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Spatial analyses of pedosphere carbon stock and sequestration potential in Louisiana's watersheds

Biao Zhong
Louisiana State University and Agricultural and Mechanical College

SPATIAL ANALYSES OF PEDOSPHERE CARBON STOCK AND SEQUESTRATION POTENTIAL IN LOUISIANA'S WATERSHEDS

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By
Biao Zhong
B.S., Beijing Forestry University, 1998
M.S., Beijing Forestry University, 2001
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DEDICATION

This dissertation is dedicated to my father, mother, elder sister, and lifetime friends.

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ABSTRACT

This dissertation research aimed to quantify current soil organic carbon (SOC) stocks across Louisiana's landscape, examine the spatial relationships between SOC and terrain factors at the watershed and river basin scales, and predict SOC changes in surface soils during future climate change. Using Louisiana as an example, a spatially-explicit modeling framework was developed that is conducive to watershed-scale prediction of soil carbon stock and change. SOC densities at the watershed scale were estimated using the USDA NRCS Soil Geographic Database (STATSGO). Louisiana watersheds and National Land Cover Database (NLCD) were used to aggregate total soil carbon and estimate average soil carbon density. Watershed drainage densities and slopes were quantified with 1:24 K Digital Elevation Models (DEM) data and the Louisiana hydrographic water features. Potential changes in SOC under 0.5° x 0.5° high-resolution climate change projections in Louisiana were simulated using a RothC model at a watershed scale under three greenhouse gas emissions scenarios (A1FI, A2, B2) based on the HadCM3 climate model. LIDAR and DEM datasets were used to assess the spatial distribution of potential inundated coastal areas; estimate the current wetland areas, SOC storage, and nitrogen contents at risk in Louisiana, classified by the National Wetlands Inventory (NWI) and DEM datasets. The research found that SOC density ranged from 22 to 108 tons/ha in the upper 30-cm soil at the watershed scale, with the highest density in emergent herbaceous wetlands. Among Louisiana's 12 river basins, the Barataria, Terrebonne, and Lake Pontchartrain Basins in southeast Louisiana showed the highest SOC density. SOC density was positively correlated with watershed drainage density (r^2=0.43), but negatively correlated with watershed slope gradient (r^2=0.52) and elevation (r^2=0.50). The modeling study on climate change effects showed that SOC storage in the top

30-cm soil layer of Louisiana forests, croplands, and grasslands would significantly decrease under all climate change scenarios. Coastal areas in southeastern Louisiana have some freshwater and estuarine wetland ecosystems that store a large quantity of organic carbon. Much of these areas have elevations less than 100 centimeters and are, therefore, prone to inundation of sea level rises during future climate change.

CHAPTER 1 INTRODUCTION

According to the Intergovernmental Panel on Climate Change (IPCC, 2007), there has been a warming trend during the past 150 years. The current average global surface temperature of 15°C is 0.74 (0.56 to 0.92) °C higher than it was 100 years ago. It has been estimated that global temperature could rise another 1.8°C to 4.0°C by the end of this century. The greenhouse gas (GHG) and aerosol emissions from fossil fuels have affected the composition of the atmosphere since the beginning of the Industrial Revolution in the mid-18th century. GHG includes carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and other gasses that absorb energy in the infrared wavelength. Among them, carbon dioxide is the primary concern because its increase has affected temperature most. Over the past 150 years, the atmospheric concentration of CO_2 has increased from about 280 to 379 ppm (IPCC, 2007). Concurrently, land-use changes, in particular urbanization, and intensive agricultural and forestry practices, have affected the physical and biological characteristics of the earth's surface. Collectively, these effects have altered global GHG emissions, radioactive forcing, and sequestration potentials.

CO_2 concentration in the atmosphere fluctuates seasonally, reflecting its linkage with the oceans, terrestrial systems, and human activities. Oscillations in the atmospheric content of CO_2 are the result of the seasonal uptake of CO_2 by photosynthesis and seasonal difference in the use of fossil fuels and in the exchange of CO_2 with the ocean. The total release of CO_2 from fossil fuels is now approximately 7 Pg C/yr (1 petagram =1 x 10^{15} g=1 billion metric tons) (Marland and Boden, 1993; Subak et al., 1993; Schlesinger, 1997; Pacala and Socolow, 2004). In global carbon cycles, various attempts to balance the carbon dioxide storage of the atmosphere have been, however, less successful. A large quantity of carbon, about 1.7 Pg/yr (Schlesinger, 1997), is

unaccounted for. Researchers suspect that boreal forests, the mostly evergreen forests on earth at high northern latitudes (43°N - 65°N), with their 16 - 20 million km^2 land surface, may house the "missing sink" of CO_2. Houghton (1995) described the global carbon balance as shown below:

Fossil fuel emissions = Atmospheric increase + Oceanic uptake+ Terrestrial uptake? (1.1)

Soils are the third largest carbon reservoirs on earth after the oceans and fossil fuels (Schlesinger, 1997). Globally, the amount of soil carbon to 1 meter depth is over two times that in the atmosphere, and three times that in terrestrial vegetation. Carbon stored in soils is mainly in organic forms. At the global scale, increasing soil organic carbon (SOC) content by only 0.01% a year could lead to carbon sequestration equal to the annual increase in atmospheric carbon dioxide (Lal et al., 1999). However, estimation of total SOC varies and bears uncertainty. The amount of organic carbon contained in soils within the surface 1 meter is estimated to range between 1400 and 1600 Pg (Post et al., 1982; Eswaran et al., 1993; Batjes, 1996; Lal, 2004a). In addition to organic carbon, soils are estimated to contain about 695 - 950 Pg in inorganic forms, largely as $CaCO_3$, in arid and semi-arid regions, whose turnover is slow (Batjes, 1996; Lal, 2004a). Soil depths also change across the landscape, further complicating the accounting of global SOC stock. These uncertainties may be reduced through additional field data collection and improved spatial assessment methods.

The U.S. government has invested heavily in the establishment of several nationwide digital spatial databases, such as the Soil Survey Geographic (SSURGO) database, the State Soil Geographic (STATSGO) database, and the National Soil Geographic (NATSGO) database (Xu and Prisly, 2000). The U.S. Department of Agriculture's (USDA) Natural Resources Conservation Service (NRCS), formerly the Soil Conservation Service (SCS), leads the National Cooperative

Soil Survey (NCSS) and is responsible for collecting, storing, maintaining, and distributing soil survey information for privately owned lands in the United States (NRCS, 1995). These databases provide spatially referenced information on soil and land cover attributes and therefore, can be used for SOC stock accounting and modeling, which will not only reduce uncertainties but serve as a cost-effective method for large-scale SOC analyses.

Louisiana has a great variety of land use types, rich with upland pine forests, bottomland hardwoods, croplands, pasture lands, and coastal wetland ecosystems. Louisiana, next to Alaska and Florida, has the largest wetland acreage (35,612 km^2) in the United States (U.S. EPA, 2009). Many wetlands in Louisiana have been, and will continue to be, subject to the development of population growth, urbanization, petroleum industry, and agriculture. SOC in the topsoil can mobilize when land use changes from native vegetation to cultivated agriculture, according to a large number of reviews (Mann, 1985; Detwiler, 1986; Johnson, 1992; Davidson and Ackerman 1993; Post and Kwon, 2000; Guo and Gifford 2002; Murty et al., 2002; Houghton and Goodale, 2004).

Carbon stocks and sequestration in soils may change through time. Projecting the future carbon stock change can help us anticipate the future climate change clearly and manage carbon sequestration better. Modeling the carbon stock over time helps assess future carbon sequestration potential. The primary objectives of this dissertation research were:

- To quantify current soil organic carbon stocks and their spatial distribution across Louisiana’s landscape;
- To determine the relationships between soil organic carbon stocks and watershed characteristics;

- To investigate land cover and land use impacts on soil organic carbon storage and dynamics;
- To predict future changes in soil organic carbon stocks across Louisiana's watersheds under different climate change scenarios.

In doing so, using Louisiana as an example, the research developed a spatially-explicit modeling framework that is conducive to watershed-scale prediction of soil carbon stock and change with geo-referenced soil and land use datasets.

This dissertation is organized in six chapters. Chapter 2, following this introduction, provides an intensive literature review on current research on global climate change, biogeochemical cycling of carbon, and SOC assessment. It discusses relevant research concepts and research needs for SOC assessment for the state of Louisiana. Chapter 3 focuses on the study of SOC stocks and spatial distribution across Louisiana's landscape, and discusses advantages of GIS applications in large-scale carbon assessment and limitations of using STATSGO in soil carbon estimation. Chapter 4 analyzes the relationships among SOC and topographic factors, including slope and elevation. Chapter 5 executes a modeling assessment on potential climate change impacts on SOC in Louisiana. Chapter 6 provides a risk analysis of inundation to Louisiana coastal areas, where a large quantity of carbon is stored in the soils. These coastal areas were not included in the modeling study because the RothC model is not applicable for waterlogged soils. The last chapter, Chapter 7, summarizes relevant findings and discusses future research needs. Because Chapters 3, 4, 5, and 6 are written as stand-alone journal articles for refereed publications, minor replications in each of these chapters' introduction may occur.

CHAPTER 2 LITERATURE REVIEW

2.1 Global Climate Change

Over the past one and a half centuries, the global average near-surface temperature has increased 0.74 ± 0.18°C (IPCC, 2007). The increasing trend appeared to be accelerating during recent years; the Intergovernmental Panel on Climate Change (IPCC, 2007) reported that global average temperature increased about 0.2°C per decade from 1990 to 2005. The current average global surface temperature is about 15°C, and it is expected to rise 1.8°C to 4.0°C by the end of this century (IPCC, 2007).

The earth's temperature increase has been widely attributed to the changes in the chemical composition of the atmosphere because of anthropogenic activities. The warming trend is in part a consequence of increasing anthropogenic greenhouse gas (GHG). The atmospheric concentration of CO_2 has increased from about 280 ppm in 1750 to 379 ppm in 2005 (IPCC, 2007). For the six illustrative emissions scenarios of the Special Report on Emissions Scenarios (SRES), the projected concentration of CO_2 in the year 2100 ranges from 600 to 1,550 ppm. Further uncertainties, especially regarding the persistence of the present removal processes (carbon sinks) and the magnitude of the climate feedback on the terrestrial biosphere, cause a variation of about -10 to +30% in the year 2100 concentration. Around each scenario, therefore, the total range is between 490 and 1,550 ppm (IPCC, 2007).

Changes in precipitation amount and frequency are highly uncertain. Globally averaged annual precipitation is projected to increase during the 21st century, though at regional scales both increases and decreases are projected of typically 5 to 20% (IPCC, 2001a). Wentz et al. (2007) concluded from climate models and satellite observations, that the total amount of water in the

atmosphere will increase at a rate of 7% per one degree Kelvin of surface warming. However, a recent analysis of satellite observations does not support this prediction from climate models of precipitation. Different trends may occur in different regions of the world. There is evidence that the frequency of extreme rainfall has increased in the United States (Karl and Knight, 1998) and in the UK (Osborn et al., 2000).

Global mean sea level has been projected to rise by 0.18 to 0.59 m between the years 1990 and 2100, for the full range of SRES scenarios, but with significant regional variations (IPCC, 2007). This rise has been primarily attributed to thermal expansion of the oceans and melting of glaciers and ice caps.

In terms of natural resources, climate change is expected to increase the extent and productivity of forests over the next 50-100 years (IPCC, 2001b). However, climate change may lead to loss of specific ecosystem types, such as salt marshes. Climate change may have significant impacts on wetland structure and function, primarily through alterations in hydrology, especially water-table level (Clair et al., 1998; Clair and Ehrman, 1998). Louisiana has a large area of coastal wetlands that are highly susceptible to sea level rise. Climate change may have significant impacts on Louisiana coastal areas.

"Climate change is global, long-term (up to several centuries), and involves complex interactions among climatic, environmental, economic, political, institutional, social and technological processes" (IPCC, 2001c). The United Nations Framework Convention on Climate Change (UNFCCC) has as its ultimate goal the "stabilization of greenhouse gas concentrations in the atmosphere at a level that will prevent dangerous anthropogenic interference with the climate system." The Kyoto Protocol to the United Nations Framework Convention on Climate Change

(UNFCCC) was created in 1997. Instruments being developed in the Kyoto Protocol are carbon trading, Joint Implementation (JI), and the Clean Development Mechanism (CDM). Other international instruments also assessed include an emission/carbon/energy tax, technology and product standards, voluntary agreements with industries, direct transfers of financial resources and technology, and coordinated creation of enabling environments (IPCC, 2001a). Significant technical progress relevant to greenhouse gas emissions reduction has been made and has been faster than anticipated. Advances are taking place in a wide range of technologies at different stages of development, e.g., the market introduction of wind turbines, efficient hybrid engine cars, the advancement of fuel-cell technology, and the demonstration of underground carbon dioxide storage. Technological options for emissions reduction include improved efficiency of end use devices and energy conversion technologies, shift to low-carbon and renewable biomass fuels, zero-emissions technologies, improved energy management, reduction of industrial by-product and process gas emissions, and carbon removal and storage (IPCC, 2001c).

Forests, agricultural lands, wetlands and other terrestrial ecosystems gain carbon through photosynthesis and lose carbon primarily as CO_2 through respiration. Biological sequestration can occur by three strategies: (a) conservation of existing carbon pools, (b) sequestration by increasing the size of carbon pools, and (c) substitution of sustainable produced biological products, e.g. wood for energy intensive construction products and biomass for fossil fuels (IPCC, 2001c).

2.2 Terrestrial Carbon Stocks and Cycles

Carbon is stored in the atmosphere, biosphere, hydrosphere, and pedosphere. The ocean pool is estimated at 38,000 Pg (1 petagram =1 10^{15}g = 1 billion metric tons), the fossil fuels pool at

4000 Pg, the soil organic carbon (SOC) pool, stored primarily in soil organic matter (SOM), at 1500 Pg up to 1 m depth and at 2400 Pg up to 2 m depth, the atmospheric pool at 750 Pg, and the vegetation pool at 610 Pg (Schlesinger, 1997; Lal, 2001, FAO, 2004).

Soils represent the third largest carbon pool on earth. The SOC pool, assuming an average content of 2400 Pg to 2m depth, is 3.2 times the atmospheric pool and 4.4 times the biotic pool. Soils contain about 75% of the C pool on land, three times more than stored in living plants and animals (Sparks, 2003).

Carbon in terrestrial ecological systems is retained in live biomass and decomposing organic matter, and its amount and distribution play an important role in the global carbon cycle. Carbon is exchanged naturally between ecological systems and the atmosphere through photosynthesis, respiration, decomposition, and combustion. Human activities have changed carbon stocks in these pools and have accelerated exchange processes among them (IPCC, 2000).

The main entry of carbon into the biosphere is through the process of photosynthesis or gross primary productivity (GPP), which is the uptake of carbon from the atmosphere by plants. Part of this carbon is lost in several processes: through plant respiration (autotrophic respiration); as a result of heterotrophic respiration and as a consequence of further losses caused by fires, drought, human activities, etc (FAO, 2004).

Many scientific issues (FAO, 2004) regarding the global carbon cycle remain unresolved or uncertain, such as the contribution of oceans to the global carbon balance (Del Giorgio and Duarte, 2002), the contribution of rivers (Richey et al., 2002), and the interaction with other biogeochemical cycles. The switch of the terrestrial biosphere from its current role as a carbon sink to a carbon source is highly controversial, as it is based on the long-term sensitivity of the

respiration of soil microbes to global warming. Long-term predictions using bio climate models yield different results depending on the temperature sensitivity function used for heterotrophic respiration. Global climate change could lead to an increase in heterotrophic respiration and decomposition of organic matter, and consequently to a decline in the sink capacity of terrestrial ecosystems (Schimel et al., 2001).

2.3 SOC Distribution across Landscape

Studies on soil at the landscape scale have focused on two contrasting and equally important parts. One approach involves detailed studies of soil characteristics and pedological processes derived from field investigations and laboratory studies. The other approach uses GIS to integrate a variety of environmental factors that correlate with soil attributes. Soil-landscapes can be described in terms of geomorphology and topography, land cover, land use, soil attributes and genesis. Soil-landscape modeling attempts to integrate soil, parent material, topography, land use and land cover, and human activities. The goal of soil-landscape modeling is to gain an understanding of the spatial distribution of soil attributes, characteristics, and behavior through time (Grunwald, 2005).

Over the past several centuries, human activities have largely altered the land surface. Changes in land use and land cover have been considered to be among the most dominant impacts on terrestrial ecosystems (Turner et al., 1990; Houghton, 1994). Land-use change and soil degradation are major processes for the release of CO_2 to the atmosphere (FAO, 2004).

Guo and Gifford (2002) reviewed 74 publications and reported a Meta analysis of the effects of land use change on SOC stocks. The study found that SOC stocks tend to decline after land use changes from pasture to plantation, from native forest to plantation, from native forest to

crop, and from pasture to crop, but tend to increase after land use changes from native forest to pasture, from crop to pasture, from crop to plantation, and from crop to secondary forest (Guo and Gifford, 2002) .

Carbon contained in the surface soil can be lost when the land use changes from native vegetation to a cultivated agricultural type (e.g., Mann, 1985; Detwiler, 1986; Schlesinger, 1997; Johnson, 1992; Davidson and Ackerman, 1993; Post and Kwon, 2000; Guo and Gifford, 2002; Murty et al., 2002; Houghton and Goodale, 2004). The average reduction is reported to be 25 - 30% in the upper one meter of soil (Houghton and Goodale, 2004).

SOC distribution at the landscape scale can be analyzed with additional information such as digital elevation models (DEM), and land use and land cover data. DEM indicate the topographic attributes for modeling SOC on the landscape, such as slope, aspect, flow direction, flow accumulation, stream length, and topographic position (Rosenberg et al., 1999).

Thompson and Kolka (2005) developed a soil-landscape model that quantified SOC with topographic variables derived from digital elevation models. They analyzed terrain attributes, such as elevation, slope gradient, slope aspect, curvature, topographic wetness index, and proximity to nearest stream, etc. Despite low coefficients of correlation between measured SOC and individual terrain attribute, the developed and validated models explained up to 71% of SOC variability using three to five terrains attributes. Soil-landscape modeling can be transportable to similar landscapes. With increasing availability of geospatial data in higher resolution, a soil-landscape modeling approach can be very useful for future SOC spatial modeling.

Arrouays and others (1998) used DEM (100 x 100-m grid) data to investigate whether topographic features influence surface SOC storage. They calculated topographic attributes on a

6000-ha area in southwest France and found that slope was the main factor controlling local variability in carbon storage, and that relating organic carbon contents to spatial available landform parameters and combining them into spatial models could provide a useful tool to improve geographical prediction of this characteristic.

Walter and others (2003) presented a method for simulations of the spatiotemporal evolution of topsoil organic carbon at the landscape scale over a few decades and under different management strategies. A virtual landscape with characteristics matching part of Brittany in France was considered for the study. Stochastic simulations and regression analysis were used to simulate spatial fields with known spatial structures: short-range, medium-range, and long-range variability. Land use evolution over time was simulated using transition matrices. Evolution of soil organic matter was estimated each year for each pixel through a rudimentary balance model that accounts for land use and the influence of soil waterlogging on mineralization rates. This spatiotemporal simulation approach at the landscape level allowed the simulation of several scales of soil variability including within-field variability.

SOC estimated in different land use types and at different scales of landscape may vary largely. Typically, SOC accounting at a large scale results in a large uncertainty. Future work should reduce uncertainties in SOC accounting for diverse land use types and landscape scales. Land use change is critical to SOC change. However, due to increased human interventions, land covers change rapidly and information on recent land use change is often difficult to obtain.

2.4 SOC Modeling at the Landscape Level

Soils vary over space and through time. They are complex and difficult to observe (Grunwald, 2005). Critical factors that affect soil formation were introduced by Dokuchaev more than a

century ago and were popularized by Jenny (1941, 1961) as follows:

$$S=f\,(cl, o, r, p, t) \quad (2.1)$$

where S is soil attribute; cl is climate factor; o is organisms (biotic factor); r is relief (topographic factor); p is parent material; t is time.

Soil organic matter (SOM) plays a central role in the availability of nutrients such as nitrogen, phosphorus, and potassium. Therefore, SOM is often used as a key indicator for soil quality becasue it enhances plant productivity. SOM is the main determinant of soil biological activity, which in turn, has a major impact on the chemical and physical properties of soils (Robert, 1996). The increase in SOM can improve aggregation and the stability of soil structure, infiltration rate and water retention, and soil resistance to erosion. Because of this importance, many modeling studies on SOM dynamics have been conducted in the past few decades.

SOC storage is controlled primarily by two processes: primary production (input) and decomposition (output). Measurements of carbon storage in an ecosystem alone reveal little about how carbon has changed in the past or will change in the future. The effect of climate and/or land-use change can be predicted only through the use of appropriate dynamic models. Modeling has been used as an effective methodology for analyzing and predicting the SOC change (FAO, 2004). Over the past three decades, many SOC models have been developed. Among them, two models have found a wide use for different geographical regions and various soil types: the CENTURY model developed by Parton et al. (1987) in North America and the Rothamsted Carbon Model developed by Jenkinson (1977, 1991) in the United Kingdom.

The Rothamsted Carbon Model, or RothC-26.3 in its current version, is a model of the turnover of organic carbon for non-waterlogged soils that allows for the effects of soil type,

temperature, moisture content, and plant cover on the turnover process. It uses a monthly time step to calculate total organic carbon (tons per hectare), microbial biomass carbon (tons per hectare) and ^{14}C (from which the radiocarbon age of the soil can be calculated) on a time scale of years to centuries (Jenkinson et al., 1987; Jenkinson, 1990; Jenkinson et al., 1991; Jenkinson et al., 1992; Jenkinson and Coleman, 1994). It needs few inputs and they are easily obtainable. It is an extension of the earlier model described by Jenkinson and Rayner (1977) and by Hart (1984).

The CENTURY model was developed primarily to estimate formation and loss of organic carbon (C), nitrogen (N), phosphorus (P), and sulfur (S) in the Great Plains agroecosystems. The model consists of several submodels and can simulate the long-term dynamics of C, N, P, and S for different plant-soil systems. CENTURY has been widely used for grassland systems, agricultural crop systems, forest systems, and savanna systems. The soil organic matter submodel simulates the flow of C, N, P, and S through plant litter and the different inorganic and organic pools in the soil (Parton et al., 1992).

The global Soil Organic Matter Network (SOMNET) was established mainly for scientific research. SOMNET has since attracted contributions from 31 leading SOM modelers and over 120 long-term experimentalists from all around the world (e.g., Smith et al., 1996a, 1996b, 1997a, 1997b; Powlson et al., 1998). The European Soil Organic Matter Network (SOMNET, http://saffron.rothamsted.bbsrc.ac.uk/cgi-bin/somnet-models) published a systematic review of these simulation models (Smith et al., 1997a).

Using twelve datasets representing different land-use types (arable, grassland, and forestry), climatic zones, and management practices, Smith and others (Smith et al., 1997b) compared the performance of nine widely used soil organic matter (SOM) simulation models: RothC,

CENTURY, CANDY, DNDC, DAISY, NCSOIL, SOMM, ITE, and Verberne. They found that only four models (RothC, NCSOIL, CENTURY, and SOMM) were able to simulate all land use types, and that six models (RothC, CENTURY, DAISY, CANDY, NCSOIL, and DNDC) performed significantly better than three others. The modeling results from RothC, CENTURY, DAISY, CANDY, NCSOIL, and DNDC were not significantly different.

CHAPTER 3 SOIL ORGANIC CARBON STORAGE AND SPATIAL DISTRIBUTION ACROSS LOUISIANA LANDSCAPE

3.1 Introduction

Carbon is the primary composition of living tissues. The carbon cycle is one of the most investigated issues in biogeochemistry (Schlesinger, 1997). Human activities have greatly altered the global cycling of carbon. The release of CO_2 in fossil fuels is now approximately 7 Pg C/yr (1 petagram =1 x 10^{15}g=1 billion metric tons) (Marland and Boden, 1993; Subak et al., 1993; Schlesinger, 1997; Pacala and Socolow, 2004), which is one of the best known values in the global carbon cycle. However, various attempts to balance the carbon dioxide budget of the atmosphere have failed because a large amount of carbon, nearly 1.7 Pg/yr (Schlesinger, 1997), is missing. Soils represent the third largest carbon pool on earth. The soil organic carbon (SOC) pool, assuming an average content of 2400 Pg to 2 m depth, is 3.2 times the atmospheric pool and 4.4 times the biotic pool (Sparks, 2003). On the global scale, increasing SOC content by only 0.01% a year could lead to carbon sequestration equal to the annual increase in atmospheric carbon dioxide (Lal et al., 1999). However, estimation of total SOC pools and fluxes vary and are uncertain.

Land use and land cover changes are the most dominant impacts on terrestrial ecosystems (Turner et al., 1990; Houghton, 1994). SOC in the topsoil can decline when land use changes from native vegetation to cultivated agriculture, according to a large number of reviews (Mann, 1985; Detwiler, 1986; Johnson, 1992; Davidson and Ackerman 1993; Post and Kwon, 2000; Guo and Gifford 2002; Murty et al., 2002; Houghton and Goodale, 2004). The average reduction is 25 - 30% in the upper meter of soil (Houghton and Goodale, 2004). The effect of glassland replacement by shrubland on carbon pools and fluxes is highly uncertain (Goodale and Davidson, 2002).

The Kyoto Protocol (1997) was ratified by more than 150 countries in the world. The carbon

emission target can be achieved under the Protocol either by reducing emissions or enhancing sinks. The Clean Development Mechanism (CDM) of the Kyoto Protocol describes a market approach to reduce carbon emission. The SOC pool will receive more attention because of its large capacity, sequestration, and trade potential. However, there are several technical problems and policy issues that must be solved for SOC credit accounting. One of the main challenges is methods and procedures for the inventory and monitoring of stocks and sequestration of soil (Ponce-Hernandez, 2004). A number of studies have examined the possibility of SOC sequestration potential for climate change mitigation (Lal, 2004b; Smith, 2004). Many studies are focused on the SOC sequestration potential for croplands (Lal et al., 1999; Smith et al., 2000; Smith, 2004). Few studies have examined a great variety of land use and land cover types, e.g. upland forests, wetlands, residential, grasslands, herbaceous, shrubland, and croplands etc, at a large scale.

Louisiana has a great variety of land use and land cover types, rich with upland and coastal wetland ecosystems. The Mississippi River flows to the Gulf of Mexico in southern Louisiana, which is the terminus of the Mississippi Basin. The objectives of this study were to quantify SOC storage, investigate its spatial distribution, and reveal its relationships at different soil depths under various land use and land cover types in Louisiana.

3.2 Methodology

3.2.1 Study Area

Louisiana lies between 89°W to 94°W longitude and 29°N to 33°N latitude. It is about 611 kilometers long and 210 kilometers wide. The total area of Louisiana covers 134,273 km^2. Louisiana land areas cover 112,835 km^2. Water covers 21,437 km^2 of Louisiana. The highest point

in Louisiana is 163 meters above sea level. The lowest point in Louisiana is 2.44 meters below sea level and is located in New Orleans. The mean elevation of the state of Louisiana is only 30.48 meters above sea level. Louisiana, next to Alaska and Florida, has the largest wetland acreage (35,612 km^2) in the United States (U.S. EPA, 2009).

3.2.2 Data Sources

SOC data were extracted from Soil Geographic Database (Figure 3.1) (STATSGO, http://www.ncgc.nrcs.usda.gov/products/datasets/statsgo/) and aggregated by the National Land Cover Database (NLCD) (Figure 3.2) to compare the SOC distribution in different land cover types.

The STATSGO database was designed primarily for regional, multistate, river basin, state, and multicounty resource planning, management, and monitoring at a scale of 1:250,000 (NRCS, 1995). Map Unit was the basic unit of STATSGO. There were 336 map units in Louisiana STATSGO from LA001 to LA347. The average area of STATSGO map units in Louisiana was 50 km^2. Each map unit can have multiple components and each component can have multiple layers.

NLCD was compiled from Landsat satellite TM imagery with a spatial resolution of 30 meters by U.S. Geological Survey (USGS). NLCD divided land cover to 21 classes. We assessed the soil organic carbon in seventeen land cover classes across Louisiana landscape. The other five classes either did not occur in Louisiana or were missing soil data. Five land cover groups, urban area, upland forest, pasture/shrub/grasslands, agriculture area, and wetlands, were generalized from seventeen Louisiana land cover classes.

3.2.3 Soil Organic Carbon (SOC) Analysis

SOC was estimated from the organic matter (OM) percentage, soil layer depth and bulk density in STATSGO. The calculation was as follows:

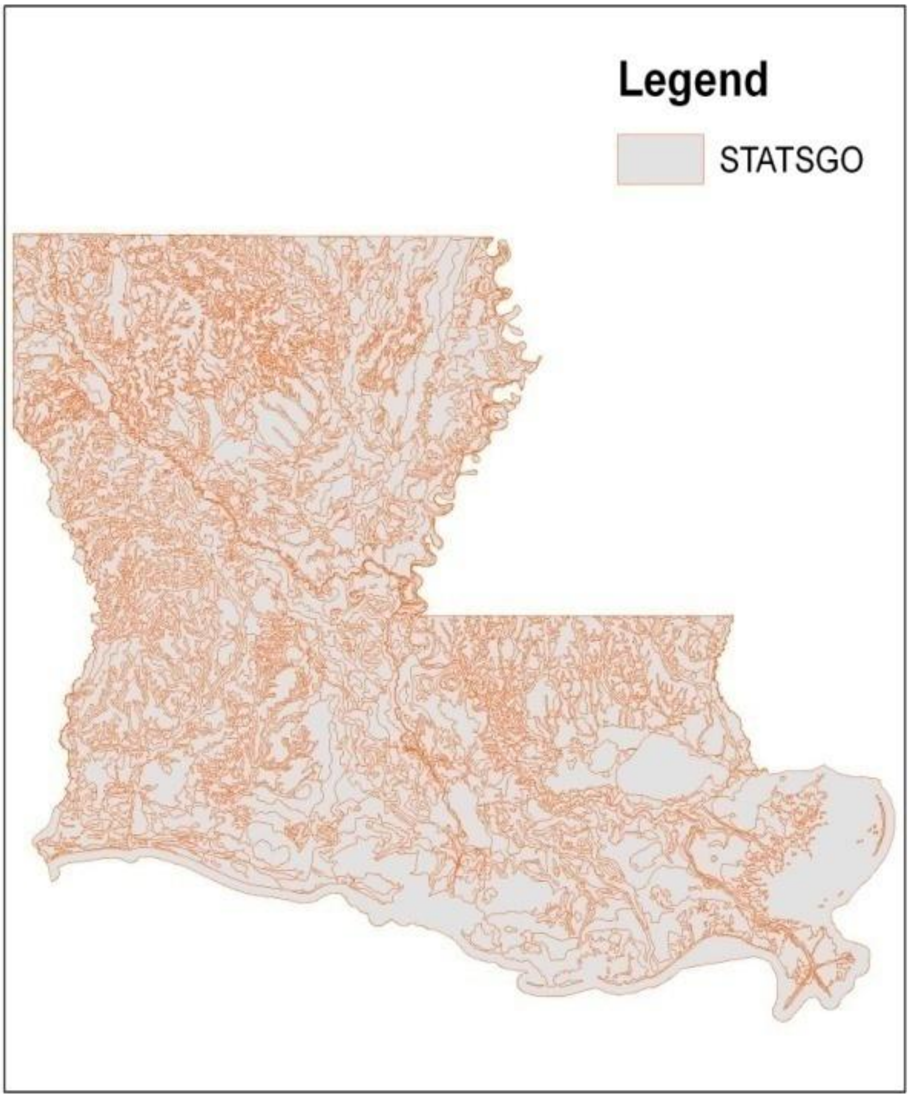

Figure 3.1 Soil map units of STATSGO map.

$$Cs = [\sum\sum (BD_{ij} * D_{ij} * SOM_{ij}) * COMP_i] / 1.724 \qquad (3.1)$$

where Cs is soil organic carbon, COMP is the area percentage of a soil series within each map unit, BD is the soil bulk density in tons m^{-3}, D is the depth of a soil layer in meter, SOM is the soil

organic matter content in percent, and the subscripts i and j are the identifiers for soil layers and components, respectively (Xu and Prisley, 2000). The Van Bemmelen factor of 1.724 was used on the assumption that organic matter contains 58% organic carbon (Nelson and Sommers, 1982).

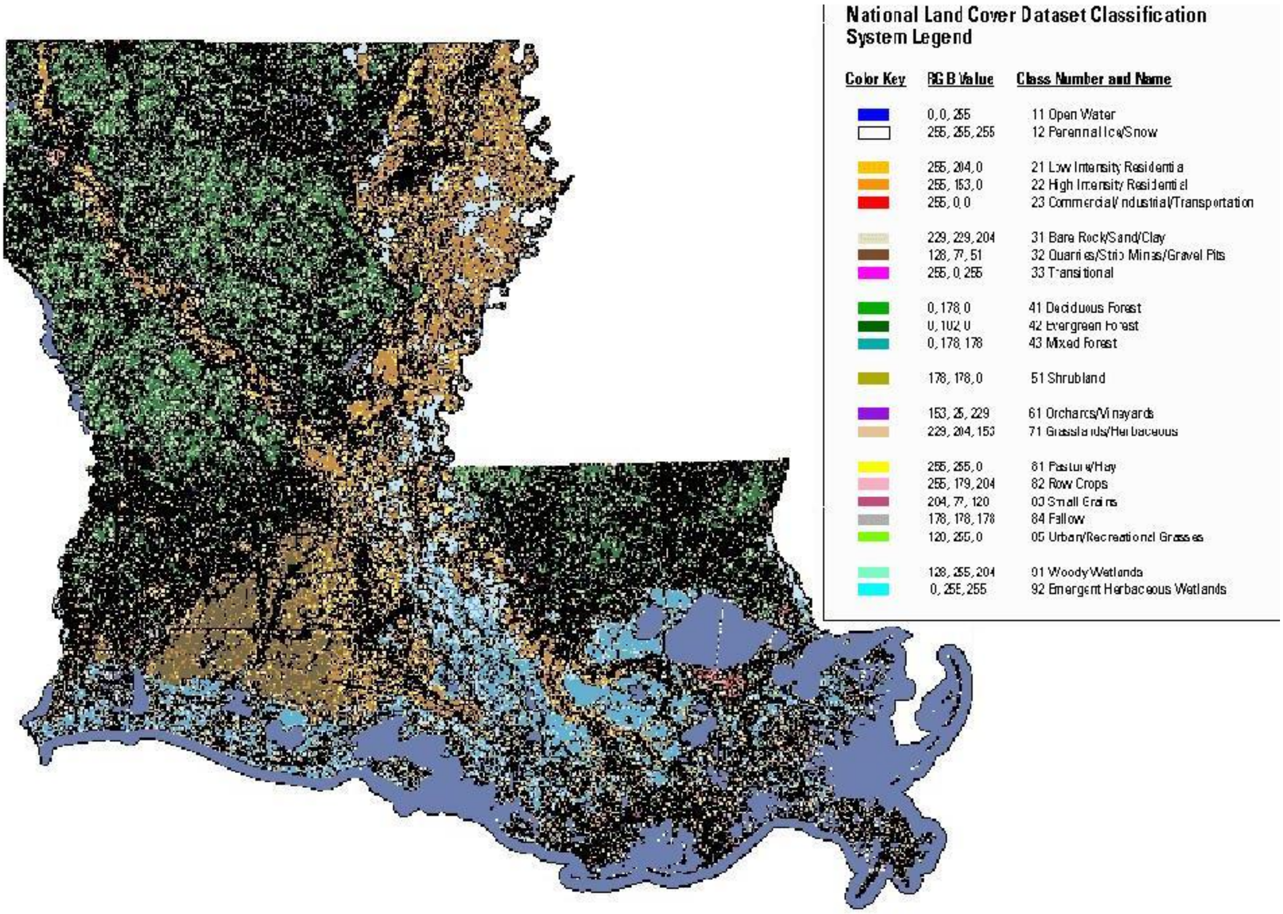

Figure 3.2 Louisiana Land Cover Dataset Classifications (1992).

The estimations of soil bulk density, depth, and soil organic matter were as below:

$$BD_{ij} = (BDL_{ij} + BDH_{ij})/2 \qquad (3.2)$$

$$D_{ij} = LAYDEPH_{ij} - LAYDEPL_{ij} \qquad (3.3)$$

$$SOM_{ij} = (OML_{ij} + OMH_{ij})/2 \qquad (3.4)$$

where the organic matter percentage, and bulk density are the average of minimum value (OML) and maximum value (OMH) for the range in OM content, minimum value (BDL), and maximum value (BDH) for the range in moist bulk density. The soil layer depth is the depth of the upper

boundary (LAYDEPH) minus the depth of the lower boundary (LAYDEPL).

A rock fragment conversion factor was used by other studies on SOC in the conterminous United States (Bliss, 2003; Guo et al., 2006a). The variables in STATSGO are INCH10L, INCH10H, INCH3L, and INCH3H. In the Louisiana area, rocks are rare in the surface soil. Those variables all were zero in STATSGO in all of Louisiana.

3.2.4 Spatial Analysis

Soil organic carbon densities were calculated and mapped across all map units at three depths: upper 30-cm, 100-cm and the maximum depths by ARCGIS 9.0 (ESRI, 2007). The maximum soil depth in STATSGO layers was 252 centimeters. SOC calculations were processed by the Visual Basic for Application (VBA) in ESRI ARCGIS and the SQL in Microsoft Access. SOC densities were aggregated by the STATSGO map units, and then by land cover classes.

The study area is the total Louisiana land areas, excluding the water areas. There are 336 map units in Louisiana STATSGO from LA001 to LA347. The average area of STATSGO map units is 50,221,429 square meters. The scale of land cover aggregation is 30 * 30 square meter grid cell.

3.3 Results and Discussion

3.3.1 SOC Storage

Soils in Louisiana contained 0.5 Pg organic carbon within the upper 30 cm. Carbon contained within the upper 100-cm depth was 0.98 Pg, and carbon contained within the entire soil was 1.4 Pg. The mean SOC densities of Louisiana in the upper 30-cm, 100-cm and the maximum depths were 44, 84, and 120 tons per hectare, respectively.

Bliss (2003) and Guo et al. (2006a) used STATSGO to estimate the SOC in the United

States. The calculation models were similar to those in this study. The rock fragment conversion factor was used in those studies for the rocky area of the United States. In this study, SOC in three depths, upper 30-cm, 100-cm and the maximum depths were estimated. Because of the likelihood of deep soil in wetlands, which were extensive, the maximum depth of SOC, which is rarely analyzed in other studies, was used in this study. Upper 20-cm, 30-cm, and 100-cm shallow-depths soil attracted the most interest because organic matter in shallow soil surface is more labile than deep soil. However, organic matter in deep soil will significantly change with dramatic land use and land cover change over decades.

The average SOC density of the maximum depth in Louisiana was 120 tons per hectare, denser than the average SOC density on conterminous United States and Alaska, 88 tons per hectare (Bliss, 2003). Guo et al. (2006a) estimated the minimum, midpoint, and maximum value of Louisiana SOC densities at 2-m depth were 41, 200, and 436 tons per hectare respectively. The midpoint value was denser than the average Louisiana SOC density of this study. The possible reason for these differences may be the different scale estimation and missing data process of STATSGO.

The map unit LA067, BARBARY-SHARKEY-WATER, had the highest SOC densities in upper 30-cm, 100-cm depths, and maximum depth, 176, 450, and 713 tons per hectare respectively. This unit is subtropical Mississippi Valley alluvium – backwater swamps. The map units with the highest SOC densities were dominated by the order of Entisols and suborder Aquents. The highest SOC density in the maximum depth at map unit scale was 713 tons per hectare, which is close to the highest SOC in all the United States, over 800 tons per hectare in Alaska and Florida wetlands (Bliss, 2003).

3.3.2 SOC Spatial Distribution

A decreasing trend of SOC density was found from the southeast coastal region to the northwest upland region. In general, alluvial river corridors showed higher carbon densities than the upland regions. The southeast coastal area of Louisiana had the highest SOC density, including the map unit LA067, which was most common in the western area of Lake Pontchartrain around the Mississippi River. The historical and current Mississippi River deltaic lobes are in the southeast area of Louisiana, which were built during the last 5-10,000 years. This area had the highest SOC density (Figure 3.3 and 3.4). The findings confirm Bliss' estimate that the highest levels of SOC are in the wetlands along the Gulf coasts as well as the wetlands along the Atlantic coasts, the coastal areas of Alaska, the Des Moines lobe of the continental glaciations in Minnesota and Iowa, and the temperate rainforest of the coastal areas of Oregon and Washington (Bliss, 2003).

SOC distribution was closely related to the drainage network. At a large scale, the shape of SOC distribution can overlay with the shape of the drainage network. The SOC densities close to streams was higher than the densities far from streams (Figure 3.5).

Southern Louisiana has much lower elevation than northern Louisiana. The rivers flow from north Louisiana to south Louisiana. The results of this study suggested lower elevation areas may have higher SOC density than higher elevations. Thompson and Kolka (2005) also found elevation had the highest correlation with SOC within a 1500-ha (15 km^2) watershed in eastern Kentucky.

3.3.3 SOC Storage in Louisiana Land Use Types

Evergreen forest covers the largest area in Louisiana, followed by the emergent herbaceous

wetlands and row crops. Emergent herbaceous wetlands had the largest carbon pool in the all three soil depths, and higher weight percentage in the deeper soil. Wetlands can hold organic matter in very deep soil. Row crops were the second largest carbon pool in 30-cm and 100-cm depths, but evergreen forest had the second largest carbon sink in maximum depths (Table 3.1). Row crops had higher organic carbon densities in upper soil surface than forest, but in deep soil, forest lands had higher organic carbon densities than croplands.

Emergent herbaceous wetlands had the highest average carbon density in each of the soil depths, which were 63, 140, and 203 tons per hectare respectively. Shrubland had the second highest carbon density in the upper 30 cm and 100-cm soil depths, 52 and 100 tons per hectare, and the third highest carbon density in the maximum soil depths, 128 tons per hectare. Grasslands or herbaceous wetlands had the second highest carbon density in maximum soil depths, 141 tons per hectare, and the third highest carbon density in the upper 100-cm soil depths, 95 tons per hectare. Deciduous forest had a little more carbon density than evergreen forest and mixed forest (Table 3.1).

In five land cover groups, wetlands, which were only 28% of the total area, had 36%, 39% and 40% of the total SOC stock in the upper 30 cm, 100-cm, and maximum soil depths. The upland forests have the largest area, 38.3%. The agriculture areas have the third largest area percentage and carbon stock percentage. However, the mean carbon densities of agriculture areas are the lowest in the maximum depth (Table 3.2).

This study illustrates the importance of wetlands in the global carbon cycle and climate change because of their large SOC pools and potential for carbon sequestration in peat formation, sediment deposition, and plant biomass (Bridgham, 2006). Peatlands, which can hold up to 100%

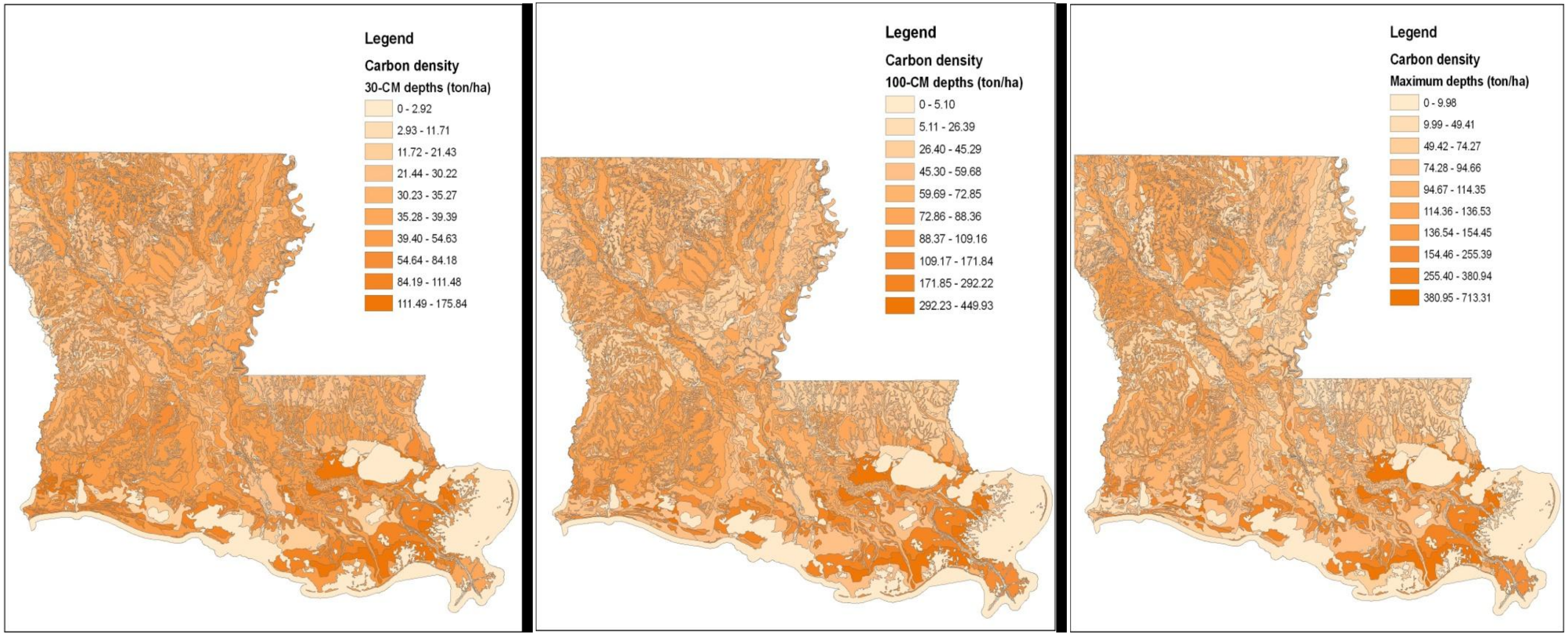

Figure 3.3 Spatial distribution of SOC in the upper 30-cm, 100-cm, and the maximal soil depths at the STATSGO map unit scale.

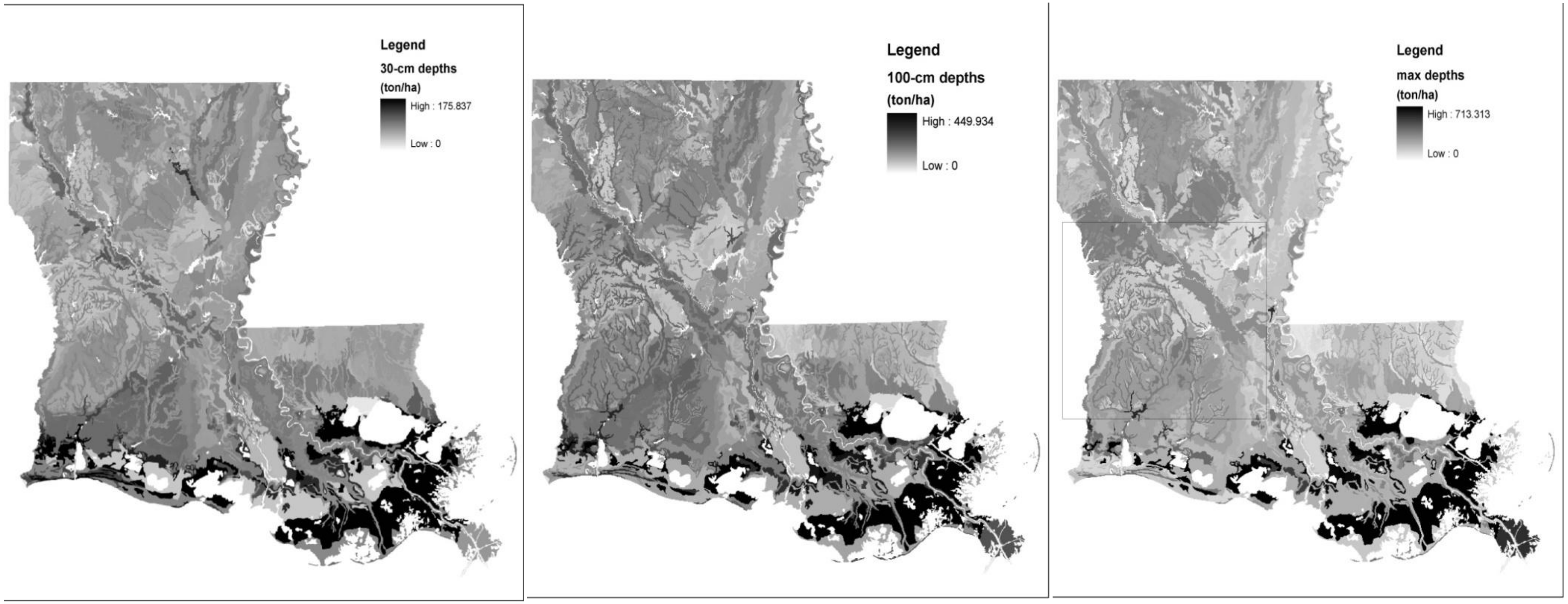

Figure 3.4 Raster map of SOC in the upper 30-cm, 100-cm, and the maximal soil depths at the STATSGO map unit scale.

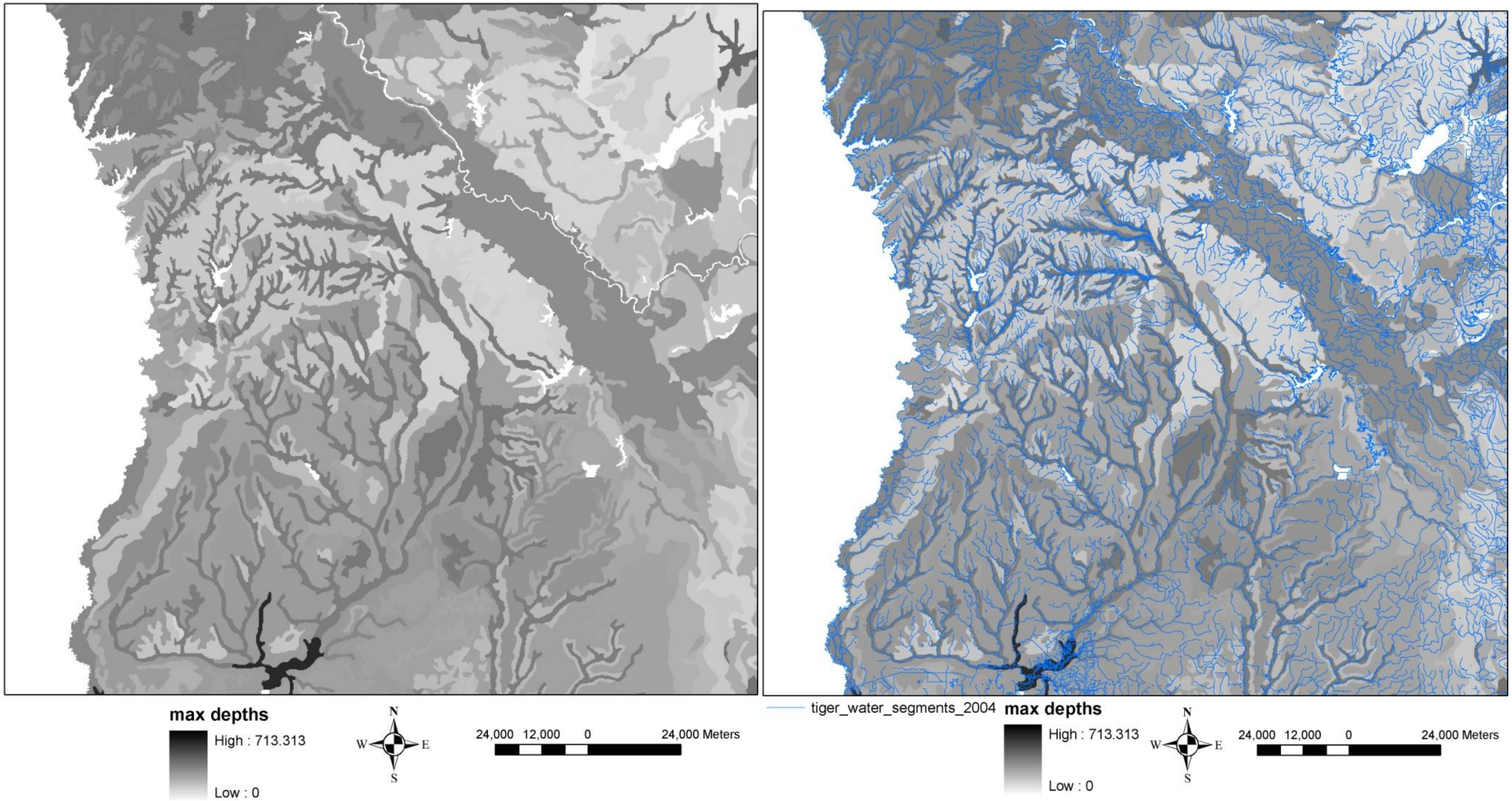

Figure 3.5 SOC density maps of the maximal soil depths and drainage pattern.

organic matter, occupy about 3% of the terrestrial global surface, yet they contain 16–33% of the SOC pool (Gorham, 1991; Maltby and Immirzi, 1993). SOC in Louisiana wetlands indicated the same trend as reported in the research of Guo et al. (2006b) in the conterminous Untied States, but Louisiana Grasslands, Herbaceous lands, and Shrubland showed much higher carbon densities than their research. This study did research on the SOC in deeper soil. Southern Louisiana had more rivers to irrigate those Grasslands, Herbaceous and Shrubland. The midpoint values of SOC density in agriculture areas in the upper 20-cm, 100-cm, and 200-cm depths in their research ranked much higher than this study.

3.3.4 Relationship between Land Use Types and SOC

High intensity residential areas and low intensity residential areas had higher carbon densities than forest and crops (Table 3.1). Urban soils in residential areas had high carbon density and had the potential to sequester large amounts of SOC (Golubiewski, 2006; Pouyat et al., 2006). They concluded that lawn management, which typically includes supplements of water and nutrients to maximize grass productivity, was the most likely reason for the relatively high SOC density of residential soils. Another possible reason may be the urban location selection. The best urban locations always had fertile soil and close to a river.

One high intensity residential area was New Orleans, the largest city in Louisiana. Much of the original area of New Orleans was emergent herbaceous wetlands, just like its neighboring areas. New Orleans has developed over wetlands for over two hundred years. Comparing the average SOC densities in different depths between high intensity residential and emergent herbaceous wetlands shows that the upper 30-cm, 100-cm and maximum depths average SOC densities decreased 18%, 41%, and 47% respectively when herbaceous wetlands changed to high intensity residential. SOC pools decreased largely in the post-urban development at cities, where native soils have relatively large SOC densities, but increase slightly in cities located in warmer and or drier climates (Pouyat et al., 2006).

Row crops areas have the lowest carbon density in the maximum depths except for the bare rock, sand and clay areas (Table 3.1). Among five land cover groups, the agriculture areas have the lowest carbon densities in the maximum depths (Table 3.2). The low carbon density there suggests that human agriculture activities may decrease the total SOC storage in the maximum depth, although the upper SOC densities are still high for the original fertile soils. SOC in the upper meter of soil will be respired when land use changes from natural ecosystems to cropland, according to a large number of reviews (Mann, 1985; Detwiler, 1986; Schlesinger, 1986; Johnson, 1992; Davidson and Ackerman, 1993; Post and Kwon, 2000; Guo and Gifford, 2002; Murty et al., 2002; Houghton and Goodale, 2004). This study confirmed that SOC density of row crops or agriculture areas in the total depth is significantly lower than that in the upper soil compared to other land cover types.

3.3.5 Relationship between SOC Estimation from STATSGO and Sampling Investigation

This study compared the estimation of OM from STATSGO to the sampling investigation results. Estimation of OM percentage, the source of SOC, was the average of minimum value (OML) and maximum value (OMH) for the range in OM content in STATSGO. Brupbacher et al. (1973) implemented a comprehensive soil sampling, identification, and chemical analyses of soil materials in 366 sites at specific locations in the Coastal Marshland area of Louisiana in 1968. Two helicopters were used in collecting the samples, taken from the surface to a depth of about 20.3 cm. A 25-gram sub-sample of air-dried soil materials were used for the determination of organic carbon, organic nitrogen and acid-extractable phosphorus, sodium, magnesium, calcium and potassium. The OM contents results from the investigation, which were recalcitrant and buried in marshes, were used in this study.

The estimation of OM percentage from STATSGO did not reflect high correlations to the sampling investigation results (Figure 3.6). The 16 points in figure 3.6 are the average OM percentage of 16 map units in STATSGO and the average OM percentage of 113 samples of soil

investigation. The large area of map units in STATSGO may be too large to compare with those wetland soil sampling points. Wetlands were inundated periodically or seasonally by fresh or saline water. The soil survey results in wetland could be different from diverse sites and seasonal condition.

3.4 Conclusions

This study used a geographically referenced soil database to estimate SOC storage across Louisiana. It is the first comprehensive assessment of terrestrial carbon distribution in the state. The average SOC density of total depth in Louisiana is 1.4 more than that of the conterminous United States and Alaska. The historical and current Mississippi River deltaic lobes, accumulated by the outflow of the Mississippi River, have the highest SOC density in the state. They are the most important area for the SOC storage. The study indicated the ultimate importance of Louisiana’s emergent herbaceous wetlands in carbon storage. The SOC density in Louisiana is twice that of forest and agriculture areas. Land use and land cover change in the emergent herbaceous wetlands and alluvial river corridor area may cause large losses of stored carbon. The grassland, herbaceous land and shrub land areas also had much higher carbon densities than forest and agriculture areas. Agriculture areas had the lowest SOC densities in the maximum depths. High intensity residential and low intensity residential areas also had higher carbon densities. Wetland soils serve an important role in removing carbon dioxide from the atmosphere and thereby slowing down global warming as a carbon sink. However, wetlands are the largest source of methane emission (22% of global methane emission). Methane has 21 times relative heat absorption of carbon dioxide. Future research is needed to predict coastal wetland change and accurate accounting of negative effect of high CH_4 emissions and positive benefits of carbon sequestration to global climate change from wetland soils.

Table 3.1 Carbon stock percentages, areas, and carbon densities by different land cover and soil depths

Land cover class name (class code)	Area percentage	Carbon stock percentage (%)			Mean carbon densities (t/ha)		
		30cm depth	1m depth	Max depth	30cm depth	1m depth	max depth
Low intensity residential (LC21)	1.523%	1.534%	1.392%	1.309%	42.34	73.39	98.42
High intensity residential (LC22)	0.320%	0.392%	0.332%	0.299%	51.37	83.32	106.94
Commercial,industrial,transportation (LC23)	0.820%	0.851%	0.796%	0.756%	43.65	77.97	105.56
Bare rock, sand, clay (LC31)	0.098%	0.081%	0.080%	0.076%	34.82	65.56	89.04
Quarries, strip mines, gavel pits (LC32)	0.056%	0.044%	0.042%	0.046%	33.00	60.31	94.81
Transitional (LC33) [1]	1.299%	1.034%	1.012%	1.090%	33.47	62.59	96.05
Deciduous forest (LC41)	9.495%	8.036%	7.808%	8.239%	35.58	66.05	99.37
Evergreen forest (LC42)	16.947%	13.756%	13.273%	14.181%	34.12	62.90	95.82
Mixed forest (LC43)	10.573%	8.554%	8.265%	8.798%	34.01	62.78	95.29
Shrubland (LC51)	0.001%	0.001%	0.001%	0.001%	52.51	99.77	128.62
Grasslands, herbaceous (LC71)	0.563%	0.621%	0.666%	0.692%	46.35	95.05	140.76
Pasture, hay (LC81)[2]	7.985%	7.309%	6.760%	6.517%	38.48	67.99	93.46
Row crops (LC82) [3]	15.589%	14.520%	13.368%	12.412%	39.15	68.87	91.17
Small grains (LC83) [4]	6.325%	7.283%	6.431%	5.562%	48.40	81.66	100.70
Urban, recreation grasses (LC85)	0.409%	0.437%	0.399%	0.371%	44.86	78.33	103.71
Woody wetland (LC91) [5]	11.423%	10.716%	10.472%	10.223%	39.44	73.63	102.48
Emergent herbaceous wetlands (LC92) [6]	16.574%	24.831%	28.902%	29.426%	62.98	140.06	203.31

[1] Transitional - Areas of sparse vegetative cover (less than 25 percent that are dynamically changing from one land cover to another, often because of land use activities. Examples include forest clearcuts, a transition phase between forest and agricultural land, the temporary clearing of vegetation, and changes due to natural causes (e.g. fire, flood, etc.)

[2] Pasture/Hay - Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops.

[3] Row Crops - Areas used for the production of crops, such as corn, soybeans, vegetables, tobacco, and cotton.

[4] Small Grains - Areas used for the production of graminoid crops such as wheat, barley, oats, and rice.

[5] Woody Wetlands - Areas where forest or shrubland vegetation accounts for 25-100 percent of the cover and the soil or substrate is periodically saturated with or covered with water.

[6] Emergent Herbaceous Wetlands - Areas where perennial herbaceous vegetation accounts for 75-100 percent of the cover and the soil or substrate is periodically saturated with or covered with water.

Table 3.2 Carbon stock percentages, areas, and carbon densities in different land cover and soil depths

Generalized land cover class	Original class codes	Area percentage	Carbon stock percentage (%)			Mean carbon densities(t/ha)		
			30cm depth	1m depth	Max depth	30cm depth	1m depth	max depth
Barren, urban area	LC 21, 22, 23, 31, 32, 85	3.38%	3.34%	3.04%	2.86%	43.49	75.70	101.40
Upland forest	LC33, 41, 42, 43	38.31%	31.38%	30.36%	32.31%	34.43	63.64	96.56
Pasture, shrub, grasslands	LC51,71, 81	8.55%	7.93%	7.43%	7.21%	39.00	69.77	96.58
Agriculture area	LC82, 83	21.91%	21.80%	19.80%	17.97%	41.82	72.56	93.92
Wetlands	LC91,92	28.00%	35.55%	39.37%	39.65%	53.37	112.95	162.17

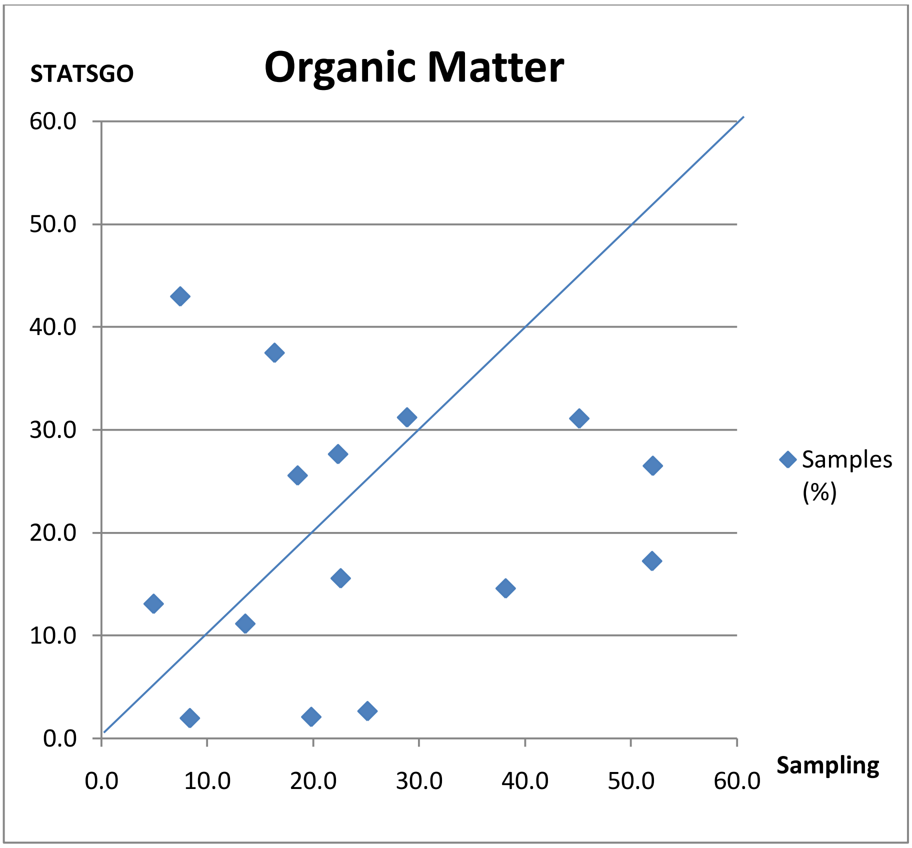

Figure 3.6 STATSGO vs. sampling investigated OM.

CHAPTER 4 RELATIONSHIPS OF SOIL ORGANIC CARBON AND TOPOGRAPHIC FACTORS IN WATERSHEDS*

4.1 Introduction

Soils represent the third largest carbon pool on earth (Sparks, 2003). Terrestrial carbon stocks vary greatly over geographical space and through time, which makes soil carbon estimation difficult across a large landscape. Early estimates of soil organic carbon stock at a global scale were made during the 1970s and 1980s (Bolin, 1970; Bohn, 1982; Parton et al., 1987). Currently, probably the most cited global soil organic carbon (SOC) stocks for different soil depths are the estimates reported by Batjes in the late 1990s (Batjes, 1996). These estimates - 684-724 Pg of carbon in the upper 30 cm, 1,462-1,548 Pg of carbon in the upper 100 cm, and 2,376-2,456 Pg of carbon in the upper 200 cm (Batjes, 1996) – were made based on a 0.5 x 0.5 latitude - longitude degree cell, representing an area of approximately 50 x 50 km^2. For each of the cells, averages of soil carbon content, soil bulk density, and other necessary soil parameters are assumed to calculate the total SOC storage. As soils are highly variable in space, these estimates bear large uncertainties.

Soil formation is affected by five environmental factors: climate, vegetation, topography, parent material, and time (Dokuchaev, 1883; as cited by Jenny, 1941 and 1961). Therefore, the accumulation and dynamics of soil carbon are complex. Spatial and temporal changes in soil carbon can be further affected by local natural and anthropogenic factors, such as natural disasters (e.g., forest fires and diseases), land use activities (e.g., agricultural/forest management practices), and land use changes (e.g., conversion of forests to residential areas). All these factors affecting soil carbon storage may interact with each other and may also be indicative of current carbon storage.

Topographic elements of a landscape can be computed from the Digital Elevation Models (DEM) dataset (Huggett, 2003). DEM reveal topographic attributes of the landscape, such as slope, aspect, surface flow direction, flow accumulation, stream length, and topographic position

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(Rosenberg et al., 1999). This information may be useful for estimating soil carbon at a watershed scale. Thompson and Kolka (2005) investigated relationships among SOC and a series of topographic variables derived from a 1:24K DEM (30 x 30 m resolution) for a 1,500-ha watershed in eastern Kentucky. They found that up to 71% of the variability in SOC storage could be explained by five terrain attributes, including slope gradient, slope aspect, curvature, topographic wetness index, and proximity to the nearest stream. Arrouays and others (1998) used DEM data (100 x 100 m resolution) to estimate forest soil carbon stock in southwestern France and suggested that slope was a main factor controlling the variability in local carbon storage. In their study on SOC in subtropical soils of China, Cheng and others (2004) found that elevation, slope exposure, slope gradient, and parent material appeared to be the major factors affecting spatial SOC distribution, as well as clay content, the most important soil parameter at the regional scale. These studies were conducted in relatively small areas.

In the United States, a State Soil Geographic (STATSGO) database was developed in the early 1990s by the U.S. Department of Agriculture, Natural Resources Conservation Service (NRCS, previously Soil Conservation Service or SCS). This database contains information on a large number of soil physical, chemical, and morphological parameters as a soil map unit, including soil organic matter content, bulk density, soil layer depth, and others that can be used to estimate SOC storage for different soil layers. Several studies (Davidson and Lefebvre, 1993; Homann et al., 1998; Bliss, 2003; Tan et al., 2004; Guo et al., 2006a) have used STATSGO in determining soil carbon at the state and regional scales. Overall, the researchers found good agreement between STATSGO data and other large-scale soil databases. Until recently, no studies were found to analyze soil carbon at the watershed scale and its association with both topographic and watershed characteristics, such as drainage density, slope gradient, and elevation.

Temperature and moisture are considered two key factors in SOC dynamics, i.e., accumulation and decomposition (Schlesinger, 1995; Borken et al., 1999; Trumbore et al., 1999;

Lal, 2004a; Borken et al., 2006; Davidson and Janssens., 2006). Under similar climatic conditions, topographic and watershed characteristics may modify these factors, therefore indirectly affecting SOC development. In general, there is a knowledge gap of how SOC storage and distribution is influenced by topographic and geomorphologic processes across landscapes. Such information can be especially useful for increasing accuracy in SOC estimation and for resource managers and policy makers to develop effective strategies and plans in integrated watershed management.

This study aimed to determine the relationships among SOC storage, topographic and watershed characteristics across all of Louisiana, USA. The state has a variety of terrain types, from the northern hilly uplands to the southern low coastal plains. The Mississippi River flows to the Gulf of Mexico in southern Louisiana, creating the vast alluvial Mississippi Delta.

4.2 Methods

4.2.1 Study Area

The study area covers the entire state of Louisiana, U.S.A., geographically located between 89°W and 94°W in longitude and between 29°N and 33°N in latitude. The state stretches 611 km from north to south and 210 km from west to east, covering a total area of 134,273 km^2. Of the total area, land occupies 112,835 km^2 and water covers 21,437 km^2. Louisiana is a low-lying state with an average elevation of 30.5 m, ranging from 2.4 m below to 163.0 m above sea level. According to the NOAA Southern Regional Climate Center report, the average annual temperature of Louisiana ranges from about 18°C in northern divisions to about 21°C in southern divisions. The mean annual precipitation of Louisiana ranges from a low of 117 cm in the north to a high of 168 cm in the south.

For its water quality planning and regulatory management, the Louisiana Department of Environmental Quality (LDEQ) delineated the state into 12 major river drainage basins ranging in size from 7,021 to 25,901 km^2, and 484 watersheds ranging in size from 0.23 to 3,115 km^2 (LDEQ, 2004; Figure 4.1). The average area of these watersheds is 267 km^2. At least 40

watersheds are dominated by open water.

4.2.2 Estimation of Soil Organic Carbon

Soil parameters that are relevant for carbon estimation including soil organic matter content,

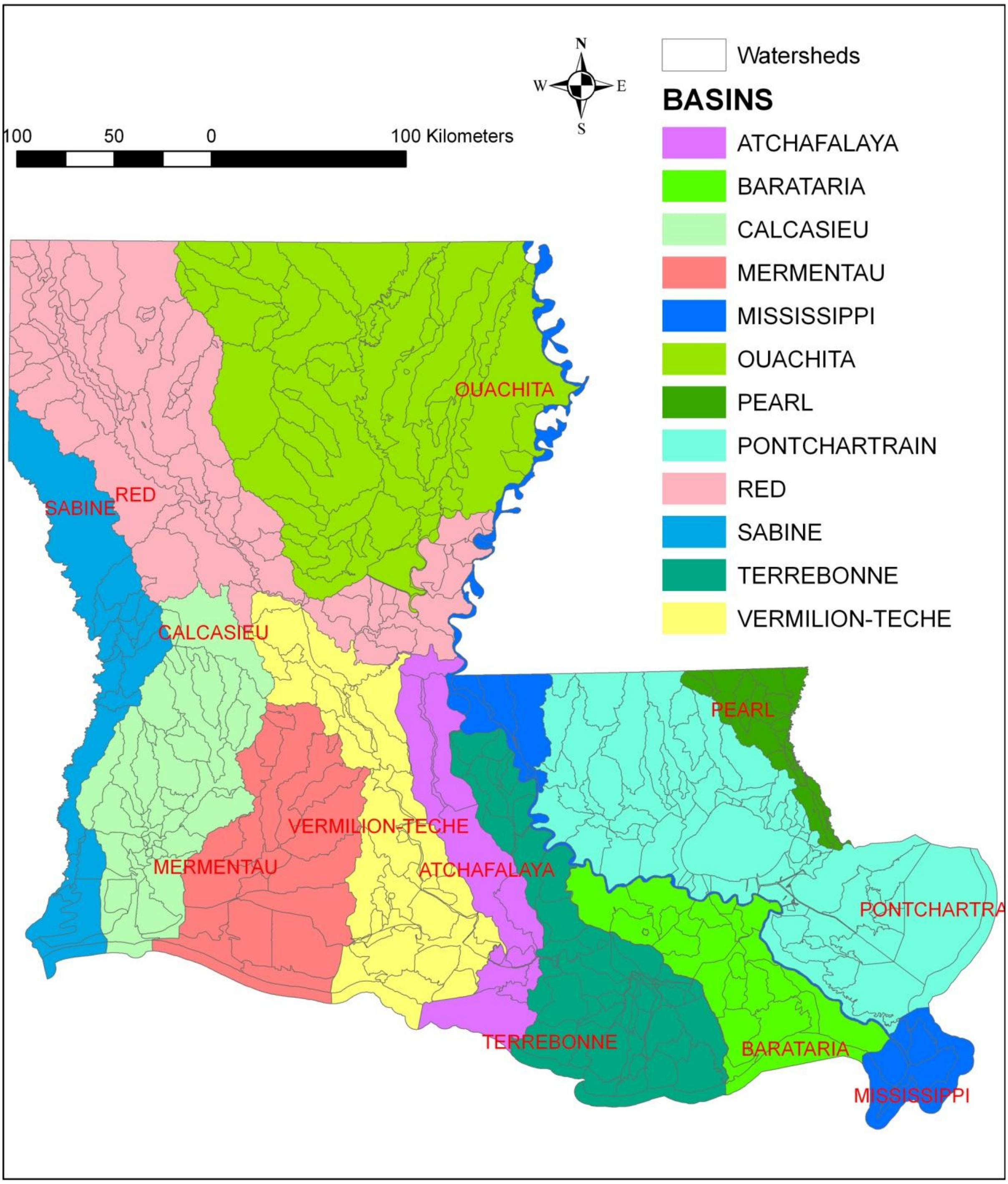


Figure 4.1. Louisiana river drainage basins and watersheds defined by the Louisiana Department of Environmental Quality (LDEQ).

soil layer depth, and bulk density were extracted from the STATSGO database. Total soil organic storage for 30cm depth, 100cm depth, and the maximum soil depth was calculated according to Xu and Prisley (2000):

$$Cs = [\ (BDij * Dij * SOMij) * COMPi] / 1.724 \qquad (4.1)$$

where Cs is soil organic carbon in metric tons, $COMP$ is the area percent of a soil series within each map unit, BD is the soil bulk density in t/m^3, D is the depth of a soil layer in meters, SOM is the soil organic matter content in percent, and the subscripts i and j are the identifiers for soil layers and components, respectively. The Van Bemmelen factor of 1.724 was used on the assumption that organic matter contains at least 58% organic carbon (Nelson and Sommers, 1982).

Soil densities (in t/ha) were calculated for the three soil depths for each soil map unit by dividing the total SOC by the corresponding map unit areas. Then, SOC at each map unit was aggregated for watersheds, and average SOC density for each watershed was calculated with the area weights of the map units in that watershed. Similarly, average SOC density for each river basin was calculated with the area weights of the watersheds in that basin.

4.2.3 Watershed Characterization Analysis

Drainage density is one typical index to characterize watersheds or drainage basins. Mathematically it is expressed as:

$$Drainage\ Density = Stream\ Length\ /\ Area \qquad (4.2)$$

where Drainage Density is the average length of streams per unit area in km/km^2, Stream Length is the total length of streams in a particular watershed or basin in km, and Area is the area of a

watershed or basin in km^2 (Brooks et al., 2003). Drainage density affects the rapidity with which water can flow to the outlet. Wetlands, lakes, or reservoirs may also affect the travel time of water flows.

Stream length was calculated using Louisiana hydrographic vector water features extracted from U.S. Census Bureau Topologically Integrated Geographic Encoding and Referencing (TIGER)/line dataset (Louisiana Oil Spill Coordinator's Office (LOSCO) and U.S. Census Bureau, 2004). LDEQ watersheds and drainage basins were used to calculate the areas.

4.2.4 Terrain and Spatial Analysis

Terrain attributes were calculated using Spatial Analyst and 3D Analyst tools in ArcGIS 9.2 (ESRI, 2007) from 1:24K DEM data with a 30m horizontal resolution and a 0.3m vertical precision (Figure 4.2), which was derived from the U.S. Geological Survey National Elevation Database (LDEQ and LOSCO, 2004). Slope gradient and elevation, probably the most relative topographic factors to SOC, were used in this study. Slope identifies the steepest downhill slope for a location on a surface. For raster data, it means the maximum rate of change in elevation over each cell and its eight neighbors (ESRI, 2007). The slope for each cell was calculated from the 3 x 3 neighborhood cells by use of the average maximum algorithm (Burrough and McDonell, 1998).

Louisiana watersheds and basins were used to aggregate and zone average soil carbon density, average slope, average elevation, and average drainage density in each watershed or basin.

4.2.5 Statistics Analysis

A total of 361 watersheds were used in statistical analyses. Watersheds with a large open water area (area > 90%), unreasonable area size or SOC were ignored because of incorrect soil data. Most watersheds with large open water areas were located in the southern coastal region.

Some researchers (Tan et al., 2004; Guo et al., 2006b) used the National Land Cover Database (NLCD) to explore the effects of environmental factors on SOC. In this study, focus is on natural topographic and watershed characteristics. It might reduce the sample sizes and lose

some of the terrain and watershed characteristics if I combined the land use and land cover effects because of the particular land cover distribution in Louisiana. The dominant land cover types in Louisiana are forests, crop lands, and wetlands. Wetlands are located on the flat southern coastal plain in the state. Crop lands are mostly in the flat fertile river valleys. Sloping hilly areas of Louisiana are mostly covered by forests.

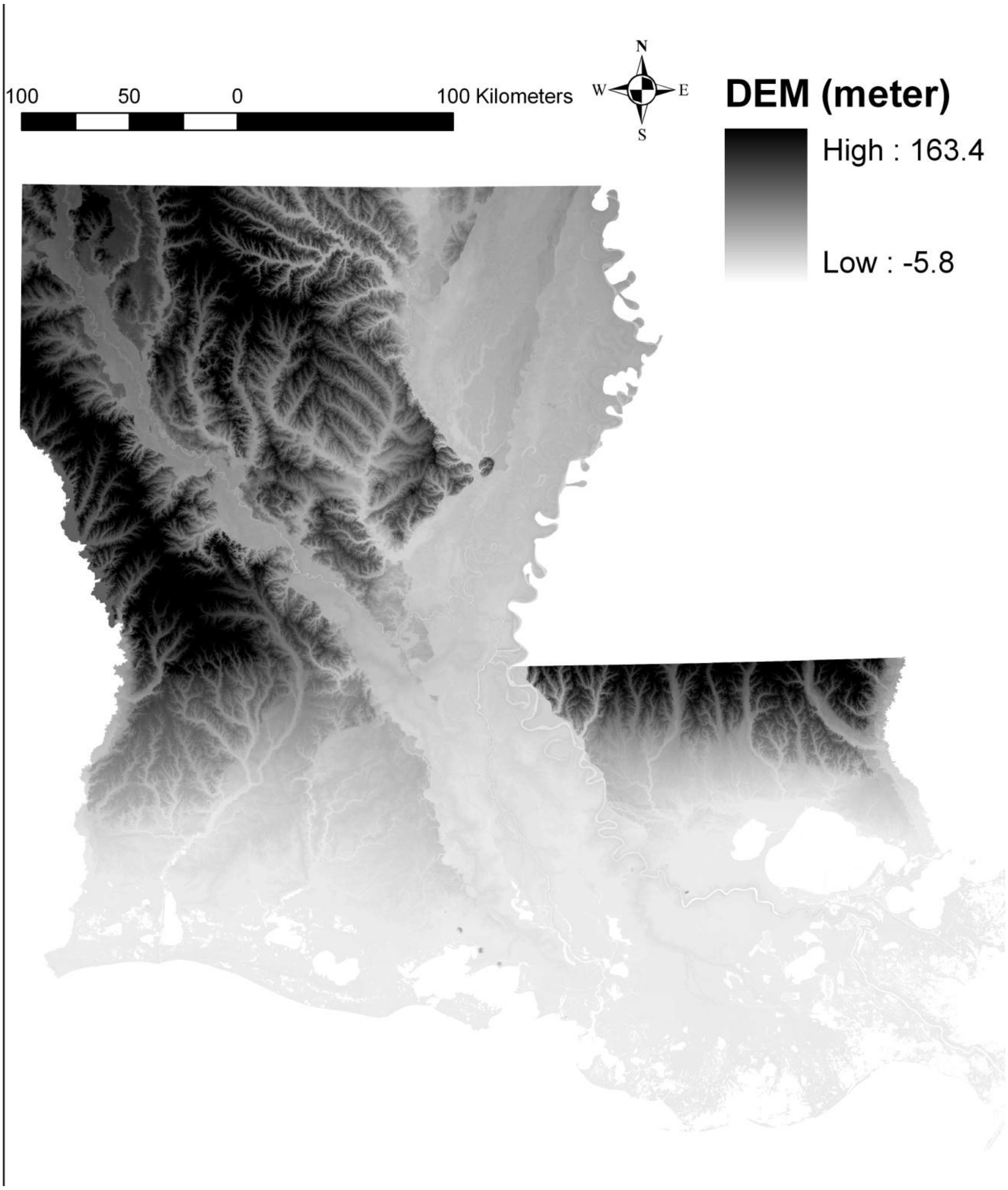


Figure 4.2. Louisiana Digital Elevation Dataset (1:24K) from LDEQ and LOSCO showing topographical changes across Louisiana.

Correlation and regression analyses were conducted to investigate the relationships among SOC, watershed, and topographic parameters at the watershed and river drainage basin scales. Pearson correlation coefficients were calculated to examine the linear correlation among those variables. Multiple linear regressions were used to determine the relationships among soil carbon density, terrain attributes, and watershed characteristics. These regressions can be generally written as follows:

$$Y = a_0 + a_1X_1 + a_2X_2 + \ldots + a_nX_n \qquad (4.3)$$

where Y is carbon density, X_1 can be drainage density, X_2 can be slope, and X_n other attributes. All statistical analyses were performed with the SAS software package (SAS Institute, 2007).

4.3 Results and Discussion

4.3.1 SOC Storage and Spatial Distribution in Louisiana Watersheds and Basins

Mean soil organic carbon densities of Louisiana watersheds in the upper 30-cm, 100-cm, and the maximum depths were 44, 86, and 122 tons per hectare, ranging from 21 to 108, 31 to 276, and 32 to 413 metric tons per hectare, respectively (Table 4.1). A decreasing trend of soil carbon density was found from the southeastern coastal region to the northwestern upland region. In general, alluvial river corridors showed higher carbon densities when compared to upland regions (Figure 4.3a).

The average SOC density of maximum depth in Louisiana watersheds (128 t/ha) is higher than the average soil carbon density reported for the conterminous United States and Alaska, 88 t/ha (Bliss, 2003). Guo and others (2006a) estimated a minimum of 41 t/ha, a midpoint of 200 t/ha, and a maximum of 436 t/ha SOC within the 2-m soil surface in Louisiana. The midpoint value is higher than the average Louisiana SOC density that I found in this study. The possible reason for these differences may be the various scale estimation and missing data treatment of STATSGO.

Three river basins in the Louisiana southeastern coastal region - Barataria, Terrebonne, and Pontchartrain Basins - showed the highest SOC storage in the state (Table 4.2). Pontchartrain and Barataria Basins hold most of the watersheds that have the highest SOC densities (Figure 4.1). The Blind River and Amite River Diversion Canal watersheds in Pontchartrain Basin, located on the eastern side of Pontchartrain Lake, have the highest SOC densities in maximum soil depths, 504 and 494 tons per hectare, respectively. Barataria Basin has the highest SOC density in the upper 30-cm, 100-cm, and the maximum depths, with 62, 142, and 202 tons per hectare, respectively.

Barataria, Terrebonne and Pontchartrain Basins are the historical and current Mississippi River deltaic lobes, which were built during the last 5,000-10,000 years with sea level rise and fall (Ritter, 1978). The outflow of the Mississippi River deposits large amounts of alluvial material to the delta region. Meanwhile, Barataria, Terrebonne and Pontchartrain Basins comprise over 10,000 km^2 of coastal wetlands, the largest SOC pool of Louisiana. This finding could be useful for future carbon credits in Louisiana coastal restoration projects, because coastal erosion and land loss is the largest environmental problem in the state. A major challenge to Louisiana's coastal restoration is to develop the most strategic, efficient, and timely strategies for science and science-based planning (Day et al., 2007).

4.3.2 Drainage Density, Slope, and Elevation Trends in Louisiana Watersheds and Basins

Louisiana's watersheds showed an average drainage density of 1.6 km/km^2, with a large variation, ranging from 0.03 to 10.01 km/km^2. In general, the upland region had lower drainage density than the coastal region. The highest drainage density area was found in the state's southeastern coastal plain (Figure 4.3b). Average slope of Louisiana's watersheds varied from 2.1 to 81.9 degrees. The watersheds with highest slope area were found in the north, and the lowest slope area was in the southern coastal area (Figure 4.3c). An average watershed slope of 2.9 degrees was found, which varied from 0.1 to 15.5 degrees (Table 4.1). Slope gradients showed a

decreasing trend from the northwest and the northern Florida Parish upland regions to the southern coastal floodplains. In the northern region, river corridors showed low slope, but rivers showed extraordinarily high slope in the southern coastal region. The Mississippi and Atchafalaya Rivers showed the highest slope in the southern coastal areas (Figure 4.3c).

The Barataria Basin, which has the highest SOC density among basins, has the highest drainage density (2.8 km/km^2), lowest average slope (10.2 degrees), smallest slope range (0.4 degrees), lowest average elevation (4.4 meters) and smallest elevation range (0.7 meters). Red, Sabine, and Ouachita Basins in northern Louisiana have the highest average slope, average elevation, and elevation range of their respective watersheds (Table 4.3).

Table 4.1 Summary statistics for soil organic carbon storage at different depths, topographic, and geomorphological characteristics at watersheds scales

Factor	Mean	Std Dev	Minimum	Maximum
SOC_30cm (t/ha)	44.2	17.5	21.7	108.0
SOC_1m (t/ha)	86.2	48.2	31.2	276.7
SOC_maximumdepth (t/ha)	122.2	71.1	32.9	413.2
drainage_density (km/km^2)	1.6	1.5	0.0	10.0
slope_mean (degree)	2.9	3.1	0.1	15.5
slope_range (degree)	31.3	20.9	2.1	81.9
elevation_mean (meter)	8.0	8.3	0.0	32.6
elevation_range (meter)	12.4	11.7	0.2	45.2
elevation_majority (meter)	6.7	7.5	0.0	35.3

Table 4.2 SOC densities in Louisiana 12 major river basins

Basins	Area	SOC density (t/ha)		
	(km^2)	30-cm depth	100-cm depth	Maximal depth
Barataria	7021.35	62	142	202
Terrebonne	10125.54	58	124	174
Pontchartrain	20527.80	53	109	155
Vermilion-Teche	10552.75	44	86	118
Mermentau	10095.53	46	85	116
Calcasieu	10508.45	43	81	112
Sabine	7563.54	35	66	100
Red	19934.29	34	63	96
Ouachita	25901.06	35	62	89
Atchafalaya	5758.23	33	61	85
Mississippi	5326.03	28	53	83
Pearl	2348.57	35	52	71

Drainage class was used in other research to examine river drainage patterns (Davidson, 1995; Tan et al., 2004). In those studies, drainage class was scored from 1 to 7, representing very poorly drained to excessively drained. It was originally used in STATSGO to indentify the natural drainage condition of the soil, for instance: well drained (W), excessive drained (E), poorly drained (P), etc. (NRCS, 1995). Drainage class showed the drainage condition at the soil survey sampling sites. At the large scale, drainage density, which was directly calculated from lengths of streams and areas of watersheds from DEM, can interpret the river drainage patterns well. Slope gradient calculated from DEM might be more suitable for large scale SOC research than slope documented in STATSGO from soil survey sampling.

This study used 1:24K DEM with a 30m horizontal resolution and a 0.3m vertical precision to calculate the terrain attributes by use of Spatial Analyst and 3D Analyst tools in ArcGIS (ESRI, 2007). However, it is necessary to mention that Light Detection and Ranging (LIDAR) DEM with a 5m horizontal resolution and a 0.2m vertical precision may produce more detailed and accurate terrain attributes. LIDAR DEM data is currently not complete for the entire state of Louisiana -- it does not cover a large portion of the state’s central and northern regions. Also, most current terrain software, such as DIGEM and Landserf, are not able to process large 1:24K DEM data with a 30m resolution, which covered the entire state of Louisiana. Computational solutions need to be found if large scale soil carbon is estimated with LIDAR DEM data.

4.3.3 Relationships among SOC, Topographic, and Watershed Characteristics in Louisiana Watersheds and Basins

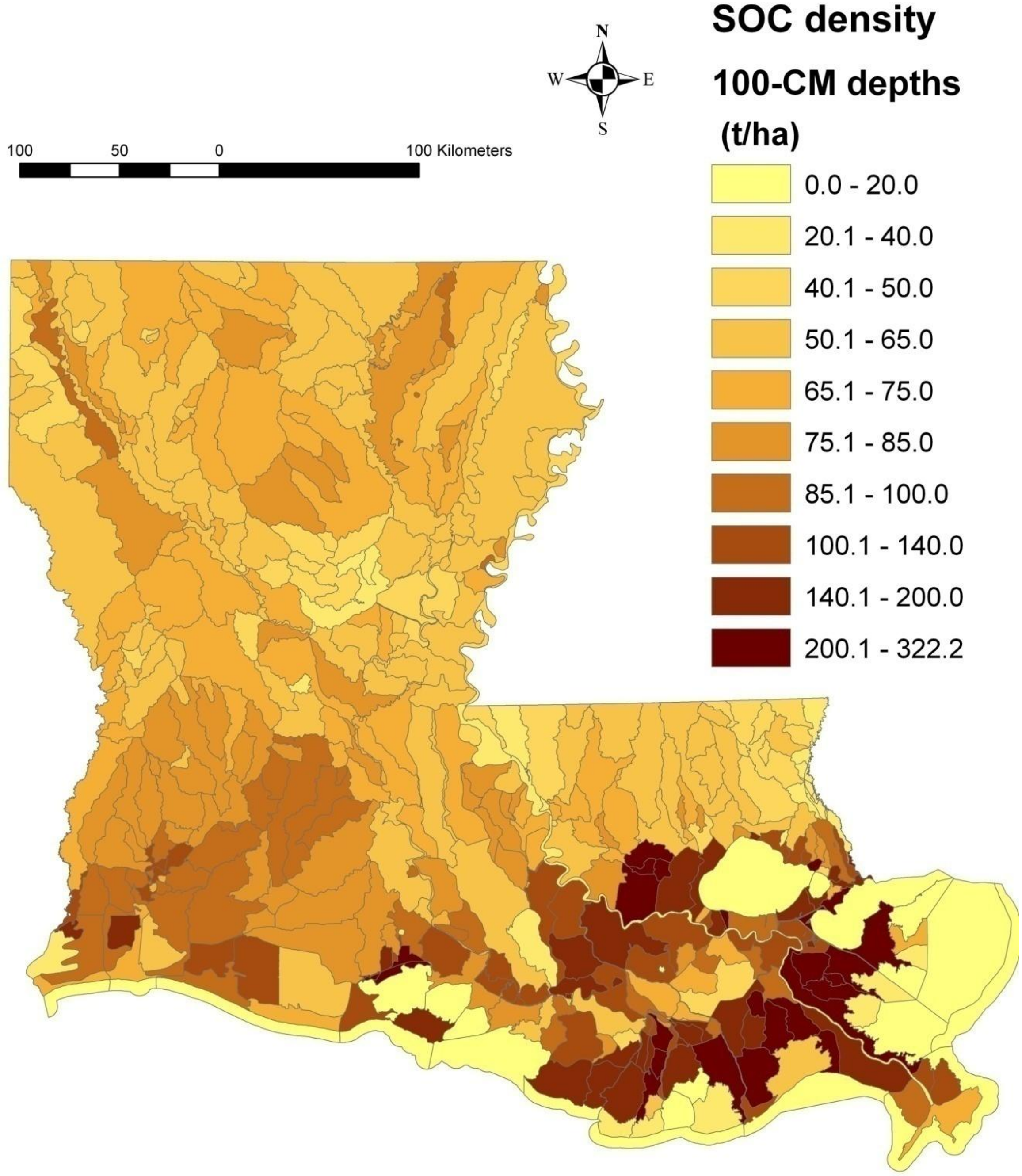
SOC densities were positively correlated with watershed drainage density (Pearson correlation coefficient, r=0.61 and p<0.0001 at the watershed scale; r=0.57 and p =0.05 at the basin scale), but negatively correlated with the average watershed slope gradient (r=-0.60 and p <0.0001 at the watershed scale; r=-0.83 and p =0.0009 at the basin scale) and average watershed elevation (r=-0.56 and p <0.0001 at the watershed scale; r=-0.66 and p =0.02 at the basin scale)

(Table 4.4 and Table 4.5). The surface soil carbon density showed higher correlation to slope and elevation than did the deep soil, but deep SOC density showed better correlation to drainage density than did upper SOC density.

Negative relationships of slope gradient to SOC are reported by Arrouays and others (1998), Cheng and others (2004), Tan and others (2004), Thompson and Kolka (2005), and Guo and others (2006b). Guo and others (2006b) found that the effect of slope on soil inorganic carbon (SIC) was even more obvious than that on SOC. The effect of elevation was positive on SOC in other literature (Cheng et al., 2004; Thompson and Kolka, 2005), which is opposite to the results of this study. One possible reason might be the difference in location of research areas. The research areas of this study were located from an inland to a large coast, compared to the inland study areas of Cheng and Thompson. For my scales of evaluation, I can conclude that elevation cannot be an independent environmental factor for interpretation of SOC.

Table 4.3 Topographical and geomorphological characteristics and their standard errors in 12 Louisiana major river drainage basins

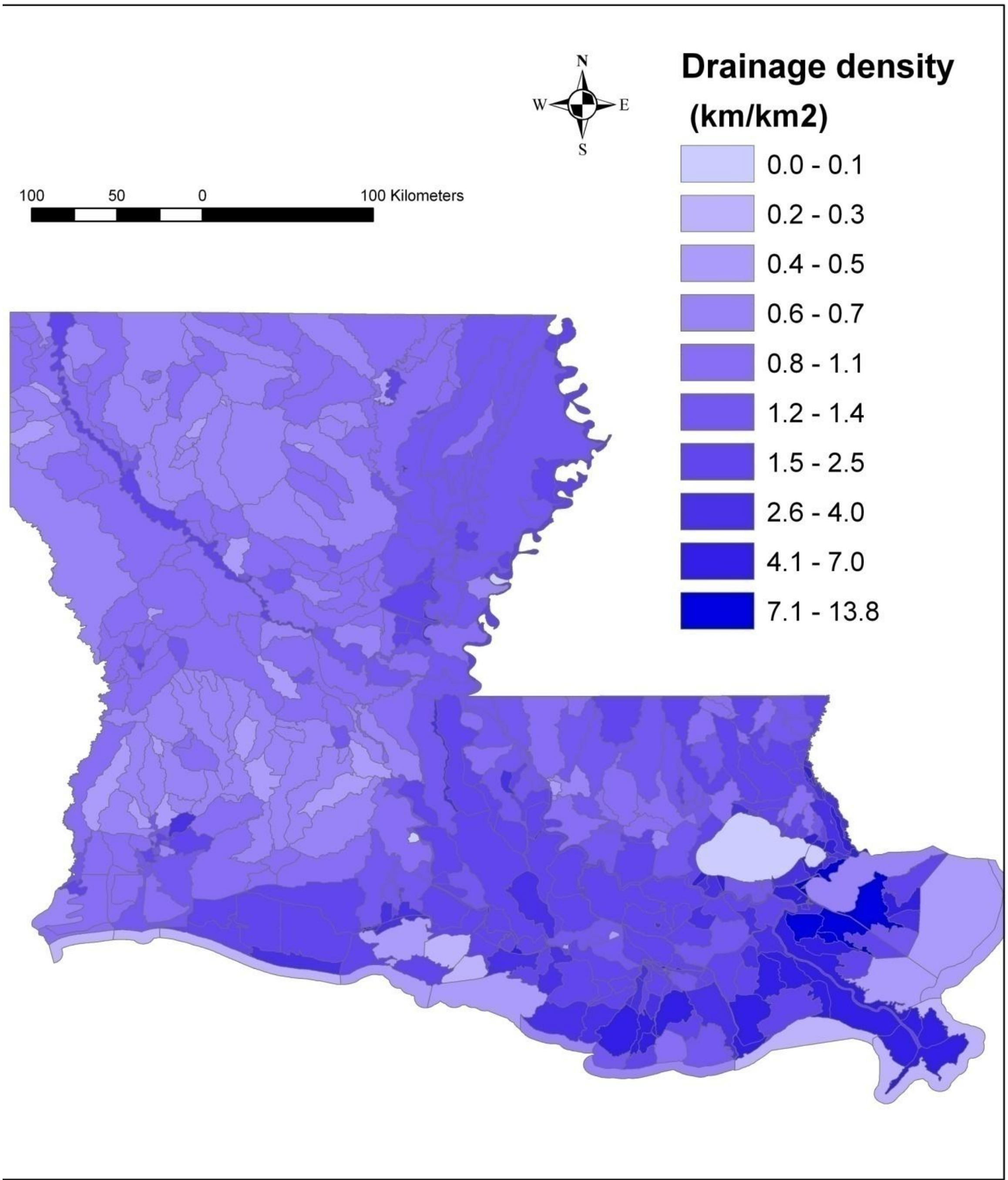
Basins	Drainage density (km/km^2)	Average Slope (degree)	Slope range (degree)	Average Elevation (meter)	Elevation range (meter)
Barataria	3.0 (±0.4)	0.5 (±0.3)	12.0 (±2.3)	0.9 (±0.2)	5.3 (±0.9)
Terrebonne	2.0 (±0.2)	0.4 (±0.1)	15.2 (±1.8)	2.4 (±0.4)	7.2 (±0.9)
Pontchartrain	3.0 (±0.4)	1.4 (±0.2)	22.3 (±2.6)	13.5 (±2.8)	27.9 (±4.6)
Vermilion-Teche	1.4 (±0.1)	1.6 (±0.3)	24.8 (±2.4)	10.9 (±2.3)	22.2 (±3.4)
Mermentau	1.2 (±0.2)	0.7 (±0.1)	15.3 (±1.4)	9.2 (±2.3)	14.8 (±2.5)
Calcasieu	0.8 (±0.1)	2.7 (±0.5)	22.7 (±1.6)	31.1 (±5.2)	45.3 (±6.3)
Sabine	0.9 (±0.1)	5.2 (±1.0)	35.7 (±5.2)	53.1 (±10.1)	68.3 (±12.2)
Red	0.9 (±0.1)	4.7 (±0.3)	45.9 (±2.2)	50.2 (±2.9)	69.2 (±4.8)
Ouachita	1.0 (±0.1)	5.2 (±0.5)	46.0 (±2.2)	39.3 (±2.5)	60.3 (±4.4)
Atchafalaya	2.2 (±0.4)	0.7 (±0.2)	21.2 (±5.1)	4.4 (±1.6)	11.6 (±2.9)
Mississippi	1.2 (±0.1)	5.8 (±1.7)	64.0 (±5.8)	27.5 (±6.4)	61.6 (±14.0)
Pearl	2.5 (±0.4)	4.4 (±0.7)	42.1 (±5.6)	36.4 (±7.0)	52.6 (±9.0)



(a)

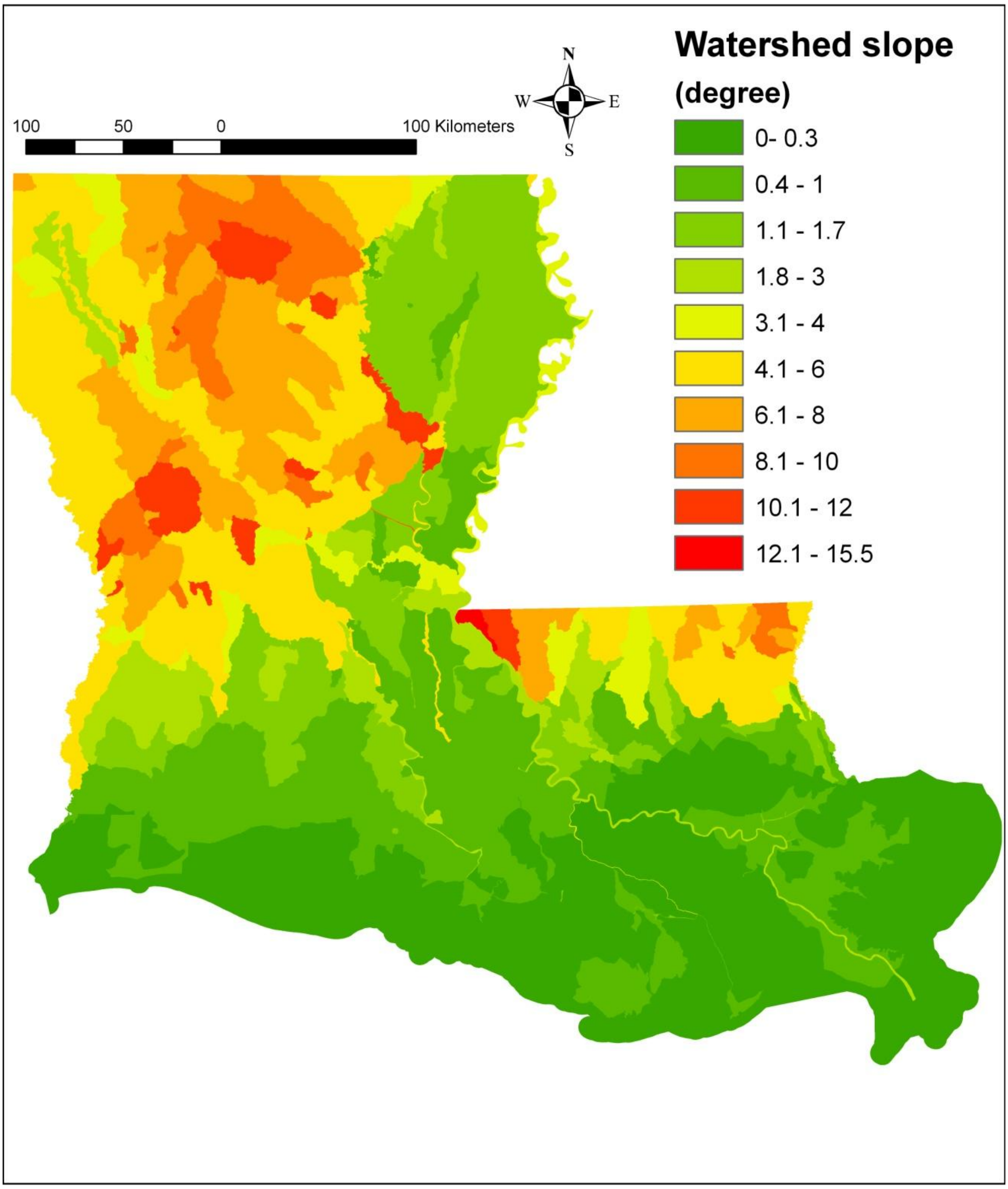
Figure 4.3. Spatial distributions across Louisiana of (a) Soil carbon densities in the surface 100-cm depths at a watershed scale, (b) Watershed drainage densities, and (c) Watershed slope gradients.

(Figure 4.3 continue)



(b)

(Figure 4.3 continue)



(c)

Table 4.4 Pearson correlation coefficients of SOC in different depths with environmental variables at the watershed scale

	SOC_30cm	SOC_1m	SOC_max	Drainage_density	Slope_mean	Slope_range	Elev_mean	Elev_range	Elev_majority
SOC_30cm	1	0.95	0.90	0.61	-0.53	-0.60	-0.56	-0.56	-0.51
SOC_1m	0.95	1	0.98	0.65	-0.46	-0.56	-0.47	-0.48	-0.43
SOC_max	0.90	0.98	1	0.64	-0.39	-0.51	-0.40	-0.42	-0.37
Drainage_density	0.61	0.65	0.64	1	-0.37	-0.42	-0.46	-0.45	-0.43
Slope_mean	-0.53	-0.46	-0.39	-0.37	1	0.69	0.85	0.81	0.78
Slope_range	-0.60	-0.56	-0.51	-0.42	0.69	1	0.70	0.82	0.63
Elev_mean	-0.56	-0.47	-0.40	-0.46	0.85	0.70	1	0.85	0.95
Elev_range	-0.56	-0.48	-0.42	-0.45	0.81	0.82	0.85	1	0.75
Elev_majority	-0.51	-0.43	-0.37	-0.43	0.78	0.63	0.95	0.75	1

All significant at the 0.001 probability level.

Table 4.5 Pearson correlation coefficients of soil organic carbon at different depths, topographic and watershed characteristics at the watershed and basin scales

	Watershed scale			Basin scale		
	SOC_30cm	SOC_1m	SOC_max	SOC_30cm	SOC_1m	SOC_max
Drainage_density	0.61***	0.65***	0.64***	0.50	0.57*	0.58*
Slope_mean	-0.53***	-0.46***	-0.39***	-0.85**	-0.83**	-0.79**
Slope_range	-0.60***	-0.56***	-0.51***	-0.71**	-0.70**	-0.66*
Elevation_mean	-0.56***	-0.47***	-0.40***	-0.66**	-0.66**	-0.61*
Elevation_range	-0.56***	-0.48***	-0.42***	-0.59*	-0.59*	-0.55

*, **, and *** = significant at 0.1, 0.01, and 0.001 probability levels, respectively.

Soil erosion and possible SOC loss are usually expected in sloping areas. Gerrard (1981) classified the movement of soil on slopes as surface water erosion, subsurface water erosion, wind erosion, and mass movement. The movements are all related, directly or indirectly, to topographic, geomorphologic, and hydrological factors. Bare, moist soil with steep slopes, strong water flows, and high runoff rate can have greater erosion potential. Seasonal soil-water movements effect the soil erosion and possible SOC loss directly; meanwhile, they partly control the distribution of organic soils by their influence on soil drainage (Daniels and Hammer, 1992).

Drainage class score was illustrated as negatively correlated to SOC (Davidson, 1995; Tan et al., 2004), in contrast to the positive relationship of watersheds or basins' drainage density to SOC in this study. Tan and others (2004) fitted drainage class score and SOC in models (R^2= 0.26, n=8 for cropland; R^2= 0.91, n=8 for forestland; R^2= 0.64, n=8 for pastureland) in Ohio, with large ranges of R^2 and small sample sizes. Davidson (1995) fitted these two variables in models in Kansas (R^2= 0.13, n=274 map units) and Montana (R^2= 0.48, n=692 map units) and suggested that other factors have to be considered, as R^2 values were all below 0.5.

The R^2 of the simple linear regression model between SOC and drainage density at the watershed scale was 0.43 (p <0.0001) (Figure 4.4a). The multiple linear regression model for drainage density, slope range, and SOC at the watershed scale is given below:

$$TOC\_1M=84.04-0.80*slope\_range+16.90*drainge\_density \qquad (4.4)$$

where TOC_1M is the SOC density of each watershed in the surface 100-cm depths,

slope_range is the range of slope gradient in each watershed; and drainge_density is the drainage density of each watershed. The R^2 of this multiple linear regression model was 0.53 (p <0.0001), which is better than the R^2 of the simple linear regression model. The correlation of soil carbon increased when using both topographic parameters, indicating that incorporating additional parameters may reduce uncertainties in the regression model results. Predicted SOC values from the multiple linear regression models are likely higher than observed SOC values at the lower SOC value area; and observed SOC values are likely higher than predicted SOC values at the higher SOC value area (Figure 4.5).

The scatter plots of SOC vs. slope range (Figure 4.4b) and SOC vs. elevation (Figure 4.4c) indicated non-linear relationships among them, instead of linear relationships. The non-linear regression models of SOC vs. slope range and SOC vs. elevation are given below:

$$TOC\_30cm = 113.2\ slope\_range^{-0.3} \quad (4.5)$$

$$TOC\_30cm = 71.78\ elevation^{-0.15} \quad (4.6)$$

where TOC_30cm is the SOC density of each watershed in the surface 30-cm depths, slope_range is the range of slope gradient in each watershed, and elevation is the average elevation in each watershed. The R^2 of these non-linear regression models are 0.52 (p <0.0001) and 0.5 (p <0.0001), which are better than the R^2 of any simple linear regression model.

The multiple linear regression model for predicting SOC with the slope and drainage density at the basin scale is given below:

$$TOC\_1M=126.4-4.0*slope\_range+17.5*slope\_mean+15.3*drainage\_density \quad (4.7)$$

where TOC_1M is the SOC density of each basin within the surface 100-cm depth, slope_range is the range of average slope gradient in each basin; and drainge_density is the average drainage density of each basin. The R^2 of this multiple linear regression model was 0.83 (p =0.0018).

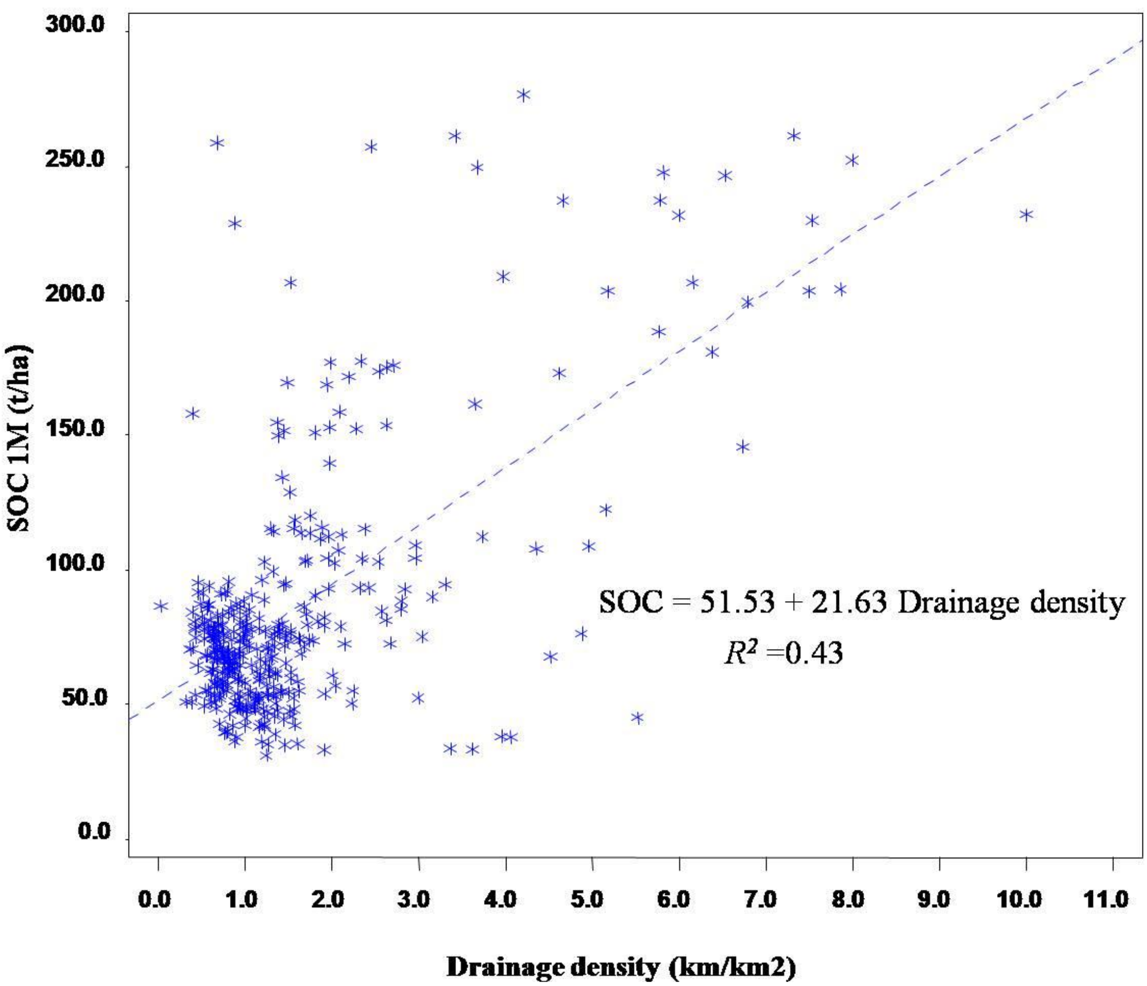
Both Pearson correlation coefficient and R^2 at the drainage basin scale were stronger than those at the watershed scale. The R^2 of the multiple linear regression model at the basin scale was 0.83 (p =0.0018), which is better than the R^2 of the multiple linear regression model at the watershed scale, 0.53 (p <0.0001). One possible reason for this is that the relationship among SOC, drainage density, and terrain characteristics at a large scale is more significant than the relationship at a small scale. At a large scale, we may find those macro trends which cannot be seen at a small scale. Another possible reason is that the sizes of watersheds are not uniform, which could result in more errors in their determination.

The current watersheds dataset was developed for the LDEQ Office of Water Resources' watershed assessment and management tasks (LDEQ, 2004). Studies based on more uniform, balanced, and natural watershed datasets are required to further test the hypothesis that relationships at the larger basin scale are better than those at the watershed scale.

4.4 Conclusions

This study assessed soil organic carbon storage and distribution across Louisiana's

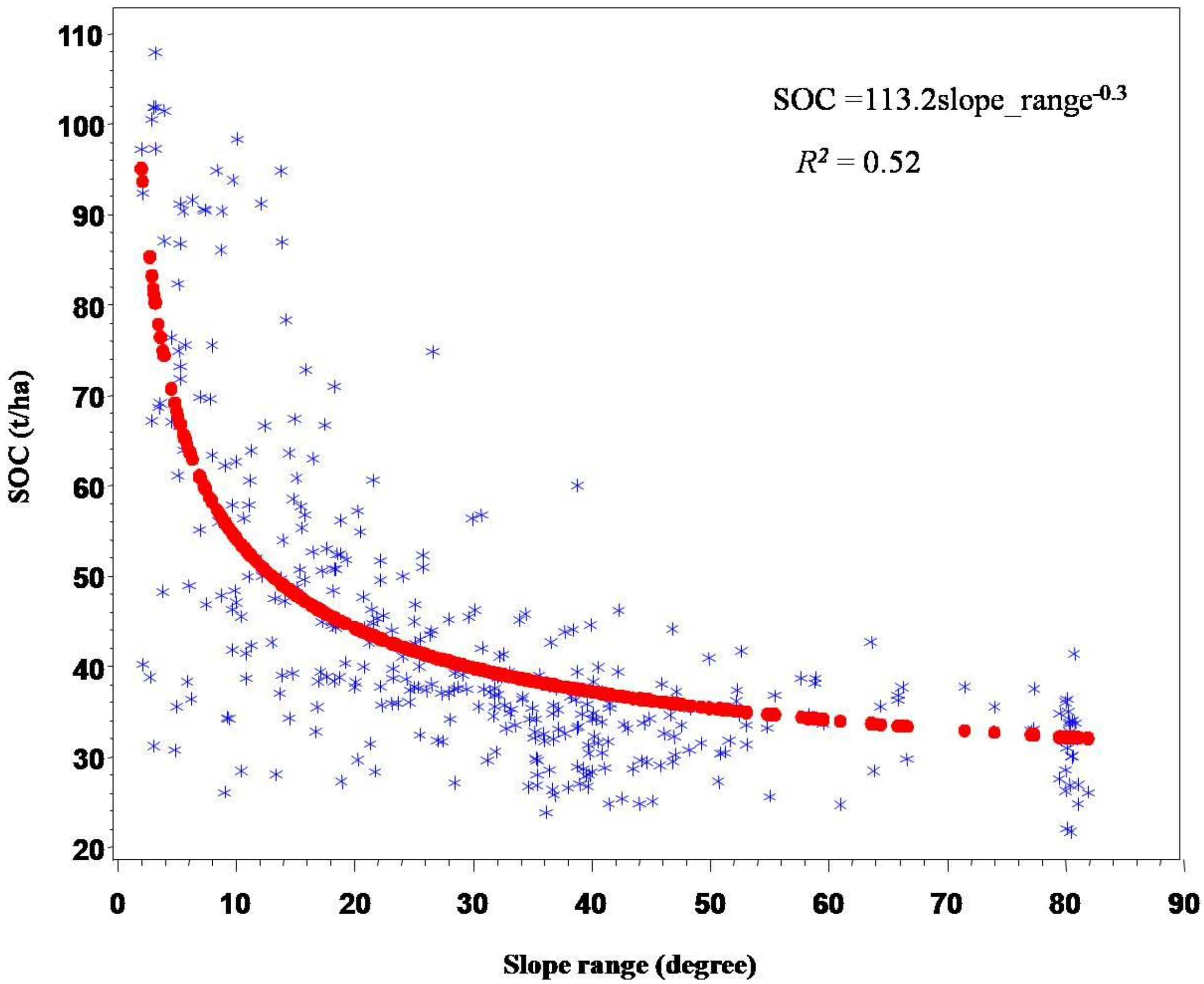
watersheds. It is the first report on the SOC density at the watershed scale and its relationships with drainage density, slope, and elevation at watershed and river basin scales. Based on my findings, I conclude that SOC at both watershed and drainage basin scales is closely related to topographic and watershed characteristics calculated directly from the 1:24K DEM data (30-m resolution). In general, SOC density is low at the watersheds with steep slope gradient. Neither elevation nor drainage density can be a single strong independent environmental factor for interpreting SOC. Our results suggest that the state's highest SOC distribution, found in the southeastern coastal areas of



(a)

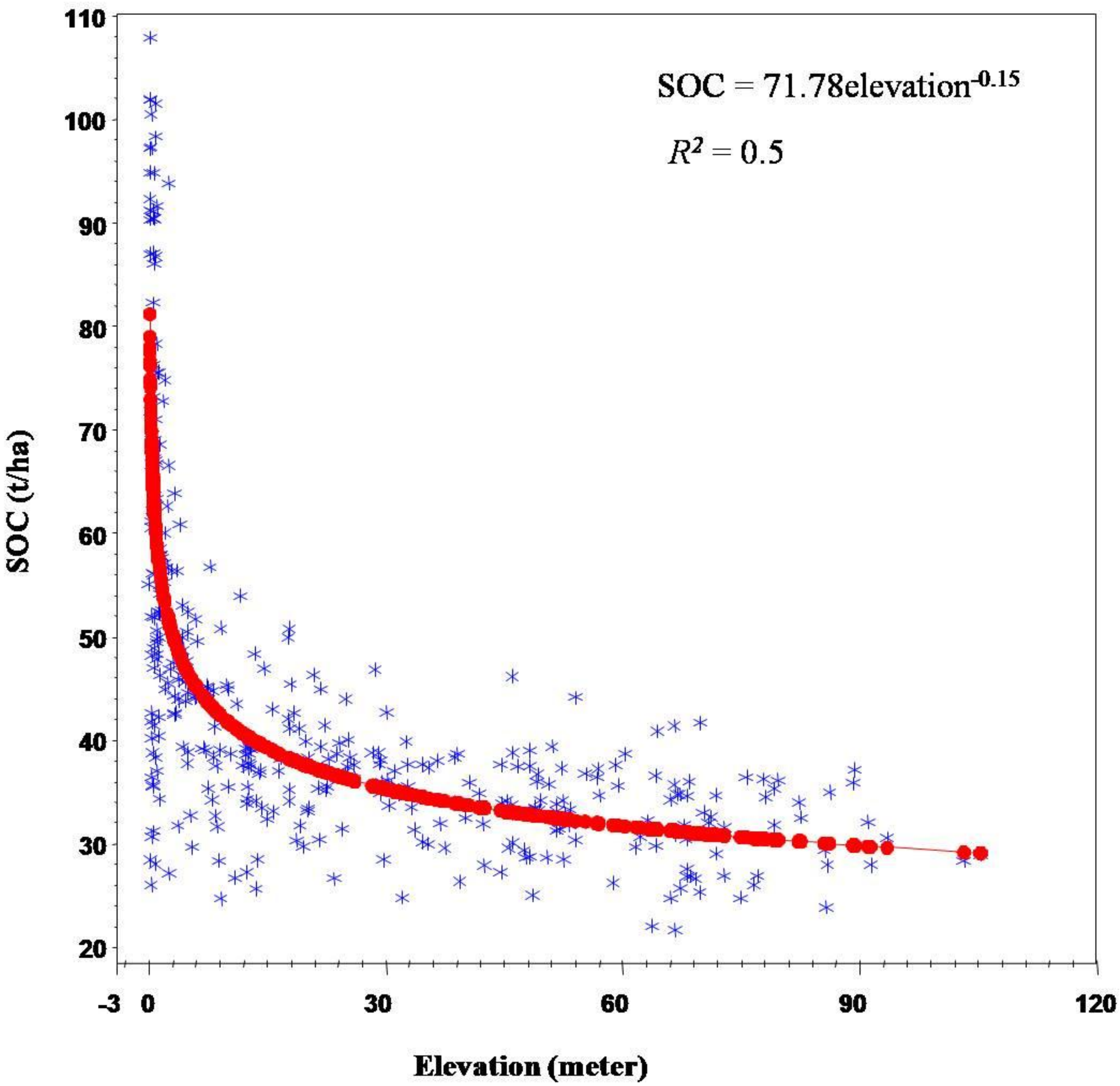
Figure 4.4 Relationships of (a) SOC with drainage density, (b) SOC with slope range, and (c) SOC with elevation.

(Figure 4.4 continue)



(b)

(Figure 4.4 continue)



(c)

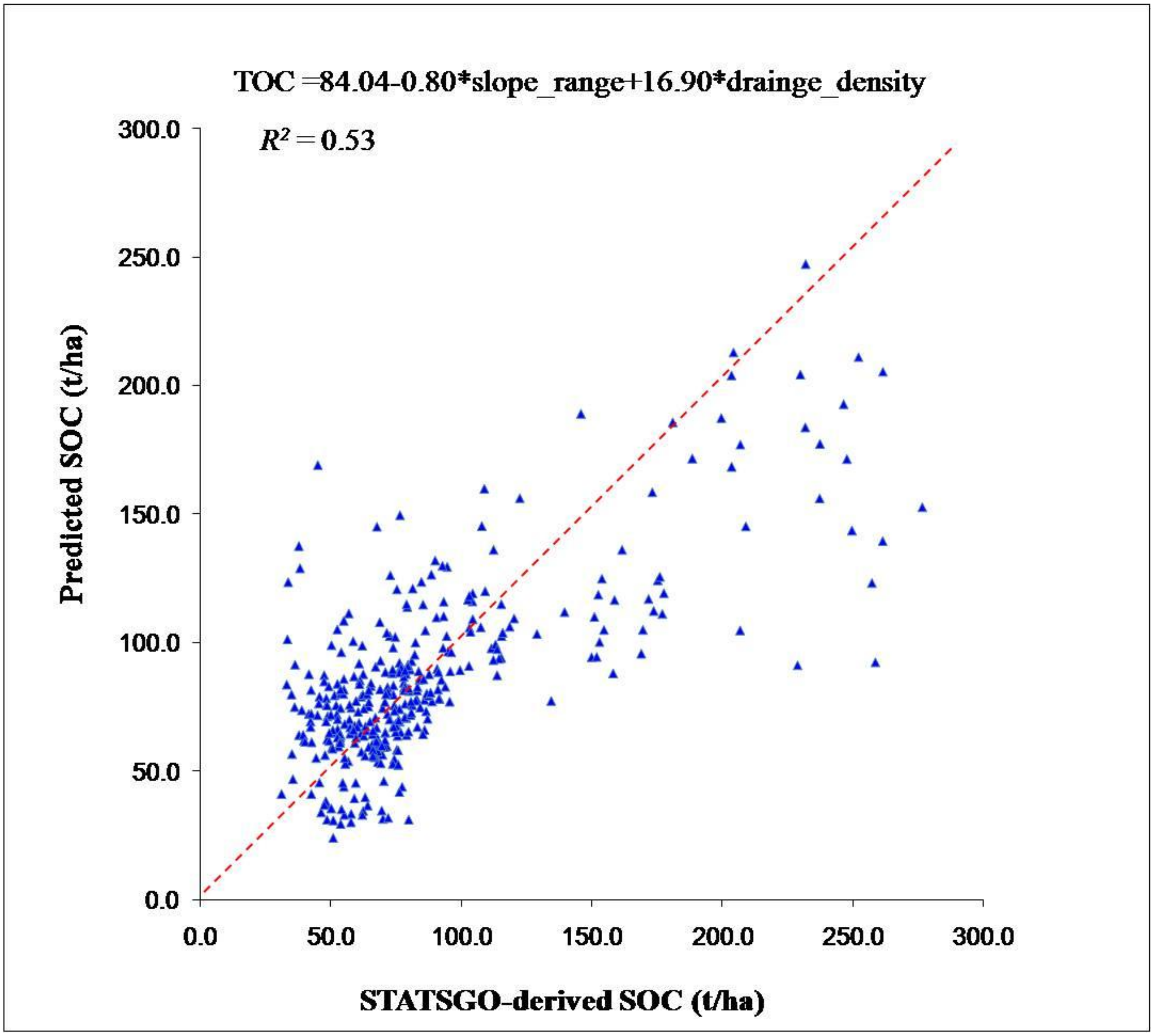


Figure 4.5. Comparison between predicted SOC density and STATSGO-derived SOC density.

Louisiana, is related to another geomorphologic environmental factor, the Mississippi River deltaic plain-building process. Further studies on the relationships among SOC, topographic, and geomorphologic features will help develop a novel approach to more accurately quantify large-scale terrestrial carbon storage utilizing geospatial databases and techniques.

CHAPTER 5 POTENTIAL SOIL ORGANIC CARBON CHANGES IN LOUISIANA

5.1 Introduction

Soil organic carbon (SOC) is a significant carbon reservoir on earth. Future changes of SOC storage are of great importance to the global carbon cycle. The movements of carbon through ecosystems and the pedosphere are more important than the amount stored in various reservoirs (Schlesinger, 1997). Climatic factor, biotic factor, topographic factor, parent material, and time are critical environmental factors that affect soil formation (Dokuchaev as cited by Jenny, 1941, 1961). Climate change may significantly alter the terrestrial carbon capacity by way of changes in such things as temperature and precipitation, which would affect the photosynthesis and respiration of terrestrial ecosystems. It is difficult to quantify and predict the carbon-cycle-climate feedbacks; especially, below-ground processes are much less understood than the above-ground processes in the carbon-cycle-climate system (Heimann and Reichstein, 2008).

In recent years, there are increasing predicting climate change effects on soil carbon storage. Smith et al. (2005, 2006, 2007) and Zaehle et al. (2007) simulated SOC changes for Europe under different climate change projections using the RothC, CANDY, or other models. Other researchers used the Global Environment Facility Soil Organic Carbon (GEFSOC) Modeling System (Falloon et al., 2007; Easter et al., 2007) to estimate SOC stocks and changes for other regions in the world, for instance, Kamoni et al. (2007) for Kenya, Cerri et al. (2007) for Brazil, Al-Adamat et al. (2007) for Jordan, and Bhattacharyya et al. (2007) for India. The GEFSOC Modeling System involved analysis

of long-term historical temperatures and rainfall data as well as current and future land use scenarios between 1990 and 2030 using three methods: the Century general ecosystem model, the RothC soil carbon decomposition model, and the IPCC method. Smith et al. (2009) assessed the impact of climate change on SOC stocks in Canada between 2000 and 2099 under IPCC IS92a and Special Report on Emissions Scenarios (SRES) B2 scenarios using the Climate Modeling and Analysis (CCCma) Coupled Global Climate Model (CGCM1,2) and the Century ecosystem model. However, very few studies have addressed the possible impacts of climate change on terrestrial carbon changes in the United States of America under the climate change projections of climate models.

Climate change may vary largely from one region to another region in the world. For the U.S., different trends may differ from the North to the South and from the East to the West. As climate change research intensifies, there is an indisputable need to refine the study of climate change at a local scale for assessing the impacts and helping to mitigate or adapt the climate change with finite resources (Karl et al., 2009). To our best knowledge, no publications have so far documented possible future climate changes in Louisiana in detail at a fine scale under the IPCC emissions scenarios based on climate models using General Circulation Models (GCMs).

The objectives of this study are threefold: 1) to determine the magnitude of temperature and precipitation changes as predicted by the Hadley climate model for Louisiana; 2) to investigate potential effects of these changes on organic carbon in surface soils across Louisiana at the watershed scale under three emissions scenarios (A1FI, A2, and B2); and 3) by doing so, using Louisiana as an example, to assess the

applicability of linking different geographically referenced databases in predicting soil carbon response to local climate changes.

5.2 Methodology

5.2.1. Study Area Conditions

The study area covered the entire state of Louisiana, U.S.A., geographically located between 89°W and 94°W in longitude and between 29°N and 33°N in latitude. The state extends approximately 611 km from north to south and 210 km from west to east, with a total area of 134,273 km^2. Of the total area, land occupies 112,835 km^2 and water 21,437 km^2. Louisiana is a low-lying state with an average elevation of 30.5 m, ranging from 2.4 m below to 163.0 m above sea level. The region is characterized by a humid subtropical climate. According to the NOAA Southern Regional Climate Center report (http://www.srcc.lsu.edu/), the average annual temperature of Louisiana ranges from about 18°C in northern divisions to about 21°C in southern divisions. The mean annual precipitation of Louisiana ranges from a low of 117 cm in the north to a high of 168 cm in the south. The dominant land cover types in Louisiana include forests, croplands, and wetlands. Cropland occurs mostly in the fertile river valleys, and the Gulf Coast Prairie. Forests mainly occupy hilly areas of Central Louisiana. Wetlands occur throughout the state with the largest percentage in the Gulf Coast marsh and alluvial plains. Louisiana, next to Alaska and Florida, has the largest wetland acreage (35,612 km^2) in the United States (U.S. EPA, 2009).

For its water quality planning and regulatory management, the Louisiana Department of Environmental Quality delineated the state into 484 watersheds ranging in size from 0.23 to 3,115 km^2 with an average area of 267 km^2 (LDEQ, 2004). Of these

watersheds, 144 are dominated by forests occurring mainly in northern Louisiana; 88 watersheds are dominated by croplands mainly on the Mississippi River and Red River floodplains; 22 watersheds are grassland (pasture and hay) in south-central Louisiana; 150 watersheds are dominated by wetlands clustering in the southern coastal areas and on the Mississippi River and Atchafalaya River floodplains; 62 watersheds are dominated by open water mainly in the coastal area (Figure 5.1). These 212 watersheds were not included in this study because the RothC model is not applicable for waterlogged soils.

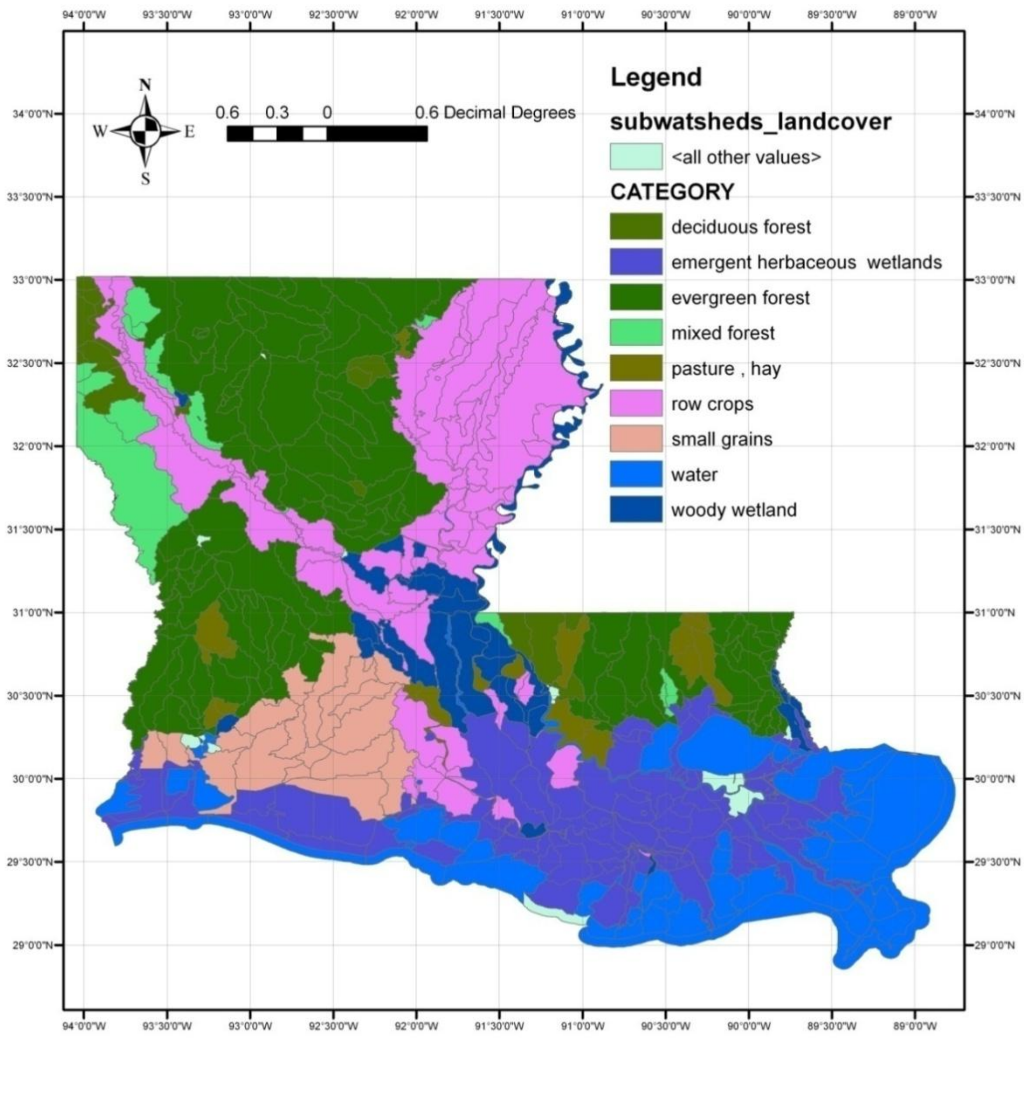


Figure 5.1 Louisiana land cover types at the watershed scale.

5.2.2. Soil Carbon Estimation across Landscape at the Watershed Scale

This study utilized a series of geographically-referenced databases to estimate current soil organic carbon storage at the watershed scale and across various land use types in Louisiana. These databases included the USDA NRCS Soil Geographic Database (STATSGO), and National Land Cover Database (NLCD).

Soil organic carbon was estimated from soil organic matter content, soil layer depth, and bulk density, extracted from the STATSGO database (Zhong and Xu, 2009). Total soil organic storage for 30cm depth was calculated according to Xu and Prisley (2000):

$$Cs = [\ (BDij * Dij * SOMij) * COMPi] / 1.724 \qquad (5.1)$$

where *Cs* is soil organic carbon in metric tons, *COMP* is the area percentage of a soil series within each map unit, *BD* is the soil bulk density in t/m^3, *D* is the depth of a soil layer in meters, *SOM* is the soil organic matter content in percent, and the subscripts *i* and *j* are the identifiers for soil layers and components, respectively. The Van Bemmelen factor of 1.724 was used on the assumption that organic matter contains 58% organic carbon (Nelson and Sommers, 1982). SOC densities (in tons/ha) was calculated for each soil map unit by dividing the total SOC by the corresponding map unit areas. Then, SOC at each map unit was aggregated for watersheds, and average SOC density for each watershed was calculated with the area weights of the map units in that watershed (Figure 5.2).

All watersheds were aggregated with NLCD to examine the land cover types at the

watershed scale across Louisiana. Zonal Majority function from ARCGIS 9.3 (ESRI, 2007) was used in the zonal analysis. In this study, forest covered deciduous forest, evergreen forest, and mixed forest; croplands covered row crops and small grains; grasslands were pasture/hay. Land cover class was defined as forest when tree canopy

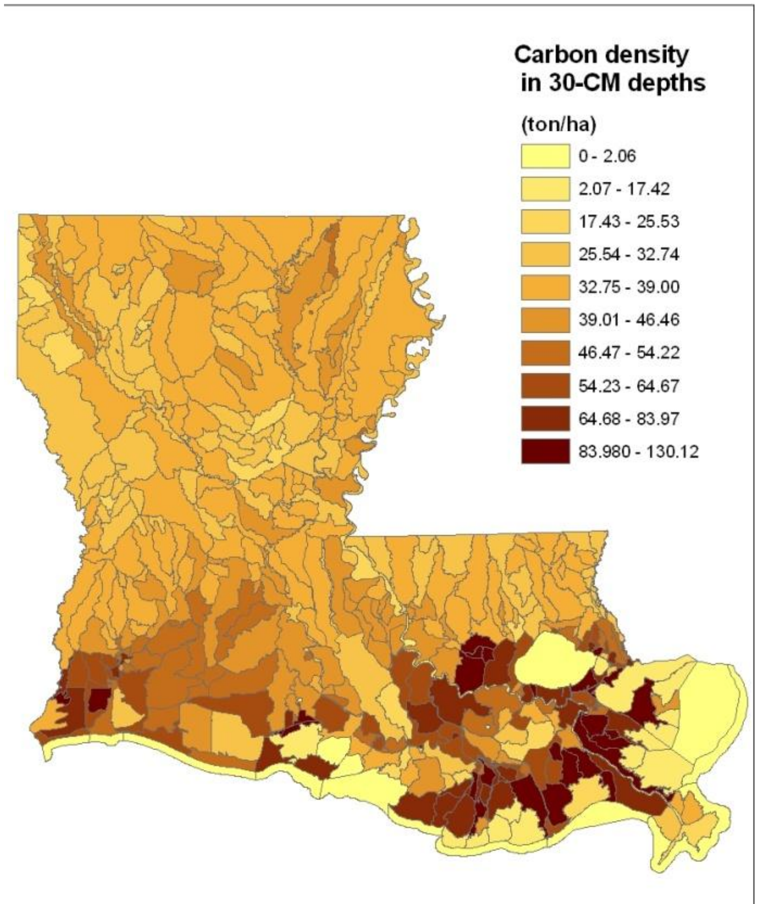


Figure 5.2 Spatial distribution of SOC in the upper 30-cm depths at the watershed scale.

accounted for 25-100 percent of the cover. According to the USGS NLCD Land Cover Class Definitions (Homer et al., 2004), areas dominated by trees where 75 percent or more of the tree species shed foliage simultaneously in response to seasonal change were classified as deciduous forest; areas dominated by trees where 75 percent or more of the tree species maintain their leaves all year were classified as evergreen forest; areas

dominated by trees where neither deciduous nor evergreen species represent more than 75 percent of the cover present were classified as mixed forest. Areas used for the production of crops, such as corn, soybeans, vegetables, tobacco, and cotton accounting for 75-100 percent of the cover, were classified as row crops; areas used for the production of graminoid crops such as wheat, barley, oats, and rice, accounting for 75-100 percent of the cover, were classified as small grains. Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops accounting for 75-100 percent of the cover were classified as pasture/hay.

5.2.3. Modeling SOC Changes

- RothC Model and Parameterization

RothC is one of the most widely used soil carbon models. It was developed and parameterized to simulate the turnover of organic carbon in non-waterlogged topsoil under varying environmental conditions, such as temperature, precipitation, evapotranspiration, soil texture, soil moisture, and land use (Coleman and Jenkinson, 1999) (Figure 5.3). It uses a monthly time step to calculate total organic carbon (tons per hectare), microbial biomass carbon (tons per hectare), and $\Delta^{14}C$ (from which the radiocarbon age of the soil can be calculated) on a time scale of years to centuries (e.g., Jenkinson et al., 1987; Jenkinson, 1990; Jenkinson et al., 1991; Jenkinson et al., 1992; Jenkinson and Coleman, 1994).

RothC computes the changes in organic carbon as it is partitioned into five basic compartments: inert organic matter (IOM), decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO), and humified organic matter (HUM) (Coleman and Jenkinson, 1999). These five compartments can be classified as four active

compartments and a small amount of inert organic matter (IOM). The IOM is one compartment resistant to decomposition. Incoming plant carbon is split between DPM and RPM, depending on the DPM/RPM ratio of the particular incoming plant material. The higher the decomposable plant material/resistant plan material ratio, the larger the

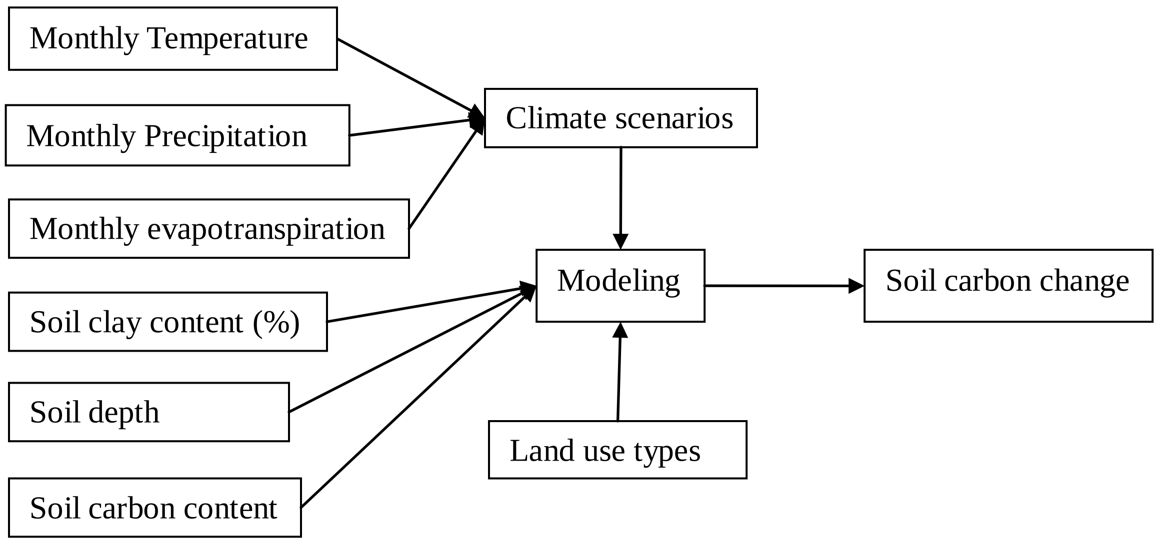


Figure 5.3 Main flow chart of RothC Model.

potential soil carbon emissions could be. These ratio values were set from the long-term field experiments at Rothamsted (Jenkinson et al., 1987; Jenkinson et al., 1992) and will not normally alter when using the model (Coleman and Jenkinson, 1999). For agricultural cropland, the model uses a DPM/RPM ratio of 1.44, i.e. 59% of the plant material is DPM and 41% is RPM. For grassland a ratio of 0.67 is used. For forest, a DPM/RPM ratio of 0.25 is used, so 20% is DPM and 80% is RPM.

Soil carbon changes in active compartments are relevant to temperature, soil moisture, soil cover, and decomposition rate and are calculated according to Coleman and Jenkinson (1999) as below:

$$Cend = e^{-abckt}\, t\, Corigin \quad (5.2)$$

where *Corigin* is original soil carbon of the active compartments in tons/ha in this study; *Cend* is the soil carbon of the active compartments at the end of the month in tons/ha; *a* is the rate modifying factor for temperature, *b* is the rate modifying factor for moisture, *c* is the soil cover rate modifying factor, *k* is the decomposition rate constant for that compartment relative to DPM/RPM ratio, *t* is 1 / 12, since *k* is based on a yearly decomposition rate.

Inert organic matter is roughly estimated by use of the equation below (Falloon *et al.*, 1998):

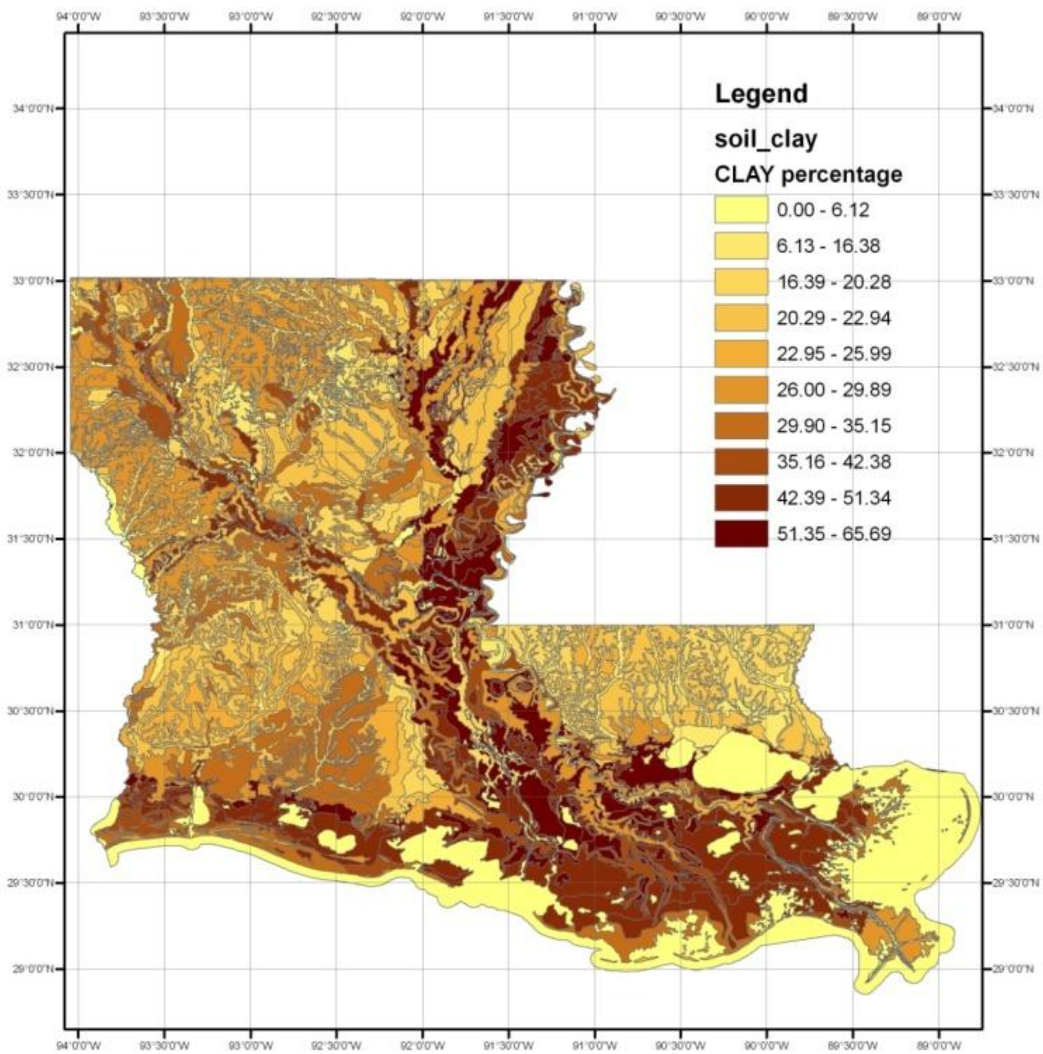
$$IOM = 0.049 TOC^{1.139} \quad (5.3)$$

where *TOC* is Total organic carbon in tons/ha; *IOM* is Inert organic matter in tons/ha.

Soil organic carbon content (Figure 5.2) and soil clay data in the model were derived from STATSGO for each watershed (Figure 5.4). Geographic coordinates were derived for climate data at a cell grid of 0.5° x 0.5°. Climate data for each of these grid cells in Louisiana were extracted from high resolution monthly mean temperature and monthly precipitation datasets provided by the Climate Research Unit, University of East Anglia, UK (Mitchell et al., 2004). Visual Basic for Application (VBA) was used to get particular cell (X, Y) climate data from grid 0.5° x 0.5° monthly temperature and precipitation between 1901-2000 and 2001-2100 (Appendix B), based on IPCC climate model HadCM3 (Hadley Centre Coupled Model, version 3) under A1FI, A2, or B2 emissions scenarios. Potential evapotranspiration (PET) of temperate soils was derived from

monthly open pan evaporation for each cell.

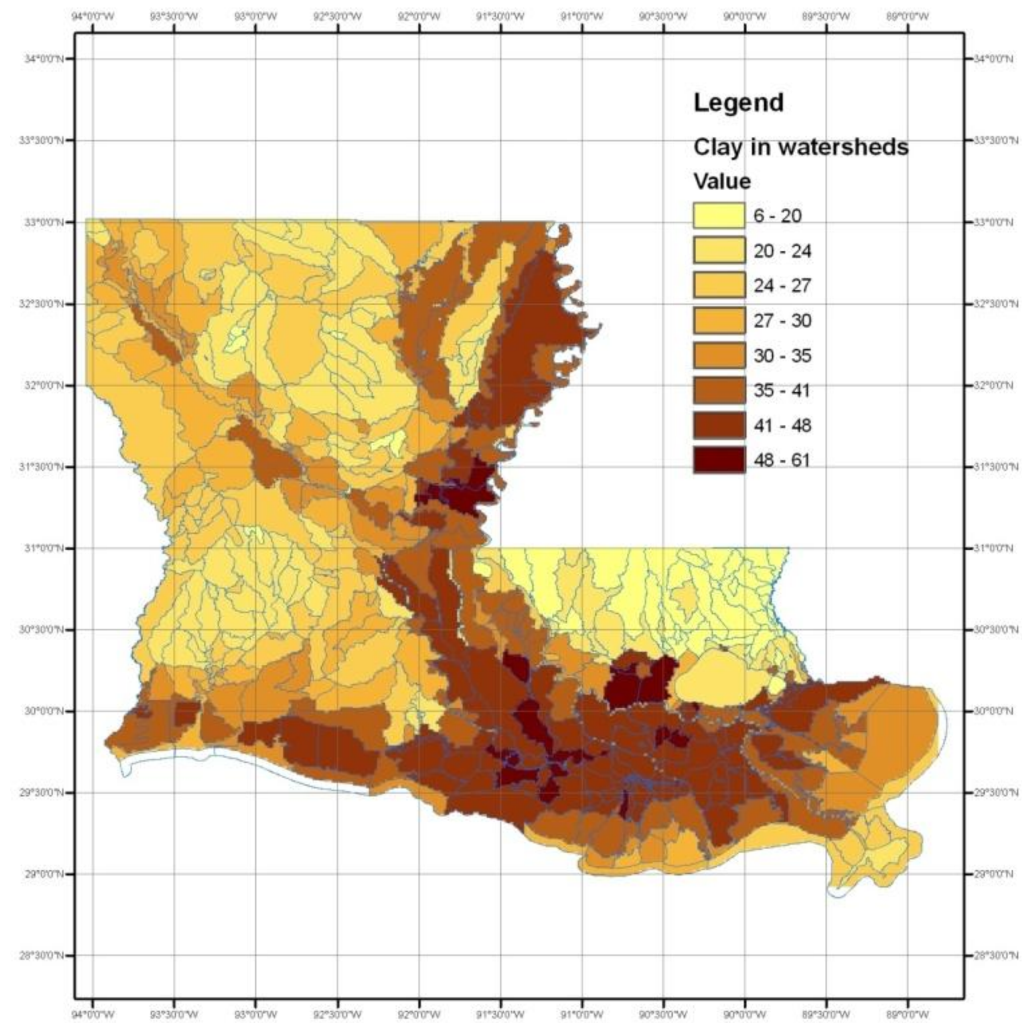
The Spatial RothC model was run with equilibrium under constant environmental conditions in multiple setting modes. Several batch data files covered input soil data, temperature, and precipitation data file names. SOC data of each watershed in modeling were categorized by land cover types: cropland, forest, and grassland.



(a)

Figure 5.4 Spatial distribution of soil clay at (a) map unit scale and (b) watersheds.

(Figure 5.4 continue)



(b)

- Climate Change Projections

IPCC SRES (Nakicenovic et al., 2000) divided the emissions scenarios into A1, A2, B1, and B2 scenario families, each of which consisted of several groups. Six scenario groups, which should be considered equally sound in the SRES, are A1B, A1FI, A1T, A2, B1, and B2. This study selected A1FI (fossil intensive, rapid economic growth, and technological change) as an even higher emissions scenario, A2 (heterogeneous world,

continuously increasing global population, slow economic growth) as a high emissions scenario, and B2 (economic, social and environmental sustainability) as a low emissions scenario. Scenarios A1FI and A2 are two of the higher greenhouse gas emissions among the scenario families. Observed carbon from fossil fuel CO_2 emissions was lower than the SRES projections from 1998 to 2001, but much higher from 2002 to 2007 (Karl et al., 2009). IPCC may have underestimated the technological challenge and overestimated the emissions reduction, as observed by the actual carbon and energy intensity from 2000 to 2005 that appeared much higher than those of the IPCC SRES assumptions for 2000 - 2100.

A large number of climate change studies using General Circulation Models (GCMs) have been conducted in recent years, both equilibrium and transient experiments, and both experiments worked with changes in greenhouse gas concentrations. Ruiz-Barradas and Nigam (2006) analyzed several IPCC GCM climate models based on the simulating interannual hydroclimate variability over North America during the warm season. Models like the Parallel Climate Model (PCM) from NCAR, and in particular HadCM3, exhibit reasonably well the observed distribution and relative importance of remote and local contributions to precipitation variability over the region, compared to the U.S. Community Climate System Model version 3 (CCSM3), the Goddard Institute for Space Studies model version EH (GISS-EH), the Geophysical Fluid Dynamics Laboratory Coupled Model version 2.1 (GFDL-CM2.1), and the Japanese Model for Interdisciplinary Research on Climate version 3.2[MIROC3.2(hires)]. The HadCM3 is the better one with proven high quality datasets such as National Centers for Environmental Predictions (NCEP)'s North American Regional Reanalysis (NARR), and the Climate Prediction

Center (CPC) U.S.–Mexico precipitation analysis during the warm season. In general, the HadCM3 is closest to the observations.

Climate datasets were provided by the Climate Research Unit (CRU), University of East Anglia, UK. These datasets included monthly mean temperature and monthly precipitation at a grid cell of 0.5° x 0.5° (Mitchell et al., 2004); Louisiana is divided into 57 of those cells (Figures 5.1, 5.4, and 5.5). Monthly values for 1900-2000 were based on interpolated observed data. Observed data were collected from a number of sources, including the World Meteorological Organization (WMO), National Climate Data Center (NCDC), National Meteorological Agencies (NMAs), and U.S. Air Force Weather Agency (New et al., 1999). Monthly values of 2001-2100 were based on the outputs from the UK Hadley Centre climate model (HadCM3) under IPCC SRES emissions scenarios.

5.2.4. Statistical Analyses

The SOC changes at each watershed in the beginning (2001-2010), middle (2041-2050), and final (2091-2100) of the simulation were tested for the effects of six land covers (deciduous forest, evergreen forest, mixed forest, pasture/hay, row crops, and small grains) and three emissions scenarios (A1FI, A2, and B2). The watershed was added as a random variable to account for variation between watersheds. The SOC simulation results of one hundred years between 2001-2100 were transposed according to the watersheds, land cover classes, and emissions scenarios. Average SOC densities for each watershed were calculated for the time periods 2001-2010 (beginning), 2041-2050 (middle), and 2091-2100 (final), each under three emissions scenarios. Then, the SOC changes were quantified for the beginning, middle, and final time periods, and the changes were statistically tested for significance.

All statistical analyses on SOC changes were performed using a SAS statistical procedure, PROC GLIMMIX (SAS Institute, 2007). F statistics from Type III tests of fixed effects to test for significant variables or interactions ($P < 0.01$) and least squares means to determine levels of class variables were used in six land cover classes and three emissions scenarios in proportion to their availability ($P<0.01$). The PDMIX800 macro (Saxton, 1998) for SAS was used to separate Tukey-Kramer ($P < 0.01$) adjusted means into letter comparisons (Appendix B).

5.3 Results and Discussion

5.3.1 Predicted Climate Change Patterns in Louisiana

The projections of the HadCM3 climate model indicate that monthly mean temperature will increase during most of the time from 2001 to 2100 in Louisiana. Projected mean temperature for spring 2100 will increase the most according to the percentages. Scenario B2 has the least temperature change; scenario A1FI has the largest temperature change (Table 5.1). Projected monthly precipitation in 2100 will decrease in winter and summer, but increase in spring and fall (Table 5.2).

Predicted climate changes of the HadCM3 climate model in Louisiana presented various possible climate change patters under A1FI, A2, and B2 scenarios in winter and summer. The greatest possible temperature change in January between 2001 and 2100 will be in the western cells of Louisiana; the least change will be in the Northeast (Figure 5.5a). However, in July between 2001 and 2100 the largest possible temperature change will move to the north part of Louisiana (Figure 5.5b). The largest possible precipitation change in January between 2001 and 2100 will be in the center and in the Northeast of Louisiana (Figure 5.5c). In July between 2001 and 2100, the Southeast would be the area

having the largest rainfall decrease (Figure 5.5d).

Table 5.1 Seasonal means of temperature and the predicted changes (in percent Δ) from 2050 to 2100 under A1FI, A2, and B2 scenarios compared to 2001 baseline in Louisiana

Year	SRES	Dec. Jan. Feb		Mar. Apr. May.		Jun. Jul. Aug.		Sep. Oct. Nov.	
		Mean (°C)	(Δ %)	Mean (°C)	(Δ %)	Mean (°C)	(Δ %)	Mean (°C)	(Δ %)
2050	A1FI	0.2	1.20%	3.8	19.02%	2.5	8.72%	2.2	10.77%
	A2	-0.5	-3.74%	3.1	15.42%	1.9	6.39%	1.6	7.84%
	B2	-0.6	-4.87%	2.9	14.37%	1.8	6.19%	1.6	7.86%
2100	A1FI	3.4	26.39%	7.7	38.65%	7.1	24.24%	6.0	29.33%
	A2	2.3	17.86%	6.5	32.81%	6.2	21.09%	5.2	25.05%
	B2	0.6	4.85%	4.4	22.12%	4.0	13.57%	3.4	16.41%

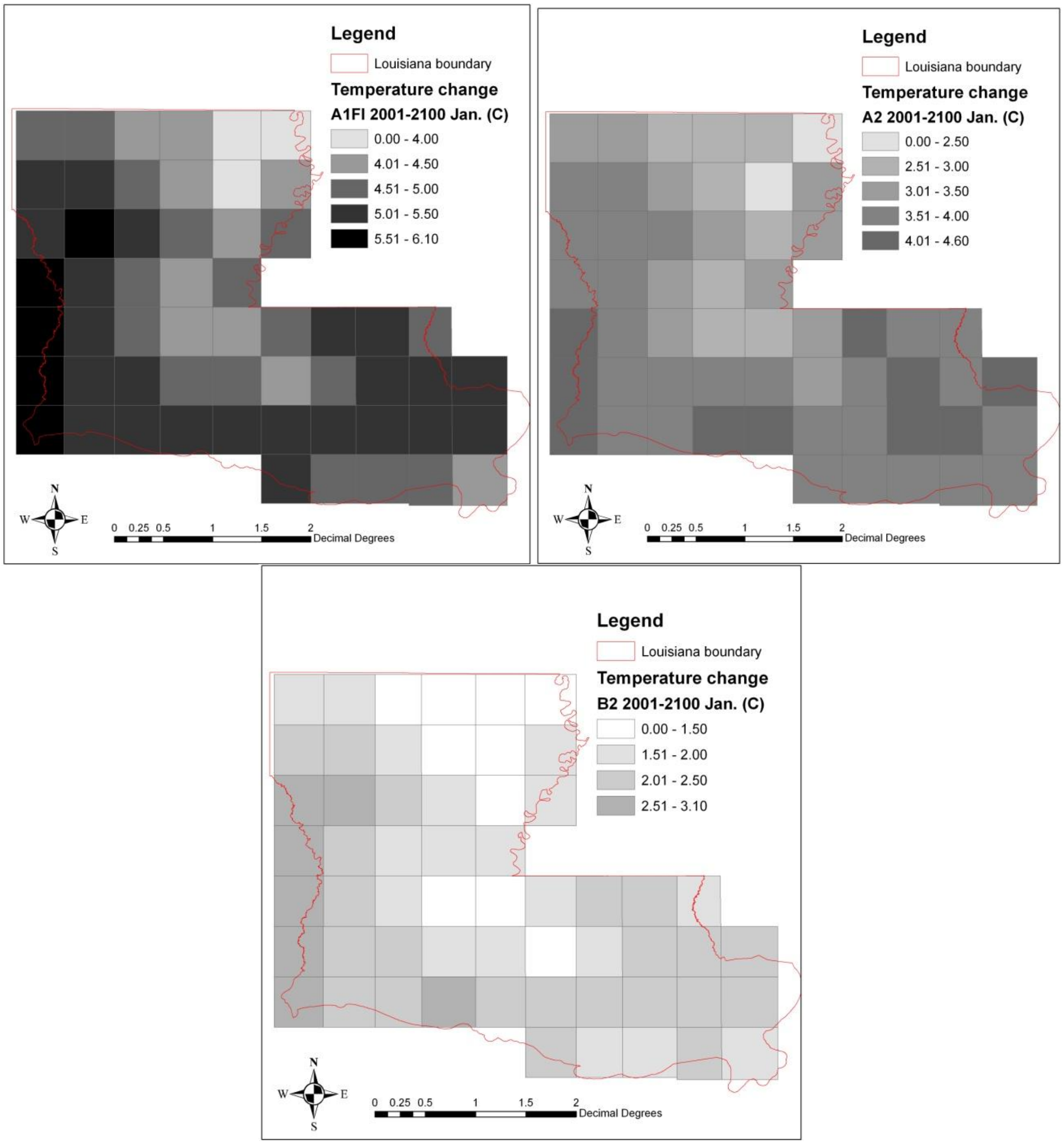
Table 5.2 Seasonal means of precipitation and the predicted changes (in percent Δ) from 2050 and 2100 under A1FI, A2, and B2 scenarios compared to 2001 baseline in Louisiana

Year	SRES	Dec. Jan. Feb		Mar. Apr. May.		Jun. Jul. Aug.		Sep. Oct. Nov.	
		Mean (mm)	(Δ %)	Mean (mm)	(Δ %)	Mean (mm)	(Δ %)	Mean (mm)	(Δ %)
2050	A1FI	-74.2	-50.00%	19.0	32.76%	-51.8	-44.08%	39.3	50.50%
	A2	-72.5	-48.34%	19.2	33.57%	-49.8	-42.61%	39.5	50.46%
	B2	-71.7	-47.66%	25.8	40.24%	-49.0	-41.75%	38.4	49.41%
2100	A1FI	-72.9	-49.22%	9.9	20.69%	-70.7	-60.87%	46.0	58.42%
	A2	-67.5	-44.79%	7.4	17.95%	-69.8	-60.45%	48.3	61.17%
	B2	-68.6	-45.30%	26.3	40.20%	-58.7	-50.43%	41.8	53.57%

Seasonal monthly mean temperatures at Baton Rouge, Louisiana between 1901 and 2000 did not show large differences. However, in summer, spring, and fall, average temperature in greenhouse gas emissions scenario A1FI and A2 will significantly increase compared to the historical temperature; in low emissions scenario B2, seasonal average temperature will increase much slower (Figure 5.6).

Future changes of total precipitation due to human-induced warming are more difficult to project than temperature (Karl et al., 2009). Changes in precipitation amount and frequency are highly uncertain. Different climate models or the same climate model

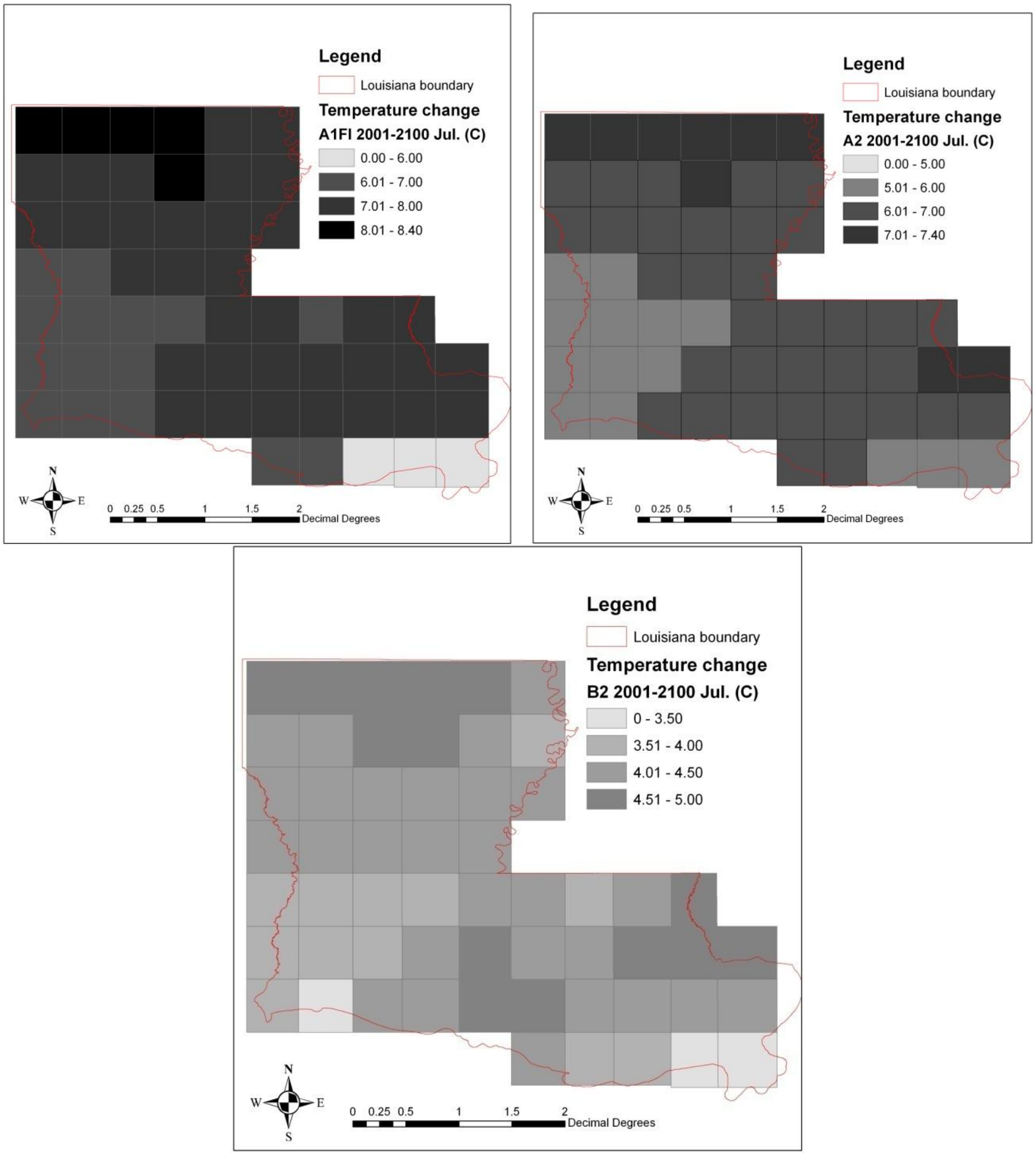
of different versions can project both increases and decreases in average annual



(a)

Figure 5.5 Temperature change in January (a) and July (b) and precipitation change in January (c) and July (d) between 2001 and 2100 in Louisiana under A1FI, A2, and B2 scenarios of HadCM3 climate model.

(Figure 5.5 continue)



(b)

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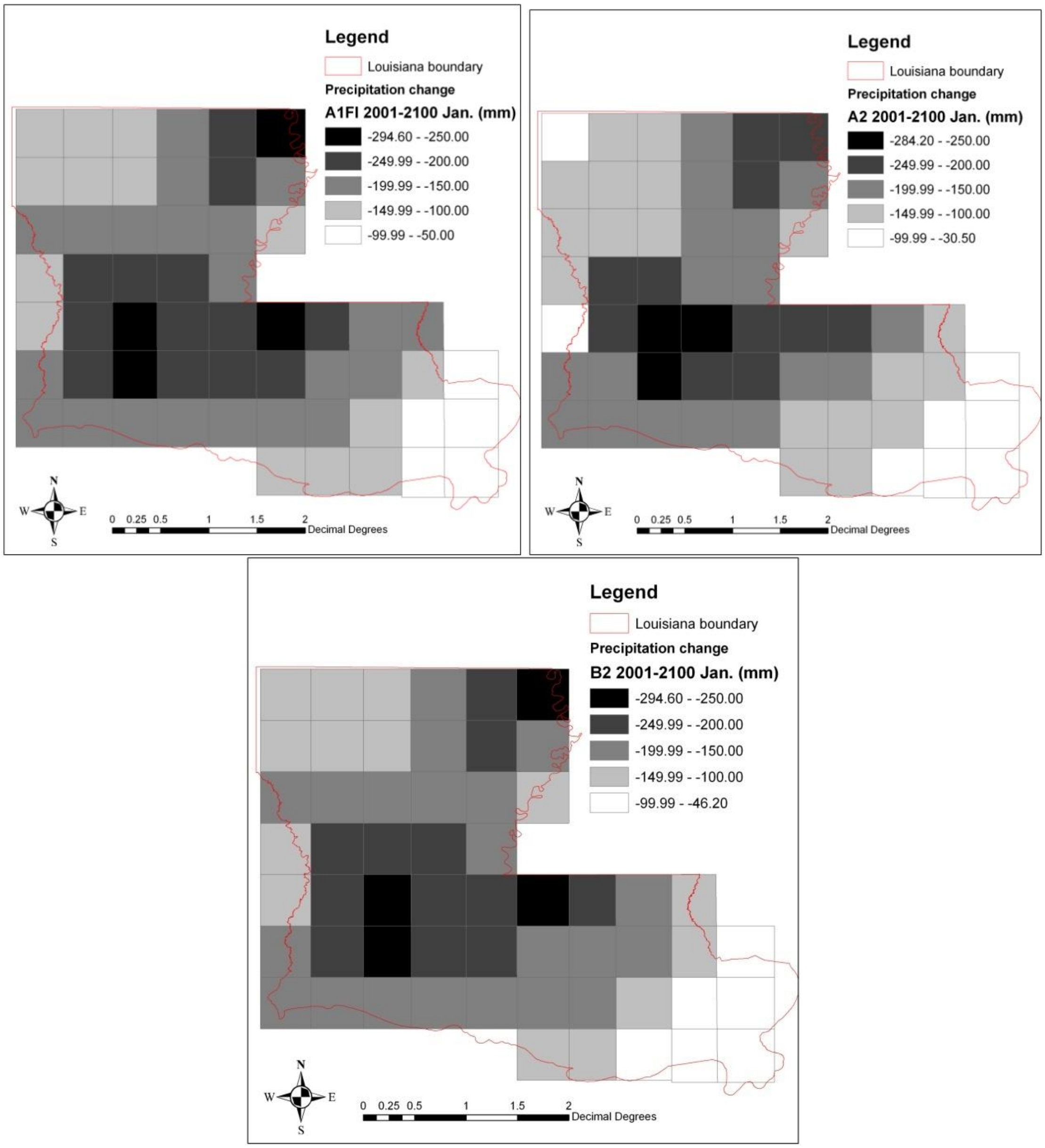

(c)

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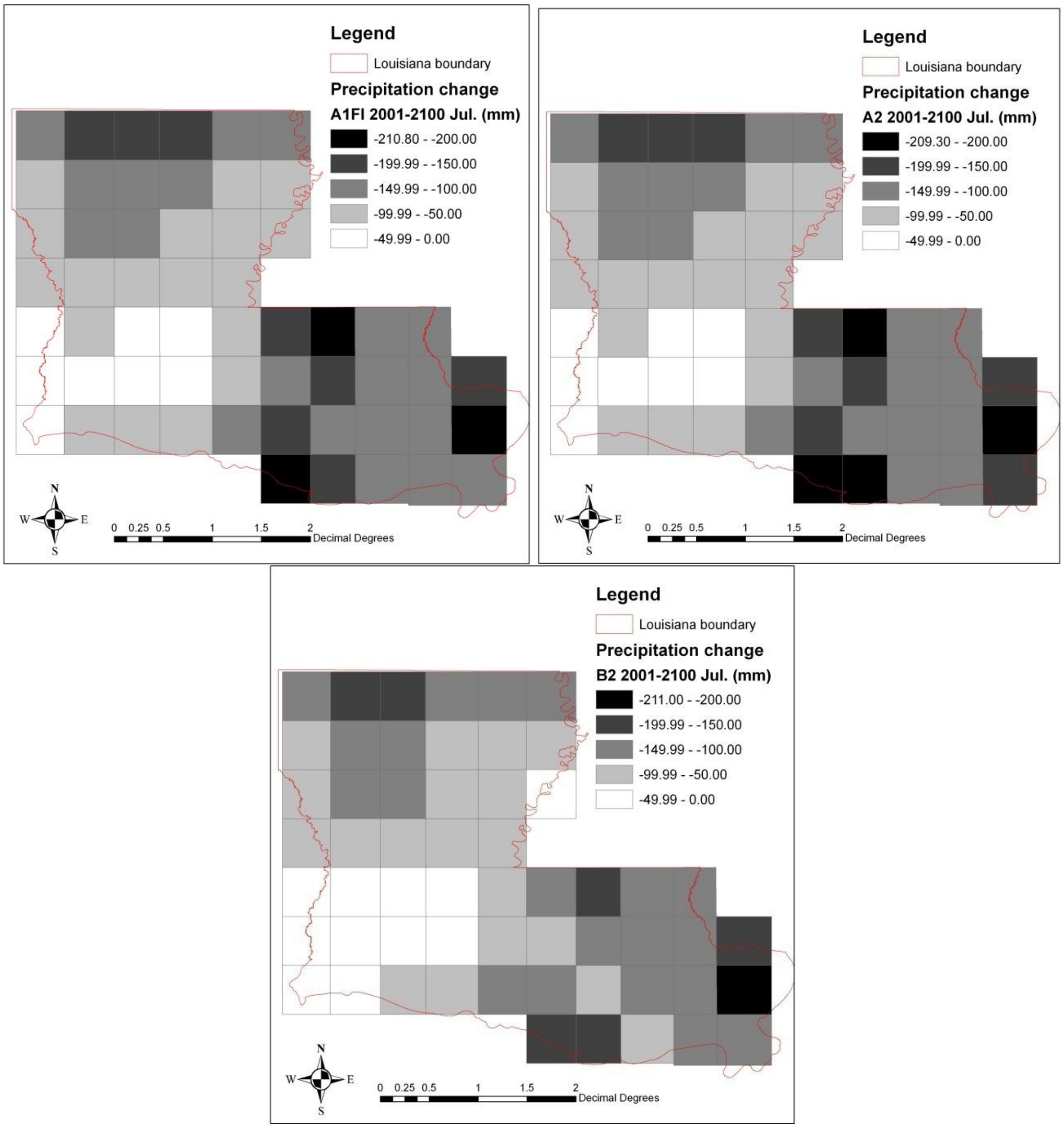
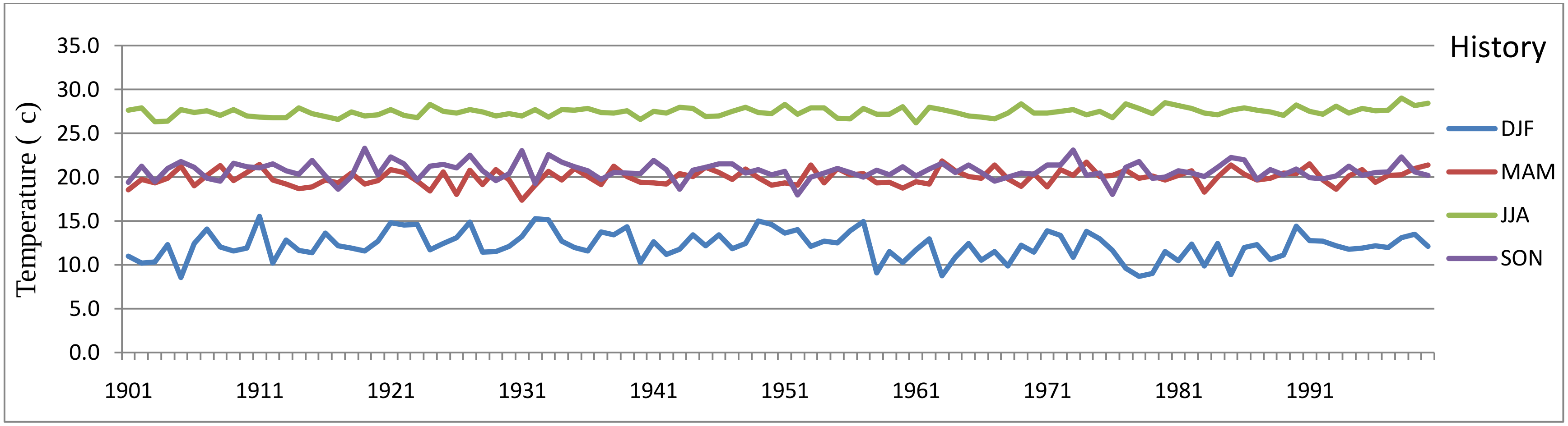


(d)



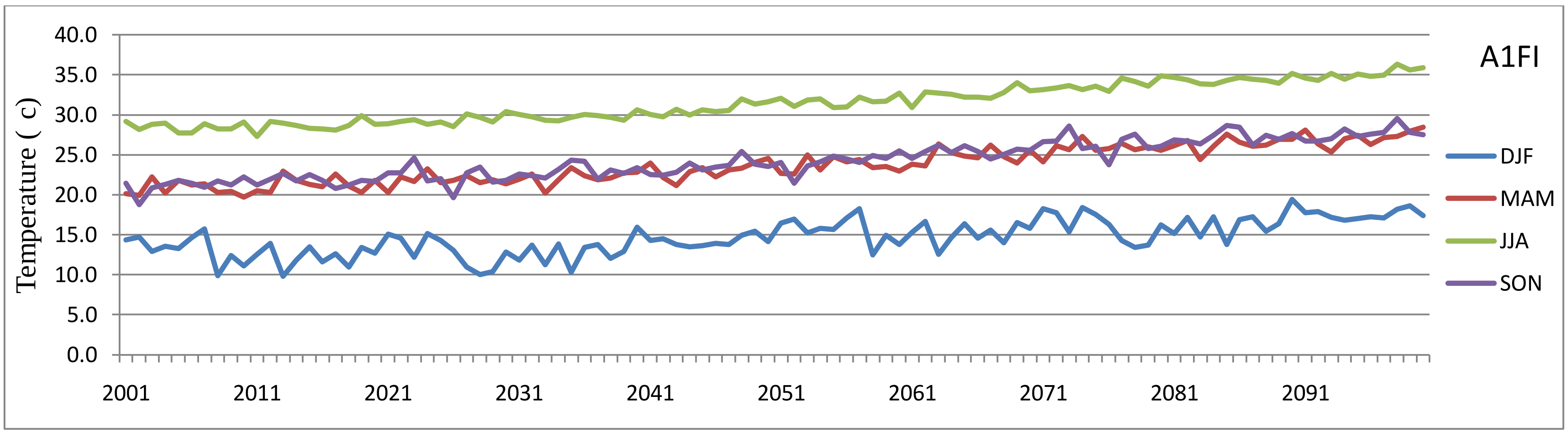
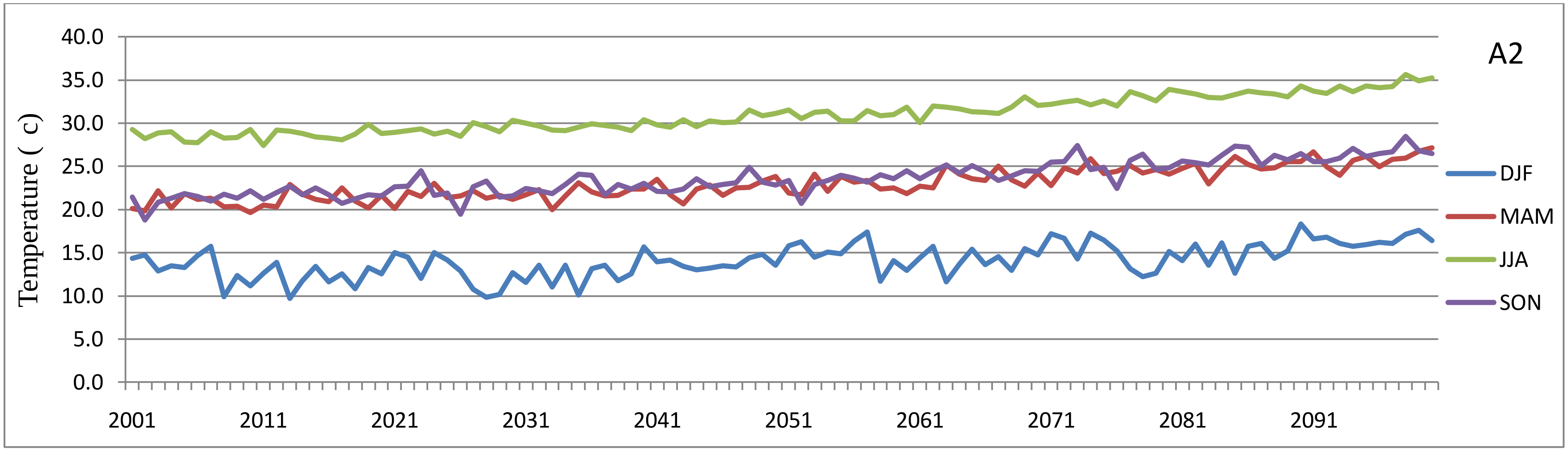
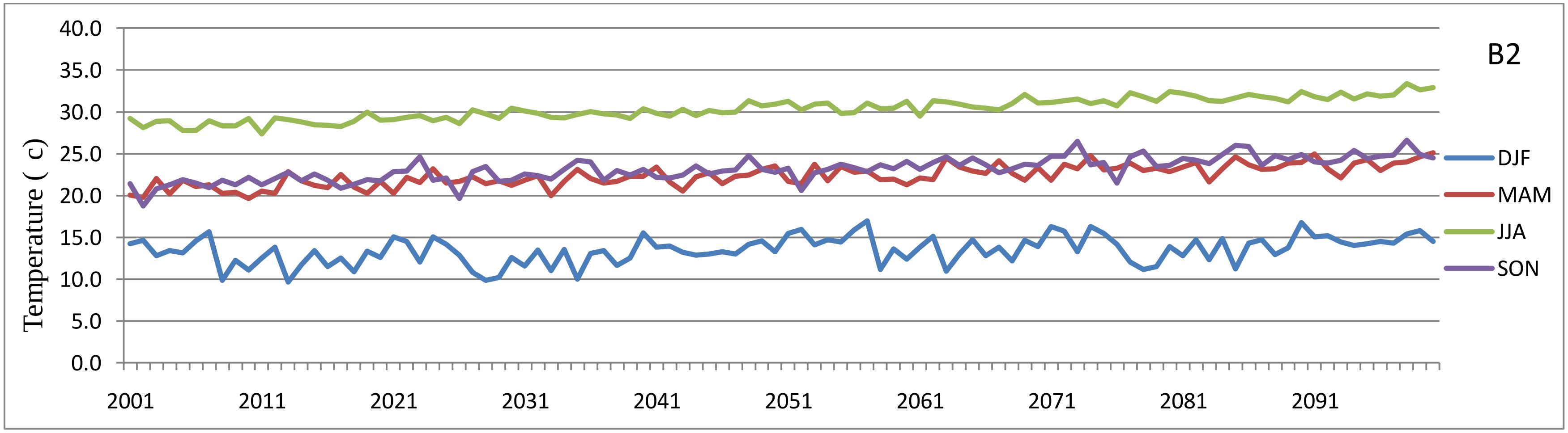


Figure 5.6 Seasonal historical temperature in 1901-2000, and projected monthly mean temperature in 2001-2100 at A1FI, A2, and B2 scenarios in Baton Rouge, Louisiana

(DJF= December, January, February; MAM=March, April, May; JJA=June, July, August; SON=September, October, November)

(Figure 5.6 continue)





precipitation in the same area. Globally averaged annual precipitation is projected to increase during the 21st century, though at regional scales both increases and decreases are projected (IPCC, 2001a). The latest report, Global Climate Change Impacts in the United States (Karl et al., 2009), showed that precipitation decrease would occur in much of the Southeast United States (including Louisiana) in all but the fall season, though precipitation over the United States as a whole has increased. The trend of precipitation change of Louisiana from the report is in agreement with the projections of the HadCM3 climate model used in this study.

Climate projections may be the largest source of uncertainty in climate change modeling study on future soil carbon storage. Zaehle and others (2007) summarized the temperature and precipitation change of four climate models, HadCM3, CSIRO2, CGCM2, and PCM2, in Europe. Among these four GCMs, over large parts of the Mediterranean, HadCM3 was reported as the most extreme climate model in terms of the increase in seasonal temperatures as well as the decline in annual precipitation and the prolongation of the summer dry season, whereas PCM2 depicts the most modest warming rate. Ruiz-Barradas and Nigam (2006) concluded that the HadCM3 is closest to the hydroclimate observations evaluated with datasets with proven high quality in North America during the warm season, compared to four U.S. climate models and one Japanese climate model. The trend of SOC changes could turn from reduction to increase or from positive to negative feedback, based on different climate models.

5.3.2 Louisiana SOC Changes under Three IPCC Emissions Scenarios

On average, the upper 30-cm of forest, cropland, and grassland soils in Louisiana contain 33, 44, and 31 tons organic carbon per hectare, respectively. The modeling shows

that the SOC stock in all these land use types would decline from 2001 to 2100. These modeling results were consistent under all three emissions scenarios A1FI, A2, and B2 (Figure 5.7) considering the climate change impacts on Louisiana SOC. Fluctuations occurred and the mean SOC would grow in the part and short term, (e.g. 2009- 2012).

Among the three emissions scenarios, the A1FI scenario showed the greatest decline in surface SOC of Louisiana forests, croplands, and grasslands soils. This may be due to the greater increase of temperature for A1FI scenario when compared to the other two emissions scenarios. The efflux of carbon from the soil surface is almost entirely from root respiration and microbial decomposition of organic matter; these processes are temperature-dependent like all chemical and biochemical reactions (Davidson and Janssens, 2006). The results of field samples and comparison of ^{14}C (Trumbore et al., 1996) indicated that temperature is a dominant control of soil carbon dynamics; increasing temperatures should speed decomposition of soil through increasing decomposition rates in SOM, causing a net transfer of carbon from fast-cycling pools to the atmosphere. The average SOC in the upper 30-cm depth of Louisiana forest soils will change from 33.0 tons per hectare in 2001 to 26.9, 28.4, and 29.2 tons per hectare in scenarios A1FI, A2, and B2, respectively. The mean SOC of Louisiana croplands in the upper 30-cm depths will change from 44.4 tons per hectare in 2001 to 36.3, 38.4, and 39.6 tons per hectare in scenarios A1FI, A2, and B2, respectively. The mean SOC of Louisiana grasslands in the upper 30-cm depth will change from 30.7 tons per hectare in 2001 to 25.4, 26.6, and 27.0 tons per hectare in scenarios A1FI, A2, and B2, respectively.

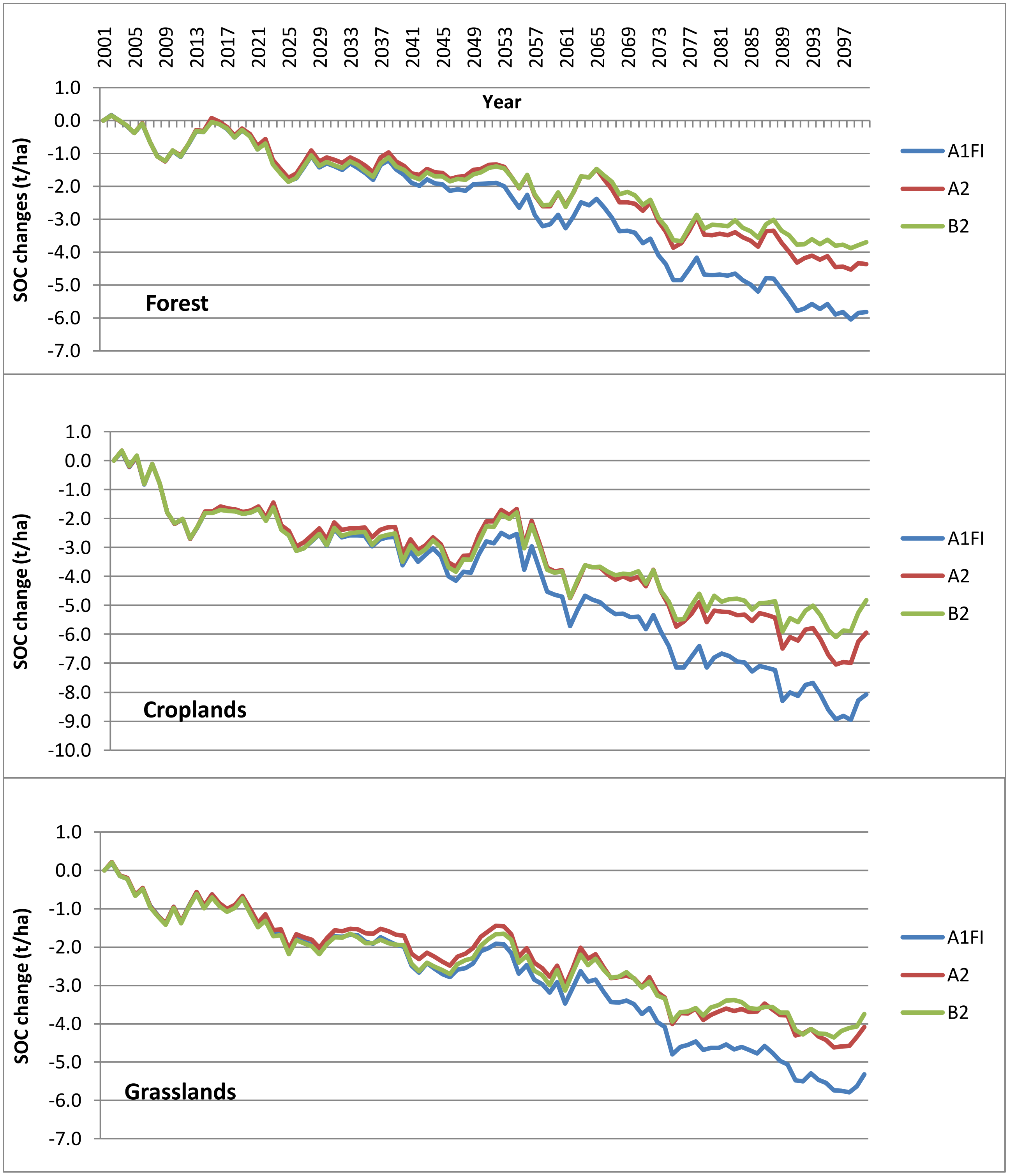


Figure 5.7 SOC changes from 2001 to 2100 in Louisiana's forests (top), croplands (middle), and grasslands (bottom) soils in reference to initial SOC content under three climate change scenarios.

The SOC changes of Louisiana from 2001 to 2100 as the results of climate changes have reasonable agreement with the modeling results of SOC changes in European forests, croplands, and grasslands (Smith et al., 2005, 2006). In this study, the decline of SOC in Louisiana forests, croplands, and grasslands varied from 12%-19%, 11%-18%, and 12%-17%, respectively, under the three emissions scenarios A1FI, A2, and B2. In Smith et al.'s modeling studies, also with the RothC model using HadCM3 climate output, the decline of surface SOC in European forests, croplands, and grasslands was reported to be 9%-15.5%, 10%-14%, and 6%-10%, respectively, under four emissions scenario; A1FI, A2, B1, and B2 (Smith et al., 2005, 2006). The global soil carbon pool has been projected to decrease by about 8% in the HadCM3-driven simulation between 1860 and 2100 using a dynamic global vegetation model, hybrid v4.1 or 5% in the HadCM2-driven simulation (White et al., 1999). The soil carbon of Canadian agricultural land would lose 160 Tg by 2099 under the SRES B2 scenario and 53 Tg under the IPCC IS92a scenario, simulated by the Century model using historical weather data and Climate Modeling and the Analysis (CCCma) Coupled Global Climate Model (CGCM1,2) (Smith et al., 2009). The other environmental factors e.g. climatic and topographic conditions, vegetable types, and soil parent materials, etc., would cause the differences of SOC decline percentages among Louisiana, European, and Canadian forests, croplands, and grasslands.

It has to be mentioned that net primary production (NPP), one of the important factors contributing SOC changes, was not considered in this study. Field experiments with free air CO_2 enrichment in some temperate forests found that the increase of atmospheric concentration of CO_2 could increase forest net primary production (Calfapietra et al., 2003; DeLucia et al., 1999; Gielen et al., 2005; Hamilton et al., 2002;

Handa et al., 2006; Hattenschwiler et al., 2002; Karnosky et al., 2003; Liberloo et al., 2006; Norby et al., 2005; Norby et al., 2002). In a recent modeling study on climate change effect on forest NPP in Louisiana, Wang and Xu (in review) reported a direct correlation of higher emissions with a rising trend of NPP rates over 2000-2050. The increase of NPP could substantially affect organic carbon input into the soil system through litter and roots, offsetting the reduction of soil carbon. The simulated soil carbon reductions in this study are higher than other reported studies on climate change effects. This may be due to the exclusion of future possible NPP changes and the associated higher organic input into soils.

5.3.3 Spatial Trends and Statistical Testing of SOC Changes across Different Land Use Types

Louisiana SOC percentage changes at watershed scale between 2001 and 2100 showed similar spatial patterns under three greenhouse gas emissions scenarios. Watersheds in the northeast part of Louisiana changed more significantly than other areas (Figure 5.8). SOC of the watersheds in the Mississippi River and Red River valleys decreased significantly from 2001 to 2100, while row crops were the dominant land cover type in the valley region. The interactions of several environmental factors: climate, soil attributes, and land cover, may have affected the SOC changes under the different IPCC emissions scenarios. Overall, the SOC changes under scenario A1FI were larger than those under scenarios A2 and B2 between 2001 and 2100.

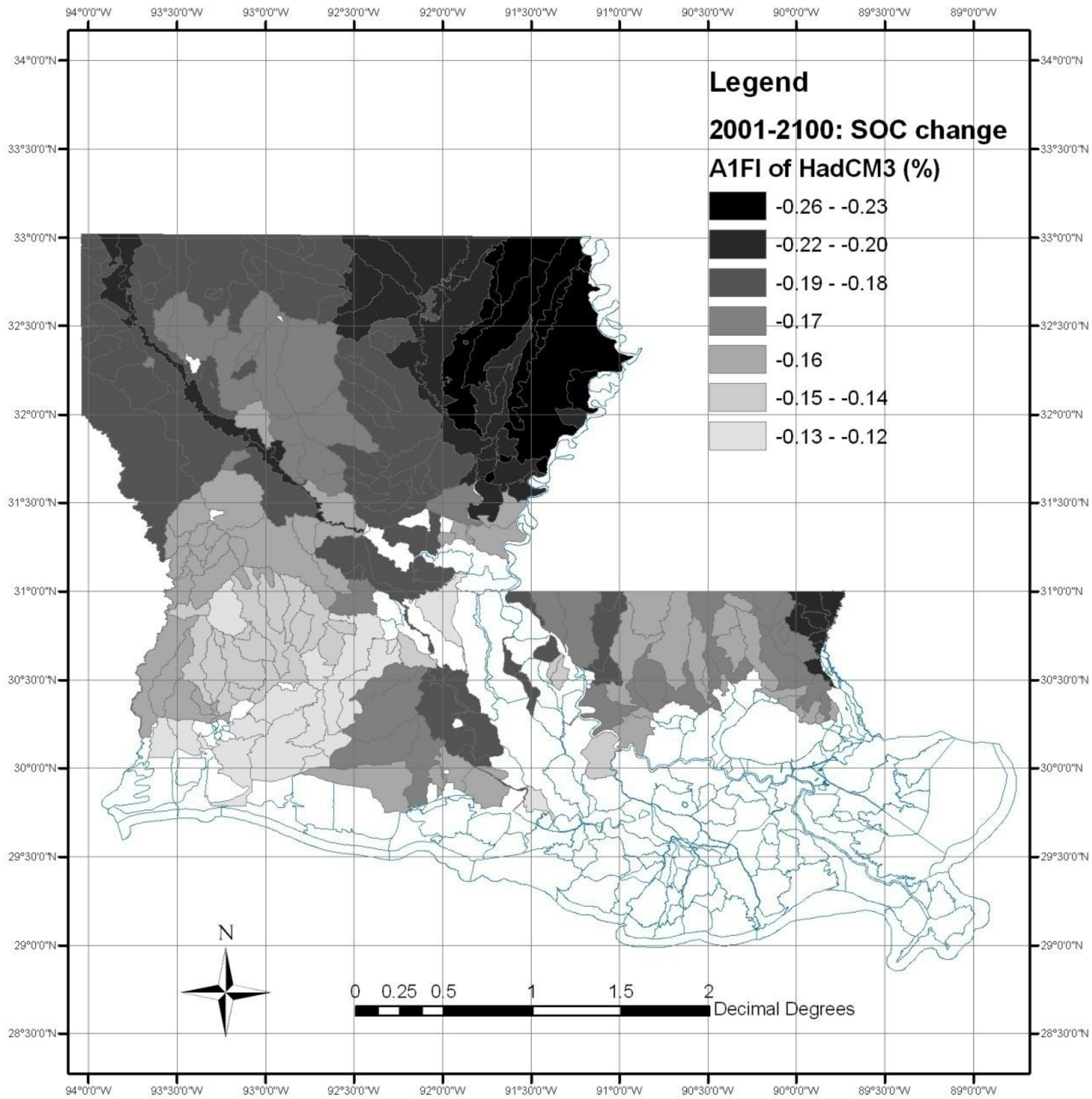
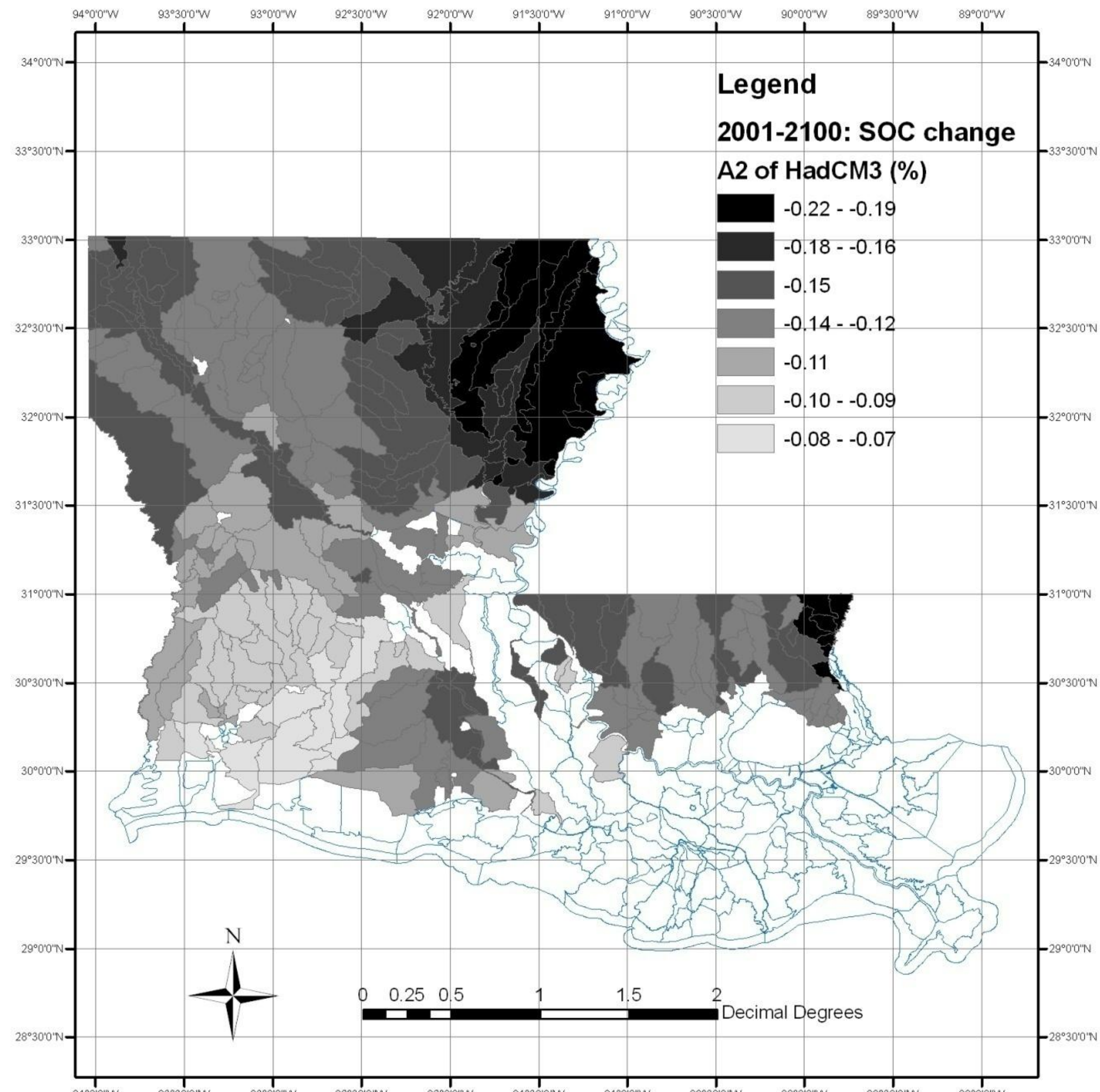


Figure 5.8 Spatial patterns of SOC percentage changes between 2001 and 2100 in Louisiana's forests, croplands and grasslands in reference to initial SOC content under three HadCM3 scenarios: A1FI, A2, and B2.

(Figure 5.8 continue)



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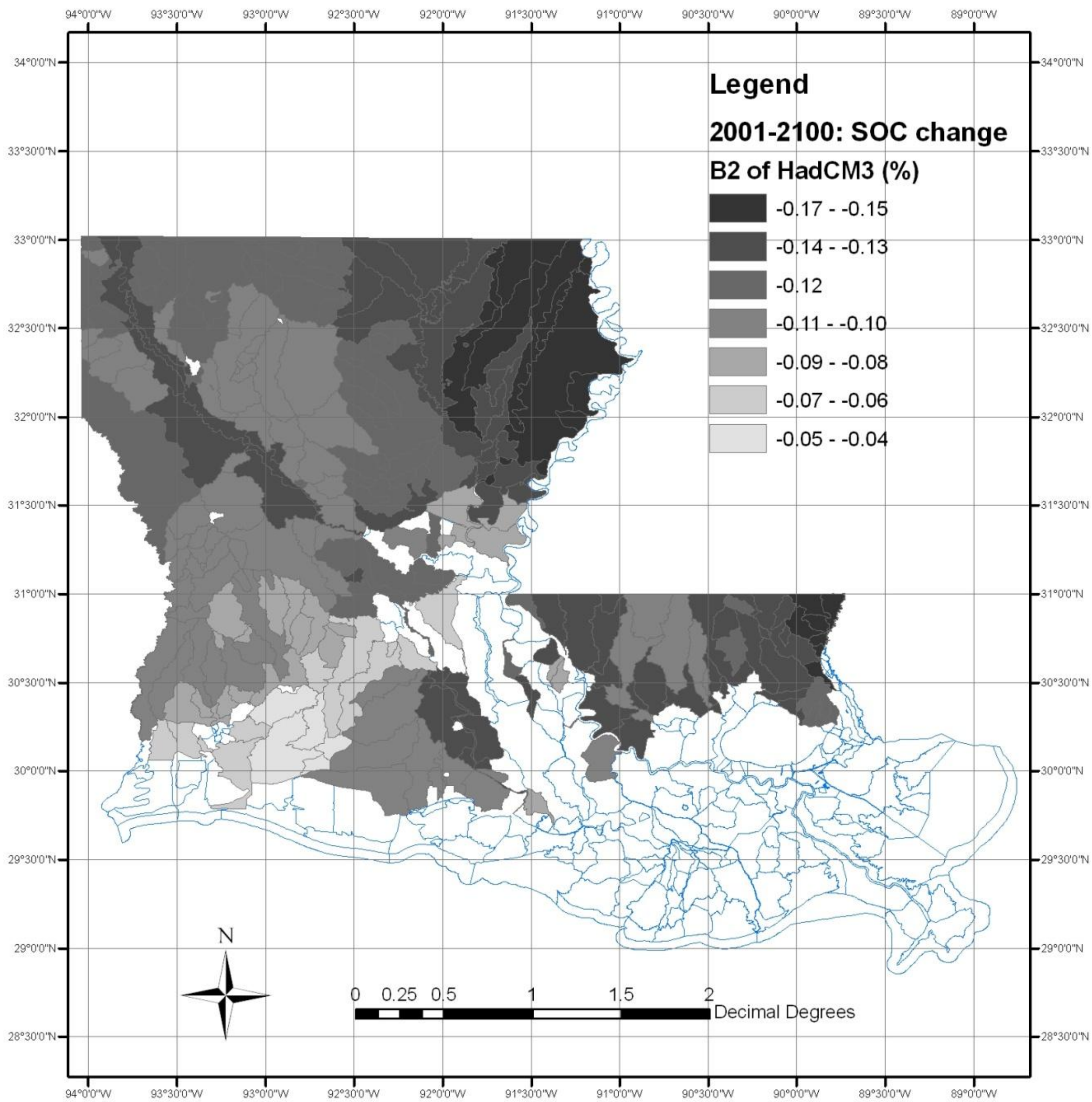
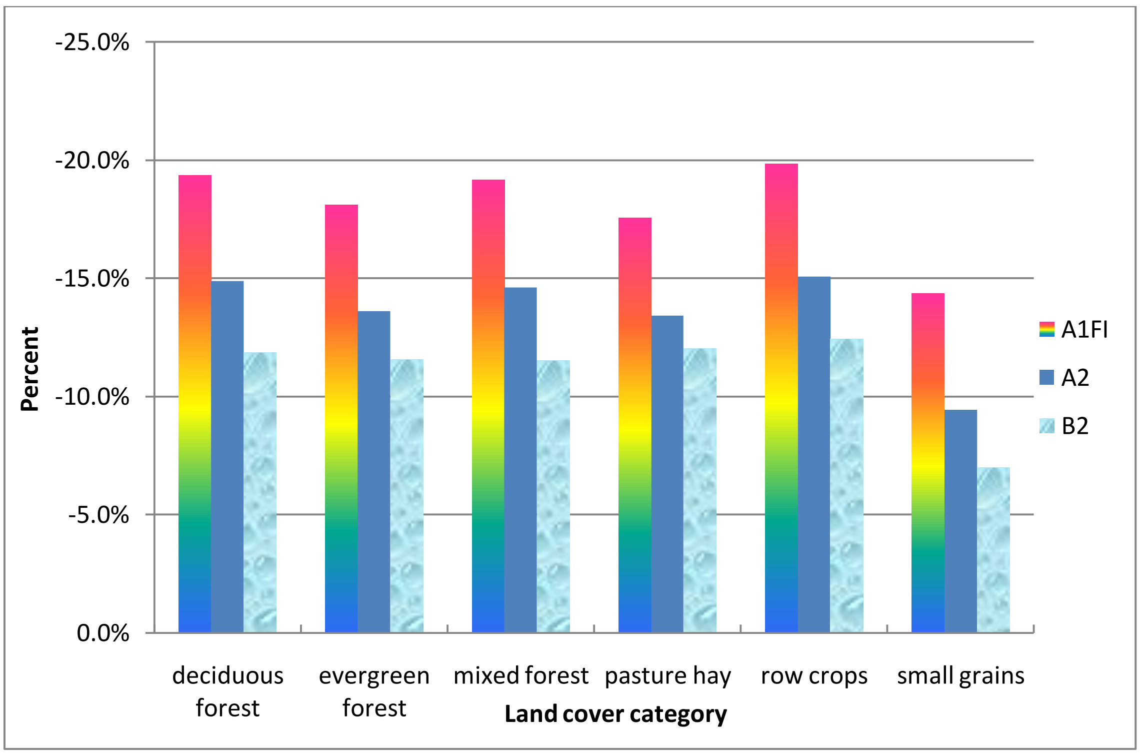


This study predicted SOC changes in Louisiana at the watershed scale and a 0.5° x 0.5° climate grid cell for a period of 100 years from 2001 to 2100. The spatial resolution 0.5° x 0.5° from CRU was higher than the typical HadCM3 spatial resolution of 2.5° x 3.75° (latitude by longitude), CGCM1 surface grid resolution of roughly 3.7º x 3.7º, and ocean grid resolution of approximately 1.8º x 1.8º (IPCC, 2001d). However, the spatial

resolution of European climate data from CRU is 10’ x 10’ grid, much higher than other continents (Smith et al., 2005, 2006).

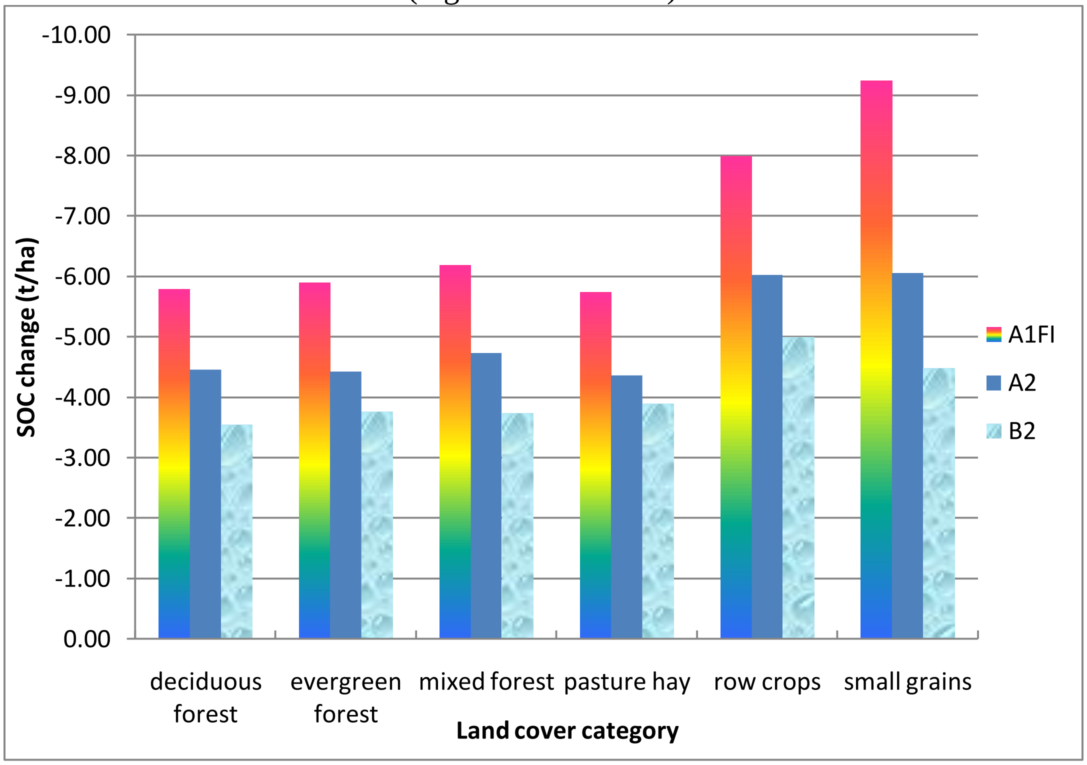
Simulated SOC in row crops had the largest percentage changes among six land cover categories on all three atmosphere greenhouse gas emissions scenarios (Figure 5.9a). Simulated SOC in small grains had the largest SOC value change from 2001 to 2100 under A1FI and A2 scenarios (Figure 5.9b). Evergreen forest and row crops were projected to be the largest total carbon release sources, considering only the climate change effects, due to their large distribution areas in Louisiana (Figure 5.9c).



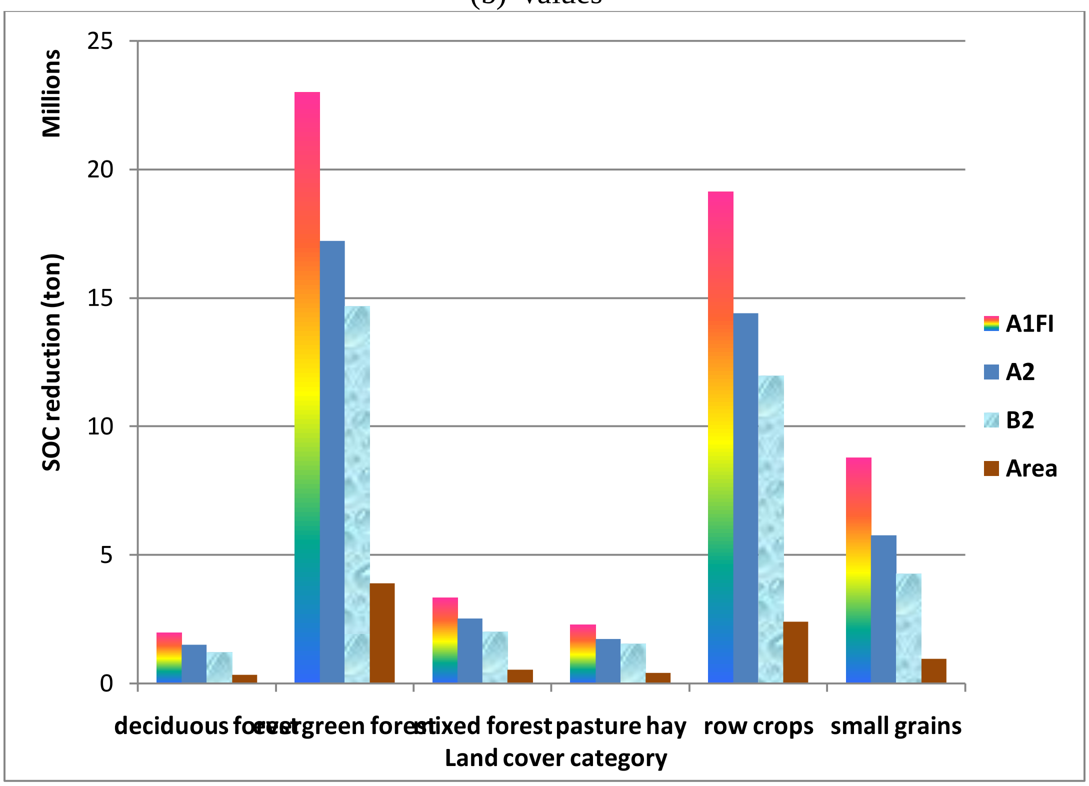
(a) Percentages

Figure 5.9 SOC changes in (a) percentages; (b) values; and (c) total SOC reduction and areas; from 2001 to 2100 in Louisiana’s soils in different land covers with reference to initial SOC contents under three emissions scenarios.

(Figure 5.9 continue)



(b) Values



(c) Total SOC reduction and areas

Louisiana average annual SOC changes were significantly different in six land cover classes ($p < 0.0001$), three emissions scenarios ($p < 0.0001$), and their interactions ($p < 0.0001$) among three periods, beginning 2001-2010, middle 2041-2050, and final 2091-2100 (Tables 5.3, 5.4, and 5.5). SOC decreases in the late 50 years were larger than the first 50 years. SOC decreases of grasslands (pasture/hay) were smaller than SOC changes of croplands (small grains and row crops), but greater than forest (deciduous forest, evergreen forest, mixed forest) (Table 5.3). The Type III Tests of Fixed Effects of the GLIMMIX procedure showed that there were no significant differences of SOC changes among deciduous forest, evergreen forest, mixed forest. The tests showed that small grains and row crops had significant differences between the beginning and middle ten years (Table 5.3), even though they were classified as the same cropland class according to the USGS NLCD Land Cover Class Definitions (Homer et al., 2004). SOC changes in deciduous forest, evergreen forest, and mixed forest were all similar because of their similar impacts of environmental factors, such as soil cover, residues input, and organic matter decomposed ratio.

SOC changes under all three emissions scenarios were significant differences ($p < 0.0001$) in 253 watersheds among three periods, beginning 2001-2010, middle 2041-2050, and final 2091-2100 (Table 5.4). The even higher emissions scenario A1FI (fossil intensive, rapid economic growth, and technological change) was projected to have the greatest effect on SOC changes over all land cover classes and periods because the temperature will have the largest change at that scenario, which agrees with others' research (Smith et al., 2005, 2006, 2007; Zaehle et al., 2007). However, the high emissions scenario A2 (heterogeneous world, continuously increasing global population,

slow economic growth) was projected to have less effect on SOC changes than the low emissions scenario B2 (economic, social, and environmental sustainability) for each detailed set of land cover classes between the beginning and middle of the 21st century (2001-2010 & 2041-2050) in Louisiana (Table 5.5), although the A2 scenario was projected to have more effect on SOC changes than B2 for overall land cover classes (Table 5.4). The simulated SOC decrease, based on climate change projections of the HadCM3 climate model, appeared to be more pronounced in the second half of the 21st century (Table 5.4), which is in agreement with the findings by Smith et al. (2007).

Table 5.3 Comparisons for three periods of SOC changes for Adjusted Least Squares Means of SOC changes, those significantly different among land cover classes according to Tukey-Kramer method and Type III Tests of Fixed Effects

Difference of years	Land cover classes	SOC changes (t/ha)			
		Mean		Std Error	Number
2001-2010 & 2041-2050	small grains	3.11	a	0.15	21
	row crops	2.34	b	0.08	67
	pasture , hay	1.89	bc	0.15	21
	evergreen forest	1.39	c	0.06	113
	mixed forest	1.28	c	0.18	14
	deciduous forest	1.20	c	0.17	17
2041-2050 & 2091-2100	small grains	3.74	a	0.13	21
	row crops	3.63	a	0.07	67
	pasture , hay	3.17	ab	0.16	21
	evergreen forest	2.95	b	0.15	113
	mixed forest	2.88	b	0.06	14
	deciduous forest	2.52	b	0.13	17
2001-2010 & 2091-2100	small grains	6.85	a	0.23	21
	row crops	5.97	a	0.13	67
	pasture , hay	4.45	b	0.28	21
	evergreen forest	4.40	b	0.23	113
	mixed forest	4.27	b	0.10	14
	deciduous forest	4.15	b	0.25	17

Adjusted Least Squares Means followed by a different letter are significantly different within a column, according to Tukey's $LSD_{0.01}$ for univariate analyses.

Table 5.4 Comparisons for three periods of SOC changes for Adjusted Least Squares Means of SOC changes, those significantly different among emissions scenarios according to Tukey-Kramer method and Type III Tests of Fixed Effects

Difference of years	Emissions scenarios	SOC changes (t/ha)		
		Mean	Std Error	Number
2001-2010	A1FI	2.11 a	0.06	253
&	A2	1.81 b	0.06	253
2041-2050	B2	1.68 c	0.06	253
2041-2010	A1FI	4.27 a	0.05	253
&	A2	3.02 b	0.05	253
2091-2100	B2	2.15 c	0.05	253
2001-2010	A1FI	6.38 a	0.09	253
&	A2	4.71 b	0.09	253
2091-2100	B2	3.96 c	0.09	253

Adjusted Least Squares Means followed by a different letter are significantly different within a column, according to Tukey's $LSD_{0.01}$ for univariate analyses.

Table 5.5 Comparisons for three periods of SOC changes for Adjusted Least Squares Means of SOC changes, those significantly different among land cover classes and emissions scenarios according to Tukey-Kramer method and Type III Tests of Fixed Effects

Difference of years	Land cover classes	Emissions scenarios	SOC changes (t/ha)	
			Mean	Std Error
2001-2010 &	small grains	A1FI	3.47 a	0.15
2041-2050	small grains	B2	2.96 bc	0.15
	small grains	A2	2.91 bc	0.15
	row crops	A1FI	2.60 bd	0.08
	row crops	B2	2.35 cefg	0.08
	row crops	A2	2.08 hij	0.08
	pasture , hay	A1FI	2.06 dehkl	0.15
	pasture , hay	B2	1.91 fimn	0.15
	pasture , hay	A2	1.70 gjopq	0.15
	evergreen forest	A1FI	1.61 klmo	0.07
	mixed forest	A1FI	1.50 hijknqr	0.19
	deciduous forest	A1FI	1.43 hijklnq	0.17
	evergreen forest	B2	1.35 np	0.07
	evergreen forest	A2	1.22 qrs	0.07
	mixed forest	B2	1.20 lmops	0.19
	mixed forest	A2	1.13 lmops	0.19
	deciduous forest	B2	1.09 mopr	0.17
	deciduous forest	A2	1.07 mopr	0.17

(Table 5.5 continue)

2041-2010 & 2091-2100	small grains	A1FI	5.46 a	0.14
	row crops	A1FI	4.92 ab	0.08
	mixed forest	A1FI	4.19 bc	0.17
	deciduous forest	A1FI	3.90 cd	0.16
	evergreen forest	A1FI	3.84 c	0.06
	small grains	A2	3.54 cde	0.14
	row crops	A2	3.51 cde	0.08
	pasture , hay	A1FI	3.32 cdef	0.14
	mixed forest	A2	3.11 defg	0.17
	deciduous forest	A2	2.88 efgh	0.16
	evergreen forest	A2	2.74 fghi	0.06
	row crops	B2	2.46 ghijk	0.08
	pasture , hay	A2	2.37 ghij	0.14
	small grains	B2	2.22 ghijk	0.14
	mixed forest	B2	2.21 hijk	0.17
	deciduous forest	B2	2.07 ijk	0.16
	evergreen forest	B2	2.06 jk	0.06
	pasture , hay	B2	1.86 k	0.14
2001-2010 & 2091-2100	small grains	A1FI	8.94 a	0.24
	row crops	A1FI	7.52 b	0.13
	small grains	A2	6.45 c	0.24
	mixed forest	A1FI	5.69 cde	0.29
	row crops	A2	5.59 cd	0.13
	evergreen forest	A1FI	5.45 cde	0.10
	pasture , hay	A1FI	5.37 cdef	0.24
	deciduous forest	A1FI	5.33 cdefg	0.26
	small grains	B2	5.18 defgh	0.24
	row crops	B2	4.81 efghi	0.13
	mixed forest	A2	4.24 fghijkl	0.29
	pasture , hay	A2	4.07 ghijklm	0.24
	evergreen forest	A2	3.96 jlm	0.10
	deciduous forest	A2	3.95 hijkm	0.26
	pasture , hay	B2	3.77 ijklm	0.24
	evergreen forest	B2	3.42 kn	0.10
	mixed forest	B2	3.41 mn	0.29
	deciduous forest	B2	3.17 ln	0.26

Adjusted Least Squares Means followed by a different letter are significantly different within a column, according to Tukey's $LSD_{0.01}$ for univariate analyses and $LSD_{0.01}$ for multivariate analyses.

Climate change would play a vital role on terrestrial carbon changes. Studying the climate change effects on soil carbon is important for understanding the below-ground processes in the carbon-cycle-climate system of the biogeochemical cycle and enhancing the sustainability of these areas. More field data is needed on the effect of human-induced land use changes on SOC dynamics under the climate change condition although the

IPCC emissions scenarios has considered the emissions of land use or land cover activities.

5.4 Conclusions

This study is the first attempt to link different geographically referenced databases to quantify soil carbon response to climate changes at the watershed scale and across different land use types. Using Louisiana as an example, the study demonstrated the credibility of geographic information systems in permitting the prediction and spatial analysis of soil carbon storage at finer scales of resolution. Beyond assessment of the methodology, the study yielded insight into carbon dynamics in a region where soil carbon represents an ultimately large pool of carbon in the terrestrial ecosystems. The projections of three greenhouse gas emissions indicated that monthly mean temperature in spring will increase the most; and monthly precipitation would decrease most of the time in the next 100 years in Louisiana. Generally, temperature and precipitation changes from the least to the most will be in the order of B2 (low emissions) <A2 (high emissions) <A1FI (even higher emissions). The trend of SOC changes in forests, croplands, and grasslands of Louisiana at watershed scale will decrease significantly, assuming other factors were stable and considering only the climate change impacts. Louisiana average annual SOC changes were significantly different in six land cover classes, three emissions scenarios, and their interactions during three periods: beginning 2001-2010, middle 2041-2050, and final 2091-2100. The simulated SOC decrease, based on climate change projections of the HadCM3 climate model, will become more pronounced after the middle of the 21st century. Climate change is an important driver of the terrestrial carbon changes in the southern United States. Long-term continuous field measurements

in all kinds of land use and climate conditions are needed to improve the modeling in future studies.

CHAPTER 6 RISK OF INUNDATION TO LOUISIANA COASTAL AREAS, WETLANDS, SOIL ORGANIC CARBON STORAGE, AND NITROGEN CONTENTS

6.1 Introduction

Global mean sea level was projected to rise by 0.18 to 0.59 m between the years 1990 and 2100, for the full range of the IPCC SRES scenarios, but with significant regional variations (IPCC, 2007). Researchers have found that the rate of sea level rise increased from the 19th to the 20th century, and that the rise is likely to accelerate in the 21st century due to anthropogenic global warming. . The global average sea level rose at an average rate of 1.8, with a range of 1.3 to 2.3, mm per year over 1961 to 2003. The rate was faster over 1993 to 2003, averaging about 3.1, with a range of 2.4 to 3.8 mm per year.

Paleoclimate information interprets that the global average sea level in the last interglacial period (about 125,000 years ago) was likely 4 to 6 m higher than during the 20th century, mainly due to the retreat of polar ice. Ice-core data indicate that average polar temperatures at that time were 3 to 5°C higher than at present (IPCC, 2007).

Wetlands are among the most valued ecosystems and play an important role in the stabilization of a climate (Mitsch and Wu, 1995). Wetland soils can contain from a few percent of organic matter to 100% (peat). Wetland soils serve an important role in removing carbon dioxide from the atmosphere and thereby slowing down global warming, creating a carbon sink. In Louisiana, over one-third of soil organic carbon (SOC) is buried in wetlands, the state's largest carbon sink. The Gulf of Mexico dead zone is one of the largest in the world. Hypoxic water areas were caused by nutrient enrichment, particularly nitrogen (N) and phosphorous.

Louisiana has experienced severe coastal wetland loss and barrier island erosion. Within the last 50 years, land loss rates have exceeded over 60 km^2 per year, and in the 1990's the rate has been estimated to be between 40 and 56 km^2 each year (LDNR, 1998). This loss represents 80% of the coastal wetland loss in the entire continental United States. The highest relative sea-level rise (RSLR) is 17.7 mm/yr at Calumet station in St. Mary's Parish from the U.S. Army Corps of Engineers tide gauge stations (Penland and Ramsey, 1990) as compared to 6.3 mm/yr at Galveston, Texas, 1.5 mm/yr at Biloxi, Mississippi, and 3.1 mm/yr sea-level rise (SLR).

Several programs are built to restore the Louisiana's coastal areas and wetlands. The federal Coastal Wetlands, Planning, Protection and Restoration Act (CWPPRA) of 1990, "Coast 2050—Toward a Sustainable Coastal Louisiana" (LDNR, 1998) developed in 1998, and the Gulf of Mexico Energy Security Act signed into law in December 2006. These programs have given million of dollars, and are expected to give billions of dollars to Louisiana per year to coastal restoration and protection. A major challenge to Louisiana's coastal restoration is to develop the most strategic, efficient and timely strategies for science and science-based planning, while minimizing the conflicts and maximizing the synergies in achieving multiple social objectives within a sustainable coastal landscape required for the future of the region (Day et al., 2007).

The objectives of this study were to (1) assess the spatial distribution of SOC storage in areas that could be potentially inundated when sea level rises; (2) estimate SOC storage, N contents, and possible inundated wetland areas classified by the National Wetlands Inventory (NWI) and elevation.

6.2 Methods

6.2.1 Study Area and Data Sources

Louisiana coastal area is from 89°W to 94°W longitude and 29°N to 30.5°N latitude. Louisiana is a low-lying state with an average elevation of 30.5 m, ranging from 2.4 m below to 163.0 m above sea level. The lowest point in Louisiana is 2.44 meters below sea level in New Orleans. Wetlands occur throughout the state with the largest percentage in the Gulf Coast marsh and alluvial plains. Louisiana, next to Alaska and Florida, has the largest wetland acreage (35,612 km2) in the United States (U.S. EPA, 2009).

This study used geographically referenced databases: USGS 1:24K Digital Elevation Models (DEM) data, Light Detection and Ranging (LIDAR) data (http://atlas.lsu.edu/lidar), SOC distribution data, and NWI digital data (http://wetlandsfws.er.usgs.gov).

NWI digital data were developed by the U.S. Fish & Wildlife Service and represents the extent, approximate location and type of wetlands. The classification system was adopted as a national classification standard in 1996 by the Federal Geographic Data Committee. These data delineate the areal extent of wetlands and surface waters as defined by Cowardin et al. (1979).

LIDAR data were derived from LIDAR measurements performed in 1999, and are presented at an elevation posting a horizontal interval of five meters and a vertical interval of 0.2 meter. These data were produced for the Louisiana Federal Emergency Management Agency (FEMA) Project under the St. Louis District U.S. Army Corps of Engineers (USACE). The entire mosaic LIDAR data in the Louisiana coastal area were made by LSU and National Wetlands Research Center in Baton Rouge.

Soil organic carbon distribution data were estimated from Natural Resources Conservation Service (NRCS) Soil Geographic Database (STATSGO). The maximum soil depth in STATSGO layers was approximately 252 centimeters. The Louisiana 1:24K Digital Elevation Dataset (2004) was derived from the U.S. Geological Survey National Elevation Database (NED) by Louisiana Department of Environmental Quality (LDEQ) and Louisiana Oil Spill Coordinator's Office (LOSCO). 1:24K DEM has a horizontal resolution of one arc-second (approximately 30 meters) and 0.3 meter vertical precision.

6.2.2 Terrain and Spatial Analyses

Inundation zones are the areas that are at risk to be flooded because of their flat and low elevation. This study divided the inundation zones into five elevation scales, which were 0 cm, 50 cm, 100 cm, 150 cm, and 200 cm. The areas of different elevation were calculated from the LIDAR and 1:24k DEM datasets. All raster cells at certain elevations in the LIDAR data were flagged. LIDAR data and 1:24k DEM data were reclassified with these five scales converted from feet units. Then, these data were zoned with wetlands and SOC datasets. Wetlands and SOC datasets were converted from vector types to raster types as processing requirements.

6.2.3 Nitrogen Density Estimation

N contents in this study were estimated by the average C: N ratios, chemical analysis result in the entire coastal marshlands of Louisiana (Brupbacher et al., 1973). The range of C: N ratios in mineral soil materials in freshwater marshes, brackish marshes, and saltwater marshes were 8.0-18.2, 9.9-23.4, and 11.7-26.0, respectively. The range of C: N ratios in organic soil materials in freshwater marshes, brackish marshes, and saltwater marshes were 10.3-28.2, 10.4-36.2, and 12.2-43.8, respectively. The

average C: N ratios used in the N density estimation in freshwater marshes, brackish marshes, and saltwater marshes were 14:1, 15:1, and 17:1, based on ranges and average ratios.

6.3 Results and discussion

6.3.1 Spatial Distribution of Elevation and SOC Storage in Louisiana Coastal Area

Southeastern Louisiana coastal areas around the Mississippi River, parts of Pontchartrain and Barataria Basins, are in the most vulnerable inundation zones, between zero and 50 centimeters elevation (Figure 6.1). The Mississippi River flows out to sea in the southeast area of Louisiana. These areas are the historical and current Mississippi River deltaic lobes built during the last 5-10,000 years, which have the highest SOC density in Louisiana.

The edges of southwestern Louisiana's coastal areas are in the safer inundation zones, between 50 and 100 centimeters, even between 100-150 centimeters.

The total inundation areas, mean soil organic carbon densities, total SOC, and percentages at six levels in LIDAR and 1:24k DEM datasets are shown in Table 1. The total inundation zones between 0 and 50 centimeters in Louisiana coastal area in LIDAR datasets were 10,892.95 km^2, compared with 7378.32 km^2 in 1:24k DEM datasets, approximately 24.79% of the total areas and 35.73% of the total SOC from LIDAR datasets (Table 6.1). The total inundation zones between 50 - 100 centimeters in LIDAR datasets were 6817.35 km^2, compared with 8572.69 km^2 in 1:24k DEM datasets. The areas of LIDAR and 1:24k DEM datasets at more than 200 centimeters were very similar, 15,839 km^2.

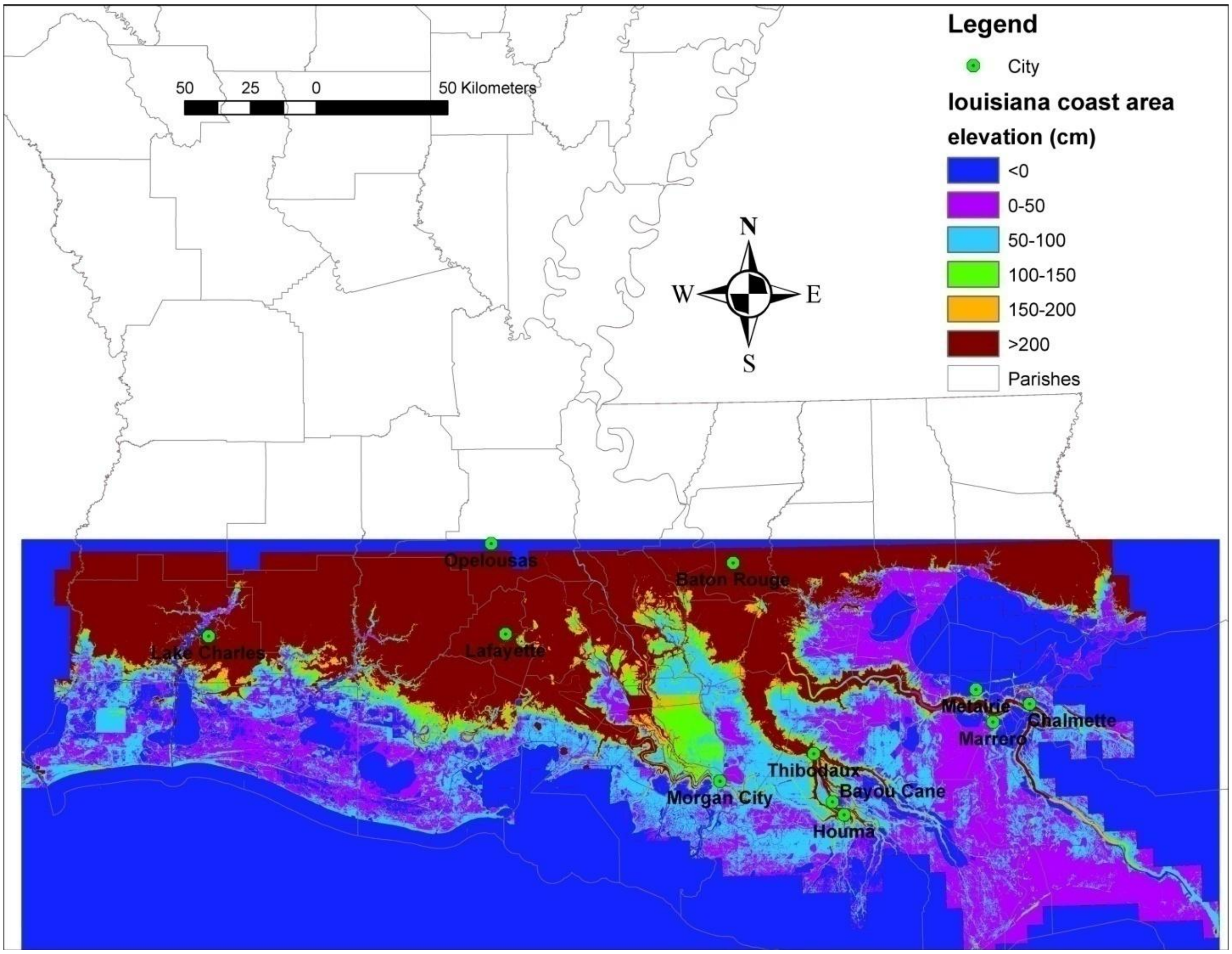


Figure 6.1 Louisiana coastal areas in LIDAR data.

The Louisiana coastal areas between 0 and 100 centimeters elevation showed the highest SOC densities and held large amounts of SOC. The mean SOC densities in the maximum soil depths in LIDAR datasets between 0 and 50 centimeters, 50-100 centimeters, and 100-150 centimeters, were 197 tons per hectare, 189 tons per hectare, and 118 tons per hectare respectively, which were lower than estimated from 1:24k DEM datasets.

The horizontal resolution of LIDAR data is five meters in these datasets, which is much higher than 1:24k DEM data and Landsat Thematic Mapper (TM) multispectral imagery, which is 30 meters. The minimum detectable spatial resolution of Landsat

Thematic Mapper (TM) multispectral imagery is 30 m for the current coastal Louisiana land loss research (Barras et al., 2003). The boundaries of these mosaic LIDAR data don't cover all of the Louisiana areas, missing the active delta zone of the southern-most Louisiana, the bird foot delta. The total inundation areas from LIDAR datasets are under-estimated for this reason, but the land loss after the data-producing date of light-detection in 1999, especially the huge land loss caused by Hurricane Katrina in 2005, offsets these under-estimations. The boundary of 1:24k DEM data is complete and better. However, 1:24k DEM data can't differentiate between the zero meter land areas and water areas. It shows the same elevation for those zero meter land areas, lakes, sea. LIDAR data differentiates among those classes, but the edges of zero meter land areas still mix with some water areas. Louisiana coastal zone boundary and Louisiana coastal wetlands conservation plan boundary made by Coastal Management Division of Louisiana Department of Natural Resources in 1998 didn't cover all those inundation areas between 0 and 50 centimeters and 100-150 centimeters.

6.3.2 Elevation and SOC Storage in Louisiana Coastal Wetlands

Large areas of freshwater forested/shrub wetlands, estuarine and marine wetlands, and freshwater emergent wetlands in Louisiana, are at risk in the inundation zones between 0 and 100 centimeters in both LIDAR and 1:24k DEM datasets (Table 6.2 and 6.3). Over 6,500 km^2 estuarine and marine wetlands, up to 4000 km^2 freshwater forested/shrub wetlands, and at least 3000 km^2 freshwater emergent wetlands, are in the inundation zones below 100 centimeters. Total wetlands area in the inundation zones below 100 centimeters are 15,173 km^2 in LIDAR datasets and 13,636 km^2 in 1:24k DEM datasets.

Table 6.1 Distribution of SOC stock in coastal Louisiana lowlands

	LIDAR					1:24,000 DEM				
Elevation(cm)	Area (km^2)	Area Percentages	Mean (t/ha)	SOC (10^6 t)	Total SOC Percentages	Area (km^2)	Area Percentages	Mean (t/ha)	SOC (10^6 t)	Total SOC Percentages
<0	6,053.91		103	62.27						
0-50	10,892.95	28.75%	197	214.92	39.63%	7378.32	19.04%	203	149.70	24.93%
50-100	6,817.35	17.99%	189	128.61	23.71%	8572.69	22.13%	223	191.60	31.90%
100-150	2,610.40	6.89%	118	30.75	5.67%	1674.80	4.32%	188	31.47	5.24%
150-200	1,731.84	4.57%	100	17.31	3.19%	5559.24	14.35%	136	75.44	12.56%
>200	15,839.45	41.80%	95	150.74	27.80%	15,556.91	40.16%	98	152.36	25.37%

Table 6.2 Size and elevation of different coastal wetlands as determined with LIDAR datasets

Elevation(cm)	Freshwater Forested /Shrub Wetland		Estuarine and Marine Wetland		Freshwater Emergent Wetland		Total areas
	Area (km^2)	Percent	Area (km^2)	Percent	Area (km^2)	Percent	Area (km^2)
Deep sea	9	0.1%	2,031	29.3%	45	1.2%	2,085
<0	342	3.8%	416	6.0%	294	7.7%	1,052
0-50	2,359	26.3%	2,375	34.2%	1,835	47.8%	6,570
50-100	2,099	23.4%	1,909	27.5%	1,458	38.0%	5,466
100-150	1,047	11.7%	177	2.6%	112	2.9%	1,337
150-200	623	6.9%	10	0.2%	25	0.6%	659
>200	2,498	27.8%	22	0.3%	68	1.8%	2,589
Total	45.4%		35.1%			19.4%	

Table 6.3 Size and elevation of different coastal wetlands as determined with 1:24k DEM datasets

Elevation(cm)	Freshwater Forested /Shrub Wetland (km^2)		Estuarine and Marine Wetland		Freshwater Emergent Wetland		Total areas
	Area (km^2)	Percent	Area (km^2)	Percent	Area (km^2)	Percent	Area (km^2)
<0	172	1.9%	573	8.1%	266	6.7%	1,011
0-50	630	7.0%	3,267	46.4%	1,984	49.7%	5,882
50-100	2,681	29.8%	2,835	40.3%	1,227	30.7%	6,743
100-150	691	7.7%	230	3.3%	219	5.5%	1,140
150-200	2,314	25.8%	120	1.7%	237	5.9%	2,670
>200	2,496	27.8%	14	0.2%	63	1.6%	2,573

Table 6.4 SOC storage of three major coastal wetlands in Louisiana

Wetland Type	Area (km^2)	Area Percentages	Mean SOC (t/ha)	Total SOC (10^6 t)	Total SOC Percentages	N density (t/ha)
Freshwater Forested /Shrub Wetland	8,978	44.8%	184	165	42.0%	13.1
Estuarine and Marine Wetland	7,047	35.2%	243	171	43.5%	14.3
Freshwater Emergent Wetland	3,999	20.0%	144	57	14.6%	9.6

Estuarine and marine wetlands showed the highest SOC density and total carbon percentage, although freshwater forested/shrub wetlands had the largest areas in coastal Louisiana. The mean SOC densities of freshwater forested/shrub wetlands, estuarine and marine wetlands, and freshwater emergent wetlands densities in the maximum soil depths in Louisiana, were 184 tons per hectare, 243 tons per hectare, and 144 tons per hectare, respectively. The SOC densities in these wetlands are much larger than average SOC densities in agriculture and forests, which were 94 and 97 tons per hectare, respectively. N densities of freshwater forested/shrub wetlands, estuarine and marine wetlands, and freshwater emergent wetlands densities were 13.1, 14.3, and 9.6 tons per hectare, respectively (Table 6.4).

Coastal wetlands have to accrete vertically to survive and keep pace with RSLR and SLR. The process of coastal wetlands vertical accretion can be explained as organic matter accumulation and mineral sedimentation accumulation (Nyman et al., 1990). Two important factors of the process are vegetation growth and sediment deposition. Plant biomass produced in wetland decays at a very slow decomposition rate because of limited oxygen in flooded wetland soils. Then organic matter is accumulated continuously and buried in wetlands permanently. When a river from in-land enters the estuaries or coastal marsh area, the speed of the river will slow down. Sediments will be deposited with the slow flow. Additionally, after the tidal wave floods the coastal wetlands, mineral sedimentation will stay in coastal wetlands. Sediment deposition adds nutrients to fertilize vegetation growth. Vegetation growth keeps sediments more stable.

The coast of Louisiana was divided into four regions based on hydrologic basins for planning purposes. Each region was broken into mapping units (LDNR, 1998). One

question is the importance and restoration order of regions or spatial parts of region. There are many objectives of coastal Louisiana restoration or protection. Carbon sequestration potential can be one objective to determine the importance or restoration order of wetlands. The spatial areas, which have higher carbon densities, should receive high priorities of restoration or protection. Considering carbon sequestration in the processing of wetland restoration or protection can bring carbon credit to those projects and gain more support.

6.3.4 Potential SOC Loss Based on the Projection of 2050 Land Loss

Coastal land loss is among the most serious environmental problems in Louisiana. CWPPRA (1990) revealed that coastal Louisiana has lost over 1.2 million acres (4,046 square kilometers) during the 20th century, an area more than 25 times larger than Washington, D.C. The state will lose an additional 431,000 acres (1,744 square kilometers) by 2050, as CWPPRA cited. Coastal Louisiana is estimated to lose nearly 514,460 acres (2,082 square kilometers) of marsh by 2050 — 21% of today's marsh as a "best estimate" (LDNR, 1998). Nearly 115,000 acres (465 square kilometers) of that loss will be prevented if the benefits of coastal restoration projects are included. Thus, with the current restoration efforts we will still lose nearly 400,000 (1,619 square kilometers) acres of marsh.

The impact of large amount land loss to SOC change in Louisiana's coastal area will be more significant than any other environmental factors. SOC loss from the terrestrial ecosystem could be approximately 32,910,655 tons using the average wetland SOC density, 203 tons per hectare.

The accurate estimation and forecast of SOC in Gulf of Mexico from wetland loss has not been adequately researched and quantified yet. One part of them could be consumed by the marine ecosystem. The others could be buried in the sea floor. Turner and others (2007) concluded that wetland loss is not likely to be a significant contribution to the carbon-loading hypoxic zone offshore. Krug (2007) and Merrifield (2007) revealed that the hundreds-to-thousands of years of accumulated oxygen-consuming nutrients and organic matter stored in wetlands are released to the hypoxic Gulf of Mexico as wetlands disintegrate.

6.4 Conclusions

This study provides new methods for coastal Louisiana restoration efforts to use high-resolution LIDAR datasets and consider the carbon sequestration potential. Southeastern Louisiana's coastal areas are in the most dangerous inundation zones. Large areas of freshwater forested/shrub wetlands, estuarine and marine wetlands, and freshwater emergent wetlands in Louisiana are in the inundation zones between 0 and 100 centimeters, which have much a higher SOC density and larger amounts of carbon than other inundation zones. Coastal Louisiana restoration projects could gain carbon credit because their function is protecting the wetlands, which hold large amounts of SOC and N. Freshwater forested/shrub wetlands, estuarine and marine wetlands, and freshwater emergent wetlands in Louisiana all have remarkably high SOC densities.

This study defined the inundation zones based on accurate LIDAR and DEM datasets. This study compared the LIDAR and DEM datasets in Louisiana. Distances from the shoreline, terrain of coastline, and seasonally fluctuating waves are additional factors used to evaluate the risk to coastal areas, wetlands, SOC, and N contents in the

future study. The current mosaic LIDAR data does not cover all of Louisiana because it is missing the southeastern active delta zone of Louisiana (bird foot delta). Multi-temporal LIDAR data which covered all of Louisiana are expected to be used in future research with Louisiana historical and natural wetlands distribution data.

CHAPTER 7 SUMMARY AND CONCLUSIONS

This research is the first comprehensive assessment of terrestrial carbon distribution and dynamics at the watershed scale in Louisiana, a state that has a great variety of land use and land cover types, rich with upland pine forests, bottomland hardwoods, croplands, pasture lands, and vast coastal wetland ecosystems. The research utilized various geo-referenced datasets and modeling techniques, and developed a spatially explicit modeling framework that is conducive to large-scale soil carbon quantification. The system is developed for Louisiana, but the approach can be applied to national soil carbon assessment at the watershed scale.

The research found that soils in Louisiana contained 0.5 Pg (1 petagram =1 x 10^{15}g =1 billion metric tons) of organic carbon within the upper 30 cm, estimated from STATSGO. Carbon contained within the upper 100-cm depth was 0.98 Pg, and carbon contained within the entire soil was 1.4 Pg. The historical and current Mississippi River deltaic lobes, accumulated by the outflow of the Mississippi River, have the highest SOC density among all Louisiana watersheds. They are the most important area for SOC storage. A decreasing trend of SOC density was found from the southeast coastal region to the northwest upland region. In general, alluvial river corridors showed higher carbon densities than the upland regions. SOC distribution was closely related to the drainage network. The SOC densities close to streams were higher than the densities far from streams.

The research indicated the ultimate importance of Louisiana's emergent herbaceous wetlands in carbon storage. Land use and land cover change in the emergent herbaceous

wetlands and alluvial river corridor areas may cause large losses of stored carbon. Grasslands, herbaceous lands, shrublands, and residential lands in Louisiana have unexpectedly higher SOC densities than forests and croplands. Agricultural land areas showed the lowest SOC densities at the maximum depths, although their SOC densities in the surface soil were higher than those of forests and grasslands. Urban soils in residential areas had high carbon densities, possibly caused by the locality of urban areas mostly on river floodplains.

The research assessed soil organic carbon storage and distribution across Louisiana's watersheds and examined the relationships of SOC density with various terrain parameters and watershed characteristics. At the watershed scale, SOC densities appeared to be positively correlated with drainage density but were negatively correlated with average slope gradient. Neither elevation nor drainage density can be an independent environmental factor for interpreting the SOC. Regression models were developed for predicting SOC density at watershed and basin scales, obtaining regression coefficients (r^2) ranging from 0.43 to 0.83. Barataria, Terrebonne, and Pontchartrain Basins in the southeastern coastal region are the largest soil carbon reservoir in Louisiana.

This research linked different geographically-referenced databases to quantify soil response to climate changes at the watershed scale and across different land use types. Using Louisiana as an example, the study demonstrated the credibility of geographic information systems in permitting the prediction and spatial analysis of soil carbon storage at finer scales of resolution. Beyond assessment of the methodology, the research yielded insight into carbon dynamics in a region where soil carbon represents an

ultimately large pool of carbon in the terrestrial ecosystems. The projections of three greenhouse gas emissions indicated that monthly mean temperature in spring will increase the most; and monthly precipitation will decrease in the next 100 years in Louisiana. Generally, temperature and precipitation changes from the least to the most will be in the order of B2 (low emissions) <A2 (high emissions) <A1FI (even higher emissions). The trend of SOC changes in forests, croplands, and grasslands of Louisiana at watershed scale will decrease significantly assuming other factors were stable and considering only the climate-change impacts. Louisiana average annual SOC changes were significantly different in six land cover classes ($p < 0.0001$), three emissions scenarios ($p < 0.0001$), and their interactions ($p < 0.0001$) among three periods: beginning 2001-2010, middle 2041-2050, and final 2091-2100. The simulated SOC decrease, based on climate change projections of the HadCM3 climate model, will become more pronounced after the middle of the 21 century (around 2050). Climate change is an important driver of the terrestrial carbon changes in the southern United States. Long-term continuous field measurements at all kinds of land use and climate conditions are needed to improve the modeling in future studies.

This research determined elevation levels of coastal wetland systems in southern Louisiana, providing important insights into future land and land carbon losses due to climate-change induced sea level rise. It compared the LIDAR and DEM datasets, gaining information on accuracy of assessing inundation risk using different elevation datasets. Southeastern Louisiana's coastal areas are in the riskiest inundation zones. Large areas of freshwater forested/shrub wetlands, estuarine and marine wetlands, and freshwater emergent wetlands in Louisiana are in the inundation zones between 0 and 100

centimeters, which have much higher SOC density and larger amounts than other inundation zones. Coastal Louisiana restoration projects could gain carbon credits because their function is protecting the wetlands, which hold large amounts of SOC and N. Freshwater forested/shrub wetlands, estuarine and marine wetlands, and freshwater emergent wetlands, in Louisiana are all having remarkably high SOC densities. The current LIDAR data does not cover entire Louisiana, mainly missing the southeastern active delta zone of Louisiana (bird foot delta). Multi-temporal LIDAR data covering the entire state can be used in future research with Louisiana historical and natural wetlands distribution data.

Sea-level rise caused by global climate change can be a serious problem to Louisiana's coast. Adaptation and mitigation is critical to reduce vulnerability to future climate change. The Kyoto Protocol, a protocol to the international Framework Convention on Climate Change, with the objective of reducing greenhouse gas which causes climate change, has been ratified by most countries in the world. The Clean Development Mechanism (CDM) and Joint Implementation (JI) projects of the Kyoto Protocol are being implemented in many countries to reduce or mitigate the greenhouse gas emissions efficiently. Cost-benefit analysis is a critical step toward carbon mitigation actions. Soils hold large carbon capacity and high carbon sequestration potential. However, it would be difficult to account for and verify SOC changes, certainly with large uncertainties. Significant technical progress, detailed soil surveys, accurate soil database building, cost reduction, method improvement, and policy support will probably make renewable SOC mitigation happen in the future moderating global climate change.

The Kyoto Protocol and emerging climate exchange markets will play a more

important role in the future carbon sequestration. Carbon sequestration accounting is one important step for soil carbon offset projects. On one hand, the SOC estimation with the latest soil databases at finer scales could benefit the SOC accounting as a possible frame of reference. On the other hand, verified SOC accounting can validate and improve the SOC estimation. A truly open and comprehensive online platform is expected to play this role. One of the examples may be the Carbon Management Evaluation Tool for Voluntary Reporting (COMET-VR), which was created by USDA NRCS to help farmers and ranchers report the effectiveness of various land management systems for agricultural soil carbon sequestration. This is a pioneer of the related efforts in terrestrial greenhouse gas assessment and mitigation using the GIS and SQL database. Such an open, user-friendly and mature platform could become a cost-effective as well as an accurate monitoring system that can be useful to carbon credit trading in the future.

REFERENCES

Al-Adamat, R., Rawajfih, Z., Easter, M., Paustian, K., Coleman, K., Milne, E., Falloon, P., Powlson, D.S. and Batjes, N.H.: 2007. Predicted soil organic carbon stocks and changes in Jordan between 2000 and 2030 made using the GEFSOC modelling system. Agriculture Ecosystems & Environment 122: 35-45.

Arrouays, D., Daroussin, J., Kicin, J. L., and Hassika, P. 1998. Improving topSOC storage prediction using a digital elevation model in temperate forest soils of France. Soil Science 163:103-108.

Barras, J.A., Beville, S., Britsch, D., Hartley, S., Hawes, S., Johnston, J., Kemp, P., Kinler, Q., Martucci, A., Porthouse, J., Reed, D., Roy, K., Sapkota, S. and Suhayda, J. 2003. Historical and projected coastal Louisiana land changes: 1978-2050: USGS Open File Report 03-334

Batjes, N. H. 1996. Total carbon and nitrogen in the soils of the world. European Journal of Soil Science 47:151–163.

Bhattacharyya, T., Pal, D.K., Easter, M., Batjes, N.H., Milne, E., Gajbhiye, K.S., Chandran, P., Ray, S.K., Mandal, C., Paustian, K., Williams, S., Killian, K., Coleman, K., Falloon, P. and Powlson, D.S. 2007, Modelled Soil Organic Carbon stocks and changes in the Indo-Gangetic Plains, India from 1980 to 2030. Agriculture Ecosystems & Environment 122: 84-94.

Bliss, N.B. 2003. Soil Organic Carbon on Lands of the Department of the Interior: U.S. Geological Survey Open-File Report 03-304

Bohn, H.L. 1982. Estimate of organic-carbon in world soils: II. Soil Science Society of America Journal 46: 1118–1119.

Bolin, B. 1970. The carbon cycle. Scientific American 223: 124–132.

Borken, W., K. Savage, E.A. Davidson, and S. Trumbore. 2006. Effects of experimental drought on soil respiration and radiocarbon efflux from a temperate forest soil. Global Change Biology 12:177-193.

Borken, W., Y. J. Xu, R. Brumme, and N.P. Lammersdorf. 1999. A climate change scenario for the CO_2 emission of a mature temperate forest: drought and re-wetting effects. Soil Science Society of America Journal 63 (6): 1848-1855.

Bridgham, S.D., Megonigal, J.P., Keller, J.K., Bliss, N.B., and Trettin, C. 2006. The carbon balance of North American. Wetlands 26: 889–916.

Brooks, K. N., P. F. Ffolliott, H. M. Gregorsen, and L. F. DeBano. 2003. Hydrology and management of watersheds. Ames, IA: Iowa State University Press.

Brupbacher, R. H., Sedberry, J. E. JR., and Willis, W. H. 1973. The coastal marshlands of Louisiana. Chemical properties of the soil materials. Louisiana State University. Dep. Agron. Agr. Exp. Sta. Bull.

Burrough, P. A. and McDonell, R. A. 1998. Principles of Geographical Information Systems. Oxford University Press, New York.

Calfapietra C, Gielen B, Galema ANJ, Lukac M, De Angelis P, Moscatelli MC, Ceulemans R, Scarascia-Mugnozza G. 2003. Free-air CO_2 enrichment (FACE) enhances biomass production in a short-rotation poplar plantation. Tree Physiol 23:805-14.

Cerri, C.E.P., Easter, M., Paustian, K., Killian, K., Coleman, K., Bernoux, M., Falloon, P., Powlson, D.S., Batjes, N.H., Milne, E. and Cerri, C.C. 2007, Predicted soil organic carbon stocks and changes in the Brazilian Amazon between 2000 and 2030, Agriculture Ecosystems & Environment 122: 58-72.

Cheng, X. F., Shi, X. Z., Yu, D. S., Pan, X. Z., Wang, H. J., and Sun, W. X. 2004. Using GIS spatial distribution to predict soil organic carbon in subtropical China. Pedosphere. 14(4): 425-431.

Clair, T.A., and Ehrman, J.M. 1998. Using neural networks to assess the influence of changing seasonal climates in modifying discharge, dissolved organic carbon, and nitrogen export in eastern Canadian rivers. Water Resources Research 34(3): 447-455.

Clair, T.A., Ehrman, J., and Higuchi, K. 1998. Changes to the runoff of Canadian ecozones under a doubled CO_2 atmosphere. Canadian Journal of Fisheries and Aquatic Science 55: 2464-2477.

Coleman, K. and Jenkinson, D. 1999. RothC-26.3. A Model for the Turnover of Carbon in Soils. Model Description and Windows Users Guide. IACR – Rothamsted, Harpenden.

Cowardin, L. M., Carter, V., Golet, F. C., and LaRoe, E. T. 1979. Classification of wetlands and deepwater habitats of the United States. US Fish and Wildlife Service FWS/OBS-79/31.

Daniels, R.B., and Hammer, R.D. 1992. Soil geomorphology. New York: Wiley.

Davidson, E.A. 1995. Spatial covariation of soil organic carbon, clay content, and drainage class at a regional scale. Landscape Ecology 10:349-362.

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

Davidson, E.A., and I.A. Janssens. 2006. Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. Nature 440(7081): 165-173.

Davidson, E.A., and P.A. Lefebvre. 1993. Estimating regional carbon stocks and spatially covarying edaphic factors using soil maps at 3 scales. Biogeochemistry 22(2): 107-131.

Day, J. W., Boesch, D. F., Clairain, E. J., Kemp, G. P., Laska, S. B., Mitsch, W. J., Orth, K., Mashriqui, H., Reed, D. J., Shabman, L., Simenstad, C. A., Streever, B. J., Twilley, R. R., Watson, C. C., Wells, J. T. and Whigham, D. F. 2007. Restoration of the Mississippi Delta: Lessons from Hurricanes Katrina and Rita. Science 315:1679-1684.

Del Giorgio, P.A., and Duarte, C.M. 2002. Respiration in the open ocean. Nature 420: 379 - 383.

DeLucia EH, Hamilton JG, Naidu SL, Thomas RB, Andrews JA, Finzi AC, Lavine M, Matamala R, Mohan JE, Hendrey GR, Schlesinger WH. 1999. Net primary production of a forest ecosystem with experimental CO_2 enrichment. Nature 284:1177-9.

Detwiler, R.P. 1986. Land use change and the global carbon cycle: The role of tropical soils. Biogeochemistry 2: 67–93.

Easter, M., Paustian, K., Killian, K., Coleman, K. and Milne, E. 2007. Climate change and its impact on soil and vegetation carbon storage in Kenya, Jordan, India and Brazil, Agriculture Ecosystems & Environment 122: 114-124.

ESRI. 2007. ArcGIS 9.2 for Windows. WWW document. http://www.esri.com

Eswaran, H., Berg, E. van den, and Reich, P. 1993. Organic carbon in soils of the world. Soil Science Society of America Journal 57:192–194.

Falloon, P., Jones, C.D., Cerri, C.E., Al-Adamat, R., Kamoni, P., Bhattacharyya, T., Easter, M., Paustian, K., Killian, K., Coleman, K. and Milne, E. 2007. Climate change and its impact on soil and vegetation carbon storage in Kenya, Jordan, India and Brazil, Agriculture Ecosystems & Environment 122: 114-124.

Falloon, P., Smith P., Coleman K., and Marshall S. 1998. Estimating the size of the inert organic matter pool for use in the Rothamsted carbon model. Soil Biology and Biochemistry 30: 1207-1211

FAO. 2004. Carbon sequestration in dryland soils. Food and Agriculture Organization of the United Nations, Rome.

Gerrard, A.J. 1981. Soils and landforms. An integration of geomorphology and pedology. London: George, Allen and Unwin.

Gielen B, Calfapietra C, Lukac M, Wittig VE, De Angelis P, Janssens IA, Moscatelli MC, Grego S, Cotrufo MF, Godbold DL, Hoosbeek MR, Long SP, Miglietta F, Polle A, Bernacchi CJ, Davey PA, Ceulemans R, Scarascia-Mugnozza GE. 2005. Net carbon storage in a poplar plantation (POPFACE) after three years of free-air CO_2 enrichment. Tree Physiol 25:1399-408.

Golubiewski, N.E. 2006. Urbanization increases grassland carbon pools: Affects of landscaping in Colorado's Front Range. Ecological Applications 16: 555-571

Gorham, E. 1991. Northern peatlands: role in the carbon cycle and probable responses to climatic warming. Ecological Applications 1:182–195.

Grunwald, S. 2005. Environmental Soil-Landscape Modeling: Geographic Information Technologies and Pedometrics. CRC Press, Taylor and Francis, Boca Raton, FL.

Guo, L. B., and Gifford, R.M. 2002. SOC stocks and land use change: a Meta analysis. Global Change Biology 8:345-360.

Guo, Y.Y., Amundson, R., Gong, P., and Yu, Q. 2006a. Quantity and spatial variability of SOC in the conterminous United States. Soil Science Society of America Journal 70:590-600.

Guo, Y.Y., Gong, P., Amundson, R., and Yu, Q. 2006b. Analysis of factors controlling SOC in the conterminous United States. Soil Science Society of America Journal 70:601-612.

Hamilton JG, DeLucia EH, George K, Naidu SL, Finzi AC, Schlesinger WH. 2002. Forest carbon balance under elevated CO_2. Oecologia 131:250-60.

Handa IT, Korner C, Hattenschwiler S. 2006. Conifer stem growth at the altitudinal

treeline in response to four years of CO_2 enrichment. Global Change Biology 12:2417-30.

Hart, P. 1984. Effects of soil type and past cropping on the nitrogen supplying ability of arable soils. PhD thesis, University of Reading, UK

Hattenschwiler S, Handa IT, Egli L, Asshoff R, Ammann W, Ko¨ rner C. 2002. Atmospheric CO_2 enrichment of alpine treeline conifers. New Phytol 156:363-75.

Heimann, M. and Reichstein, M. 2008. Terrestrial ecosystem carbon dynamics and climate feedbacks, Nature 451: 289-292.

Homann, P.S., P. Sollins, M. Fiorella, T. Thorson, and J.S. Kern. 1998. Regional soil organic carbon storage estimates for western Oregon by multiple approaches. Soil Science Society of America Journal 62(3): 789-796.

Homer, C. C. Huang, L. Yang, B. Wylie and M. Coan. 2004. Development of a 2001 National Landcover Database for the United States. Photogrammetric Engineering and Remote Sensing, Vol. 70, No. 7, July 2004, pp. 829-840.

Houghton, R.A. 1994. The worldwide extent of land-use change. BioScience 44: 305-13.

Houghton, R.A. 1995. Changes in the storage of terrestrial carbon since 1850. pp. 45–65, In R. Lal, J. Kimble, E. Levine, B.A. Stewart (Eds.): Soils and Global Change. CRC/Lewis Publishers, Boca Raton, FL, USA.

Houghton, R. A., and Goodale, C. L. 2004. Effects of land-use change on the carbon balance of terrestrial ecosystems. Ecosystems / Land Use Change. AGU 85-98.

Huggett, R. J. 2003. Fundamentals of Geomorphology, London; New York: Routledge.

IPCC. 2000. Land Use, Land-Use Change, and Forestry: Special Report of the IPCC. Cambridge University Press, Cambridge, UK. Available online http://www.ipcc.ch/pub/srlulucf-e.pdf

IPCC. 2001a. Climate Change 2001: Synthesis Report. Cambridge University Press, Cambridge, UK. Available online http://www.grida.no/climate/ipcc_tar/

IPCC. 2001b. Climate Change 2001: Impacts, Adaptation and Vulnerability. Cambridge University Press, Cambridge, UK. Available online http://www.grida.no/climate/ipcc_tar/

IPCC. 2001c. Climate Change 2001: Mitigation. Cambridge University Press, Cambridge,

UK. Available online http://www.grida.no/climate/ipcc_tar/

IPCC. 2001d. Climate Change 2001: The Scientific Basis. Cambridge University Press, Cambridge, UK. Available online http://www.grida.no/climate/ipcc_tar/

IPCC. 2007. Climate change 2007: synthesis report. Contribution of Working Group I, II and III to the fourth assessment report of the Intergovernmental Panel on Climate Change (Core Writing Team, R. K. Pachauri & A. Reisinger (Eds.)). Geneva, Switzerland: IPCC.

Jenkinson, D.S. 1990. The turnover of organic carbon and nitrogen in soil. Philosophical Transactions of the Royal Society, London B 329:361-368.

Jenkinson, D.S., Adams, D.E., and Wild, A. 1991. Model estimates of CO_2 emissions from soil in response to global warming. Nature 351(6322): 304-306.

Jenkinson, D.S. and Coleman, K. 1994. Calculating the annual input of organic matter to soil from measurements of total organic carbon and radiocarbon. European Journal of Soil Science 45:167-174.

Jenkinson, D.S., Harkness, D.D., Vance, E.D., Adams, D.E., and Harrison, A.F. 1992. Calculating net primary production and annual input of organic matter to soil from the amount and radiocarbon content of soil organic matter. Soil Biology & Biochemistry. 24(4): 295-308.

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

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

Jenny, H. 1941. Factors of Soil Formation. McGraw-Hill, New York.

Jenny, H. 1961. EW Hillgard and the Birth of Modern Soil Science. Farallo Publ., Berkeley, CA.

Johnson, D. W. 1992. Effects of forest management on SOC storage. Water Air and Soil Pollution 64: 83–120.

Karl, T.R. and Knight, R.W. 1998. Secular trends of precipitation amount, frequency and intensity in the United States., Bulletin of the American Meteorological Society. 79: 231–241.

Karl, T.R., Melillo, J.M., and Peterson, T.C. 2009. Global Climate Change Impacts in the United States, (eds.). Cambridge University Press.

Kamoni, P. T., Gicheru, P. T., Wokabi, S. M., Easter, M., Milne, E., Coleman, K., Falloon, P. and Paustian, K. 2007. Predicted soil organic carbon stocks and changes in Kenya between 1990 and 2030. Agriculture Ecosystems & Environment 122(1): 105-113.

Karnosky DF, Zak DR, Pregitzer KS, Awmack CS, Bockheim JG, Dickson RE, Hendrey GR, Host GE, King JS, Kopper BJ, Kruger EL, Kubiske ME, Lindroth RL, Mattson WJ, McDonald EP, Noormets A, Oksanen E, Parsons WFJ, Percy KE, Podila GK, Riemenschneider DE, Sharma P, Thakur R, Sober A, Sober J, Jones WS, Anttonen S, Vapaavuori E, Mankovska B, Heilman W, Isebrands JG. 2003. Troposheric O_3 moderates responses of temperate hardwood forests to elevated CO_2: a synthesis of molecular to ecosystem results from the Aspen FACE project. Functional Ecology 17:289-304.

Krug, E. C. 2007. Coastal change and hypoxia in the northern Gulf of Mexico: Part I. Hydrology and Earth System Sciences 11:180-190.

Krug, E. C., and Merrifield, K. 2007. Marine modification of terrestrial influences on Gulf hypoxia: Part II. Hydrology and Earth System Sciences 11:191-209.

Kyoto Protocol. 1997. Kyoto Protocol to the United Nations Framework Convention on Climate Change. New York: United Nations.

Lal, R. 2001. World cropland soils as a source or sink for atmospheric carbon. Advances in Agronomy 71: 145 - 191.

Lal, R. 2004a. Soil carbon sequestration impacts on global climate change and food security. Science 304(5677): 1623-1627.

Lal, R. 2004b. Soil carbon sequestration to mitigate climate change. Geoderma 123:1–22

Lal, R., Kimble, J. M., Follett, R. F., and Cole, C. V. 1999. The Potential of U.S. Cropland to Sequester Carbon and Mitigate the Greenhouse Effect. Lewis Publishers, Boca Raton, Florida.

LDNR. 1998. Coast 2050: Toward a Sustainable Coastal Louisiana Louisiana Coastal Wetlands Conservation and Restoration Task Force and the Wetlands Conservation and Restoration Authority. Louisiana Department of Natural Resources, Baton Rouge, LA, USA.

Liberloo M, Tulva I, Raı¨m O, Kull O, Ceulemans R. 2006. Photosynthetic stimulation under long-term CO_2 enrichment and fertilization is sustained across a closed Populus canopy profile (EuroFACE). New Phytologist 173:537-49.

Louisiana Department of Environmental Quality. 2004. Basin Subsegments from LDEQ source data, Geographic NAD83, LOSCO (2004) [basin_subsegments_LDEQ_2004]: Louisiana Department of Environmental Quality, Baton Rouge, LA.

Louisiana Department of Environmental Quality, and Louisiana Oil Spill Coordinator's Office. 2004. Louisiana Digital Elevation Dataset from LDEQ source data, UTM Zone 15 NAD83, LOSCO (2004) [24KDEM_LDEQ_2004]: State coverage 1, Louisiana Oil Spill Coordinator's Office (LOSCO), Baton Rouge, LA.

Louisiana Oil Spill Coordinator's Office (LOSCO), and U.S. Department of Commerce, U.S. Census Bureau, Geography Division. 2004. TIGER/Line Hydrography for Louisiana, Geographic NAD83, LOSCO (2004) [tiger_water_segments_2004]: TIGER/Line Files, Louisiana Oil Spill Coordinator's Office (LOSCO), Baton Rouge, LA.

Maltby, E. and Immirzi, P. 1993. Carbon dynamics in peatlands and other wetland soils, regional and global perspectives. Chemosphere 27:999–1023.

Mann, L. K. 1985. A regional comparison of carbon in cultivated and uncultivated alfisols and mollisols in the central United States. Geoderma 36: 241–253.

Marland, G. and Boden. T. 1993. The magnitude and distribution of fossil-fuel-related carbon releases. 117-138. In heimann, M. (ed.), The Global Carbon Cycle. Springer-Verlag, New York.

Mitchell, T.D., Carter, T.R., Jones, P.D., Hulme, M., and New, M. 2004. A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: the observed record (1901–2000) and 16 scenarios (2001–2100). Tyndall Centre for Climate Change Research Working Paper 55: 25.

http://www.tyndall. ac.uk/publications/working_papers/wp55.pdf

Mitsch, W.J. and X. Wu. 1995. Wetlands and global change. In, R. Lal , J. Kimble, E. Levine, and B.A. Stewart (eds.), Advances in Soil Science, Soil Management and Greenhouse Effect. Boca Raton, Florida: Lewis Publishers. pp. 205-230.

Murty, D., Kirschbaum, M. F., McMurtrie, R. E., and McGilvray, H. 2002. Does conversion of forest to agricultural land change SOC and nitrogen? A review of the literature. Global Change Biology 8:105–123.

Nakic´enovic´, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Gru¨bler, A., Jung, T.Y., Kram, T., Emiliola Rovere, E., Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Riahi, K., Roehrl, A., Rogner, H.-H., Sankovski, A., Schlesinger, M.E., Shukla, P.R., Smith, S., Swart, R.J., van Rooyen, S., Victor, N., and Dadi, Z., 2000. Special Report on Emissions Scenarios. Cambridge University Press, Cambridge.

Nelson, D. W. and Sommers, L. E. 1982. Total carbon, organic carbon and organic matter. In: A.L. Page, R.H. Miller, and D.R. Keeney (eds.): Methods of Soil Analysis, 539-579. American Society of Agronomy, Wisconsin, USA.

New, M., Hulme, M., and Jones, P., 1999. Representing Twentieth-Century Space-Time Climate Variability. Part I: Development of a 1961–90 mean monthly terrestrial climatology. Journal of Climate 12:829–856.

Norby RJ, DeLucia EH, Gielen B, Calfapietra C, Giardina CP, King JS, Ledford J, McCarthy HR, Moore DJP, Ceulemans R, De Angelis P, Finzi AC, Karnosky DF, Kubiske ME, Lukac M, Pregitzer KS, Scarascia-Mugnozza G, Schlesinger WH, Oren R. 2005. Forest response to elevated CO_2 is conserved across a broad range of productivity. Proceedings of the National Academy of Sciences 102:18052-6.

Norby RJ, Hanson PJ, O'Neill EG, Tschaplinski TJ, Weltzin JF, Hansen RA, Cheng W, Wullschleger SD, Gunderson CA, Edwards NT, Johnson DW. 2002. Net primary productivity of a CO_2-enriched deciduous forest and the implications for carbon storage. Ecological Applications 12:1261-6.

NRCS. 1995. State Soil Geographic (STATSGO) Data Base Data use information. United States Department of Agriculture. Natural Resources Conservation Service. National Soil Survey Center.

Nyman, J. A., DeLaune, R. D. and Patrick, Jr., W. H. 1990. Wetland soil formation in the rapidly subsiding Mississippi River Deltaic Plain: Mineral and organic matter relationships. Estuarine, Coastal and Shelf Science 31: 57–69.

Osborn, T. J., Hulme, M., Jones, P. D., and Basnet, T. A. 2000. Observed trends in the daily intensity of United Kingdom precipitation. International Journal of Climatology 20: 347–364.

Pacala, S. and Socolow, R. 2004. Stabilization wedges: solving the climate problem for the next 50 years with current technologies. Science 305: 968–972.

Parton, W.J., McKeown, R., Kirchner, V. and Ojima, D. 1992. CENTURY users manual. Colorado State University, Natural Resource Ecology Laboratory. Ft. Collins, USA.

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

Penland S., and Ramsey K.1990. Relative sea level rise in Louisiana and the Gulf of Mexico: 1908-1988: Journal of Coastal Research, v. 6: 323-342

Ponce-Hernandez, R. 2004. Assessing carbon stocks and modeling win-win scenarios of carbon sequestration through land-use changes. Food and Agriculture Organization of the United Nations, Rome.

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

Post, W. M. and Kwon, K.C. 2000. SOC sequestration and land-use change: processes and potential. Global Change Biology 6: 317–327.

Pouyat, R. V., Yesilonis, I. D. and Nowak, D. J. 2006. Carbon storage by urban soils in the United States. Journal of Environmental Quality 35: 1566-1575

Powlson, D.S., Smith, P., Coleman, K., Smith, J.U., Glendining, M.J., Korschens, M. and Franko, U. 1998. A European network of long-term sites for studies on soil organic matter. Soil and Tillage Research 47: 263-274.

Richey, J. E., Melack, J. M., Aufdenkampe, A. K., Ballester, V. M., and Hess, L. L. 2002. Outgassing from Amazonian rivers and wetlands as a large tropical source of atmospheric CO_2. Nature 416: 617 - 620.

Ritter, D. F. 1978. Process geomorphology, W. C. Brown Co, Dubuque, Iowa.

Robert, M. 1996. Le sol: interface dans l'environnement. ressource pour le développement, Paris.

Rosenberg, N. J., R. C. Izaurralde, and Malone, E.L. (eds.). 1999. Carbon Sequestration in Soils: Science, Monitoring and Beyond. Battelle Press, Columus, Ohio.

Ruiz-Barradas, A., and Nigam, S. 2006. IPCC's twentieth-century climate simulations: Varied representations of north American hydroclimate variability. Journal of Climate

19:4041-4058.

SAS Institute. 2007. SAS User's Guide, Release 9.1. SAS Institute, Cary, NC.

Saxton, A. M. 1998. A macro for converting mean separation output to letter groupings in Proc Mixed. Pages 1243–1246 in Proc. 23rd SAS Users Group Int. SAS Inst. Inc., Cary, NC.

Schimel, D.S., House, J. I., and Hibbard, K.A. 2001. Recent patterns and mechanisms of carbon exchange by terrestrial ecosystems. Nature 414: 169-172.

Schlesinger, W. H. 1986: Changes in soil carbon storage and associated properties with disturbance and recovery. In: The Changing Carbon Cycle: a Global Analysis. [Trabalka, J.R. and D.E. Reichle (eds.)]. Springer-Verlag, New York, pp. 175-193.

Schlesinger, W. H. 1995. An Overview of the Carbon Cycle, in Lal, R., Kimble, J., Levine, E., and Stewart, B. A. (eds.), Soils and Global Change, CRC Lewis Publishers, Boca Raton, pp. 9–25.

Schlesinger, W. H. 1997. Biogeochemistry: An Analysis of Global Change. Academic Press, San Diego, California, USA.

Smith, J., Smith, P., Wattenbach, M., Gottschalk, P., Romanenkov, V.A., Shevtsova, L.K., Sirotenko, O.D., Rukhovich, D.I., Koroleva, P.V., Romanenko, I.A. and Lisovoi, N.V.: 2007, Projected changes in the organic carbon stocks of cropland mineral soils of European Russia and the Ukraine, 1990-2070. Global Change Biology 13:342-356.

Smith, J., Smith, P., Wattenbach, M., Zaehle, S., Hiederer, R., Jones, R.J.A., Montanarella, L., Rounsevell, M.D.A., Reginster, I., and Ewert, F. 2005. Projected changes in mineral soil carbon of European croplands and grasslands, 1990-2080. Global Change Biology 11: 2141-2152.

Smith, P. 2004. Carbon sequestration in croplands: the potential in Europe and the global context. European Journal of Agronomy 20:229–236

Smith, P., Powlson, D.S., Smith, J.U., and Falloon, P. 1997a. SOMNET. A Global Network and Database of Soil Organic Matter Models and Long-Term Experimental Datasets. The Globe 38: 4-5.

Smith, P., Powlson, D. S., Smith, J. U., and Glendining, M. J. 1996a. The GCTE SOMNET. A global network and database of soil organic matter models and long-term datasets. Soil Use and Management 12: 104.

Smith, P., Powlson, D. S., Smith, J.U., Falloon, P.D., and Coleman, K. 2000. Meeting Europe's climate change commitments: quantitative estimates of the potential for carbon mitigation by agriculture. Global Change Biology 6:525–539

Smith, P., Smith, J. U., and Powlson, D. S. 1996b. Soil Organic Matter Network (SOMNET): 1996 Model and Experimental Metadata. GCTE Report 7. GCTE Focus 3. Wallingford, Oxon, 259.

Smith, P., Smith, J., Wattenbach, M., Meyer, J., Lindner, M., Zaehle, S., Hiederer, R., Jones, R.J.A., Montanarella, L., Rounsevell, M., Reginster, I., and Kankaanpaa, S. 2006. Projected changes in mineral soil carbon of European forests, 1990-2100. Canadian Journal of Soil Science 86: 159-169.

Smith, P., Smith, J.U., Powlson, D.S., McGill, W.B., Arah, J.R.M., Chertov O.G., Coleman, K., Franko, U., Frolking, S, Jenkinson, D.S., Jensen,L.S., Kelly, R.H., Klein-Gunnewiek, H., Komarov, A., Li, C., Molina, J.A.E., Mueller, T., Parton, W.J., Thornley, J.H.M. and Whitmore, A.P. 1997b. A comparison of the performance of nine soil organic matter models using seven long-term experimental datasets. In P. Smith, D.S. Powlson, J.U. Smith & E.T. Elliott, eds. Evaluation and comparison of soil organic matter models using datasets from seven long-term experiments. Geoderma 81: 153–225.

Smith, W.N., Grant, B.B., Desjardins, R.L., Qian, B., Hutchinson, J. and Gameda, S.: 2009, Potential impact of climate change on carbon in agricultural soils in Canada 2000-2099. Climatic Change 93: 319-333.

Sparks, D. L. 2003. Environmental soil chemistry. Academic Press, Amsterdam, Boston.

Subak, S., Raskin, P., and Hippel., D. von. 1993. National greenhouse gas accounts: Current anthropogenic sources and sinks. Climatic Change 25: 15-58

Tan, Z.X., R. Lal, N.E. Smeck, F.G. Calhoun, B.K. Slater, B. Parkinson, and Gehring, R.M. 2004. Taxonomic and geographic distribution of soil organic carbon pools in Ohio. Soil Science Society of America Journal 68:1896-1904.

Thompson, J. A. and Kolka, R. K. 2005. SOC storage estimation in a forested watershed using quantitative soil-landscape modeling. Soil Science Society of America Journal 69:1086-1093.

Trumbore, S. E., O. A. Chadwick, and R. Amundson. 1996. Rapid exchange of soil carbon and atmospheric CO_2 driven by temperature change. Science 272:393-396.

Turner, B.L., II, Clark, W. C., Kates, R. W., Richards, J.F., Mathews, J.T. and Meyer, W.B. (eds.). 1990. The Earth as Transformed by Human Action. Cambridge University Press, Cambridge.

Turner, R. E., N. N. Rabalais, R. B. Alexander, G. McIsaac, and Howarth, R. W. 2007. Characterization of nutrient, organic carbon, and sediment loads and concentrations from the Mississippi River into the Northern gulf of Mexico. Estuaries and Coasts 30:773-790.

U.S. Environmental Protection Agency. 2009. America's Wetlands (http://www.epa.gov/OWOW/wetlands/vital/toc.html).

Walter, C., Rossel, R. A. V., and McBratney, A. B. 2003. Spatio-temporal simulation of the field-scale evolution of organic carbon over the landscape. Soil Science Society of America Journal 67:1477-1486.

Wang F.G., and Xu Y.J. Predicting climate change effects on forest net primary productivity in subtropical Louisiana, USA. Forest Ecology and Management (under review).

Wentz, F.J., Ricciardulli, L., Hilburn, K. and Mears, C. 2007. How much more rain will global warming bring? Science 317(5835): 233-235.

White, A., Cannell, M.G.R. and Friend, A.D. 1999. Climate change impacts on ecosystems and the terrestrial carbon sink: a new assessment, Global Environmental Change-Human and Policy Dimensions 9: S21-S30.

Xu, Y. J. and Prisley, S. P. 2000. Linking STATSGO and FIA data for spatial analyses of land carbon densities. Proceedings CD ROM of the 3rd USDA Forest Service Southern GIS Conference.

Zaehle, S., Bondeau, A., Carter, T.R., Cramer, W., Erhard, M., Prentice, I.C., Reginster, I., Rounsevell, M.D.A., Sitch, S., Smith, B., Smith, P.C. and Sykes, M. 2007. Projected changes in terrestrial carbon storage in Europe under climate and land-use change, 1990-2100. Ecosystems 10: 380-401.

Zhong, B. and Xu, Y.J. 2009. Topographic Effects on Soil Organic Carbon in Louisiana Watersheds, Environmental Management 43: 662-672.

APPENDIX A: LETTER OF PERMISSION

From Paul, Melinda, Springer US <Melinda.Paul@springer.com>
To bongreat@gmail.com

Date Tue, Oct 6, 2009 at 4:13 PM
Subject RE: Your article in Environmental Management (9182)
Mailed-byspringer.com

Dear Dr. Zhong,

Permission is granted for your to use the material as you request provided that full acknowledgement is given to the original source of publication.

Thank you for your contribution to Environmental Management.

With kind regards,

+++++++++++++++
Melinda (Lindy) Paul
Springer
Senior Editor
Environmental Science
233 Spring St | New York, NY 10013-1578
tel (781) 347-1835
melinda.paul@springer.com

From: Biao Zhong [mailto:bongreat@gmail.com]
Sent: Monday, October 05, 2009 3:52 PM
To: Golive@springer.com
Cc: Dale, Virginia H.
Subject: Re: Your article in Environmental Management (9182)

Dear Dr. Dale and other editors,

The following article entitled "Topographic Effects on Soil Organic Carbon in Louisiana Watersheds" has been published in the Environmental Management. The data, tables, and figures from this manuscript will also be published as a chapter of my dissertation of Louisiana State University. This dissertation will be submitted to the graduate school this coming Nov. May I get a permission to publish my manuscript to my dissertation? What else should I do for the copyright issue?

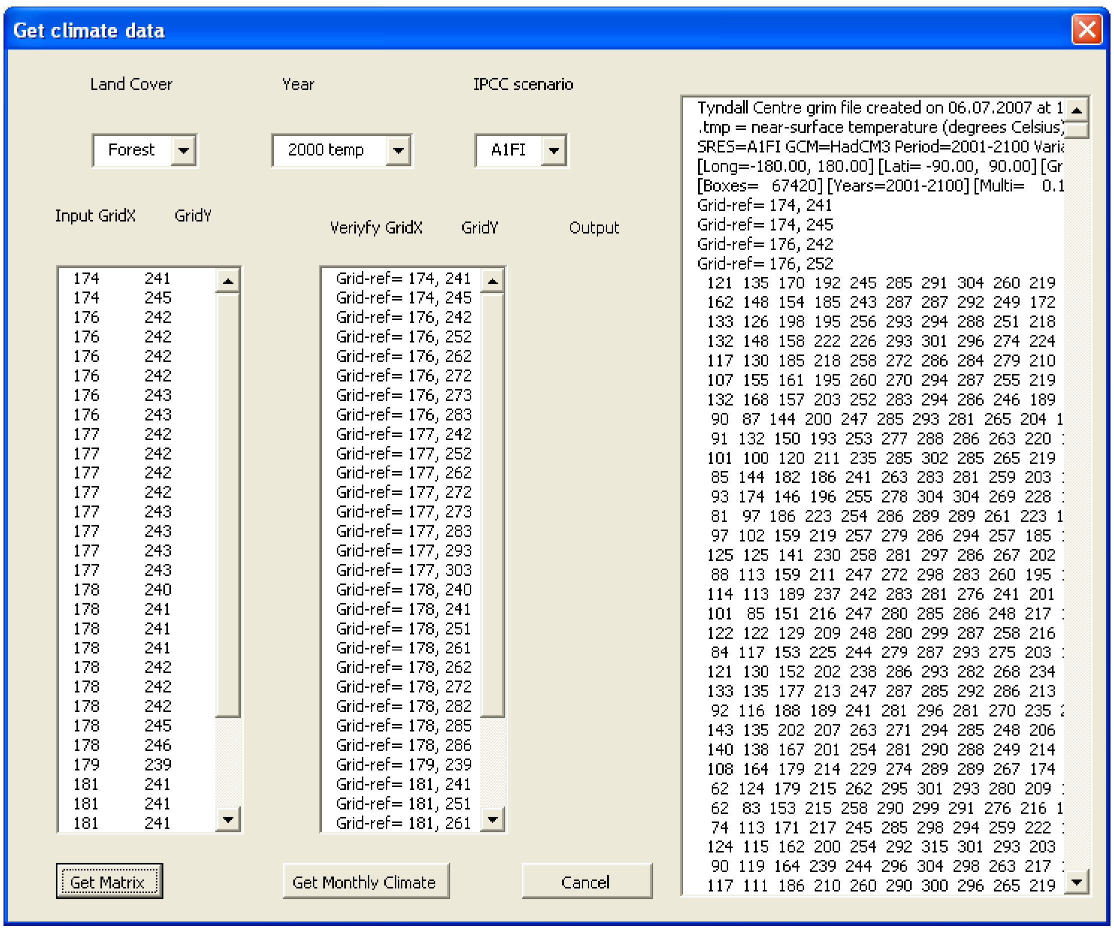
Thanks!

Yours Sincerely,
Biao Zhong

APPENDIX B: SOURCE CODES

Source code for getting climate data:

This function was written using Visual Basic or VBA to get the monthly temperature or precipitation data and to get particular cell (X, Y) climate data from a large amount of climate matrix data. It can be used for somebody who hopes to use the same climate matrix data, high resolution grid 0.5°x0.5° monthly temperature, and precipitation between 1901-2000 and 2001-2100, from Climate Research Unit, University of East Anglia, U.K.



Private Sub Monthlyclimate_Click()

'01/06/2008, written by Biao Zhong, at LSU. The objective of the program is to get the monthly temperature or precipitation data
'strSourceFile: Grid Cell numbers, GridX & GridY, Source Grid file have to be sorted ascending
'strSourceFile2: source climate data files, temperature or precipitation
'strTargetFile: output climate data files, temperature or precipitation

```
Dim filenum              As Integer
Dim fileContents        As String
Dim fileContents2      As String
Dim fileInfo()          As String 'for grid source
Dim fileInfo2()         As String ' for grid climate
Dim i                   As Long
Dim j                   As Long
Dim k                   As Long
Dim m                   As Integer ' for Grid x and y
Dim n                   As Integer
Dim GridX(150)          As Integer
Dim GridY(150)          As Integer
Dim num                 As Integer
'Dim num2                As Double
Dim tmpData As String
Dim tmpgrid As String
Dim strSourceFile As String, strSourceFile2 As String, strTargetFile As String

ListBox1.Clear
ListBox2.Clear
ListBox3.Clear

DIR_Initialize2 strSourceFile, strSourceFile2, strTargetFile
'Get the sources and output file names

num = 0
filenum = FreeFile

Open strSourceFile For Binary As #filenum
    fileContents = Space(LOF(filenum))
    Get #filenum, , fileContents
Close filenum
fileInfo = Split(fileContents, vbCrLf)
'Get the rows of source data file, saving in arrays

filenum = 1 'FreeFile
If Dir(strTargetFile, vbNormal) <> "" Then
    Kill strTargetFile
End If
Dim Filestr() As String

Open strTargetFile For Append As #filenum
    For i = 1 To UBound(fileInfo) - 1
        If i <> intRow - 1 Then
            Print #filenum, fileInfo(i)
```

```
                ListBox1.AddItem fileInfo(i)
                GridX(i - 1) = Left(fileInfo(i), 4)
                GridY(i - 1) = Right(fileInfo(i), 4)
                'num = num + 1
            End If
        Next
    Close #filenum


    Open strSourceFile2 For Binary As #filenum
        fileContents2 = Space(LOF(filenum))
        Get #filenum, , fileContents2
    Close filenum
    fileInfo2 = Split(fileContents2, vbCrLf)

    filenum = 1 'FreeFile
    If Dir(strTargetFile, vbNormal) <> "" Then
        Kill strTargetFile
    End If

    m = 0
    n = 0
    Open strTargetFile For Append As #filenum
        ' loop
        For i = 4 To UBound(fileInfo2) - 1
            If i <> intRow - 1 Then
                tmpgrid = GridX(m) & ", " & GridY(m)
                If Right(fileInfo2(i), 8) = tmpgrid Then
                    k = i + 101
                    num = Right(fileInfo2(i), 3)
                    tmpData = Right(Left(fileInfo2(i), 13), 3) & num
                    ListBox3.AddItem tmpData

                    tmpData = tmpData & fileInfo2(i + 1) & fileInfo2(i + 25) &
fileInfo2(i + 50) & fileInfo2(i + 75) & fileInfo2(i + 100)
                    Print #filenum, tmpData

                  m = m + 1
                If GridX(m - 1) < GridX(m) Then
                 n = 0
                End If
                'End If
                End If
            End If
        Next
    Close #filenum
```

```
    'MsgBox "done"
End Sub

Private Sub Getdata_Click ()

'12/06/2007, by Biao Zhong, in LSU to get particular cell (X, Y) climate data from large amount climate matrix data.
'strSourceFile    Grid Cell numbers, GridX & GridY, Source Grid file have to be sorted ascending
'strSourceFile2    source climate data files, temperature or precipitation
'strTargetFile    output climate data files, temperature or precipitation

    Dim filenum            As Integer
    Dim fileContents       As String
    Dim fileContents2      As String
    Dim fileInfo()         As String 'for grid source
    Dim fileInfo2()        As String ' for grid climate
    Dim i                  As Long
    Dim j                  As Long
    Dim k                  As Long
    Dim m                  As Integer ' for Grid x and y
    Dim n                  As Integer
    Dim GridX(150)         As Integer
    Dim GridY(150)         As Integer
    Dim num                As Integer
    'Dim num2              As Double
    Dim tmpData As String

    Dim tmpgrid As String
    Dim strSourceFile As String, strSourceFile2 As String, strTargetFile As String

    ListBox1.Clear
    ListBox2.Clear
    ListBox3.Clear

    DIR_Initialize strSourceFile, strSourceFile2, strTargetFile

        'intRow = 5
    num = 0
    filenum = FreeFile

    Open strSourceFile For Binary As #filenum
        fileContents = Space(LOF(filenum))
        Get #filenum, , fileContents
    Close filenum
    fileInfo = Split(fileContents, vbCrLf)
```

‘ Get the rows of sourcefile

```
filenum = 1 'FreeFile
If Dir(strTargetFile, vbNormal) <> "" Then
      Kill strTargetFile
End If
Dim Filestr() As String

Open strTargetFile For Append As #filenum
                  For i = 1 To UBound(fileInfo) - 1
            If i <> intRow - 1 Then
                  'Print #filenum, "insert content"
                  Print #filenum, fileInfo(i)
                  ListBox1.AddItem fileInfo(i)
                  GridX(i - 1) = Left(fileInfo(i), 4)
                  GridY(i - 1) = Right(fileInfo(i), 4)
                  'num = num + 1
            End If
      Next
Close #filenum

Open strSourceFile2 For Binary As #filenum
      fileContents2 = Space(LOF(filenum))
      Get #filenum, , fileContents2
Close filenum
fileInfo2 = Split(fileContents2, vbCrLf)

filenum = 1 'FreeFile
If Dir(strTargetFile, vbNormal) <> "" Then
      Kill strTargetFile
End If

Open strTargetFile For Append As #filenum
      For i = 0 To 5 - 1
            If i <> intRow - 1 Then
                  'Print #filenum, " insert content "
                  Print #filenum, fileInfo2(i)
                  ListBox2.AddItem fileInfo2(i)
            End If
      Next
Close #filenum

m = 0
n = 0
Open strTargetFile For Append As #filenum
      For i = 4 To UBound(fileInfo2) - 1
```

```
                If i <> intRow - 1 Then
                    'Print #filenum, " insert content "
                    tmpgrid = GridX(m) & ", " & GridY(m)
                    If Right(fileInfo2(i), 8) = tmpgrid Then
                        k = i + 101
                        num = Right(fileInfo2(i), 3) + 10 * n
                        tmpData = Left(fileInfo2(i), 15) & num
                        Print #filenum, tmpData
                        ListBox2.AddItem tmpData
                        ListBox3.AddItem tmpData
                        For j = i + 1 To k - 1
                            Print #filenum, fileInfo2(j)
                            'ListBox2.AddItem fileInfo2(j)
                       Next
                       'n = 1
                    Do While GridX(m) = GridX(m + 1) And GridY(m) = GridY(m + 1)
                      'If GridX(m) = GridX(m + 1) And GridY(m) = GridY(m + 1) Then
                            n = n + 1 ' for add number
                                k = i + 101
                                num = Right(fileInfo2(i), 3) + 10 * n
                                   'i + 101 * (n - 1)
                                'num2 = Right(fileInfo2(i), 3) + 0.1 * n
                                tmpData = Left(fileInfo2(i), 15) & num
                                    Print #filenum, tmpData
                                    ListBox2.AddItem tmpData
                                    ListBox3.AddItem tmpData
                                For j = i + 1 To k - 1
                                    Print #filenum, fileInfo2(j)
                                    'ListBox2.AddItem fileInfo2(j)
                               Next
                               m = m + 1 ' for Grid array
                            'End If
                        Loop
                     m = m + 1
                    If GridX(m - 1) < GridX(m) Then
                     n = 0
                    End If
                    'End If
                    End If
                End If
            Next
        Close #filenum
        'MsgBox "done"
End Sub
```

Source code in statistical analysis using SAS:

```
Data IA.L1;
/*L1 is the SOC simulation results for the next 100 years under three emission scenarios
across all land cover types*/
set IA.aaa;
if majority < 90 and subsegment>0    then output;
/*Majority means the land cover types. Majority 91 means woody wetlands; and Majority
92 means emergent herbaceous wetlands. Subsegment is the watershed id*/
Run;

/*** The following procedure calculates the SOC changes for the means of time periods
2001-2010 (beginning), 2041-2051 (middle), and 2091-2100 (final) ***/

data IA.LA (keep = category C30CM subsegment    C2010A1FI C2050A1FI
C2100A1FI C204XA1FI C209XA1FI C205XA1FI
C2010A2 C2050A2 C2100A2 C204XA2 C209XA2 C205XA2 C2010B2 C2050B2
C2100B2 C204XB2 C209XB2 C205XB2);

set IA.L1;
C2010A1FI = ( _A1FI_2001 + _A1FI_2002 +_A1FI_2003+_A1FI_2004+_A1FI_2005
+_A1FI_2006+_A1FI_2007+_A1FI_2008 + _A1FI_2009 +_A1FI_2010)/10;

C2050A1FI = ( _A1FI_2041 + _A1FI_2042 +_A1FI_2043+_A1FI_2044+_A1FI_2045
+_A1FI_2046+_A1FI_2047+_A1FI_2048 + _A1FI_2049 +_A1FI_2050)/10;

C2100A1FI = ( _A1FI_2091 + _A1FI_2092 +_A1FI_2093+_A1FI_2094+_A1FI_2095
+_A1FI_2096+_A1FI_2097+_A1FI_2098 + _A1FI_2099 +_A1FI_2100)/10;

C204XA1FI= C2010A1FI - C2050A1FI;
C209XA1FI= C2010A1FI - C2100A1FI;
C205XA1FI= C2050A1FI - C2100A1FI;

C2010A2 = ( _A2_2001 + _A2_2002 +_A2_2003+_A2_2004+_A2_2005
+_A2_2006+_A2_2007+_A2_2008 + _A2_2009 +_A2_2010)/10;

C2050A2 = ( _A2_2041 + _A2_2042 +_A2_2043+_A2_2044+_A2_2045
+_A2_2046+_A2_2047+_A2_2048 + _A2_2049 +_A2_2050)/10;

C2100A2 = ( _A2_2091 + _A2_2092 +_A2_2093+_A2_2094+_A2_2095
+_A2_2096+_A2_2097+_A2_2098 + _A2_2099 +_A2_2100)/10;

C204XA2= C2010A2 - C2050A2;
C209XA2= C2010A2 - C2100A2;
C205XA2= C2050A2 - C2100A2;
```

```
C2010B2 = ( _B2_2001 + _B2_2002 +_B2_2003+_B2_2004+_B2_2005
+_B2_2006+_B2_2007+_B2_2008 + _B2_2009 +_B2_2010)/10;

C2050B2 = ( _B2_2041 + _B2_2042 +_B2_2043+_B2_2044+_B2_2045
+_B2_2046+_B2_2047+_B2_2048 + _B2_2049 +_B2_2050)/10;

C2100B2 = ( _B2_2091 + _B2_2092 +_B2_2093+_B2_2094+_B2_2095
+_B2_2096+_B2_2097+_B2_2098 + _B2_2099 +_B2_2100)/10;

C204XB2=   C2010B2   - C2050B2;
C209XB2=   C2010B2   - C2100B2;
C205XB2=   C2050B2   - C2100B2;
run;

data IA.LB (keep = category   subsegment   C204XA1FI C209XA1FI C205XA1FI
 C204XA2 C209XA2 C205XA2 C204XB2 C209XB2 C205XB2);
set IA.LA;
run;

/* The following procedure transposes data sets from one form to another */
Proc transpose data = IA.LB out=IA.LC;
by SUBSEGMENT CATEGORY;
Run;

Data IA.LD; set IA.LC;
Rename _NAME_= model_year;
Rename   col1 = carbon_est;
Run;

/* The following procedure extracts two variables from one variable */
Data IA.LE; set IA.LD;
if length(model_year) >9
then
do
Scenario=substr(model_year,6,7);
year = substr(model_year,2,4);
end;
else
do
Scenario=substr(model_year,6,6);
year = substr(model_year,2,4);
end;
*length = length(model_year);
Run;
```

```
data IA.LF1 IA.LF2 IA.LF3 ;
       set IA.LF;
       if year = '204X' then output IA.LF1;
       if year = '209X' then output IA.LF2;
         if year = '205X' then output IA.LF3;
run;

proc glimmix data =IA.LF1 ic=q ;
class category SCENARIO subsegment;
model carbon_est=category|SCENARIO    /    htype=3;
lsmeans category|scenario/adjust = Tukey pdiff alpha=0.01 maxdec=2;
random subsegment(category); /*The watershed was added as a random variable*/
ods output diffs=ppp;
ods output lsmeans=mmm;
parameter = round(parameter,0.01);
run;

%include 'D:\work\data\SAS\pdmix800.sas';
%pdmix800(ppp,mmm,alpha=.01,sort=yes);
/* The PDMIX800 macro (Saxton, 1998) for SAS was used to separate Tukey-Kramer (P
< 0.01) adjusted means into letter comparisons*/
parameter = round(parameter,0.01);
run;

proc glimmix data =IA.LF2 ic=q ;
class category SCENARIO subsegment;
model carbon_est=category|SCENARIO    /    htype=3;
lsmeans category|scenario/adjust = Tukey pdiff alpha=0.01;
random subsegment(category);
ods output diffs=ppp;
ods output lsmeans=mmm;
run;

%include 'D:\work\data\SAS\pdmix800.sas';
%pdmix800(ppp,mmm,alpha=.01,sort=yes);
parameter = round(parameter,0.01);
run;

proc glimmix data =IA.LF3 ic=q ;
class category SCENARIO subsegment;
model carbon_est=category|SCENARIO    /    htype=3 ;
lsmeans category|scenario/adjust = Tukey pdiff alpha=0.01;
random subsegment(category);
ods output diffs=ppp;
ods output lsmeans=mmm;
run;
```

```
%include 'D:\work\data\SAS\pdmix800.sas';
%pdmix800(ppp,mmm,alpha=.01,sort=yes);
parameter = round(parameter,0.01);
run;
```

VITA

Biao Zhong was born in the City of Yichun, Jiangxi Province, China. He received his Bachelor of Engineering in information management in 1998, Master of Science in GIS in 2001 from Beijing Forestry University. After that, he worked as an engineer in Beijing until he became a student in the doctoral program in the School of Renewable Natural Resources in Louisiana State University at Baton Rouge, Louisiana, U.S.A.

He is a well-rounded person with many interests and great expectations. He discovered a better way to change his thinking and improve his global view: learning in United States. He finally landed in the United Sates and began his study at Louisiana State University in 2005 after he sacrificed his respected former job and overcame many obstacles.