperative Extension (UCCE) Crop Cost and Return reports.

Preliminary results indicate that, as a whole, California agricultural soils are sequestering carbon. However, there are large differences in carbon dynamics across crop types and counties. In general, pastures are the largest sink of carbon. Cotton, corn, rice with winter flooding, tomatoes, citrus, and deciduous fruit cropping systems are additional sinks of carbon. On the other hand, truck crops (e.g., lettuce), beans, oats, and winter wheat cropping systems appear to be a net source of carbon, thus causing a decrease in soil carbon. Areas of rice paddies (without winter flooding), beets, sorghum, sunflowers, and viticulture do not appear to be significant sources or sinks of carbon. Fresno, Kern, and Kings counties had the largest net carbon sequestration—primarily because of their large areas of pasture and cotton production. San Joaquin, Monterey, and Santa Barbara were net sources of carbon due to their relatively large areas of truck crops (e.g., lettuce) and relatively little cotton and pasture.

Conclusions, Recommendations, and Benefits to California

Based on an initial validation activity using long-term SOC data for California, DNDC model simulations capture long-term SOC dynamics in agricultural soils in California. However, there are large uncertainties in the magnitude of SOC dynamics, due to uncertainties in initial soil conditions and crop residue management.

Nevertheless, these preliminary results suggest that: (1) management of agricultural soils in California has the potential for increasing C sequestration and reducing N_2O emissions, and (2) effective alternative management policies or regulations should be spatially differentiated.

Implementing the following recommendations would help improve understanding of overall carbon dynamics and GHG emissions in California:

- Establish a program to collect data on agricultural management practices, to improve the spatial representation of mangement practices and account for regional and cropping system differences. Critical data should include information on residue and manure management.
- For future study, use the updated Natural Resources Conservation Service's Soil Survey Geographic (SSURGO) database. The improved spatial and thematic resolution of these data will result in improved model estimates of carbon dynamics and GHG emissions.
- Further validate the DNDC model, to better quantify the model's performance in simulating carbon dynamics, N_2O, and CH_4 over a range of California agroecosystems. This validation should consist of: (1) performing model validations using existing carbon dynamics field data, and (2) developing a field measurement program to cover critical gaps in field data across a range of major crops and management systems.
- Evaluate alternative mitigation scenarios for: no-till, conservation tillage, and convential tillage; optimized fertilizer application rates; and the use of cover crops.

California benefits from this work through an improved understanding of how to reduce its net contribution to atmospheric carbon through the agricultural strategies. This effort (and the implementation of the follow-on activities recommended above) can: (1) help identify areas in the state where these agricultural modifications will be feasible, and (2) help quantify benefits for specific regions and methods, thus enabling state decision makers to weigh the benefits against other potential mitigation measures.

Abstract

Agriculture represents a significant opportunity for greenhouse gas (GHG) mitigation projects through soil carbon sequestration and reductions of methane (CH_4) and nitrous oxide (N_2O) emissions. Projects that result in soil carbon sequestration and reductions in CH_4 and N_2O emissions often result in compound environmental benefits through improved soil structure, which in turn can improve air and water quality. It is well known that carbon sequestration will inherently increase N_2O (in upland soils) and CH_4 (in wetland soils) emissions, due to the coupling of carbon and nitrogen biogeochemical cycles. Thus, the net offset between reductions in atmospheric CO_2 and increases in atmospheric CH_4 and N_2O can be significant, and in some cases can result in a net increase in atmospheric CO_2 equivalents. Therefore, assessing the efficacy of carbon sequestration projects in California agriculture must include comprehensive analyses that examine the impacts of management decisions on all greenhouse gases. Process-based models have been developed to examine the complex interactions of agricultural management practices, soil C dynamics and CH_4 and N_2O emissions. An agroecosystem biogeochemistry model—Denitrification-Decomposition (DNDC)—was used for this scoping study, to assess recent trends in SOC dynamics and CH_4 and N_2O emissions at the county-scale for California. Preliminary results indicate that, as a whole, California agricultural soils are sequestering carbon. However, there are large differences in carbon dynamics across crop types and counties. There are large uncertainties in our estimates of magnitude of SOC dynamics and trace gas emissions, due to uncertainties in initial soil conditions and crop residue management. Nevertheless, these preliminary results suggest that: (1) management of agricultural soils in California has the potential for increasing C sequestration and reducing N_2O emissions, and (2) effective alternative management policies or regulations should be spatially differentiated.

1.0 Background

1.1. Role of Agriculture in Greenhouse Gas Mitigation

Agriculture represents a significant opportunity for greenhouse gas (GHG) mitigation projects through soil carbon sequestration and reductions of methane (CH_4) and nitrous oxide (N_2O) emissions. Recently, significant investments have been made in assessing carbon sequestration projects in agricultural soils, because of the potential for trading carbon credits, coupled with the significant environmental benefits that can be achieved through improved soil quality, soil fertility, and reduced erosion potential. Changes in farming management practices, such as tillage, fertilization, irrigation, and manure amendment are currently being evaluated for their potential in mitigating GHGs emitted from the agricultural sector. For example, it has been widely reported that replacing conventional tillage with no-till results in soil organic carbon (SOC) storage (Lal et al. 1999; Smith et al. 2000). The carbon (C) sequestration potential of agricultural lands is being studied with experimental or modeling approaches in a number of ongoing research projects (e.g., Eve et al. 2002; Falloon et al. 2002; Paustin et al. 2002; Rickman et al. 2002.).

Historically, conversion of natural ecosystems to managed agricultural systems during the 17th, 18th, and 19th centuries resulted in a dramatic loss of soil organic matter caused by mineralization and erosion. Clearing, tilling, and draining native soils for agricultural production has released large amounts of carbon dioxide to the atmosphere from the soils' fertile soil organic matter pool (Lal et al. 1999). The soil organic matter in topsoil has depleted as much as 40% to 60% of the original soil organic carbon (Cambardella 1992). Lal (1998) estimated the loss of soil organic content from U.S. cropland soils at about 5 petagrams (Pg), which equals approximately 5 billion metric tons. Therefore, U.S. cropland has a potential to sequester approximately 5 Pg of carbon through improved soil management practices (Lal 2000).

Robertson's studies (2000) at the Kellogg Biological Station (KBS) Long Term Ecological Research site (LTER) showed that fields that have never been in agricultural production contain 40% to 50% more carbon by weight than active agricultural fields. Agricultural fields under no-till conservation tillage cropping methods were found to sequester 300 kg carbon per hectare per year; whereas, conventionally tilled crops exhibited no annual carbon sequestration (Robertson 2000). Other estimates of carbon sequestration rates for conservation tillage range from 500 kilograms of carbon per hectare pre year (kg / C / ha / yr) to 600 kg / C / ha / yr (Lal 1998). The United States Department of Energy also estimates that the conversion from conventional tillage to conservation tillage methods could potentially sequester 300 kg C / ha / yr.

Unfortunately, most of the published research focuses only on the soil C dynamics, with little attention to other GHGs—namely, nitrous oxide (N_2O) and methane (CH_4)—which may offset gains in GHG emissions if not managed properly. Few of the reports assessed the impacts of the carbon sequestration induced by the management alternatives on N_2O or CH_4 emissions from the same lands. This omission is a drawback when evaluating carbon, because there is an inherent relationship between carbon storage and N_2O or CH_4 emissions in agricultural soils.

1.2. Carbon and Nitrogen Biogeochemical Processes

In nature, chemical elements typically act in a coupled fashion determined by their chemical structures and abundances. The elemental coupling is one of the basic concepts of biogeochemistry. The coupling of carbon and nitrogen (N) is one of the best examples of biogeochemical coupling. Both C and N are essential elements for most life forms and are abundant in the atmosphere, the hydrosphere, and the biosphere. Photosynthesis, the process initiating the primary production of green plants, synthesizes atmospheric C into biomass C, based on the N compounds, chlorophyll. The coupled C and N in plant tissues will be incorporated in the soil after the plants die. In the soil environment, the coupled C and N will start their decoupling processes by way of soil microbes as they derive energy by breaking down the organic compounds. The processes will result in the separation of C and N by converting the C-N compounds into dissolved organic carbon (DOC) or inorganic C (e.g., CO_2) as well as inorganic N (e.g., ammonium or nitrate). The energy is usually generated during the process by transferring electrons from the C atoms existing in the organic compounds to oxygen. If O_2 is depleted in the soil, certain groups of microbes (e.g., denitrifiers) can use other oxidants as electron acceptors. After oxygen, the most ready-reduced oxidant is nitrate. As soon as the microbes transfer the electrons from organic C to nitrate, nitrous oxide (N_2O) and dinitrogen (N_2) will be produced (Firestone 1982). The same is true for CH_4 production, although the process occurs under more reductive conditions related to hydrogen production. These processes demonstrate how SOC content and N_2O are related through the coupling and decoupling of C and N in the upland plant-soil systems. In summary, increase in SOC storage elevates soil DOC and available N content through decomposition, which in turn will stimulate activity of a wide scope of soil microbes, including nitrifiers and denitrifiers, which are responsible for N_2O production in the soils.

1.3. Nitrous Oxide Emission and Soil Carbon Content

The correlation of N_2O production with soil C abundance has been observed in a wide scope of field measurements and laboratory experiments conducted over the past five decades. This relation comes from the following four observations:

- *Higher N_2O fluxes have been measured from the soils with higher organic matter contents.* Many researchers have measured N_2O fluxes from several contiguous plots under similar climate and management conditions, the higher N_2O emissions were mostly observed at the plots with higher SOC content. Among the observations, organic soils constantly emitted the highest N_2O fluxes (Bremner and Shaw 1958; Bowman and Focht 1974; Burford and Bremner 1975; Stanford et al. 1975; Pluth and Nommik 1981; Duxbury et al. 1982; Terry et al. 1981; Goodroad and Keeney 1984; Pang and Cho 1984; Klingensmith 1987; Robertson and Tiedje 1987; Mosier et al.1991; Vinther 1992; and Papen and Butterbach-Bahl 2000).
- *The pattern of spatial variation in N_2O fluxes has been found related to SOC content.* Several researchers have conducted precise field measurements that focused on the spatial variation of N_2O fluxes at small scales. For example, equipped with the dense chamber array sampling method, Ambus and Christensen (1994) observed marked spatial variability of N_2O fluxes within a small field (0.18 ha) of grassland in

Denmark. After glucose amendment, the N_2O fluxes increased by several fold, while the spatial variation of the N_2O fluxes were diminished. The results imply that DOC content was one of the major limiting factors for N_2O production in the experimental site. Federer and Klemedtsson (1988) measured N_2O fluxes from the forest soils within two small watersheds in Sweden, and concluded that the organic fraction in the soils explained 81% of the spatial variation in N_2O production rate.

- *Soil organic carbon content has been identified as a key factor to N_2O production through incubation experiments.* Incubation experiments provide a unique opportunity for distinguishing the effect of single factors. The incubation experiments carried out by Müller et al. (1980), Melillo et al. (1983), and Federer and Klemedtsson (1988) with the soil samples from Finland, the United States, and Sweden, respectively, demonstrated a positive correlation between higher N_2O fluxes from the soils with greater organic carbon content. Leffelaar and Wessel (1988) conducted denitrification kinetic experiments, and found that DOC, nitrate and redox potential were the major factors controlling N_2O production in soils. Any one of the three could limit N_2O emissions.
- *An increase in N_2O emissions due to the addition of organic matter into the soils has been observed extensively worldwide* (e.g., in the U.S. cropland by Goodroad et al. 1984; in the U.K. grassland, bush, and forest soils by Clayton et al. 1997 and Thomson et al. 1997; in German pasture soils by Flessa et al. 1996; and in Chinese cropland by Dong et al. 2000). For example, Christensen (1983) observed that manure amendment in a managed grassland in Denmark not only increased total N_2O emissions from 16.4 (in the urea applied plot) to 182 (in the manure amended plot) g N / ha / day, but also elevated the N_2O / N input rate from 8.2% to 37%. Dong and his colleagues observed that amendment of organic matter in the cropland soils in North China increased the fertilizer-induced N_2O fluxes from 0.67% to 20% of the amount of N applied (Dong et al. 2000). These results imply that the manure-induced increase in N_2O emissions is not due solely to the increase in soil N content. In Bouwman et al. (2002a,b) reviews of published literature, they note that N_2O emissions for the same fertilizer rate tend to increase with higher soil carbon content.

1.4. Process-based Models and Agricultural Mitigation of Greenhouse Gases

Based on experimental observations and biogeochemical analysis, SOC and nitrate or nitrite have been recognized to be dominant factors affecting soil N_2O emissions. Soil temperature, moisture, pH, redox potential, and other substrate concentrations can also affect N_2O production. These soil environmental factors are driven by a group of primary drivers (e.g., climate, topography, soil texture, vegetation, and anthropogenic activity) on the one hand, and drive a series of biochemical or geochemical reactions that determine N_2O production and consumption, on the other hand. It is the complex interactions among the primary drivers, soil environmental factors, and the biogeochemical reactions that result in the observed, highly variable N_2O fluxes. For example, conversion from conventional tillage to no-till could simultaneously alter soil temperature, moisture, redox potential, soil DOC, and available N content. These affected factors could then simultaneously and collectively alter the direction and rates of decomposition, nitrification, denitrification, and substrate diffusion, which collectively determine N_2O emission.

Process-based modeling is the only solution to bring the complex system into a calculable framework. During the last decade, process models have been developed that focus on the correlation between soil C dynamics and N_2O emissions.

During the recent years, projects focusing on C sequestration are becoming popular. Several reports released recently discussed the potential of the alternative management practices in sequestering atmospheric C. Unfortunately, most of the research reports or proposals have not addressed non-CO_2 greenhouse gases, especially N_2O. Actually, N_2O is an important GHG, because of its high radiative efficiency (310 times higher than CO_2) and relation with a series of farming practices (Li 1995; Robertson et al. 2000; Li et al. 2001). The net offset between reductions in atmospheric CO_2 and increases in atmospheric N_2O can be significant, and in some cases can result in a net increase in atmospheric CO_2 equivalents (Robertson et al. 2000). Aulakh et al. (1984) and Robertson et al. (2000) observed N_2O emissions from cultivated soils with conventional tillage and no-till in the United States, and found that N_2O emissions were higher from the no-till cropland. It is clear that scientifically sound process-based models are needed to compile and evaluate potential agricultural mitigation of GHGs.

1.5. Greenhouse Gas Emissions from California Agriculture

California agriculture emits CH_4 and N_2O from various agricultural sources, including enteric fermentation, agricultural soil management, rice paddy cultivation, and manure management. In 1999, agriculture in California generated approximately 28.4 million metric tons carbon dioxide equivalent (MMT CO_2 eq.) of GHG emissions, which is approximately 7% of the state's total emissions (CEC 2002). Nitrous oxide and methane accounted for 15.57 and 12.85 MMT CO_2 eq., respectively. Agricultural soils were the dominant source of N_2O (95% of total emissions), and enteric fermentation and manure management were the dominant agricultural sources of CH_4 (approximately 96%). Direct emissions of N_2O from agricultural soils accounted for 5.78 MMT CO_2 eq., with indirect emissions accounting for 8.96 MMT CO_2 eq. These emission inventories were developed using emission factor approaches as specified in IPCC guidelines, with some California specific emission factors.

2.0 Objectives

It is well known that carbon sequestration will inherently increase N_2O (in upland soils) and CH_4 (in wetland soils) emissions due to the coupling of carbon and nitrogen biogeochemical cycles. Thus, the net offset between reductions in atmospheric CO_2 and increases in atmospheric CH_4 and N_2O can be significant, and in some cases can result in a net increase in atmospheric CO_2 equivalents. Therefore, assessing the efficacy of carbon sequestration projects in California agriculture must include comprehensive analyses that examine the impacts of management decisions on all GHGs.

The objective of this scoping study is to use an existing process-based soil biogeochemical model called Denitrification-Decomposition, or DNDC, to simulate recent SOC dynamics and N_2O emissions at the county scale for California and, based on the simulation results, to make recommendations for more detailed studies on carbon sequestration and N_2O emissions under a wide scope of alternative management scenarios. Researchers are assessing the impact of several management alternatives (e.g., changing irrigation practices, use of manure amendments, use of reduced tillage or no-till, use of cover crops, and other alternative farming practices) on county-scale estimates of SOC dynamics, and CH_4 and N_2O emissions. These management alternatives are presented to illustrate how changes in management practices impact SOC dynamics and GHG emissions across cropping systems and counties in California. Outputs of this scoping study include:

- county-scale databases on crop types, crop acreage, fertilizer use, climate, and soil statistics by major crop types;
- county-scale estimates of annual carbon dynamics in agricultural soils under baseline conditions;
- county-scale estimates of CH_4 and N_2O emissions under baseline conditions;
- county-scale estimates of annual carbon dynamics in agricultural soils under alternative management practices;
- county-scale estimates of CH_4 and N_2O emissions under alternative management practices; and
- recommendation of a county for the further research on SOC dynamics and CH_4 and N_2O emissions.

This scoping report presents results from the baseline scenario as well as the following alternative scenarios: over-irrigation (110% of agronomic demand), differences in climate, change in fraction of crop residue incorporated into the soils, and use of manure amendments. The goal of this scoping study report is to initiate and support discussions regarding future field and modeling research and a discussion of critical data needs for detailed modeling of carbon sequestration and GHG emissions n California.

3.0 Methodology

3.1. Input Databases

To develop county-level simulations of carbon dynamics and GHG emissions, DNDC requires county data on climate, crop types and acreages, soils, and management practices.

Climate: Climate inputs to DNDC include daily values of minimum and maximum air temperature, precipitation, and solar radiation. Climate data were obtained from: (a) the National Climate Data Center (NCDC), (b) California Irrigation Management System, (CIMIS), and (c) DAYMET. National Climate Data Center and CIMIS historical climate archives contain station data for weather stations throughout California. Alternatively, DAYMET is a model that generates daily surfaces of temperature, precipitation, humidity, and radiation over large regions of complex terrain (Thornton and Running 1999; Thornton et al. 1997). Using weather station and elevation parameters as input, DAYMET has generated an 18-year (1980–1997) daily climate data set at 10 km resolution. We extracted climate data from the DAYMET system based on county centroids.

Crop Acreages: The crop acreages were derived from GIS coverages based on the California Department of Water Resources (DWR) analyses of aerial photos and field surveys. The photos and surveys were taken in the mid 1990s, with the bulk acquired in 1994–1997. The DWR databases contained data for only 41 out of 58 counties in California. Based on the 1997 National Agricultural Statistics Service (NASS) statistics, the missing 17 counties contain less than 1.4% of total crop area in the state and thus were omitted from this analysis, because we did not have other sources of consistent data that include maps of the crop type. Total crop area for the 41 counties included in our study was 38,344 square kilometers (km^2). Deciduous fruit and nuts and cotton were the largest crop areas. Figure 1 presents that breakdown of total area by crop type. Figure 2 presents total crop area by county. Detailed crop areas by county are provided in Tables 3 and 4 (see Supplemental Tables and Figures).

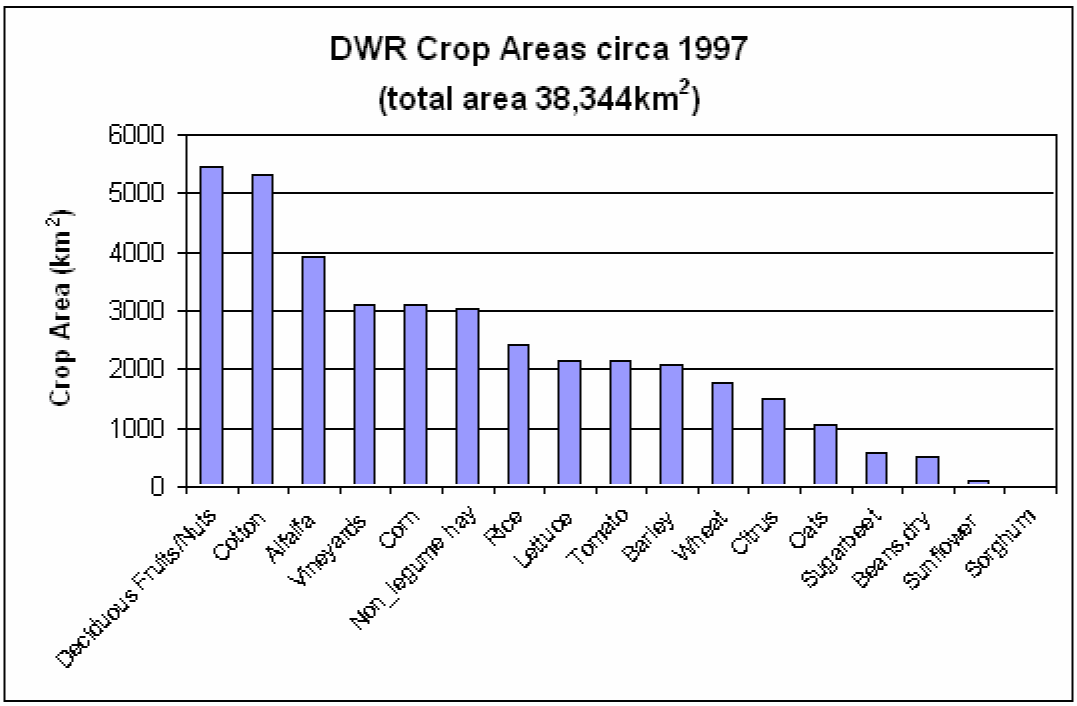


Figure 1. Total crop areas based on Department of Water Resources database

The 1997 California Census of Agriculture reported 43,752 km^2 of cropland in the state, with 34,572 km^2 of it harvested. Excluding the 17 counties not provided in the DWR database, the census reported 34,015 km^2 of harvest croplands for 1997. Although the total cropland acreage remained fairly constant from 1987 to 1997, the area of harvested croplands increased by 10% from 1987 to 1997, with harvested areas in 1987 and 1992 of 31,089 m^2 and 31,431 m^2, respectively (USDA 1997 Census of Agriculture). The California Agricultural Statistics Service (CASS) data are useful for general distribution of crop types across counties; however, the data do not provide sub-county maps of crop locations, and

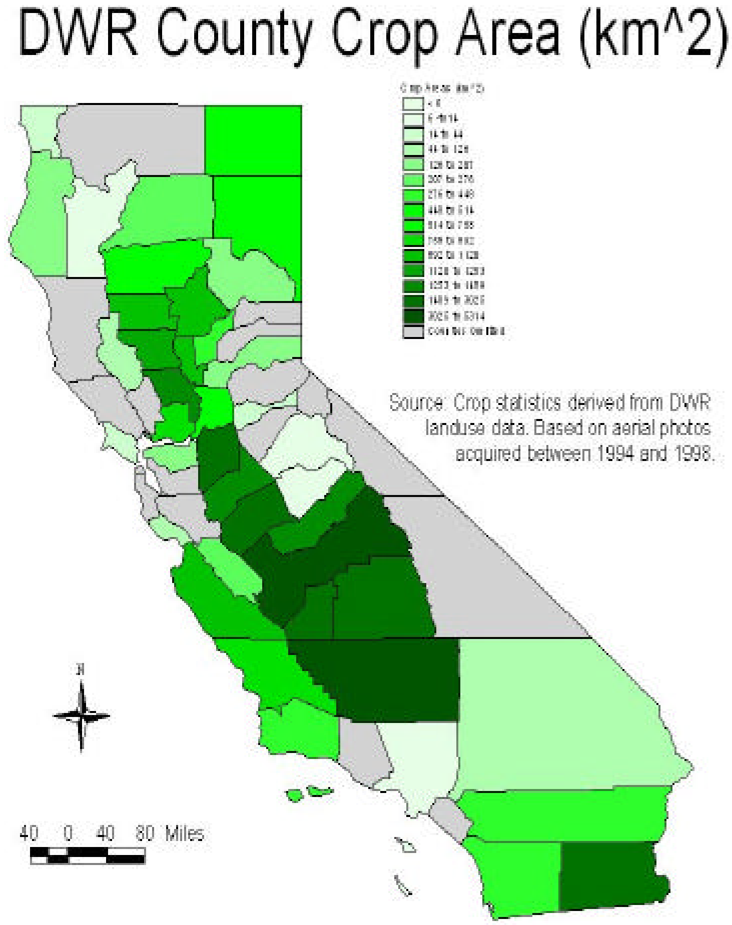


Figure 2. Crop Distribution by county. The 17 counties not included are grey.

thus cannot be merged with the STATSGO and SUSRGO soils databases described below. Additional datasets, such as the National Resources Inventory (NRI) and California Department of Conservation's Farmland Mapping and Monitoring Program (FMMP) were also available. However, although these databases do provide specific locations of croplands, they not provide specific information on crop types.

Some crop polygons in the DWR database were broadly classified as field crop (field-99), grain crops (grain-99), and pasture (pasture-99). These are areas where DWR did not provide specific crop information, just broad crop type. We allocated these areas based on the proportions of the observed subclasses within each county. For example, if a county has 100 ha of alfalfa, 50 ha of non-legume hay, and 60 ha of pasture-99, then alfalfa and non-legume hay subclasses represent 66.67% and 33.33% proportions of observed subclasses.

So, we would then allocate the 60 ha of pasture-99 as 40 ha of alfalfa and 20 ha of non-legume hay.

California has a wide variety of specialty crops (the DWR Truck crop class includes, for example, artichokes, lettuce, berries, and tomatoes), with large annual variability in cropping area. Farmers often change specialty crops from one year to the next. The DWR database was derived from aerial photos acquired over several years. Therefore, since our objective of this scoping study was to look at general trends across cropping systems and counties, we assumed that the total area of truck crops was evenly split into crops with either very low or moderate post-harvest biomass residues. For the simulations, low-biomass-residue crops were modeled as lettuce and moderate biomass residue crops were modeled as tomatoes.

Soils: Soil data were obtained from both the Natural Resources Conservation Service (NRCS) STATSGO (1:250,000) and SSURGO (1:18,000) databases. SSURGO provides detailed information that was designed for analyses at the landowner, farm, or county level. However, at the present time, SSURGO data is not available for all counties in California; therefore, for this scoping study we used the STATSGO database (see Figure 3 for example).

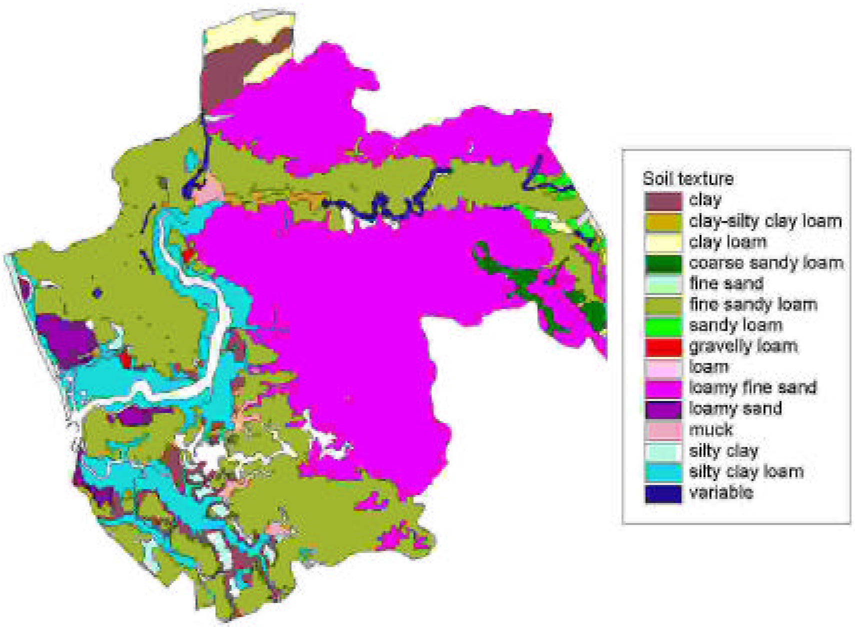


Figure 3. Example of STATSGO soils database used for this scoping study. Soil texture for the Elkhorn Slough watershed in Monterey County.

For future detailed studies for single counties, SUSRGO data will be the most appropriate database. Both soil datasets contain the same soil parameters, and thus are easily merged. DNDC uses four soil properties: (1) soil bulk density, (2) clay fraction, (3) pH, and (4) organic carbon content. The minimum and maximum values of these properties are provided in the databases and are utilized in our analysis for providing ranges of model simulations and uncertainty analyses. For each county, we calculated the minimum, maximum, area-weighted minimum and area-weighted maximum values of clay fraction, bulk density, organic matter, and pH. Data were compiled by overlaying our DWR land use data on the STASTGO GIS data and then area-weighted statistics were derived for four major crop groups: pasture, rice, woody crops, and grains / field / truck crops. The woody crop class included all areas with deciduous fruits and nuts, citrus, and vineyards. Area-weighted statistics are provided in Tables 5 through 8 in the Supplemental Tables and Figures.

Fertilizer Use: Summary data on fertilizer application rates by DWR crop class were obtained from Potter et al. (2001). They derived the fertilizer rates based on numerous discussions with faculty at the California State University Fresno Plant Science Department, University of California (UC) Extension, various growers associations, and Dow Agrosciences. Potter et al. (2001) have a table with rates for eight general DWR classes and four major growing regions. For this scoping study, although these fertilizer use estimates vary by four major growing regions, we decided to use a single nominal application rate for our baseline analysis (see Table 1). However, to examine the sensitivity of our results on fertilizer application rates, we ran a scenario with a 25% reduction in fertilizer application rates.

Crop Planting, Harvesting, and Tillage Practices: For each crop, we collected data from CARB on planting, cultivation, and harvesting periods, as well as on land preparation (e.g., tillage type, tillage dates, and tillage frequency). The California Air Resources Board collected the data through numerous consultations with UC Extension, UC agronomists, crop consultants, and farmers as part of their fugitive dust study. Data were obtained directly from Patrick Gaffney and Hong Yu at CARB. Table 1 lists tillage dates for each crop class modeled.

Irrigation: The DWR database contains information on the irrigation status for each agricultural polygon. Based on this database, most of the crops in California are irrigated. Our discussions with CDFA and UC researchers also indicated that most crops are irrigated, but that irrigation practices are highly variable across California. For this scoping project, we have set the baseline conditions for irrigation based on agronomic demand.

Therefore, irrigation is simulated based on climate data and crop evapotranspiration with sufficient irrigation to prevent crop water deficit. Clearly this is the ideal irrigation scheme. DNDC uses an irrigation index to set irrigation practices. An irrigation index of 1 simulates a level of irrigation that is used to meet agronomic demand. To examine the impact of over irrigation, we ran a simulation with the irrigation index set at 1.1 to simulate over-irrigation by 10%.

Water management for rice paddies: We simulated continuous flooding throughout the rice cropping cycle. The use of winter flooding is becoming more frequent (Matt Summers 2003, pers. comm.), so we simulated winter flooding on 50% of the rice fields in each county.

Table 1. Baseline fertilizer and tillage practices

Crop	Total (kg N/ha)	Application Dates (with rate kg/ha)	Tillage Dates
Cotton	140	4 / 1 (100) and 6 / 1 (40)	3 / 1 and 12 / 1
Sugarbeet	140	4 / 1 (100) and 6 / 1 (40)	3 / 1 and 12 / 1
Corn	140	4 / 1 (140)	1 / 15 and 12 / 1
Sorghum	140	4 / 1 (140)	1 / 15 and 12 / 1
Beans, dry	140	6 / 1 (140)	3 / 1 and 12 / 1
Sunflower	140	6 / 1 (140)	3 / 1 and 12 / 1
Barley	100	6 / 1 (100)	3 / 1 and 12 / 1
Wheat	100	12 / 1 (30) and 2 / 1 (70)	8 / 5 and 10 / 15
Oats	100	6 / 1 (100)	3 / 1 and 12 / 1
Alfalfa	0	NA	1 / 5 and 11 / 1
Non-legume hay	50	5 / 1 (50)	1 / 5 and 11 / 1
Citrus	140	4 / 1 (70) and 7 / 1 (70)	25-Dec
Deciduous Fruit	110	4 / 1 (55) and 7 / 1 (55)	25-Dec
Rice	120	5 / 1 (120)	3 / 1, 4 / 1, and 11 / 1
Vineyards	70	3 / 1 (35) and 6 / 1 (35)	4 / 1 and 11 / 1
Lettuce	265	3 / 1 (165) and 6 / 1 (100)	1 / 15 and 11 / 1
Tomato	265	3 / 1 (165) and 6 / 1 (100)	1 / 15 and 11 / 1

Source: Potter et al. (2001) and CARB Fugitive Dust study (pers. comm. Hong Yu)

Manure: Manure use is not widespread in California. Manure usage is typically confined to areas near dairies where forage crops are grown. Although farmers know that manure effluent contains nutrients, they traditionally have not quantified the amount of nutrients in manure applied to their fields and thus have augmented the manure with traditional fertilizers (S. Pettygrove, pers. comm.). However, in counties with many large dairies, like San Joaquin, manure usage can be significant. Therefore, one of our scenarios examines the impact of including manure amendment as a general management practice with an application rate of 2000 kg C / ha.

Crop physiological and harvest data: DNDC use a suite of parameters for simulating crop growth, including, for example, carbon and nitrogen allocation, water requirements, light use efficiencies, and optimum yield. In addition, for each crop we estimate the fraction of total biomass that is harvested, which in turn indicates the amount of crop residue. Values for these parameters were collected from literature, discussions with UCCE staff, CDFA, and a national EPIC (USDA Environmental Policy Integrated Climate model) database. For our baseline analysis, we assume that 50% of the aboveground crop residue remains on site. We also present a scenario where 90% of the aboveground crop residue remains on site. Table 2 provides a listing of the default parameters used for this scoping study. Based on these parameters, for example, corn produces almost 2800 kg C/ha (11,145 kg C/ha, total biomass times 0.25, the root fraction of total biomass) of belowground biomass. Assumptions on the fraction of biomass harvested and percentage of residue left on site have a tremendous impact on carbon sequestration and GHG emissions, and thus can be a significant source of uncertainty.

Table 2. Default DNDC crop parameters used for this scoping study

	DNDC Input Crop Parameters (see listing at end of table)											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Corn	11,145	0.37	0.38	0.25	53.4	35	85	73	368	5.0	2.0	2550
Wheat	3,956	0.40	0.40	0.20	31.2	18	48	71	513	3.0	0.5	2000
NL Hay	22,000	0.40	0.15	0.45	57.4	50	70	50	770	3.0	0.5	2500
Barley	6,140	0.30	0.43	0.27	34.5	19	44	61	550	3.0	0.5	3000
Oats	4,606	0.28	0.47	0.25	39.1	25	50	50	597	3.0	0.5	1650
Alfalfa	14,222	0.45	0.13	0.42	53.8	50	60	50	770	3.0	0.5	3000
Sorghum	6,116	0.35	0.40	0.25	54.7	35	85	75	322	5.0	2.0	2600
Cotton	4,580	0.19	0.56	0.25	27.7	16	40	30	646	4.0	0.7	3800
Beets	6,376	0.80	0.15	0.05	99.6	110	80	70	397	4.0	0.5	2550
Rice	7,506	0.45	0.48	0.07	42.9	35	40	55	710	6.0	0.5	2250
Sunflower	2,401	0.30	0.45	0.25	25.0	15	50	30	350	3.0	5.0	1500
Beans	2,946	0.30	0.45	0.25	25.6	15	40	35	550	3.0	0.5	1900
Fruit & Nut	6,882	0.50	0.20	0.30	35.7	30	50	50	550	3.0	2.5	3000
Citrus	5,381	0.50	0.20	0.30	37.5	30	50	50	550	3.0	2.5	3000
Grapes	3,496	0.50	0.20	0.30	36.1	30	50	40	550	3.0	1.5	3000
Lettuce	1,428	0.64	0.15	0.20	12.7	10	30	20	900	4.2	0.2	1400

[1] Total biomass C at harvest under optimum growing conditions (kg C / ha)
[2] Harvested fraction of total biomass
[3] Leaf and stem fraction of total biomass
[4] Root fraction of total biomass
[5] C / N ratio for total plant at harvest time
[6] C / N ratio for harvested parts
[7] Root C / N ratio at harvest time
[8] C / N ratio for leaves and stems at harvest time
[9] Water requirement, in g of water required for producing 1 g dry matter of harvested biomass
[10] Max LAI (Leaf Area Index)
[11] Max height (m)
[12] Thermal degree days (TDD) accumulated during growing season (degrees C)

3.2. Modeling

The Denitrification-Decomposition (DNDC) model is a process-based model that simultaneously models soil carbon dynamics and N_2O emissions. DNDC was constructed based on four basic concepts: (1) biogeochemical abundance, (2) field, (3) coupling, and (4) cycling. DNDC consists of six submodels for soil climate, crop growth, decomposition, nitrification, denitrification, and fermentation (Figure 4). The six interacting submodels have included the fundamental factors and reactions, which integrate C and N cycles into a computing system (Li et al. 1992, 1994; Li 2000). DNDC has been validated against numerous data sets observed worldwide. During the last several years, DNDC has been independently tested by the researchers in many countries and applied for their national C sequestration and N_2O inventory studies. By tracking crop biomass production and decomposition rates, DNDC accurately tracks short- and long-term SOC dynamics. DNDC models growth of over 40 types of crops based on such factors as their optimum yield; partitioning of assimilated C to root, leaf, stem, and grain; C/N ratios of root, leaf, stem, and grain; and water requirement.

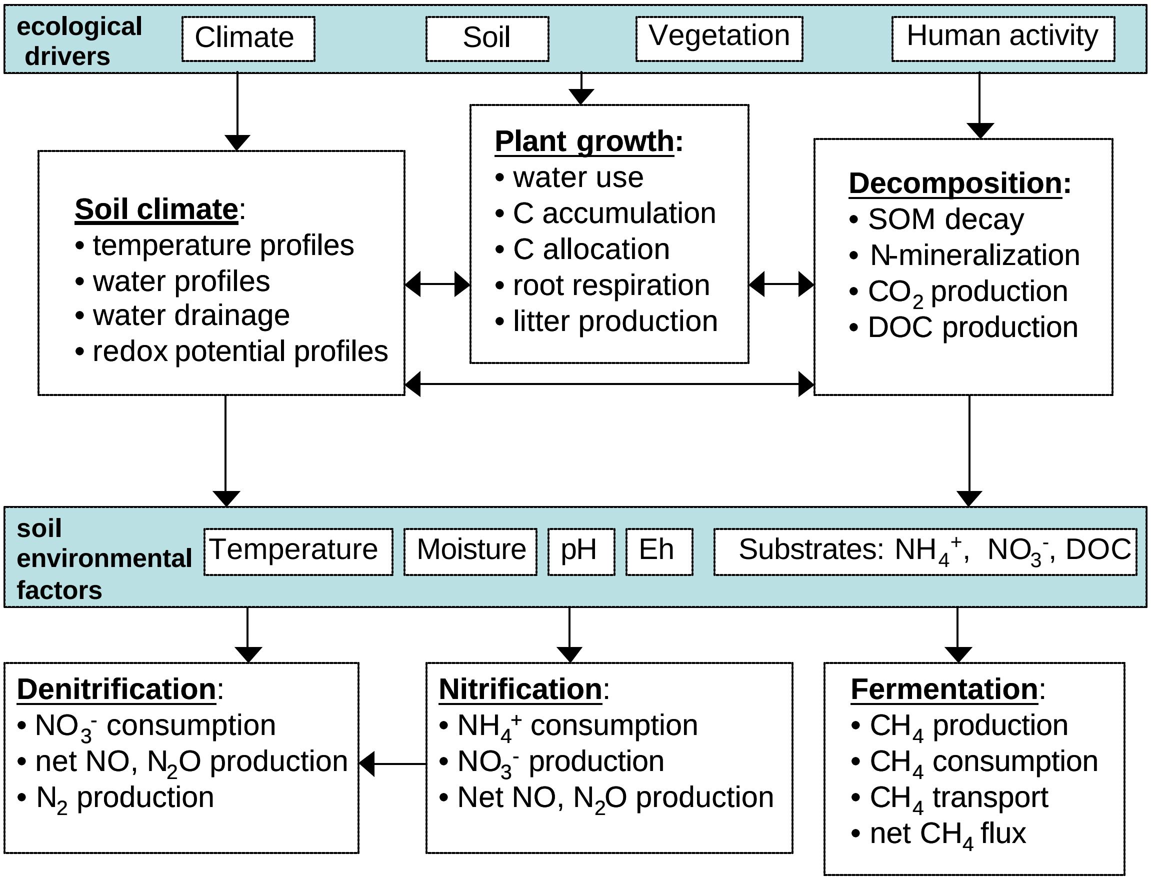


Figure 4. DNDC model structure

At harvest, the quantity and quality of residue (i.e., the root litter and aboveground litter) are determined based on the crop parameters, which vary across crop types. For example, corn usually produces 2,800 and 4,200 kg C/ha of below-ground (i.e., root) and aboveground (i.e., leaf and stem) litter, respectively (see Table 2).

In contrast, lettuce only produces 280 and 210 kg C/ha of below-ground and aboveground litter, respectively. Harvest terminates root growth and turns 100% of the root biomass into root litter, which is automatically incorporated in the soil profile. A user-defined fraction of the aboveground litter defines the amount of the aboveground litter left in the field after harvest. Tillage following harvest will incorporate this part of the aboveground litter into the soil profile. As soon as the litter is incorporated in the soil, the litter will be partitioned into three soil litter pools: (1) very labile, (2) labile, and (3) resistant. The partitioning fractions are calculated based on the C/N ratio of the fresh litter.

For example, the C/N ratio for corn leaves and stems is 73 (see Table 2). Based on the equations adopted in DNDC, 5%, 40%, and 50% of the fresh corn litter will be partitioned into very labile, labile, and resistant soil litter pools, respectively. In contrast, the C / N ratio for lettuce leaves and stems is 20 (see Table 2). Based on the same equations in DNDC, 12%, 83%, and 5% of the fresh lettuce litter will be partitioned into very labile, labile, and resistant soil litter pools, respectively.

Because each of the soil litter pools possesses its own specific decomposition rate, the partitioning algorithms will determine the difference in the bulk decomposition rate for each of the simulated specific crop residues. Through these mechanisms, DNDC is able to precisely track the turnover of crop litter in the soils driven by its quantity and quality (i.e., C / N ratio) as well as by the soil temperature, moisture, and aeration. In DNDC, tillage affects SOC decomposition rates through two mechanisms. At first, tillage increases soil aeration, which elevates decomposition rates. Second, tillage redistributes SOC in the soil profile through the physical disturbance. Overall decomposition rates would decrease as more SOC is redistributed into the deep soil layers where the oxygen partial pressure is relatively low. DNDC tracks both effects and determines the net impacts.

DNDC predicts N_2O emissions by tracking the reaction kinetics of nitrification and denitrification driven by climatic conditions, soil properties, and management practices.

With its prediction capacity of both SOC and N_2O, DNDC is ready to serve offset analysis between C sequestration and N_2O emissions for agroecosystems. Since C sequestration and N_2O emission are both affected by many environmental factors (but in different ways), shifting from one location to another will inherently alter the effects of any management alternatives on the net global warming potential (GWP). DNDC, with its fundamental biogeochemical processes, can quantify both carbon sequestration and non-CO_2 greenhouse gas emissions, and can assess the net GWP effects of alternative management practices across climatic zones, soil types, and management regimes when coupled with GIS data for regional assessments.

DNDC quantifies SOC dynamics by tracking inputs and outputs of eight SOC pools, namely very labile, labile, and resistant litter; labile and resistant microbial biomass; labile and resistant active humus (i.e., humads); and passive humus at a daily time step (Figure 5).

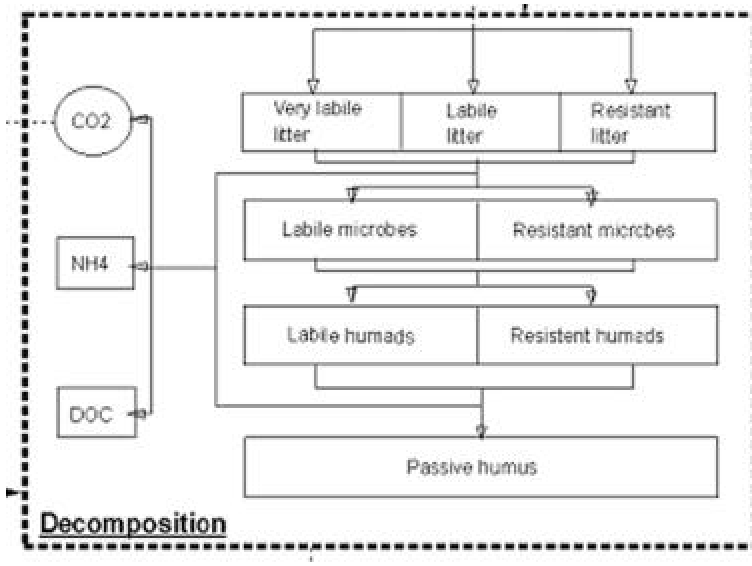


Figure 5. DNDC models soil organic carbon (SOC) dynamics by tracking the dynamics of eight SOC pools

Each of the sub-pools has a specific decomposition rate, which is subject to variations in the soil temperature and moisture. The major source of SOC is litter incorporation. Especially, when the crop is harvested, all of the roots will be incorporated in the soil profile, and a fraction of the aboveground residue will be left in the field until the next tillage incorporates it into the soil. The SOC balance is hence determined by the total decomposition rates, which leads SOC loss, and the total litter incorporation, which leads SOC gain. The decomposition rates are well-modeled by DNDC, based on the SOC contents in all of the SOC pools and soil temperature / moisture conditions. Soil organic carbon gain must rely on a user-determined fraction of aboveground crop residue. Because crop residue incorporation is the most important source for SOC, any deviation in the fraction of crop residue incorporation will affect the modeled accuracy. Unfortunately, this information (i.e., fraction of aboveground crop residue incorporation) is usually missing or not precisely reported in most of publications or reports. The inaccuracy in the amount of crop residue incorporated in soil is actually the most important factor introducing uncertainties in the modeled SOC sequestration (Li et al. 1994; Li et al. 2003).

For this scoping study, SOC dynamics and N_2O and CH_4 emissions were modeled with DNDC version 8.2 for baseline and alternative scenarios.

3.3. Management Scenarios

Given the objectives of this general scoping study, several scenarios were modeled to examine differences in broad management practices. The objective of the scenario analyses is not necessarily to prescribe a single management practice for all counties in California, but rather to highlight the general impact on carbon sequestration and GHG emissions across counties. Thus, while management practices in the scenarios may represent potential practices in some regions, they are likely not representative of potential management practices for all counties and cropping systems. Nevertheless, these scenarios are useful for assessing potential impacts on the trends in SOC dynamics and GHG emissions.

3.3.1. Baseline scenario

For our baseline management scenario we ran the simulation using a single year (1997) of climate data with the nominal tillage practices (Table 1), standard fertilizer application rates (Table 1), fully irrigated (irrigation index 1.0), no manure amended, and 50% of aboveground litter (residue) incorporation. We chose to run our baseline analysis over a single year (rather than a long-term analysis) to focus our scenario comparisons on the impact of management, rather than both climate and management. Although it is clear that the impact of various management decisions will vary depending on climate conditions, we felt for this scoping activity that varying management condition was a more tractable analysis. However, we did run an 18-year scenario for two counties to examine long-term dynamics and sensitivity to initial soil conditions.

3.3.2. Alternative scenarios

In several scenarios that were modeled, we changed only a single input data set—either climate or management practices, relative to the baseline assumptions. At this point, we have run the following scenarios:

- **1983 climate:** Since our baseline year 1997 was a relatively hot and dry year for California, we ran a scenario using climate data for 1983, which was relatively cool and wet year.
- **Alternative litter incorporation**: We varied our assumption regarding the amount of residue left on site from our baseline assumption of 50% to 90% of aboveground litter incorporation. This was simulated for all counties.
- **Alternative irrigation**: Our baseline scenario had the irrigation index set at 1, signifying that crops were irrigated to exactly meet agronomic demand. Since over-irrigation is often practiced in California, we ran a scenario where crops were over irrigated by 10% by setting our irrigation index at 1.1, with 90% residue incorporation.
- **Alternative manure amendment**: Our baseline scenario had no manure amendments. For this scenario we applied 2000 kg C/ha with 90% residue incorporation for all of crops in all counties.
- **Multiyear climate**: We ran a scenario using 18 years of climate data (1980 through 1997) for two counties (Fresno and Sutter), with 90% residue incorporation.

4.0 Validation

DNDC uses two categories of parameters: internal and external. Internal parameters include, for example, all of the coefficients employed in the equations for calculating such factors as soil temperature and moisture profiles, microbial growth, crop growth, chemical reactions, decomposition, nitrification, denitrification, and gas diffusion. Examples of external parameters include meteorological conditions, soil properties, crop physiology and phenology, farming management practices, etc. All of the internal parameters are fixed as part of the source code; however, the external parameters are defined by the users. During the development of DNDC, all of the internal parameters were calibrated by the model developers against field data available to the developers. Examples of these internal parameters can be found in Li et al. 1992, 1994 and Li 2000.

Because DNDC is a process-based model, it was constructed with a group of basic laws or equations from text books on physics, chemistry, and biology. To link the equations to the field-scale conditions, most of the coefficients in the equations must be calibrated. After the calibration, coefficients were fixed, and are not changed from one application to another. As new users run DNDC for their specific applications, most users test the model against their own observations that are independent of field data used to develop the model. We refer to this process as *validation* throughout this report. Based on indirect and direct feedback, most of the users obtained satisfactory results by setting their external parameters based on local conditions (e.g., soil texture, soil organic matter (SOM) partitioning, crop physiological or phenology constants, crop residue fraction for incorporation) without adjusting any of the internal parameters in DNDC. Actually, it is difficult for users to alter these internal parameters, as they are embedded in the source code. So the validation results reported in Figure 7 is an example demonstrating independent validation of DNDC's capacity, in which the internal parameters remained static.

4.1. Validating Carbon Dynamics

A recent study published an analysis of soil survey data that was collected at 125 sites in the 1940s and 1950s and resurveyed in 2001 (DeClerck et al. 2003). It reported that at the state level, total soil carbon increased; however, the magnitude and sign of change varied significantly by land use and geographic region. Dr. Singer provided us with the soil carbon data from this study. In addition, he provided the current available land use information for each site. Without information on the historical land use, we assumed no land use change over the past 50 years. Using the initial SOC conditions based on historical soil surveys and general soil pH, bulk density, and soil texture from our GIS database for each county, we simulated 50 years of SOC dynamics for 27 sites in Colusa, Fresno, and Glenn counties. The remaining sites will be analyzed. In addition, Dr. Laosheng Wu at UC Riverside has been conducting research on the impact of irrigation on soil carbon stocks. Dr. Wu has agreed to provide his field data for further model validation.

In spite of the many unknown factors (e.g., land-use history, used only one-year climate data (1990) for 50 years, uncertainties with crop residue management), the modeled SOC changes were consistent with observations ($R^2 = 0.62$) across the 27 sites tested to date (Figure 6). Both the observations and modeled results indicate that:

- SOC increased in pasture and rice paddies,
- all of the row-crop sites lost SOC, and

- SOC changes at tree-crop sites were highly variable, implying that the tree litter management (e.g., fraction of residue incorporation) could be highly differentiated from site to site.

Despite the potential for major uncertainties from: (1) fraction of crop residue incorporation, (2) initial SOC content, (3) land-use history during the simulated 50 years, and (4) interannual climate variability, our model simulations capture the general trends of carbon dynamics in California agricultural soils at these sites. Examples of the 50-year annual carbon dynamics for a few sites are provided in Figures 30–32 in the Supplemental Tables and Figures.

Observed and DNDC-modeled average annual SOC changes at 27 sites in agricultural lands in Colusa, Fresno and Glenn Counties, CA during 1949-1999

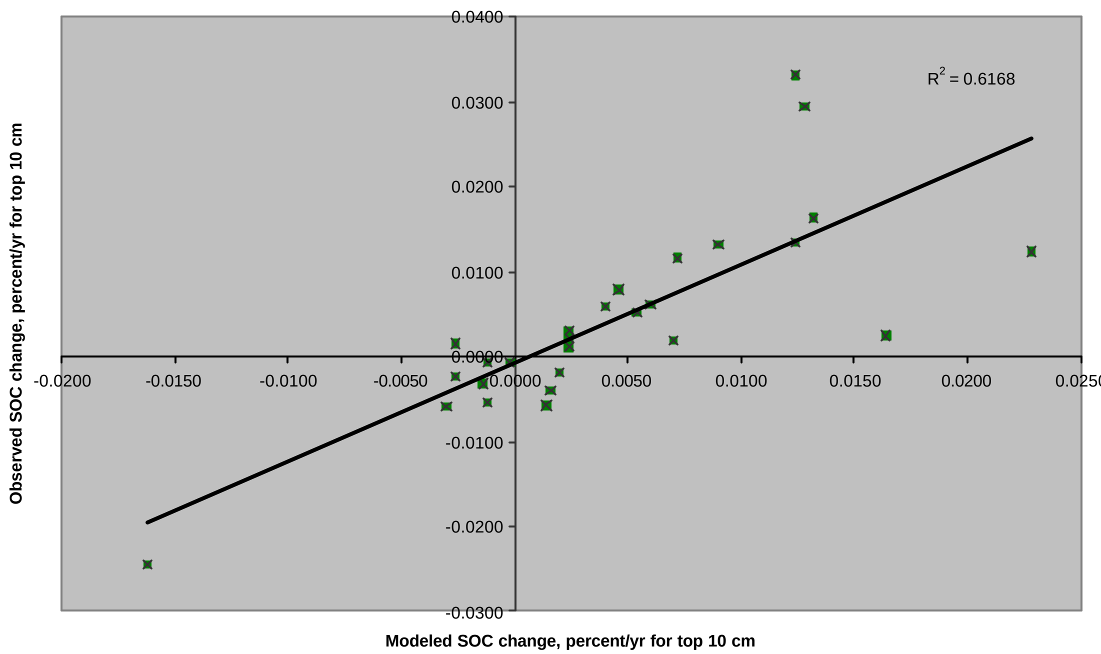


Figure 6. Validation of DNDC carbon dynamics for several cropping systems in California. Field observations were provided by Singer (DeClerck et al. 2003).

4.2. Validating Nitrous Oxide and Methane Emissions

For this scoping study, we did not have field data yet on N_2O or CH_4 emissions from California soils. However, DNDC has been validated across a wide range of agroecosystems under a broad variety of climate conditions (Figure 7). In anticipation of further studies detailing SOC dynamics and GHG emissions, we are collecting data from published studies on trace gas emissions from California agriculture. For example, we are discussing a validating our model predictions with a series of methane studies that examined the impact a rice straw incorporation versus burning (W. R. Horwath, pers. comm.).

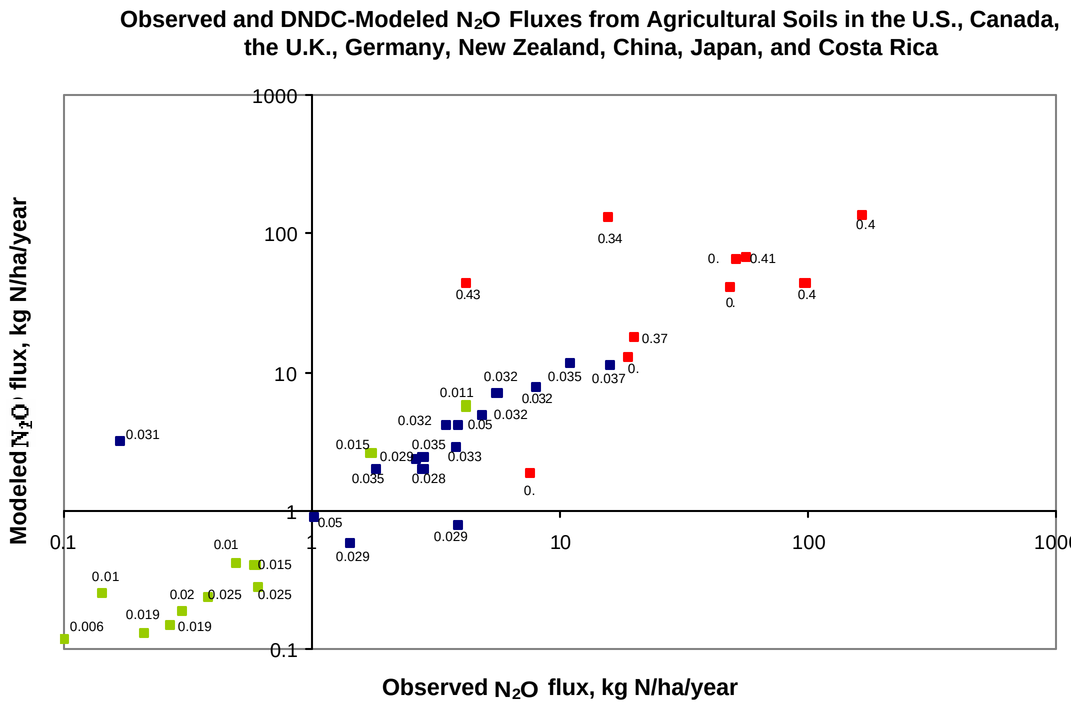


Figure 7. Nitrous oxide validation of DNDC across a range of agricultural systems in several regions worldwide. SOC content in percent for each site is indicated by the labels. (Source: Li et al. 2004.)

5.0 Results and Discussion

DNDC models SOC dynamics and non-CO_2 gas emission at site to regional scales, with quantified uncertainties. Our simulation results are presented in ranges using an approach we call the Most Sensitive Factor (MSF) method. This approach has been discussed in details in several former papers (Li et al. 1996; Li et al. 2002; Li et al. 2003).

In brief, because in general SOC dynamics and N_2O emissions are most sensitive to the initial SOC content (relative to soil pH, texture, and bulk density), the maximum and minimum SOC content, commonly obtained in a county soil survey data, are recorded for the county in the GIS database to support DNDC simulations. DNDC runs each cropping system in each county twice with the maximum and minimum SOC values, respectively. The two model runs will produce two results of SOC change (or N_2O flux). The two flux values form a range, which we contend will, with a high probability, be wide enough to include the “real” flux.

For example, our MSF method has been compared with a traditional statistical approach, Monte Carlo analysis, for two counties in California. 99% of SOC changes and 63% of N_2O fluxes predicted by Monte Carlo approach are located within the ranges predicted by MSF method (Figure 8). The comparison of SOC and N_2O indicated that the MSF method is reliable. Considering the huge difference in the computing time between Monte Carlo and MSF (3 hours vs. 10 seconds), we adopted MSF for our regional predictions. Based on this methodology, our results for modeled SOC changes or N_2O fluxes are presented as ranges. These ranges are based on the ranges of soil carbon conditions provided in the STATSGO soil databases. Given the wide range in SOC values for each polygon, or region, in the STATSGO data, our results have large ranges in estimates of soil carbon sequestration and GHG emissions. The results presented in ranges should provide more realizable and reliable pictures about the GHG fluxes with the unavoidable uncertainties at regional scale.

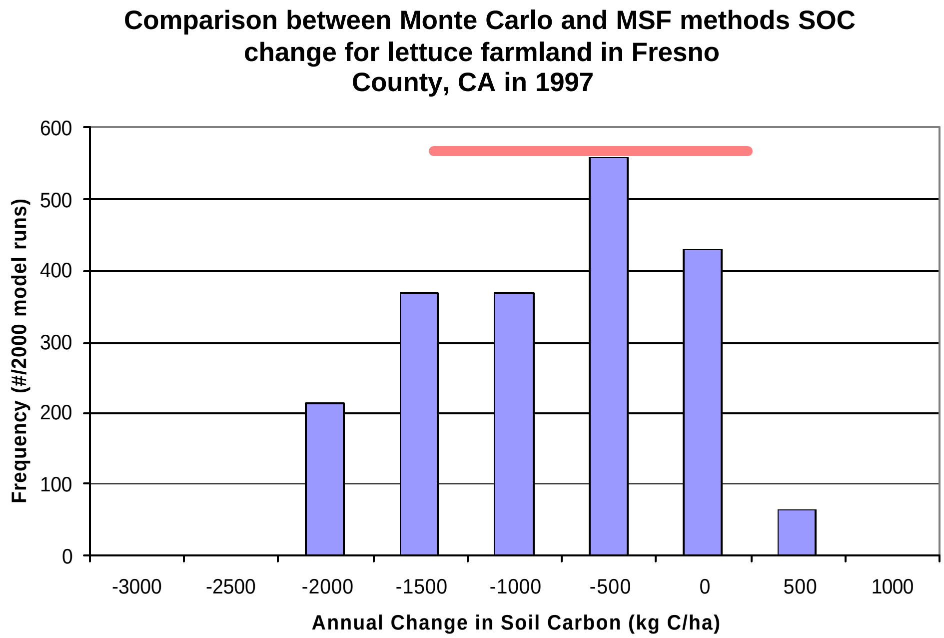
5.1. Baseline Scenario

5.1.1. Carbon sequestration

Based on our baseline assumptions and scenario for 1997, California agricultural soils were either a small source of carbon (-0.6 teragrams of carbon, or Tg C), or sequestered 6.1 Tg C, which in terms of GWP is -22.4 to 2.2 MMT CO_2 eq. The cropping systems of cotton, corn, alfalfa, non-legume hay (or pasture), citrus, and deciduous fruit orchards made positive contributions. This sequestration is likely due to the high litter production of these cropping systems. SOC was reduced for lettuce, dry beans, and sunflower cropping systems (reduced 0.003–0.8 Tg C), likely due to their low litter production. The SOC content for other crops (e.g., rice, sorghum, barley, wheat, oats, tomato, and grapes) were moderately changed with an increase or decrease, depending on the soil conditions. Figure 9 presents ranges by crop type for all of California. County level changes in SOC are provided in Figures 10 and 11. The counties with SOC increases by more than 0.1 Tg C were Fresno, Imperial, Kern, Kings, Lassen, Madera, Merced, Modoc, Stanislaus, Tehama, and Tulare. SOC decreased in Colusa, Monterey, San Joaquin, and Santa Barbara counties. The remaining counties basically maintained SOC balance or slightly increased.

Average carbon sequestration by county (Figure 12) was variable, due to large differences in carbon sequestration rates across cropping systems (Figure 13), soil conditions, and total cropping areas by county. Initial SOC content conditions had a significant impact on the modeled carbon sequestration rates. Pasture, tree crops, cotton, and corn systems had the highest sequestration rates. The low biomass truck crops (modeled as lettuce) consistently had negative sequestration rates. The remaining crops had either positive or negative sequestration rates, depending on the initial SOC content.

These baseline results are basically consistent with the site analyses used for our model validation, described in Section 4.1.



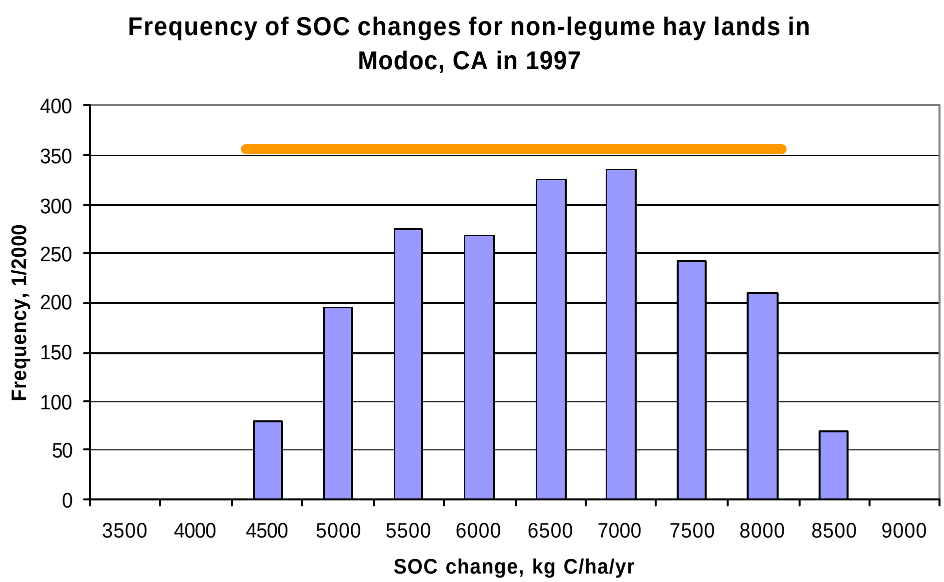


Figure 8. Comparison between MSF and Monte Carlo approaches. Comparison on annual SOC changes in croplands in Fresno and Modoc Counties, CA between Monte Carlo approach (vertical blue bars) and Most Sensitive Factor method (horizontal orange lines). More than 80% of SOC changes predicted by Monte Carlo approach are located within the ranges predicted by MSF method.

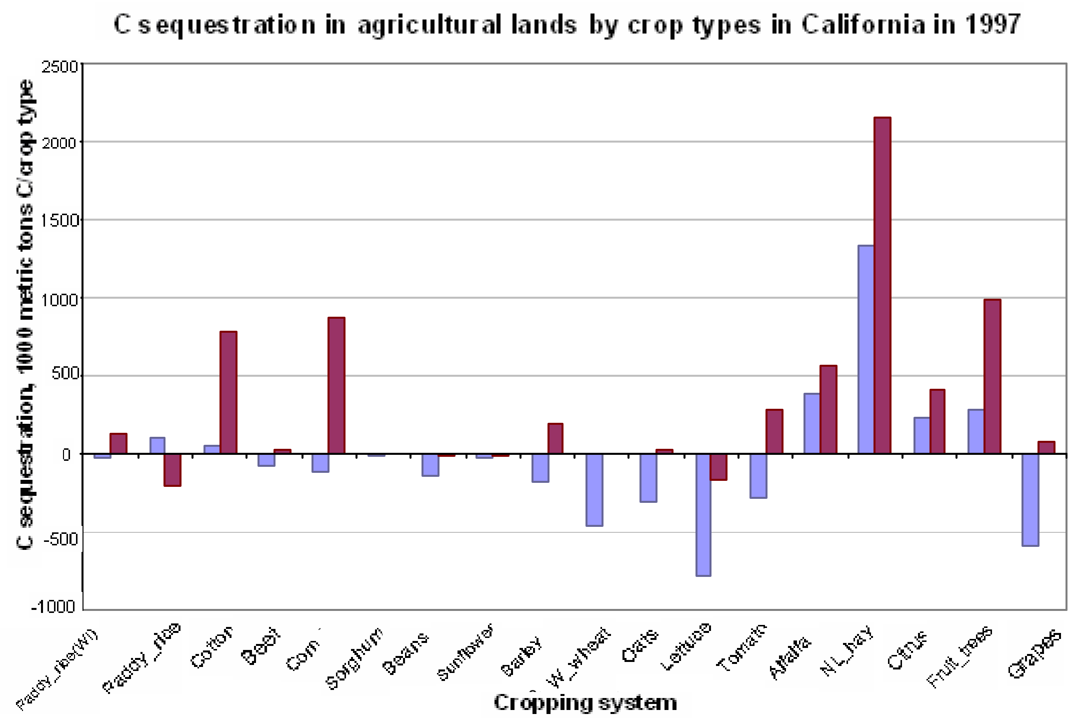


Figure 9. Ranges in C Sequestration by crop type (totals for California) based on the max initial SOC (blue) and min initial SOC (maroon) content for each county.

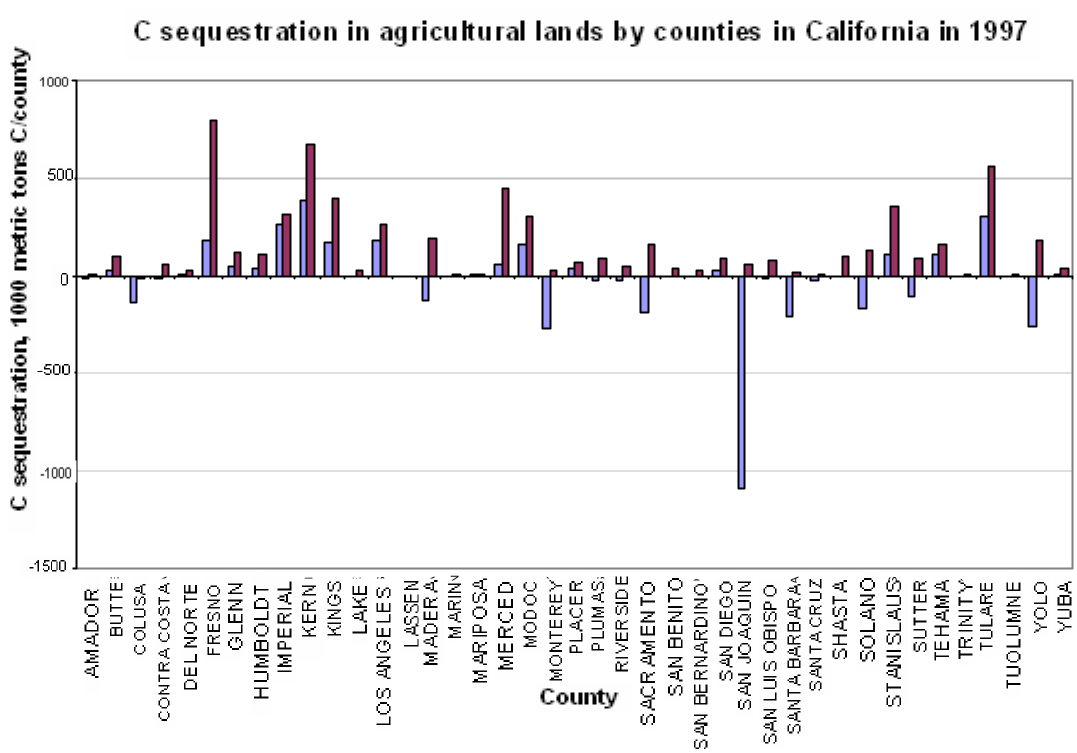
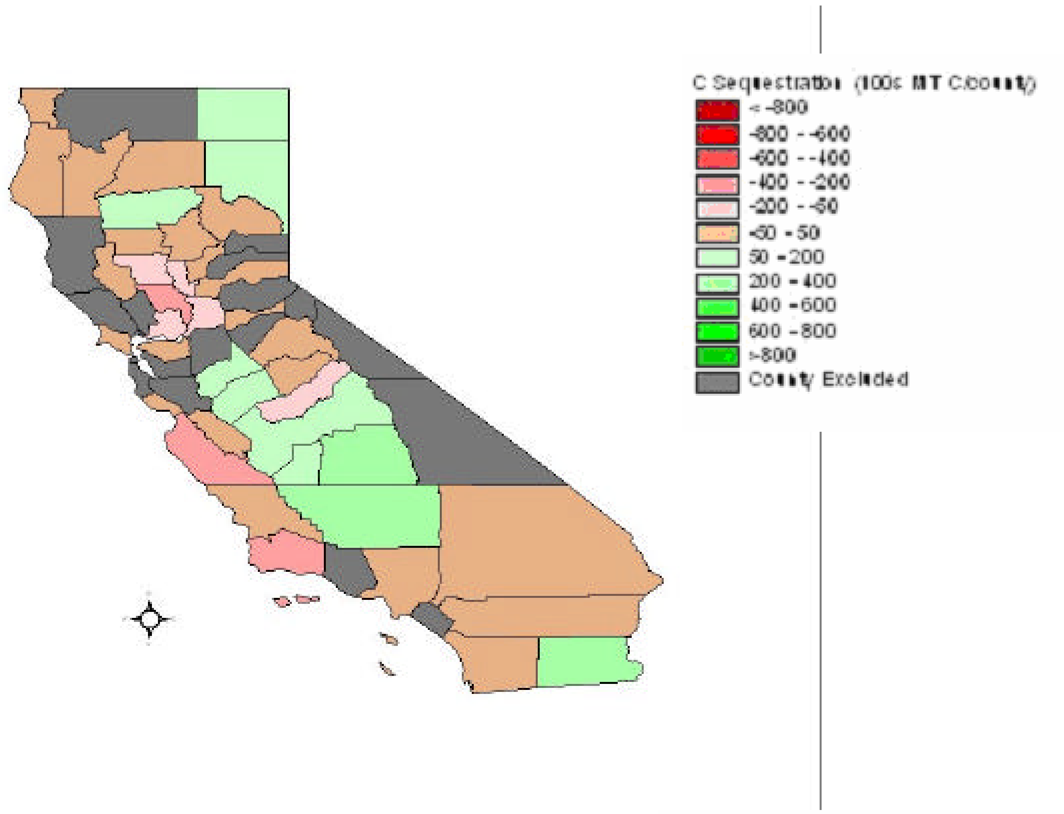


Figure 10. County carbon sequestration totals based on the maximum initial SOC (blue) and minimum initial SOC (maroon) contents for each county



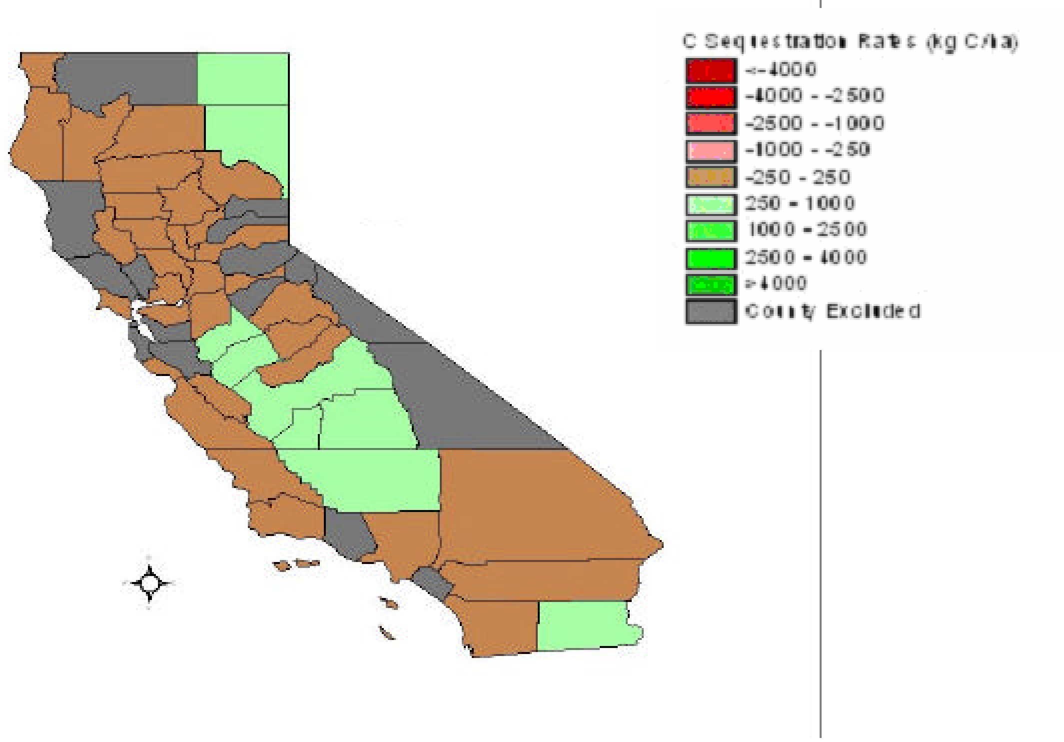
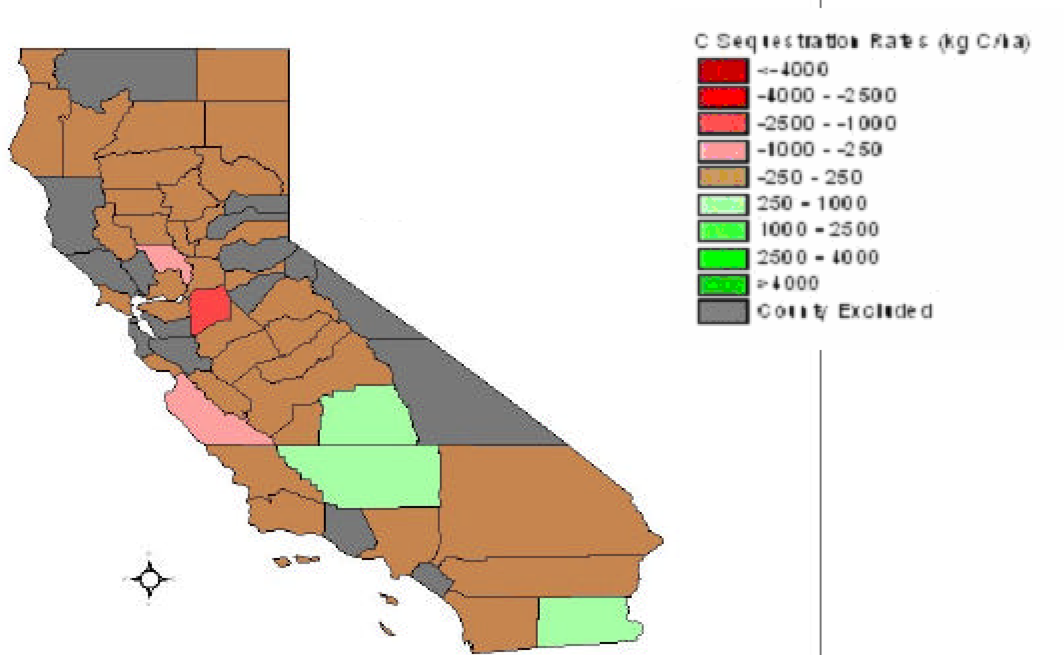


Figure 11. County carbon sequestration ranges, based on initial SOC content. Results from higher (max) initial SOC content are presented in the upper graphic, and those representing lower (min) initial SOC content are presented in the lower graphic.



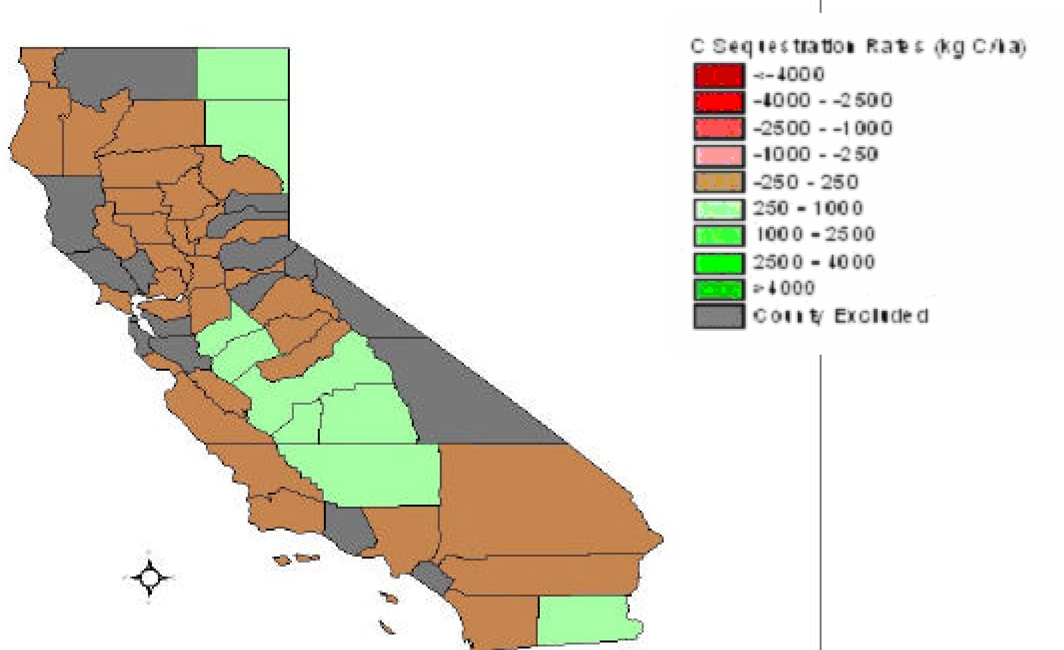


Figure 12. County average carbon sequestration rates based on max (upper graphic) and min (lower graphic) SOC ranges, from STATSGO

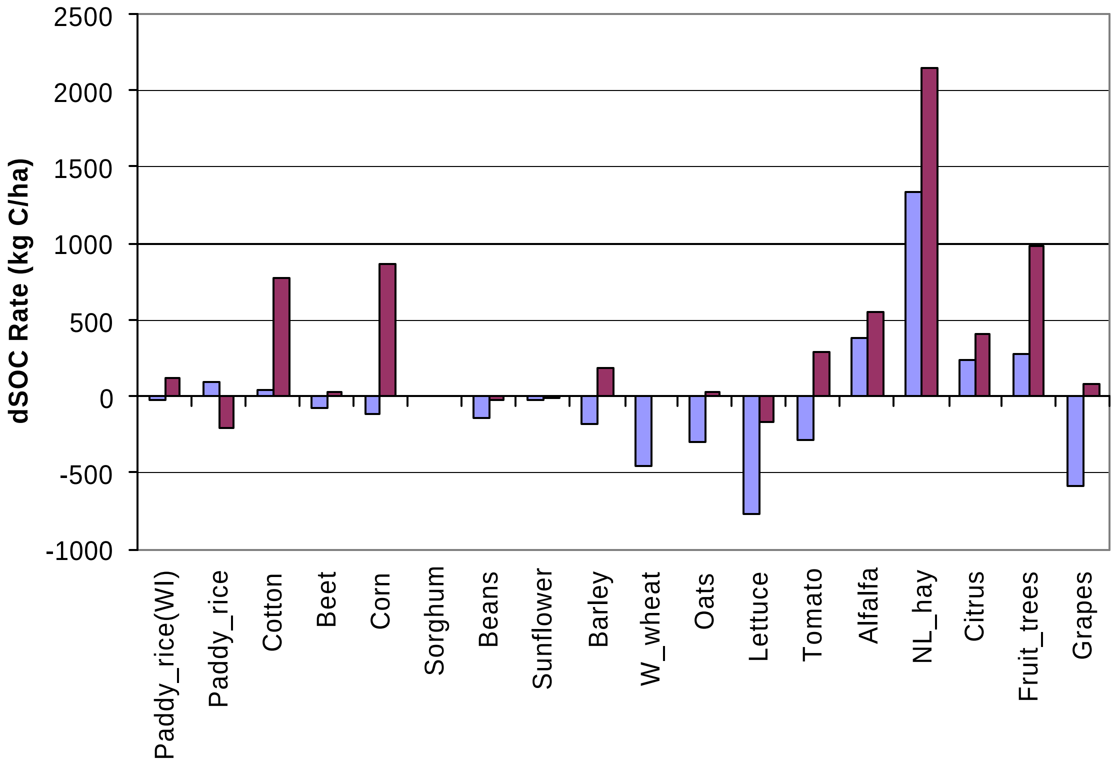


Figure 13. Average extreme carbon sequestration rates, by crop type

5.1.2. Nitrous oxide emissions

Based on our baseline assumptions and scenario for 1997, California agricultural soils emitted between 0.21-0.51 Tg N of nitrous oxide (or in terms of GWP, 10.0 to 24.7 MMT CO_2 eq.). Fresno and San Joaquin counties had the highest total N_2O emissions (Figure 14), likely due to the large fertilizer-intensive crops. Trinity, Amador, Humboldt, and Marin counties had the highest N_2O emissions rates (Figure 15), likely due to their relatively high SOC content. The cropping systems of cotton, corn, and grapes made the highest contributions to total nitrous oxide emissions (Figure 16). Once again the large range in our emissions estimates is due to the wide range between the minimum and maximum SOC values provided in the STATSGO soils database and the strong relationship between SOC and N_2O emissions rates.

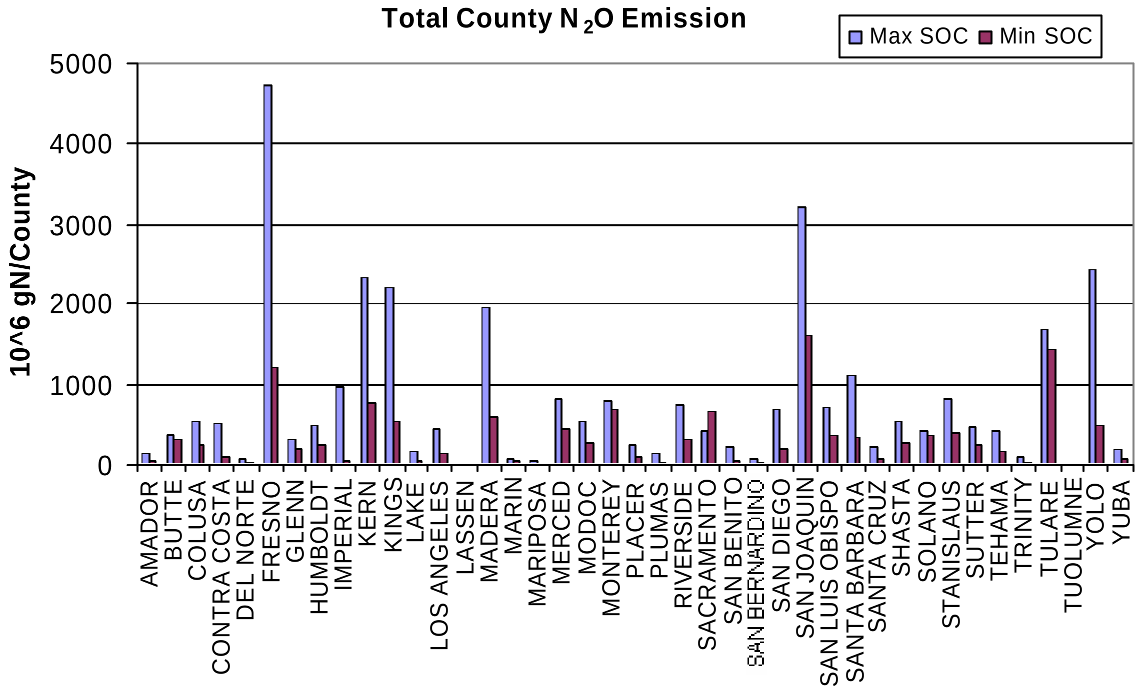


Figure 14. Total nitrous oxide emissions by county

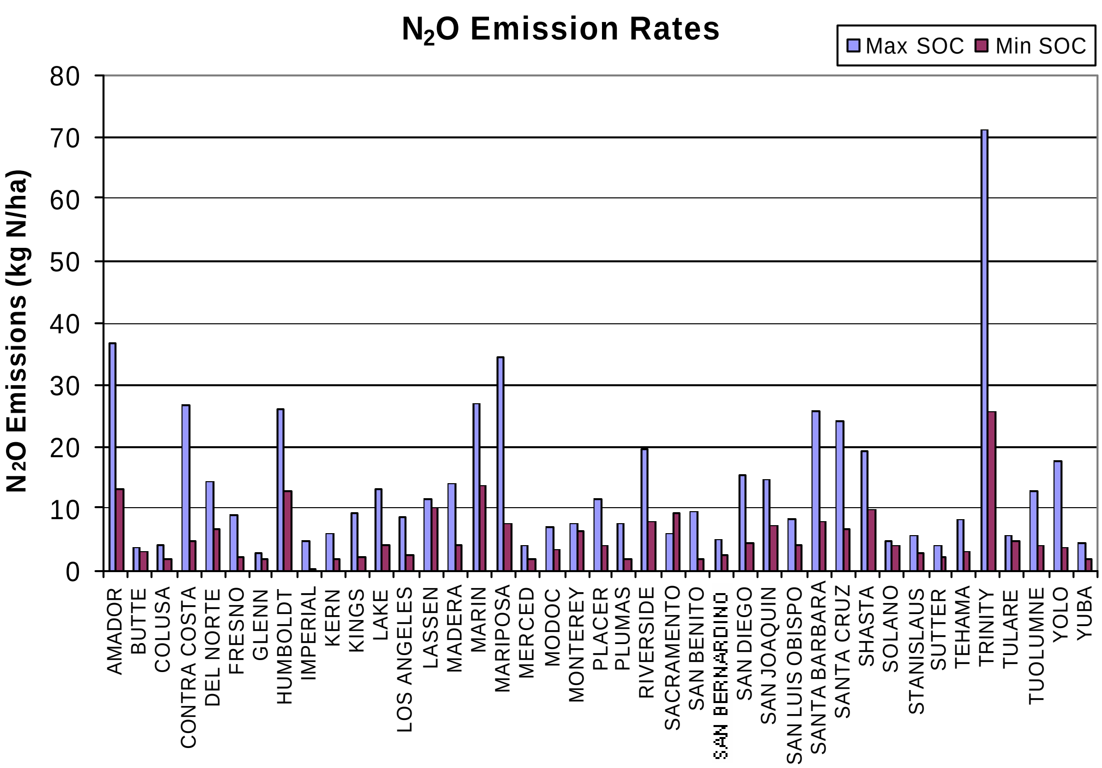


Figure 15. Nitrous oxide emission rates by county

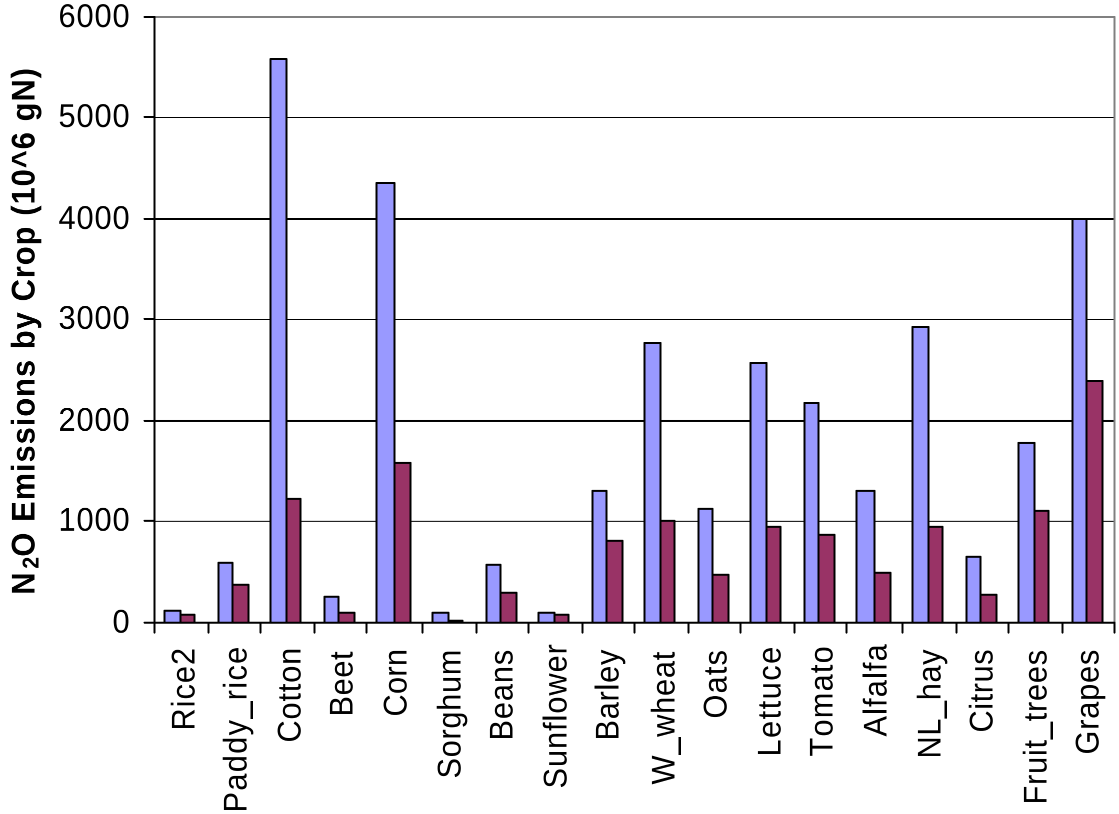


Figure 16. Total N_2O emissions by crop type

The patterns of N_2O emissions based on county or crop type are very different from that of SOC dynamics. For example, lettuce had negative contribution to C sequestration but great contribution to N_2O emissions. The results imply that assessing net effects in terms of both carbon and N_2O is warranted for evaluating potential mitigation strategies.

5.2. Alternative Management Scenarios Impact on Carbon Sequestration

The impact of the four alternative management scenarios on average carbon sequestration rates is illustrated in Figure 17. In general:

- **Climate impact**: Shifting climate data from 1997 to 1983 resulted in a slight increase in total carbon sequestration for California, likely due to slightly cooler and wetter weather resulting in lower decomposition rates.
- **Impact of residue incorporation:** Increasing aboveground litter residue incorporation from 50% to 90% significantly increased C sequestration rates by about 700 kg C / ha / yr. With higher residue incorporation conditions, California agricultural soils were a significant sink (2.2 to 9.0 Tg) of carbon. On the other hand,

if all aboveground residue is removed from the field, then agricultural soils could be a small 0.4 Tg sink to a large 7.8 Tg source of carbon.

- **Impact of manure amendment:** Increasing manure application from 0 to 2000 kg C/ha with 90% residue incorporation substantially elevated C sequestration in California agricultural lands to 9.6–16.5 Tg C.
- **Over-irrigation impact:** Increasing the irrigation index from 1.0 to 1.1 slightly increased C sequestration, most likely due to the decreased decomposition rates under higher soil moisture conditions.

We also analyzed how alternative management practices influence carbon sequestration rates by crop types. Figures 18 and 19 illustrate differences in carbon sequestration rates for those crops that exhibited high positive or small negative sequestration rates in the baseline analysis, respectively. For all crops, an increase to 90% residue incorporation resulted in a increase in soil carbon, relative to the baseline analysis. A reduction to 0% aboveground residue incorporation resulted in a decrease in carbon sequestration (i.e., led to a loss of soil carbon). Manure amendment led to an increase in soil carbon relative to baseline conditions.

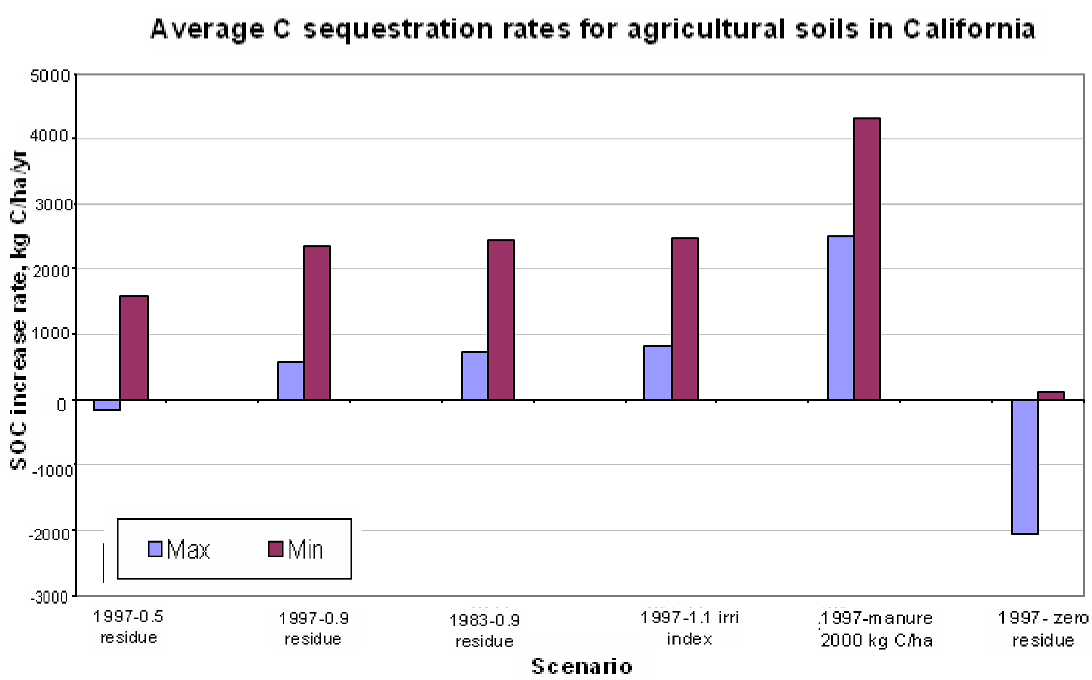


Figure 17. Average carbon sequestration rates across management scenarios

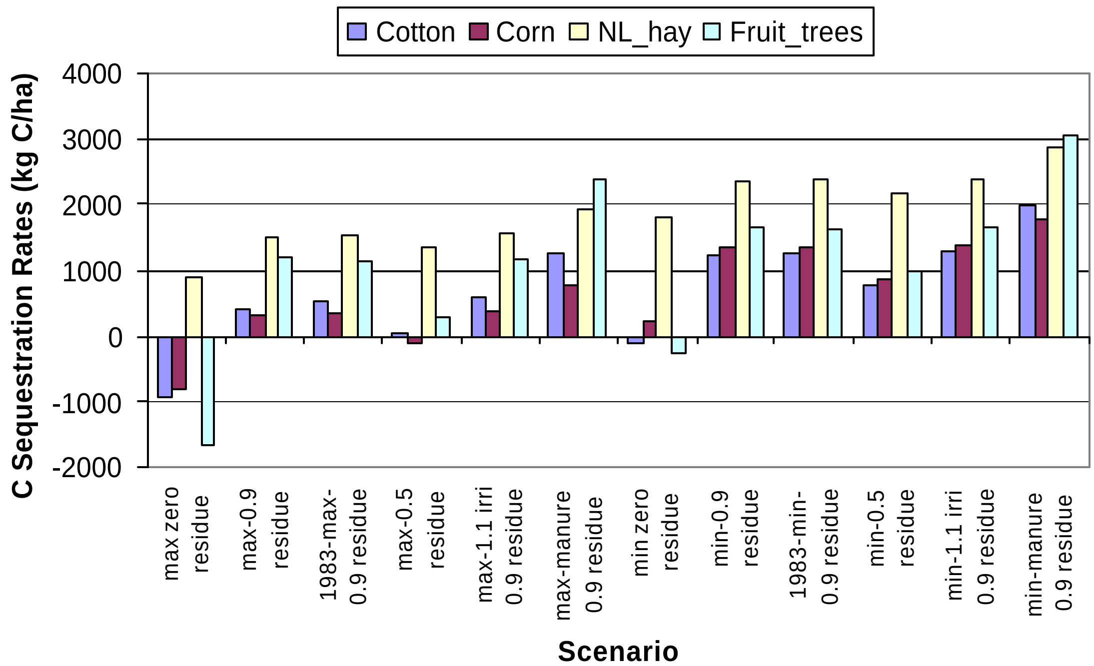


Figure 18. Average carbon sequestration rates by crop and management scenario for cotton, corn, non-legume hay, and deciduous fruit trees

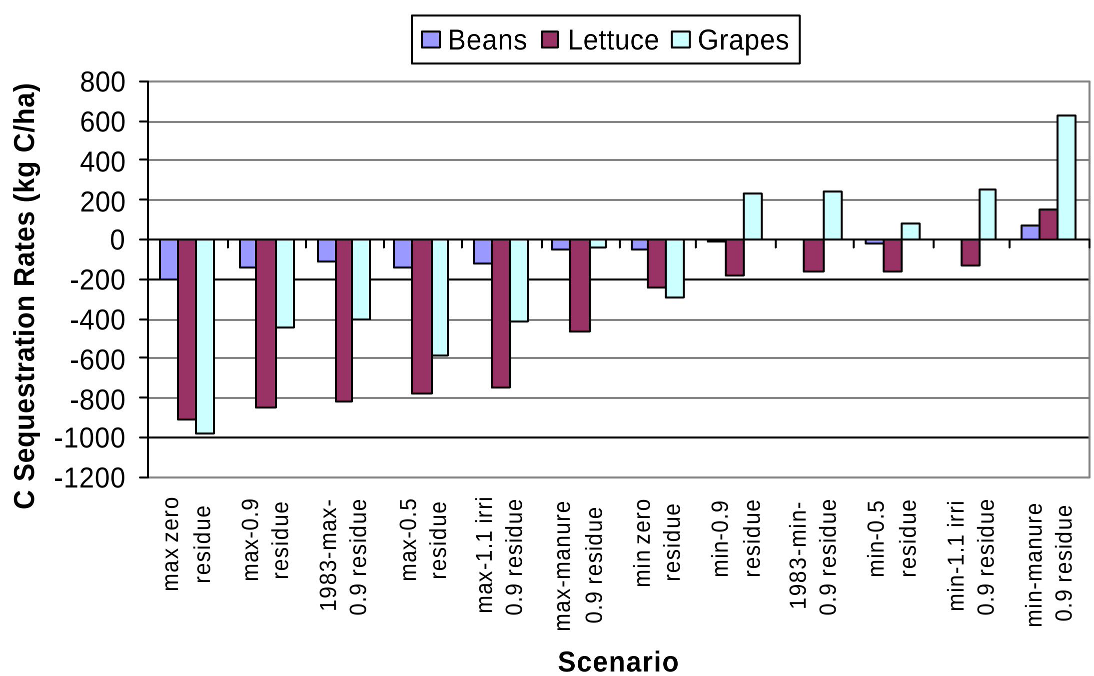


Figure 19. Average carbon sequestration rates by crop and management scenario for beans, lettuce, and grapes

Additional management scenarios are being considered for sequestering carbon in agricultural soils: including a change in tillage through adoption of either reduced tillage or no-till, use of cover crops, and reduction in overall fertilizer application rates (see next steps discussion in Section 7).

5.3. Multiyear Analysis

For Sutter and Fresno counties, we used climate data from 1980 through 1997 to examine longer-term carbon dynamics. The modeled results illustrate that the interannual changes in SOC basically follow a general shape of parabolic curves. The results are consistent with the consensus that after long-term cultivation changes in soil carbon stocks can be minimal as the system reaches a new “equilibrium” if the climate, soil type, and land use system have been constant during the entire time span. In the real world, especially in agricultural soils, this is rarely the case, as farming practices are not constant year by year. In fact, for most agricultural soils, SOC content is dynamic and never reaches equilibrium. For a long-term simulation such as 18 years in this study, the SOC in the first several years is always in a transition from the user-defined initial content toward a new equilibrium with higher rates of change than in the later years. Figures 20 through 23 all illustrate these general patterns of carbon dynamics simulations in DNDC, although the parabolic curves are not absolutely smooth, due to the interannual variations in the climatic conditions. However, the results indicate that:

- under constant management conditions, SOC approaches an equilibrium for all of the cropping systems;
- different cropping systems affect SOC dynamics differently, mainly driven by the amount of crop litter incorporation;
- initial SOC content has a large impact on net carbon dynamics and the rate at which the system approaches equilibrium; and
- lower SOC leads to higher sequestration rates.

Based on the above-described results, long-term C sequestration cannot be calculated by simply multiplying one year of observed SOC change. Only process-based models can provide a reasonable solution for estimating multiyear SOC dynamics.

Figure 24 illustrates the large interannual variability of N_2O emissions attributable to differences in timing of precipitation, irrigation, and fertilization. It is also clear that the magnitude of interannual variability of N_2O emissions is related in part to SOC conditions (likely influencing DOC concentrations). In this case, higher SOC leads to higher interannual variability.

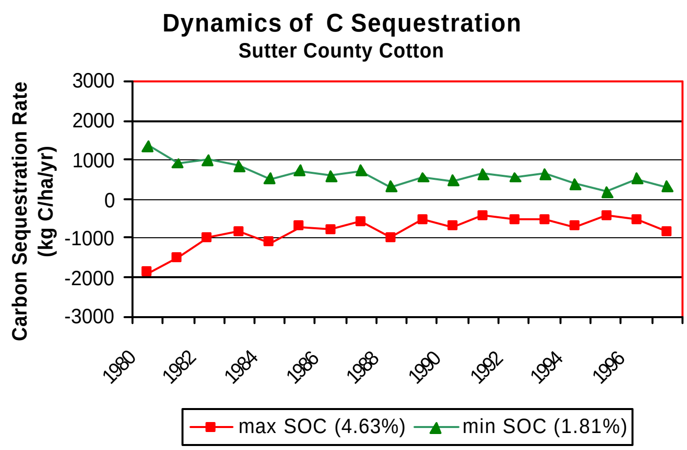


Figure 20. Long-term soil carbon dynamics for cotton in Sutter county

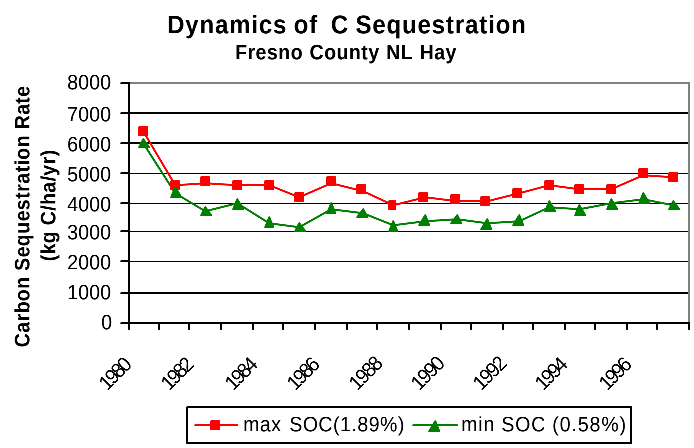


Figure 21. Long-term soil carbon dynamics for non-legume hay in Fresno county

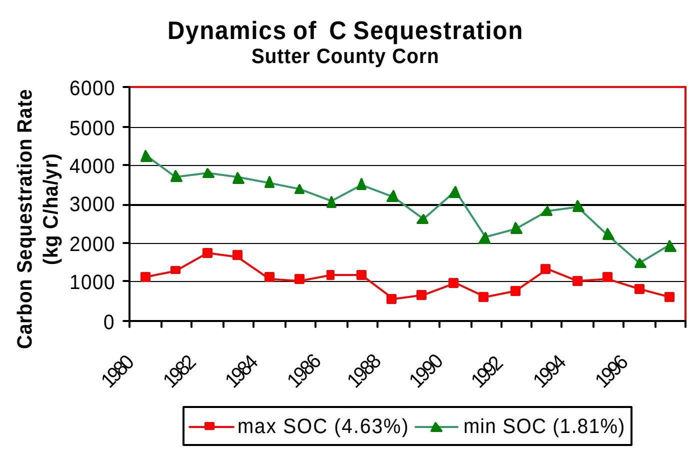


Figure 22. Long-term soil carbon dynamics for corn in Sutter county

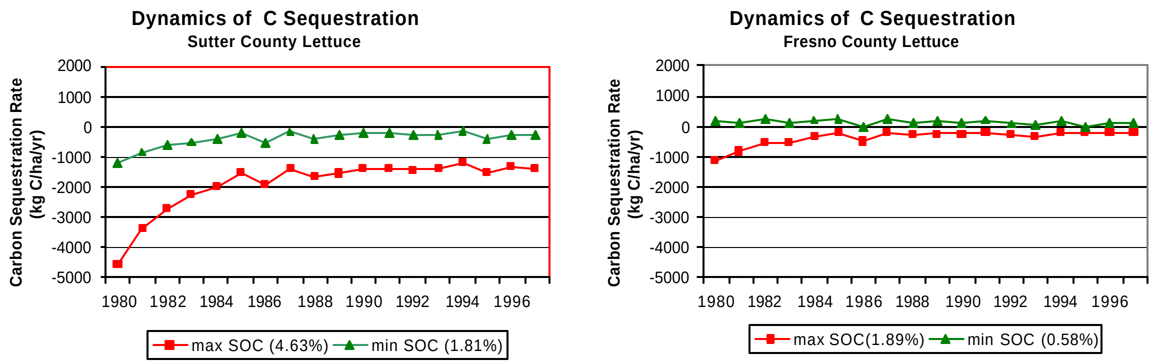


Figure 23. Long-term soil carbon dynamics for lettuce in Sutter and Fresno counties

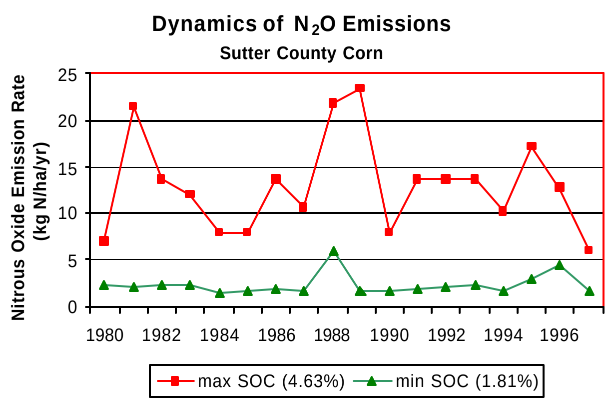


Figure 24. Interannual variability in N_2O Emission for corn in Sutter county

6.0 Conclusions

The modeled SOC dynamics or N_2O emissions presented in this report are provided in ranges, although we do not know exactly where the “real” values are located within the specified ranges. A large uncertainty in our analysis comes from crop residue incorporation estimates. In the baseline scenario, we assume 50% of aboveground residue was incorporated after harvest. Clearly, this assumption is a starting point to illustrate the impact of residue management on carbon dynamics and GHG emissions and does not represent actual management practices for all crops and all counties.

Figures 25 and 26 illustrate that an assumption of 90% residue incorporation results in model estimates of total and rates of carbon sequestration are much higher than the baseline example (Figures 11 and 12). For example, we are currently obtaining publications (Jenkins et al. 1992; Jenkins and Turn 1994) that indicate a big portion (84% for almonds and 95% for walnuts) of fruit-tree residue is burned on an annual basis (CEC 2002). If this is a case for most cropping systems, the predicted C sequestration rates should be significantly reduced. To illustrate this point, we ran a scenario for another extreme where 100% of the aboveground residue was removed from the field (0% aboveground residue incorporation). In this case, agricultural soils in California were either a small sink (0.4Tg) or significant source (7.8 Tg) of carbon.

On the other hand, although no manure was applied for our baseline scenario, we know that in some regions, especially counties with many dairies, that manure effluent is indeed applied to forage crops. If any manure is applied, then the C sequestration rate will be increased, relative to the baseline estimates. Obtaining better management data, especially for manure use and residue incorporation, will substantially improve the modeled results and should be the focus of a more detailed study for up to few counties.

However, even though the provided SOC dynamics and N_2O emissions estimates have large uncertainties, we are still able to assess the impact of various management scenarios by looking at modeled ranges which are comparable using their maximum and minimum values. Utilizing this methodology, we have distinguished the most important crops and counties regarding their contributions to carbon sequestration and/or N_2O emissions in California. We expect this pilot study will provide a sound basis for more comprehensive assessments on GHG inventory and mitigation in California.

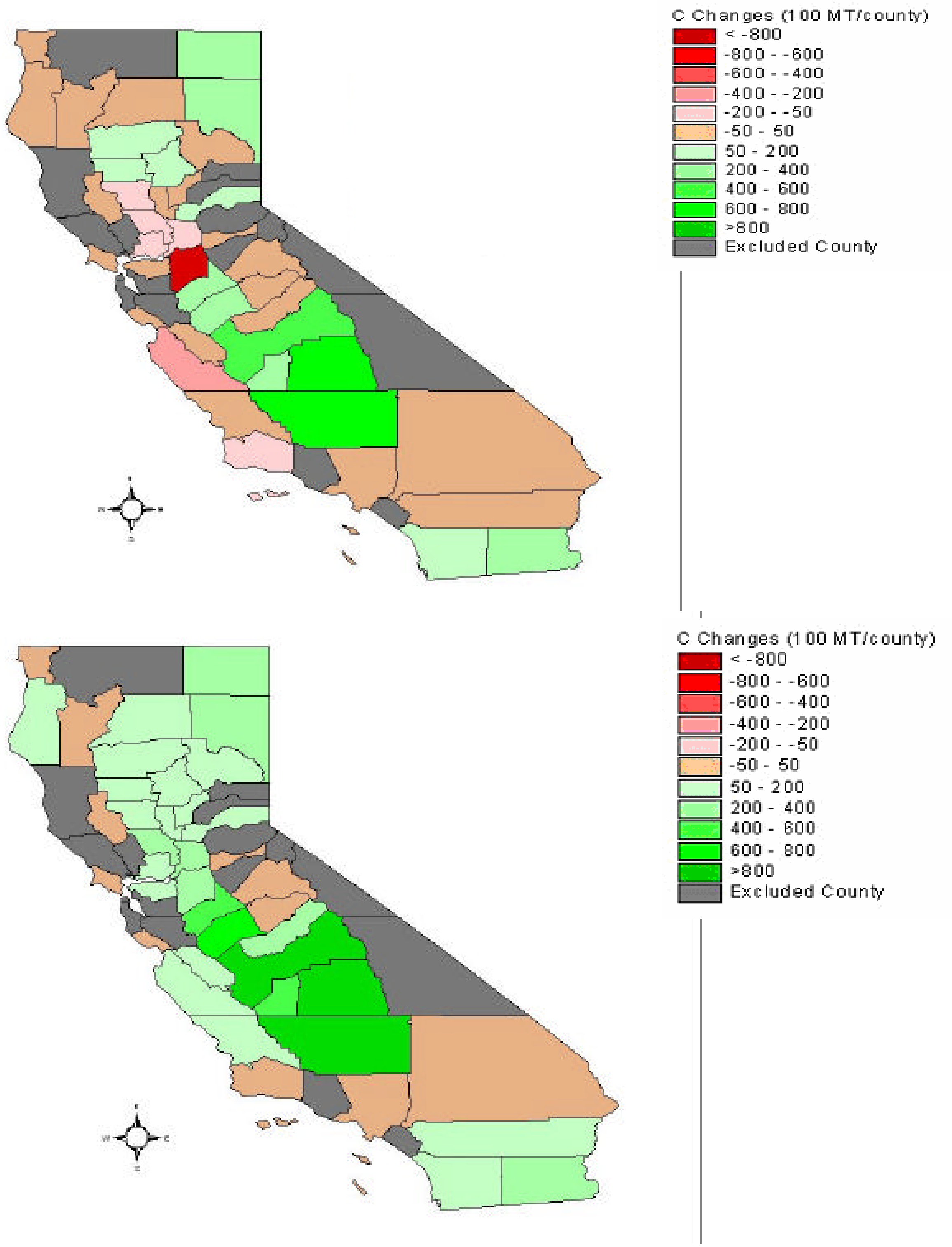


Figure 25. County carbon sequestration totals for 90% residue incorporation scenario. Higher and lower initial SOC content are presented in the upper and lower graphics, respectively.

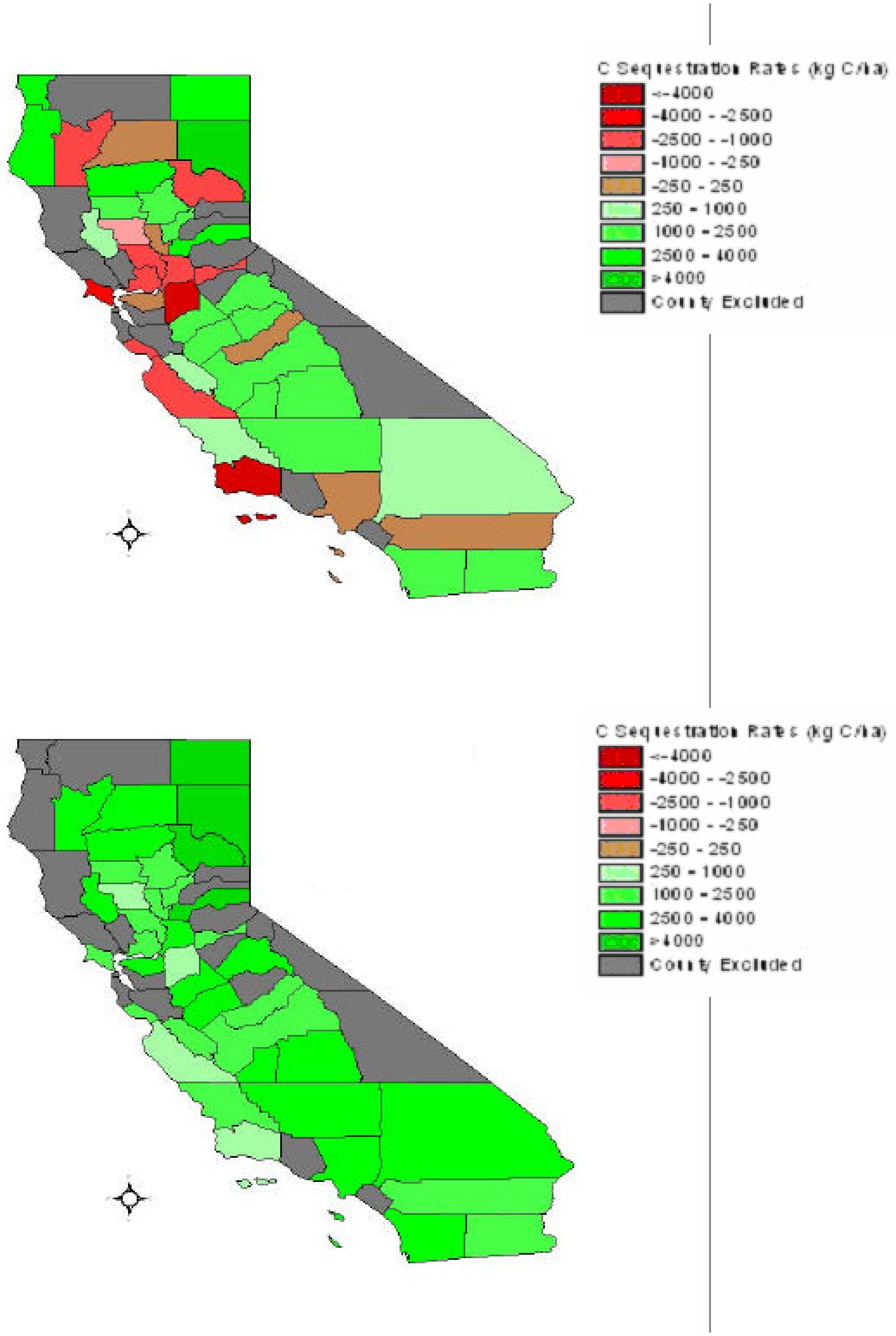


Figure 26. Average county carbon sequestration rates for 90% residue incorporation scenario. Higher and lower initial SOC content are presented in upper and lower graphics, respectively.

Because DNDC has a unique capability to simulate SOC dynamics, N_2O emissions, and CH_4 fluxes from aerobic and anaerobic soils, we compared 100-year GWP across counties in California (Figures 27–28). There is a wide range in both the sign and magnitude of GWP ranges across counties, suggesting that opportunities for mitigating GHG emissions vary across California. For paddy rice, our model estimates indicate emissions factors across counties ranging from 243 to 347 kg CH_4 / ha. These factors are 2 to 3 times the factor used in the CEC emission inventory report (CEC 2002). This large difference is likely due to the residue incorporation assumption and to a smaller degree the use of winter flooding. We assumed 90% residue incorporation, the CEC factor assumes a significant amount of residue burning. It is well known that rice straw incorporation can lead to increased CH_4 fluxes from rice cultivation in California (Fitzgerald et al. 2000; Cicerone et al. 1992).

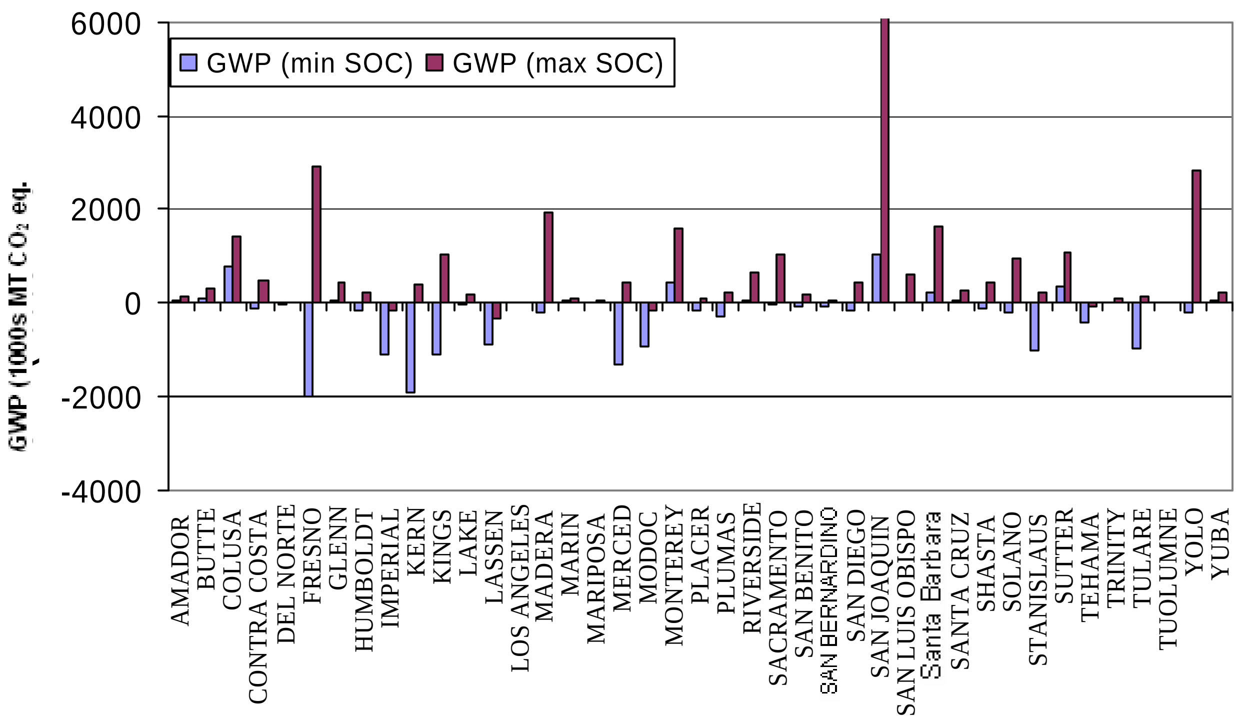


Figure 27. County 100-year GWP ranges from the baseline scenario

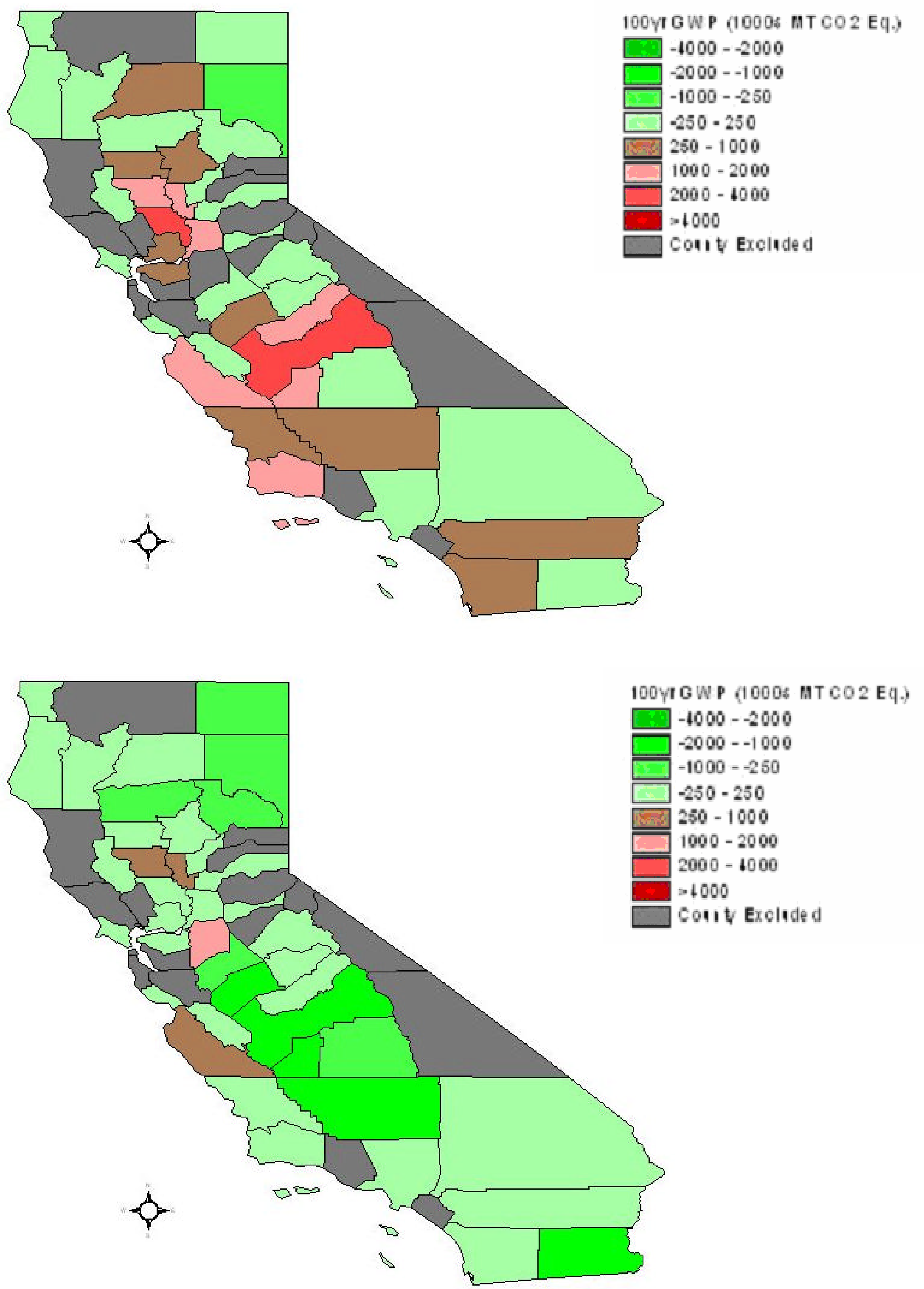


Figure 28. Net GWP from agricultural soils. Higher and lower initial SOC content are presented in the upper and lower graphics, respectively.

7.0 Research Recommendations

Based on the estimates of soil carbon dynamics and GHG emissions provided in this scoping study, it is clear that there are large uncertainties in carbon dynamics and GHG emissions from agricultural soils in California as a whole. We contend that there is a relatively good understanding of the general processes that control soil carbon dynamics and GHG emissions and models exist to perform reliable inventories and assessment of GHG mitigation opportunities. Thus, the bulk of the uncertainty is a result of the quality of two critical inputs for modeling soil carbon dynamics and GHG emissions in agricultural systems of California:

1. **Quantification of management practices at the landscape scale**
2. **Soil carbon databases**

Based on our modeling analysis, the range (or uncertainty) in average carbon sequestration rates across the 0% to 90% residue incorporation management scenarios was comparable to the uncertainty range in sequestration rates attributable to soil carbon minimum and maximum values for each management scenario. Figure 17 shows these ranges in uncertainty. We compared the mid-point (average of minimum and maximum values) for each range carbon sequestration rate estimates for the 0% and 90% residue incorporation scenarios. Their difference in rates was 2,430 kg C / ha, which is comparable to the ranges provided for the individual 0%, 50%, and 90% residue incorporation scenarios (1,748, 1,770, and 2,153 kg C / ha, respectively). Therefore, the lack of good data on residue management and the large range in soil carbon estimates at the county scale contributed equally to the large uncertainties in our model estimates.

Clearly, the uncertainties in this modeling analysis can be reduced significantly using existing data that are available but were beyond the scope of this study. The following recommendations highlight a couple of improvements that focus on using better spatial resolution data for California: (1) move beyond county averages in terms of soil characteristics (e.g., organic soils in San Joaquin) and climate conditions (use gridded climate data across each county rather than a single location, like the centroid approach used in the scoping study), and (2) use regionally specific crop fertilizer practices based on local climate and soils

The following recommendations are made to improve understanding of overall carbon dynamics and GHG emissions in California, ability to assess California-specific mitigation alternatives and for improving techniques for compiling emission inventories for California:

- ***Management Data Collection***. A program to collect data on agricultural management practices is needed. Data collection should be conducted to obtain a better spatial representation of management practices to account for regional and cropping system differences. The critical data needs include residue management and manure amendment. These data are required to more accurately estimate soil C inputs. Residue management practices have changed significantly in California in response to past regulatory actions, such as the Rice Straw Burning Reduction Act of 1991 and more recent bans on burning agricultural residue (e.g., the SB 705 goal to phase out open field burning of agricultural waste). California has approximately 2,700 dairies, which generate over 30 million tons of manure annually. Land application of manure can have a large impact on soil carbon stocks and direct and indirect GHG emissions. Data on regional patterns of manure quality (e.g., C / N ratio), manure application rates (lb. / acre), and application methods / forms (e.g., liquid slurry, solids) would be useful.

- ***GIS Soil Databases.*** Soil properties, in particular SOC content, have a significant influence on carbon dynamics and trace gas emissions. STATSGO soil survey data (1:250,000 scale) were used for the scoping study. Tables 5, 6, and 7 in the Supplemental Tables and Figures contain the area-weighted statistics by major crop type for each county based on the STATSGO GIS database. The large range in soil properties for a given agricultural area translates into very large uncertainties in model estimates. Fortunately, NRCS is already addressing this need. It has been compiling an improved soil survey data called the Soil Survey Geographic (SSURGO) database, with mapping scales ranging from 1:12,000 to 1:63,360. As of December 2003, over 80% of the data from the San Joaquin Valley, Sacramento Valley, and Central Coast regions of California have been entered into the SUSRGO database, and ultimately, NRCS plans to include data for the entire state. Use of the improved spatial and thematic resolution SUSRGO data will improve model estimates of carbon dynamics and GHG emissions.
- ***Further model validation.*** Although DNDC has been validated across a wide range of agroecosystems worldwide (see Section 4), additional validation is important to quantify how well the model performs in simulating carbon dynamics, and N_2O and CH_4 emissions for the wide range in Californian agroecosystems. We recommend two parallel activities: (1) perform model validation using existing field data on carbon dynamics (e.g., DeClerck et al. 2003), CH_4 emissions (e.g., Cicerone et al. 1992; Fitzgerald et al. 2000; Lauren et al. 1994) and N_2O emissions (e.g., Venterea and Rolston 2000) for California, and (2) develop a field measurement program to cover critical gaps in field data across a range of major crops and management systems. Models can be useful for prioritizing field measurements needs based on previous validation studies and simulations to identify potential large ranges in emissions across climate, crops, and management systems.
- ***Evaluation of additional management scenarios***. This scoping study covered management scenarios focusing on residue incorporation, manure management, and irrigation. However, several additional scenarios should be considered for studying mitigation alternatives, including for example:
- no-till, conservation tillage, and conventional tillage;
- optimized fertilizer application rates (see Table 2 for baseline application rates); and
- use of cover crops.

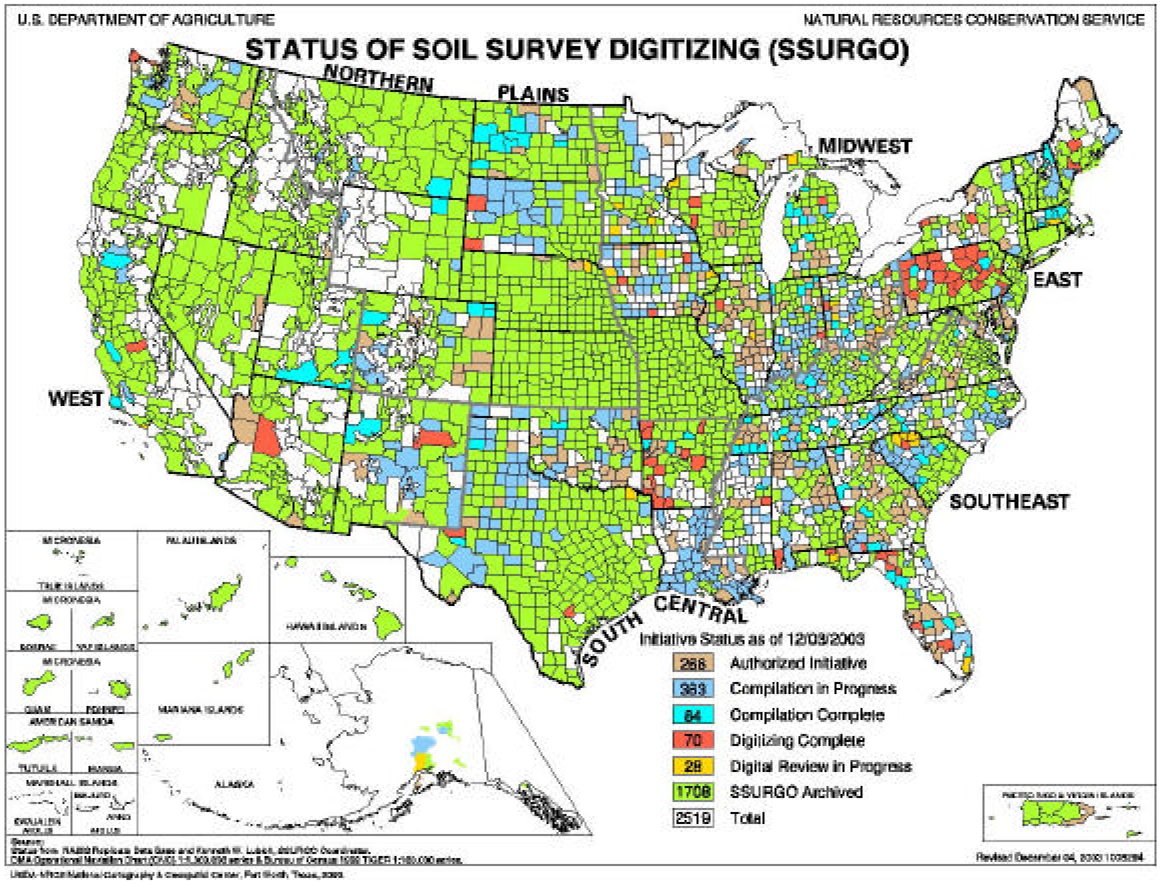


Figure 29. SUSRGO GIS database development status as of December 2003

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9.0 Supplemental Tables and Figures

Table 3. County crop areas for grains and field crops (in hectares)

County	Cotton	Beets	Corn	Sorghum	Beans	Sunflower	Barley	Wheat	Oats
AMADOR	0	23	387	0	0	0	108	108	108
BUTTE	0	1,139	2,291	0	1,056	359	0	5,135	0
COLUSA	6,284	470	4,754	234	2,748	606	99	13,556	0
CONTRA COSTA	0	0	5,666	0	164	0	953	953	953
DEL NORTE	11	0	11	0	0	0	0	0	0
FRESNO	188,756	7,272	10,501	0	726	5	11,607	11,607	11,607
GLENN	401	376	9,493	227	1,653	2,933	672	9,169	727
HUMBOLDT	0	0	260	0	37	0	319	319	319
IMPERIAL	161	27,535	2,604	0	50	0	1,476	42,489	158
KERN	105,798	2,300	14,968	403	3,510	0	47,908	0	0
KINGS	134,339	140	30,700	1,391	5	0	9,649	9,649	9,649
LAKE	145	0	146	0	0	0	14	63	752
LOS ANGELES	0	0	0	0	0	0	0	0	0
LASSEN	0	63	10	3	1,296	0	32	2,451	3,093
MADERA	20,956	159	6,343	15	3,515	0	11,298	0	0
MARIN	0	0	0	0	0	0	637	637	637
MARIPOSA	0	0	0	0	0	0	2	2	2
MERCED	38,543	3,486	25,056	0	68	0	5,056	5,056	5,056
MODOC	101	1,691	100	0	1,895	0	9,939	1,945	452
MONTEREY	0	35	2,593	0	0	0	5,060	5,060	5,060
PLACER	0	0	433	0	0	0	822	822	822
PLUMAS	0	0	0	0	0	0	377	0	0
RIVERSIDE	0	0	817	0	323	0	4,205	11,883	2,326
SACRAMENTO	0	1,190	22,209	390	0	0	453	7,522	0
SAN BENITO	0	85	1,721	0	0	0	3,140	3,140	3,140
SAN BERNARDINO	0	0	1,030	0	0	0	120	0	1,139
SAN DIEGO	0	0	70	0	6,868	648	38	1,421	2,107
SAN JOAQUIN	0	2,729	38,457	247	20	0	10,148	10,148	10,148
SAN LUIS OBISPO	0	0	343	0	1,697	0	33,462	4,180	14,957
SANTA BARBARA	0	0	446	0	0	0	0	2,827	2,928
SANTA CRUZ	0	0	47	0	0	0	46	46	46
SHASTA	0	227	175	5	2,042	1,633	743	66	531
SOLANO	0	4,107	11,390	20	12,675	1	9,209	9,209	9,209
STANISLAUS	29	27	24,651	0	3,977	263	1,875	1,875	1,875
SUTTER	1,139	1,528	12,027	99	173	88	0	0	7,925
TEHAMA	0	157	2,135	0	5,101	15	449	5,087	798
TRINITY	2	0	2	0	0	0	0	0	69
TULARE	32,627	1,821	47,216	1,167	786	2,855	28,769	0	0
TUOLUMNE	0	0	0	0	0	0	0	0	0
YOLO	3,535	2,052	30,681	617	39	0	10,001	10,001	10,001
YUBA	0	0	625	0	0	0	0	0	554

Table 4. County crop areas for pasture, rice, truck crops, deciduous fruits, citrus, and vineyards (in hectares)

County	Alfalfa	NL Hay	Citrus	Deciduous	Rice	Lettuce	Tomato	Vineyards
AMADOR	117	914	11	354	0	41	41	1357
BUTTE	1321	3439	2910	35492	49076	100	100	17
COLUSA	3185	1633	48	15653	58564	8376	8376	760
CONTRA COSTA	1622	2865	2	2837	0	1425	1425	372
DEL NORTE	0	3806	0	2	0	265	265	0
FRESNO	35386	7172	13411	54213	1931	39475	39475	98238
GLENN	5601	9959	2472	19966	36907	759	759	625
HUMBOLDT	192	16914	3	55	0	108	108	2
IMPERIAL	75197	18479	2869	13	0	19849	19849	108
KERN	43473	3730	20168	72005	0	16906	16906	41842
KINGS	17637	1619	464	12053	0	2945	2945	2100
LAKE	149	2404	19	6870	477	10	10	1581
LOS ANGELES	0	0	15	0	0	4	4	0
LASSEN	15252	27467	0	6	292	198	198	0
MADERA	14637	4688	2689	37263	173	964	964	36811
MARIN	0	645	43	3	0	22	22	51
MARIPOSA	0	1327	4	34	0	0	0	66
MERCED	32950	24151	146	47111	2276	7994	7994	7606
MODOC	15480	39038	0	31	1456	1843	1843	0
MONTEREY	937	1169	674	273	0	33141	33141	17169
PLACER	6	7516	75	1288	8641	101	101	39
PLUMAS	2586	13802	0	2	0	92	92	0
RIVERSIDE	3511	3054	8535	153	0	1669	1669	348
SACRAMENTO	2988	12491	165	3613	4618	2037	2037	10707
SAN BENITO	531	439	0	2964	0	3925	3925	1094
SAN BERNARDINO	1076	1637	3224	215	0	569	569	1824
SAN DIEGO	29	2748	23552	288	0	3469	3469	63
SAN JOAQUIN	24850	14200	106	43448	2424	16765	16765	31120
SAN LUIS OBISPO	1711	2888	1330	6291	0	5247	5247	5731
SANTA BARBARA	1037	2565	4546	921	0	11179	11179	4970
SANTA CRUZ	4	454	20	1724	0	3346	3346	24
SHASTA	2366	17016	409	789	1171	211	211	15
SOLANO	9233	7586	41	5655	0	5002	5002	944
STANISLAUS	13989	25657	284	56146	1191	5329	5329	6426
SUTTER	2040	2636	180	27981	42858	6641	6641	39
TEHAMA	2147	13006	6448	14482	1281	98	98	72
TRINITY	16	946	0	42	0	7	7	23
TULARE	39562	3311	55902	50362	0	1712	1712	34668
TUOLUMNE	230	230	0	106	0	5	5	2
YOLO	16865	0	122	10424	12306	13024	13024	3819
YUBA	5802	0	392	13802	15782	90	90	184

Table 5. STATSGO county soils data for deciduous fruits and nuts, citrus, and vineyard crop group

COUNTY	SOC (%)		Clay Fraction		pH		Bulk Density	
	A.W.Max	A.W.Min	A.W.Max	A.W.Min	A.W.Max	A.W.Min	A.W.Max	A.W.Min
AMADOR	4.52	1.70	0.19	0.09	6.86	5.72	1.30	1.15
BUTTE	2.74	0.92	0.27	0.18	7.59	6.07	1.54	1.41
COLUSA	2.97	1.31	0.34	0.24	7.41	6.18	1.52	1.39
CONTRA COSTA	2.23	1.07	0.52	0.34	8.38	5.92	1.56	1.42
DEL NORTE	2.00	1.00	0.20	0.10	6.00	5.00	1.20	1.10
FRESNO	1.11	0.53	0.21	0.10	8.00	6.10	1.57	1.46
GLENN	1.50	0.68	0.23	0.15	7.36	5.74	1.55	1.44
HUMBOLDT	5.75	2.53	0.20	0.10	6.91	5.77	1.48	1.36
IMPERIAL	0.74	0.24	0.11	0.04	8.40	7.66	1.62	1.52
KERN	0.93	0.43	0.20	0.10	8.33	7.24	1.58	1.48
KINGS	1.94	0.97	0.19	0.11	8.36	6.56	1.60	1.49
LAKE	2.79	0.95	0.28	0.18	7.19	5.69	1.37	1.29
LOS ANGELES	3.00	1.00	0.34	0.23	8.26	6.10	1.49	1.36
LASSEN	2.00	1.00	0.15	0.10	8.40	7.40	1.55	1.45
MADERA	1.65	0.57	0.19	0.09	7.65	6.10	1.56	1.46
MARIN	3.00	1.00	0.30	0.18	7.30	5.60	1.50	1.40
MARIPOSA	1.39	3.70	0.12	0.23	5.36	6.70	1.18	1.39
MERCED	1.57	0.63	0.15	0.09	7.75	6.19	1.62	1.51
MODOC	2.95	1.12	0.26	0.17	7.30	6.10	1.27	1.16
MONTEREY	2.99	1.22	0.26	0.15	7.16	5.44	1.46	1.35
PLACER	3.25	1.10	0.21	0.10	7.14	5.56	1.55	1.33
PLUMAS	2.30	1.00	0.22	0.13	6.74	5.40	1.50	1.38
RIVERSIDE	1.57	0.64	0.20	0.12	7.97	6.34	1.58	1.46
SACRAMENTO	4.08	1.10	0.31	0.20	7.18	5.83	1.51	1.41
SAN BENITO	2.77	1.00	0.52	0.35	8.13	6.02	1.44	1.34
SAN BERNARDINO	3.00	1.00	0.41	0.29	8.09	6.10	1.47	1.32
SAN DIEGO	1.06	0.49	0.18	0.08	7.26	5.48	1.59	1.49
SAN JOAQUIN	3.10	1.16	0.28	0.18	7.86	6.58	1.57	1.46
SAN LUIS OBISPO	1.08	0.52	0.19	0.09	7.25	5.55	1.60	1.50
SANTA BARBARA	3.28	0.94	0.22	0.12	7.13	5.86	1.59	1.47
SANTA CRUZ	2.94	0.89	0.34	0.21	7.73	5.63	1.46	1.37
SHASTA	1.71	0.62	0.19	0.10	7.68	5.73	1.55	1.45
SOLANO	6.55	1.46	0.46	0.36	7.55	6.00	1.39	1.26
STANISLAUS	2.15	0.83	0.22	0.14	7.92	6.29	1.58	1.47
SUTTER	3.97	1.01	0.27	0.20	7.79	6.11	1.50	1.40
TEHAMA	1.07	0.50	0.19	0.10	7.52	5.64	1.58	1.48
TRINITY	9.88	4.45	0.18	0.07	6.54	5.18	1.49	1.35
TULARE	1.22	0.60	0.27	0.15	7.31	6.02	1.52	1.42
TUOLUMNE	4.88	1.95	0.21	0.11	6.52	5.17	1.35	1.11
YOLO	6.57	1.50	0.46	0.34	7.54	5.97	1.39	1.27
YUBA	2.94	0.82	0.26	0.18	7.26	5.87	1.53	1.43

Table 6. STATSGO county soils data for grains, field crops, and truck crop group

COUNTY	SOC (%)		Clay Fraction		pH		Bulk Density	
	A.W.Max	A.W.Min	A.W.Max	A.W.Min	A.W.Max	A.W.Min	A.W.Max	A.W.Min
AMADOR	2.73	1.72	0.17	0.06	7.48	6.12	1.52	1.45
BUTTE	2.63	0.93	0.30	0.19	7.78	6.10	1.54	1.41
COLUSA	4.12	1.80	0.42	0.32	7.79	6.65	1.52	1.35
CONTRA COSTA	5.70	1.60	0.50	0.34	8.01	5.61	1.48	1.35
DEL NORTE	4.23	1.93	0.23	0.15	7.39	6.28	1.45	1.34
FRESNO	1.89	0.58	0.52	0.35	8.42	7.28	1.44	1.26
GLENN	1.99	0.89	0.27	0.18	7.04	5.68	1.54	1.42
HUMBOLDT	3.90	1.78	0.22	0.14	7.36	6.25	1.48	1.38
IMPERIAL	0.53	0.03	0.18	0.09	8.40	7.87	1.52	1.42
KERN	0.68	0.17	0.20	0.11	8.78	7.37	1.56	1.46
KINGS	2.00	1.00	0.51	0.41	8.40	7.23	1.48	1.30
LAKE	5.22	1.72	0.28	0.18	7.01	5.54	1.33	1.21
LOS ANGELES	3.00	1.00	0.27	0.18	8.40	6.10	1.50	1.40
LASSEN	2.97	1.46	0.30	0.21	7.75	6.63	1.42	1.29
MADERA	2.15	0.62	0.20	0.11	8.55	6.80	1.54	1.44
MARIN	3.65	1.65	0.23	0.13	6.77	5.60	1.53	1.43
MARIPOSA	2.00	1.00	0.25	0.12	7.30	5.60	1.55	1.40
MERCED	2.18	0.77	0.28	0.21	8.41	7.01	1.51	1.40
MODOC	2.73	1.24	0.23	0.15	7.94	6.62	1.45	1.30
MONTEREY	2.94	1.10	0.36	0.24	7.75	5.78	1.44	1.33
PLACER	1.91	0.88	0.20	0.11	7.07	5.58	1.66	1.54
PLUMAS	10.82	3.61	0.40	0.26	7.30	6.10	1.24	1.11
RIVERSIDE	1.46	0.61	0.22	0.13	8.20	6.78	1.55	1.44
SACRAMENTO	5.14	1.25	0.35	0.25	7.30	5.98	1.47	1.37
SAN BENITO	2.70	1.00	0.51	0.35	8.07	6.52	1.47	1.36
SAN BERNARDINO	2.39	0.84	0.25	0.16	8.17	6.02	1.50	1.40
SAN DIEGO	1.43	0.58	0.19	0.09	6.81	5.62	1.54	1.44
SAN JOAQUIN	7.07	2.39	0.39	0.28	8.00	6.32	1.48	1.35
SAN LUIS OBISPO	1.40	0.57	0.20	0.10	7.39	5.88	1.59	1.49
SANTA BARBARA	3.47	0.92	0.17	0.07	7.59	6.71	1.59	1.49
SANTA CRUZ	2.94	0.89	0.33	0.21	7.73	5.63	1.46	1.37
SHASTA	3.12	1.57	0.19	0.10	7.21	5.83	1.62	1.52
SOLANO	4.05	1.44	0.49	0.36	8.01	6.63	1.50	1.31
STANISLAUS	1.93	0.82	0.30	0.20	8.10	6.26	1.56	1.45
SUTTER	4.63	1.81	0.50	0.37	8.21	7.16	1.51	1.32
TEHAMA	1.08	0.51	0.20	0.11	7.19	5.47	1.57	1.47
TRINITY	4.89	2.20	0.20	0.13	6.90	5.80	1.38	1.15
TULARE	1.21	0.60	0.26	0.17	8.55	7.09	1.55	1.43
TUOLUMNE	3.59	1.39	0.24	0.12	6.65	5.60	1.33	1.15
YOLO	5.00	1.70	0.51	0.36	8.04	6.81	1.47	1.30
YUBA	1.30	0.55	0.25	0.15	6.62	5.63	1.59	1.49

Table 7. STATSGO county soils data for the pasture class

COUNTY	SOC (%)		Clay Fraction		pH		Bulk Density	
	A.W.Max	A.W.Min	A.W.Max	A.W.Min	A.W.Max	A.W.Min	A.W.Max	A.W.Min
AMADOR	2.54	1.53	0.18	0.08	7.30	5.79	1.53	1.45
BUTTE	3.41	1.16	0.35	0.23	7.51	6.13	1.52	1.37
COLUSA	3.59	1.56	0.40	0.28	7.61	6.45	1.52	1.37
CONTRA COSTA	4.69	1.42	0.55	0.37	8.26	5.88	1.48	1.34
DEL NORTE	3.95	1.91	0.24	0.17	7.64	6.47	1.46	1.35
FRESNO	1.55	0.66	0.31	0.20	8.51	6.94	1.52	1.40
GLENN	1.66	0.79	0.24	0.16	6.80	5.42	1.55	1.43
HUMBOLDT	4.11	2.02	0.25	0.17	7.69	6.51	1.45	1.35
IMPERIAL	0.53	0.03	0.17	0.08	8.41	7.87	1.54	1.44
KERN	0.54	0.03	0.18	0.10	8.94	7.38	1.55	1.45
KINGS	2.00	1.00	0.43	0.34	8.40	7.07	1.51	1.35
LAKE	4.97	1.79	0.26	0.15	6.97	5.56	1.28	1.16
LOS ANGELES	3.00	1.00	0.27	0.18	8.40	6.10	1.50	1.40
LASSEN	3.22	1.49	0.36	0.24	7.86	6.75	1.33	1.21
MADERA	2.15	0.62	0.21	0.12	8.99	7.13	1.52	1.42
MARIN	3.26	1.26	0.40	0.27	7.35	5.86	1.49	1.34
MARIPOSA	3.19	1.18	0.21	0.11	6.62	5.44	1.33	1.11
MERCED	2.11	0.73	0.26	0.19	8.47	6.98	1.52	1.42
MODOC	4.27	1.93	0.27	0.18	7.58	6.28	1.39	1.22
MONTEREY	4.17	1.56	0.28	0.18	7.61	5.78	1.35	1.25
PLACER	2.18	0.86	0.21	0.10	7.06	5.58	1.60	1.39
PLUMAS	8.66	2.89	0.35	0.25	7.18	6.03	1.31	1.16
RIVERSIDE	1.66	0.65	0.23	0.14	8.25	6.84	1.54	1.43
SACRAMENTO	2.18	0.78	0.27	0.17	6.84	5.75	1.56	1.47
SAN BENITO	2.83	1.00	0.53	0.36	8.35	6.94	1.50	1.37
SAN BERNARDINO	2.51	0.88	0.25	0.17	8.24	6.11	1.53	1.42
SAN DIEGO	1.77	0.65	0.24	0.13	7.18	5.78	1.54	1.43
SAN JOAQUIN	5.66	2.13	0.33	0.22	7.90	6.29	1.51	1.39
SAN LUIS OBISPO	1.09	0.53	0.19	0.09	7.26	5.60	1.60	1.50
SANTA BARBARA	3.46	0.91	0.16	0.07	7.36	5.79	1.59	1.49
SANTA CRUZ	3.00	1.00	0.57	0.38	8.84	7.72	1.54	1.39
SHASTA	3.52	1.44	0.20	0.12	6.94	5.56	1.54	1.43
SOLANO	4.36	1.69	0.50	0.36	8.24	7.07	1.53	1.33
STANISLAUS	1.80	0.72	0.23	0.14	7.93	6.22	1.58	1.47
SUTTER	3.43	1.22	0.37	0.26	7.62	6.44	1.53	1.39
TEHAMA	1.15	0.52	0.20	0.11	7.02	5.38	1.56	1.46
TRINITY	6.25	3.03	0.21	0.13	6.94	5.62	1.46	1.26
TULARE	1.13	0.54	0.23	0.15	8.87	7.33	1.56	1.45
TUOLUMNE	3.33	1.38	0.22	0.11	6.84	5.43	1.41	1.21
YOLO	5.26	1.80	0.51	0.37	8.12	6.94	1.47	1.30
YUBA	1.43	0.65	0.25	0.14	6.72	5.61	1.58	1.47

Table 8. STATSGO county soils data for rice paddy areas

COUNTY	SOC (%)		Clay Fraction		pH		Bulk Density	
	A.W.Max	A.W.Min	A.W.Max	A.W.Min	A.W.Max	A.W.Min	A.W.Max	A.W.Min
BUTTE	4.63	1.80	0.50	0.36	8.19	7.07	1.50	1.32
COLUSA	4.30	1.96	0.39	0.31	7.69	6.56	1.53	1.36
FRESNO	2.01	0.81	0.51	0.40	8.40	7.70	1.40	1.26
GLENN	3.50	1.65	0.32	0.26	7.36	6.13	1.54	1.39
LAKE	1.00	0.50	0.25	0.10	6.53	4.53	1.55	1.45
LASSEN	1.22	0.61	0.53	0.35	7.74	6.54	1.31	1.16
MERCED	1.25	0.60	0.29	0.20	9.32	7.76	1.44	1.34
MODOC	14.85	7.45	0.38	0.20	8.00	6.49	0.94	0.65
PLACER	1.15	0.57	0.24	0.14	6.62	5.60	1.62	1.51
SACRAMENTO	4.54	1.72	0.49	0.35	8.10	7.04	1.51	1.33
SAN JOAQUIN	1.10	0.53	0.16	0.06	7.32	5.64	1.60	1.50
SHASTA	4.81	2.85	0.18	0.09	6.75	5.65	1.56	1.46
STANISLAUS	2.16	1.02	0.19	0.09	7.37	5.98	1.55	1.47
SUTTER	3.45	1.39	0.42	0.30	7.66	6.66	1.54	1.38
TEHAMA	1.14	0.50	0.21	0.12	6.50	5.10	1.55	1.45
YOLO	4.89	1.95	0.55	0.39	8.38	7.35	1.50	1.30
YUBA	1.14	0.51	0.25	0.15	6.52	5.56	1.59	1.49

The following figures (30–32) illustrate the 50-year changes in SOC for pasture, row crop, and tree crop simulations for 3 of the 27 sites analyzed as part of our validation exercise using the DeClerck et al. (2003) data.

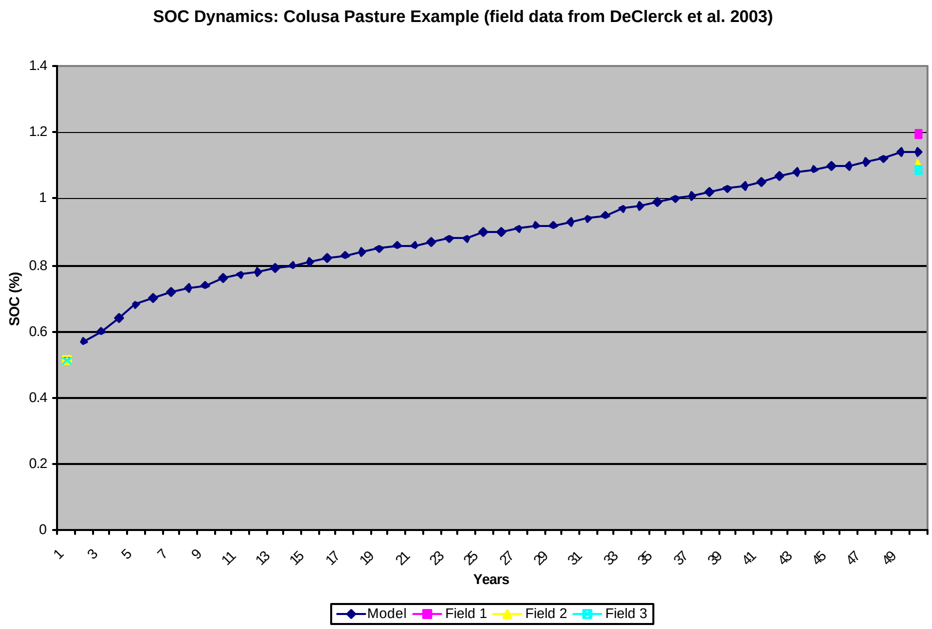

Figure 30. 50-year simulation for validation: Colusa county pasture example

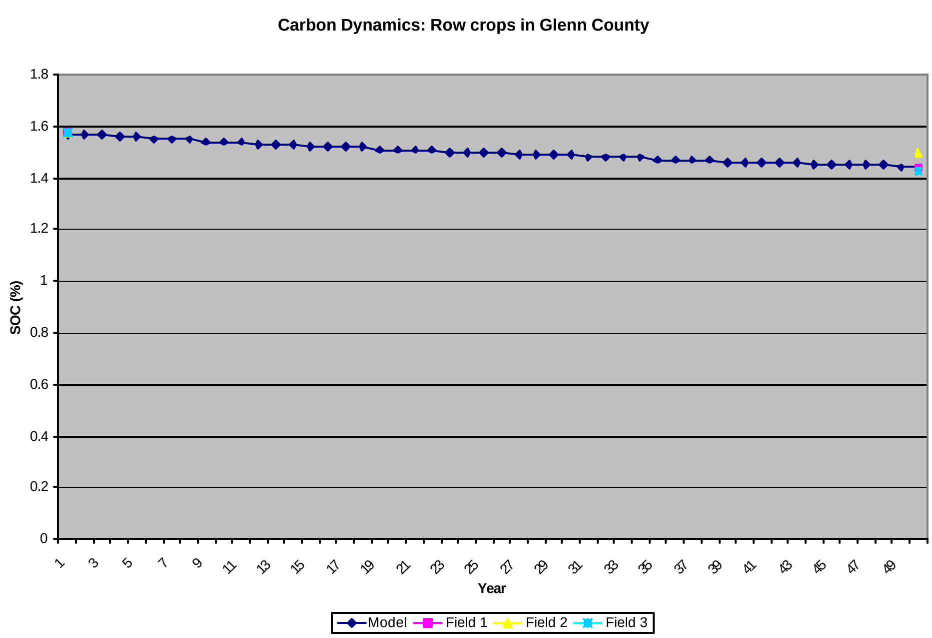

Figure 31. 50-year simulation for validation example for row crops in Glenn County

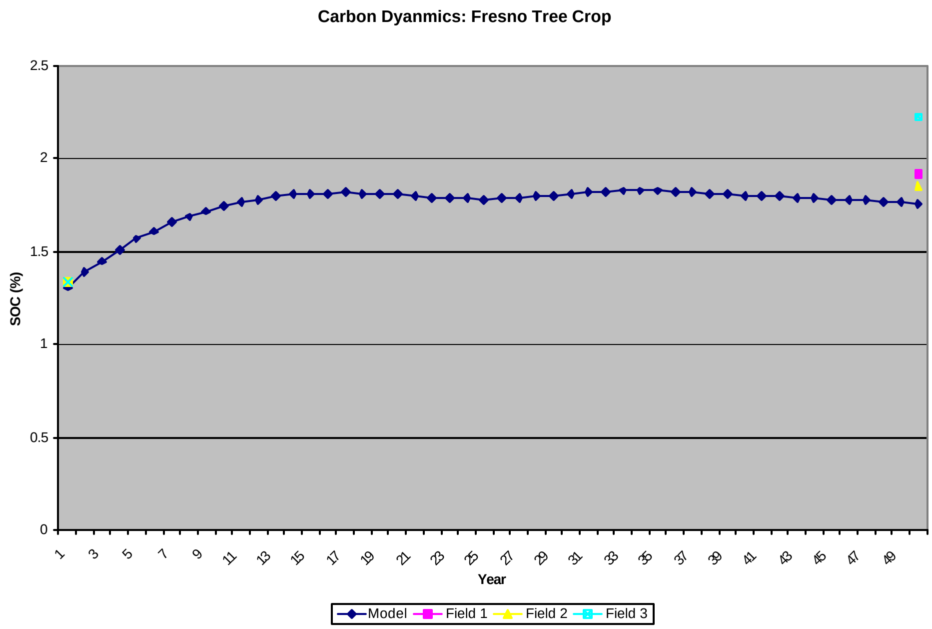

Figure 32. 50-year simulation for tree crops in Fresno