ESTIMATING POTENTIAL CARBON SEQUESTRATION IN CONSERVATION RESERVE PROGRAM (CRP) TRACTS IN THE CENTRAL HIGH PLAINS OF THE UNITED STATES

By

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CHAPTER I

1.0 INTRODUCTION

1.1 Background to the Study

Increase in atmospheric carbon dioxide (CO_2) has been well documented, and has been suggested to raise the mean global temperature and perhaps disturb climates in unforeseen ways (IPCC 2007). While the effort to reduce the increasing emission rate of atmospheric CO_2 and other greenhouse gases has mainly been based on emission reductions, the interest in using soils and vegetation as carbon (C) sinks is increasingly becoming popular (Lal 2001; Olsson et al. 2001, Byrne 2011). This interest requires reliable, robust and cost-effective methods for the monitoring and verification of carbon sequestration in soil and biomass (Lal et al. 1999) as well as reasonable predictions of carbon sequestration potential. Human activities have led to environmental problems such as desertification and erosion associated with overgrazing and excess fuel wood harvesting, conversion of natural ecosystems into cropland and pasture land, and agricultural intensification causing losses of soil carbon which are, among other activities, the ultimate drivers of global climate change (Millennium Ecosystem Assessment 2003). The threat of global climate change has prompted policy makers to consider ways of offsetting greenhouse gas emissions through carbon sequestration projects which help remove CO_2 from the atmosphere (Kucharik 2004).

For instance, Hendrickson (2003) has observed that global climate change, including warmer temperatures, higher CO_2 concentrations, increased nitrogen deposition, increased frequency of extreme weather events, and land use change, affects soil carbon inputs (plant litter), and carbon outputs (decomposition). Thus, capturing and storing carbon in biomass and soil in the agricultural sector has gained widespread acceptance as a potential greenhouse gas mitigation strategy (Feng et al. 2004). Consequently, research attention is increasingly focused on understanding the mechanisms by which various land use practices can sequester carbon, including the introduction of cover crops on fallow land, the conversion of conventional tillage to conservation tillage, and the retirement of land from active production to a grass cover or trees (Feng et al. 2004; Mitchel et al. 1996). Several researchers have indicated that forest establishment and restoration offer one of the most attractive means to mitigate global warming (Moulton and Richards, 1990; Adams et. al., 1993; Parks and Hardie 1995; Plantinga 1997; Alig. et. al., 2002). This is because forests have the potential to sequester large amounts of carbon, the technology for establishing large areas of additional forests already exists, the costs of forest carbon sequestration at low levels are relatively modest, and forests have environmental benefits beyond carbon sequestration.

In the same vein, Williams et al. (2000) have observed that grasslands can also sequester a substantial amount of carbon and have estimated that the temperate grasslands of the world would increase its carbon sequestration to an additional 1.3 Pg (Petagram) in just the top 15 cm of soil over the next CENTURY if land is retired from active tillage to a grass cover. This amount is very significant because with increasing levels of carbon dioxide (CO_2) and greenhouse gases (GHG) in the environment, carbon sequestration in grasslands would serve as one of several management practices agricultural producers can implement on the farm to help reduce the amount of CO_2 and GHG in the air and increase carbon levels in the soil in the form of soil organic carbon (SOC). However, studies have also shown that gains in soil carbon can be quickly eliminated with return to cultivation (Torbert et al. 2004). The pool of organic carbon in soils plays a key role in the carbon cycle and has a large positive impact on the greenhouse effect (Lal et al. 1995). Soils contain an estimated 1.5 x 10^{15} g of carbon, or twice as much as the atmosphere and three times the level held in terrestrial vegetation (Post et al. 1990). In addition, soil carbon plays a key role in determining long-term soil fertility necessary to sustain profitable long-term agricultural production (Mitchel et al. 1996). Therefore, the ability to sequester carbon in soils by proper tillage and erosion management provides enough and long-term justification for soil conservation programs.

In the last two decades, public funding of agro-environmental programs has nearly tripled, with programs that retire highly erodible and other environmentally sensitive land from crop production accounting for more than 85% of federal conservation expenditure (Claassen 2003). For example, in 1986 the Conservation Reserve Program (CRP) began converting highly erodible and other environmentally sensitive land from crop production to perennial grasses and trees (Mitchel et al. 1996). The 1990 Farm Bill mandated conservation compliance to be fully implemented by 1995 for producers participating in federal commodity programs. Although these policies were not explicitly intended to enhance carbon sequestration in agricultural soils, both programs clearly affect soil organic carbon (SOC) in several soils (Mitchel et al. 1996). CRP, the largest land retirement program with an annual budget of about $1.6 billion, currently enrolls about 10% of the United States' cropland (Feng et al. 2004). However, there is scant information on the changes in SOC that accrue from key soil conservation programs and policies (Hendrickson 2003). The response of farmers to these policies and the resulting effects on SOC are difficult to model across large regions of the United States because of the diverse agricultural practices currently in use. Numerous tillage practices, crop rotations, conservation practices, nutrient management practices, and irrigation types need to be taken into account for effective modeling. In addition, large regions have thousands of different soils, diverse topography, and varied climates (Mitchel et al. 1996). Various models and approaches have been developed to describe soil carbon dynamics at the field level. Noteworthy among these are applications based on biophysical process models such as CENTURY (Parton et al. 1987). It should be noted, however, that this approach does not adequately account for the effects of soil erosion or provide the flexibility to analyze the effect of management changes such as tillage, crop rotation, or fertilizer rate. The cumulative impact on SOC of even small annual losses of carbon in eroded soil can become significant after prolonged cultivation and may constitute a large portion of the SOC decrease observed with the initiation of cultivation (Bouwman 1990; Donigian et al. 1994). Thus, it is imperative to compliment this shortcoming with a finer resolution model such as the DAYCENT model (Parton et al. 1998; Kelly et al. 2000).

Lal (1995) estimates that 20 percent of carbon displaced with eroded soil is decomposed and emitted to the atmosphere, although Johnson and Kern (1991) estimate a value of up to 50 percent. In its report on climate-change mitigation strategies for forest and agricultural sectors, the U.S. Environmental Protection Agency (USEPA), concludes that more thorough investigation of the impact of no-till practices on SOC levels and better tracking of eroded SOC is needed to quantify the soil conservation policy impacts on SOC levels (USEPA 1995). It is difficult to predict management and climate change effects on ecosystem dynamics across regions through field experimentation alone, because of the difficulties of manipulating experiments without changing the system being studied (Thornley and Cannell 1997). Environmental models offer an alternative, because of their repeatability (recurrence) at various scales without any disturbance to the study area. Modeling has been used as an effective methodology for analyzing and predicting the effects of land management practices on the level of soil carbon. A number of process-based models have been developed over the last two decades to fulfill specific research tasks and consequently each model varies in its suitability for application to new contexts. In general, efforts to link GIS and environmental modeling software has attempted to combine the functionality of two independently designed software modules by linking them through common files, and has been largely successful over the last three decades. As noted by Goodchild et al. (1996) GIS combines the power of environmental modeling software to model environmental processes with the power of GIS to perform input, output, and basic housekeeping functions such as preliminary resampling or transformation of data. In such combinations, GIS usually performs, among other things, preprocessing and postprocessing functions including coordinate transformation and projection change; resampling and conversion between data models and structures, and clipping of data to fit study areas. A case in point is the attempt by Bromberg et al. (1996) to integrate GIS and the CENTURY model to manage and analyze data. This effort follows their success with linking CENTURY to the scientific geographic information system (SGIS) that provides the ability to analyze temporal data by utilizing commercially available public-domain software tools. In this study, a two-model integrated approach is adopted for estimating the amount of carbon sequestered on CRP tracts in the Central High Plains (CHP) of the U.S. Here, CENTURY, a monthly time step and DAYCENT, a daily time step models were used to simulate above ground and below ground carbon dynamics in CRP tracts in the CHP region of the U.S. The simulation results were then integrated into a GIS framework to evaluate the impact of land use such as CRP on carbon sequestration potential in the study area.

1.2 Problem Statement

Terrestrial carbon sequestration is the process through which CO_2 from the atmosphere is absorbed by trees, plants and crops through photosynthesis, and stored as carbon in biomass (tree trunks, branches, foliage and roots) and soils (USEPA 2006). The term "sinks" is also used to refer to forests, croplands, and grazing lands, and their ability to sequester carbon. Agriculture and forestry activities can also release CO_2 to the atmosphere. Therefore, a carbon sink occurs when carbon sequestration is greater than carbon release over a time period (USEPA 2006; 2007).

Scientists have long known that forests sometimes act as "carbon sinks," absorbing more of the greenhouse gas carbon dioxide than they release. In the same vein, a team of researchers has identified a mechanism through which grasslands appear to demonstrate the same property (Hu et al. 2001). These findings may have important implications as scientists and policy-makers around the world debate ways to lower levels of atmospheric carbon dioxide, believed to be a major contributor to the greenhouse effect and global climate change. The link between greenhouse gases and global climate change is likely, but it is very controversial and still debatable. It is, however, not the main focus of this research. According to Hu et al. (2001) grasslands can act as carbon sinks when atmospheric carbon dioxide is elevated. Numerous data indicate that soil microbes quickly respond to changes in carbon and nitrogen availability and may play critical roles in determining the potential of grasslands, and other terrestrial ecosystems, too, to act as a carbon sink (Hu et al. 2001).

The net CO_2 flux between terrestrial ecosystems and the atmosphere is determined by the ratio between the rates of two global processes: CO_2 emission caused by respiration of soil heterotrophic microorganisms and animals decomposing litter; and, a CO_2 sink as net primary production (NPP) of plants (Gilmanov 2006). The sequestration of CO_2 in ecosystems leads to reduction in emissions. However, the allocation of sequestered carbon is very important: assimilation in NPP is considered as a temporary stock, while C accumulation in such a stable pool as soil organic matter (SOM) is preferable (Jones and Donnelly 2004). In turn, soil C is divided into pools with different resistance to decomposition: (i) a light fraction, which includes easily decomposable organic substances such as plant detritus and products of their initial decomposition, microbial biomass and microbial metabolites; (ii) stable humus, which is plant organic material resistant to decomposition and humic substances protected by clay minerals (Krull, et al. 2003). As C sequestration in stable humus is one of the most effective greenhouse gases (GHG) mitigation options, an assessment of both the rate of SOM accumulation and the decomposability of newly formed organic matter is urgently needed.

Our goal here is to attempt an evaluation of the above assertions by answering the following questions with respect to the CHP. Which grassland and agricultural management practices sequester carbon better? And if we identify those management practices, how much carbon can these grasslands and agricultural practices sequester? What indices or methods would be used and how well can carbon sequestration be estimated? How much carbon sequestration occurs in the CHP of the United States? In addition, we may also ask, what is the potential for additional sequestration to offset greenhouse gas emission? What are the other environmental effects of sequestration practices? Although some of these issues have been studied extensively, most of them have been done on a global scale and not very specific to the study area. Thus, this study will attempt to answer these questions in relation to the CHP.

1.3 Hypotheses

Carbon sequestration occurs in an ecosystem when the amount of carbon dioxide absorbed by growing plants is greater than the amount of the gas released by decomposing plant material (Anthor 1995). Guo and Glifford (2002) have estimated that soil C stocks decline after land use changes from pasture to plantation (−10%), native forest to plantation (−13%), native forest to crop (−42%), and pasture and grassland to crop (−59%). Soil C stocks increase after land use changes from pasture to native forest (+ 8%), crop to pasture (+ 19%), crop to plantation (+ 18%), and crop to secondary forest (+ 53%).

Carbon dynamics of grasslands may play an important role in regional and global carbon cycles (Yongqiang et al. 2007). Due to variations in climatic factors and topography from place to place, variations in vegetatation coverage, temporal and spatial variations of SOC in grasslands also exist. Examination of SOC for grasslands shows different patterns of temporal variation in different ecosystems (Yongqiang et al. 2007). The extent of temporal variation increases with the increase of SOC of the ecosystem.

Spatially, SOC density has shown remarkable variations in highly heterogeneous ecosystems. These variations suggest that (i) SOC density in grasslands can remarkably respond to climate change over a long period of time, and (ii) that net carbon exchange rate between the grassland ecosystems and the atmosphere may change from year to year (Verburg, et al. 2004). In addition to these climatic, topographic and vegetation variations, soil types and management systems (including land use change) will impact the amount and distribution of carbon that has or can be sequestered at any given location at a point in time. Thus, we hypothesize that:

(1) if a change in land use results in a decrease in soil carbon, then the reverse process usually would lead to an increase in soil carbon; for example, a change from agriculture or pasture to CRP. In this case we expect CRP lands to sequester more carbon than non-CRP lands such as agricultural and pasture.

(2) An unmanaged land would lead to an increase in carbon sequestration compared to a managed land. For example a CRP land should sequester more carbon than land that has been subjected to grazing or fire as management practices.

To test these hypotheses, the following goal and objectives are considered.

1.4 Goal and Objectives of Research

The main goal of this research is to examine long term trends in carbon sequestration in CRP tracts in the CHP region of the U. S.

To achieve this goal, the following objectives are considered:

1. To develop a Geospatial Database pertaining to soils, land cover, and climate for the CHP region.
2. To estimate the carbon sequestration potential in CRP since 1985 in the CHP region of the U.S. using an integrated modeling and GIS approach.

3. To compare the estimated amount of carbon sequestered in the study area before and after conversion to CRP.
4. To evaluate alternate management practices in post-CRP such as grazing, fire and biofuel (alfalfa) on carbon sequestration and their implications for policy.

The goal and objectives of the study were achieved through the employment of CENTURY and DAYCENT models, which were used to test carbon and other gas fluxes. The model subroutines are described along with their integration within the model.

1.5 The CENTURY Model

Developed 15 years ago, the CENTURY model is now one of the most widely used and validated SOM models worldwide (Romanya 2000, Fallon et al. 2002). As an SOM model, CENTURY can not only simulate the dynamics of carbon (C) and nitrogen (N), which link mostly with greenhouse gas (GHG) emissions, but also simulates the dynamics of phosphorus (P) and sulfur (S), which mostly contribute to groundwater pollution. This model has been used to examine the change rate of C and N storage in the soil after converting the land use from agriculture to forest, after crop rotation and after different tillage, and conservation practices, and can give relatively accurate long-term simulation of SOM dynamics.

In this study, the CENTURY model was used to simulate the SOC changes for pre-CRP and post-CRP conditions. Figure 1.1 is the brief diagram of the CENTURY model, where NPP refers to net primary productivity, t is material turnover time, H_2O_{soil} stands for soil water content, T_{soil} means soil temperature, D refers to decomposition and H is harvest. The SOM change rate as well as the amount of carbon sequestration resulting from implementing conservation practices can be estimated with this model. The model was used to achieve objectives 2, 3, and 4 presented in section 1.4.

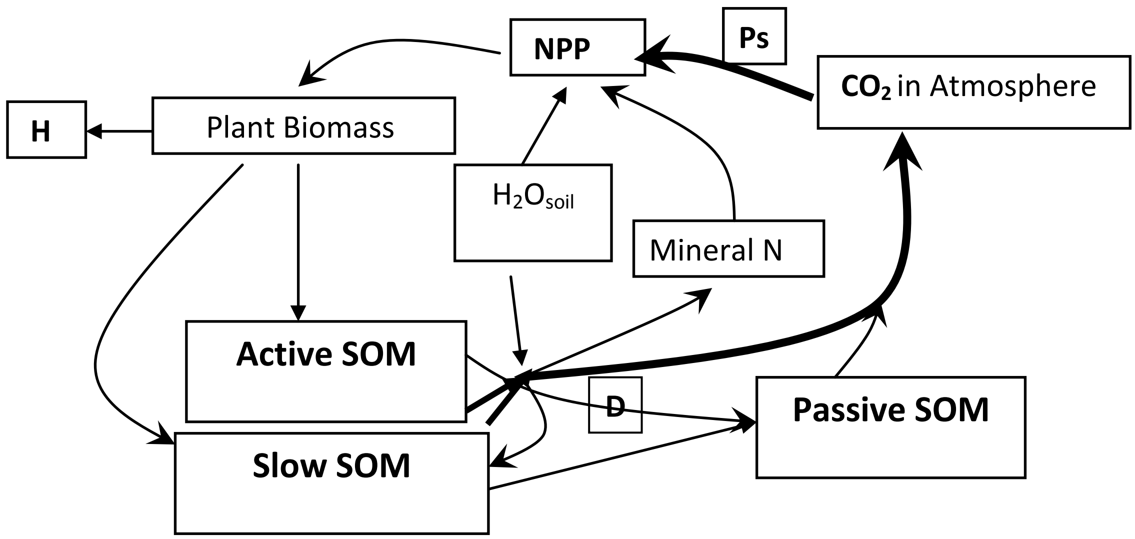

Figure 1.1: Flow diagram of CENTURY model (after Parton et al. 1992).

The simulation period of the CENTURY model (Figure 1.1) for estimating SOC dynamics can be several thousand years, and it is impossible to calibrate and validate the input parameters in a conventional scheme. In this study, most CENTURY parameters were taken from previous researches in the grassland region of the U.S., which have been calibrated and validated through long-term modeling experiments (Potter et al. 2003). Some related parameters, such as crop rotation and tillage practices, have been adopted from Yiridoe et al. (1997), in order to evaluate alternate management practices and their implications for policy.

1.5.1 Soil Organic Matter Submodel: The SOM submodel includes three soil organic matter pools (active, slow and passive) with different potential decomposition rates. Above and belowground plant residues and organic animal excreta are partitioned into structural and metabolic pools as a function of the lignin to N ratio in the residue. The structural pools which contain all the plant lignin have much slower decay rates than the metabolic pools (Metherell et al. 1993).

1.5.2 Water Budget, Leaching and Soil Temperature: The CENTURY model includes a simplified water budget model which calculates monthly evaporation and transpiration water loss, water content of the soil layers, snow water content, and saturated flow of water between soil layers. Average monthly soil temperature near the soil surface is calculated using equations developed by Parton (1984). The actual soil temperature used for decomposition and plant growth rate functions is the average of the minimum and maximum soil temperatures (Metherell et al. 1993).

1.5.3 Nitrogen Submodel: The N submodel has the same structure as the soil C model. The N flows follow the C flows, and are equal to the product of the carbon flow and the N:C ratio of the state variable that receives the carbon. The C:N ratio of the structural pools remains fixed while the N contents of the metabolic pools vary as a function of the N content of the incoming plant residue. The C:N ratios of organic matter entering each of the three soil pools vary as linear functions of the size of the mineral N pool (Metherell et al. 1993)

1.5.4 Phosphorus Submodel: The P submodel has the same general structure as the N submodel. The major difference is that there are five mineral P pools (labile P, sorbed P, strongly sorbed P, parent P, and occluded P). The organic part of the P submodel operates in the same way that the N submodel works; C:P ratios of organic fractions are fixed for the structural P pool and vary as a function of the labile P pool for the active, slow, and passive SOM pools (Metherell et al. 1993).

1.5.5 Sulfur Submodel: The structure of the sulfur submodel is similar to the P submodel. The only major difference is that the S model does not include occluded or sorbed pools. Organisms in the soil and plant roots take up S from soil solution and start the formation of organic S compounds. The organic component of the S model operates in the same way as the organic N and P submodels with the C:S ratio of the structural pool being fixed while the C:S ratios for the active, slow and passive pools vary as a function of the labile S pool (Metherell et al. 1993).

1.5.6 Plant Production Submodel: The CENTURY model is set up to simulate the dynamics of grasslands, agricultural crops, forests, and savanna (tree-grass) systems. The grassland/crop production model simulates plant production for different herbaceous crops and plant communities (e.g. warm or cool season grasslands, wheat and corn). Both plant production models assume that the monthly maximum plant production is controlled by moisture and temperature and that maximum plant production rates are decreased if there are insufficient nutrient supplies. (Metherell et al. 1993).

1.6 The DAYCENT Model

DAYCENT (Parton et al. 1998; Kelly et al. 2000) presented in Figure 1.2 is a terrestrial ecosystem model used to simulate exchanges of C, N, and trace gases among the atmosphere, soils, and vegetation. DAYCENT is of intermediate complexity; important processes are presented mechanistically but the model makes use of empirically derived equations, and the required input parameters are often available for many regions (Del Grosso et al. 2001). DAYCENT (Parton et al. 1998; Kelly et al. 2000) is the daily time step version of CENTURY ecosystem model. CENTURY (Parton et al. 1994) operates at a monthly time step. DAYCENT includes sub-models for plant productivity, decomposition of dead plant material and SOM, soil water and temperature dynamics, and trace gas fluxes (Figure 1.2). The model is 1-dimensional, water and temperature flows are simulated vertically throughout the soil profile. Lateral flow of water is not simulated except that overland runoff occurs when rainfall events of sufficient magnitude occur given the permeability of the surface soil layer. Key submodels include plant growth with dynamic C allocation among plant components, soil organic matter decomposition and nutrient mineralization, and nitrous oxide (N_2O) emissions from nitrification and denitrification (Parton et al. 2001). A major strength of the model is the required inputs (daily climate, soil texture, vegetation cover, land management) are relatively easy to acquire for many systems. Major weaknesses are that the model does not account for all the controls on denitrification (e.g. microbial community, lateral flow of water) and the controls that are accounted for are on relatively coarse spatial and temporal scales compared to the scales at which denitrification actually occurs (Del Grosso et al. 2000; 2001; 2006).

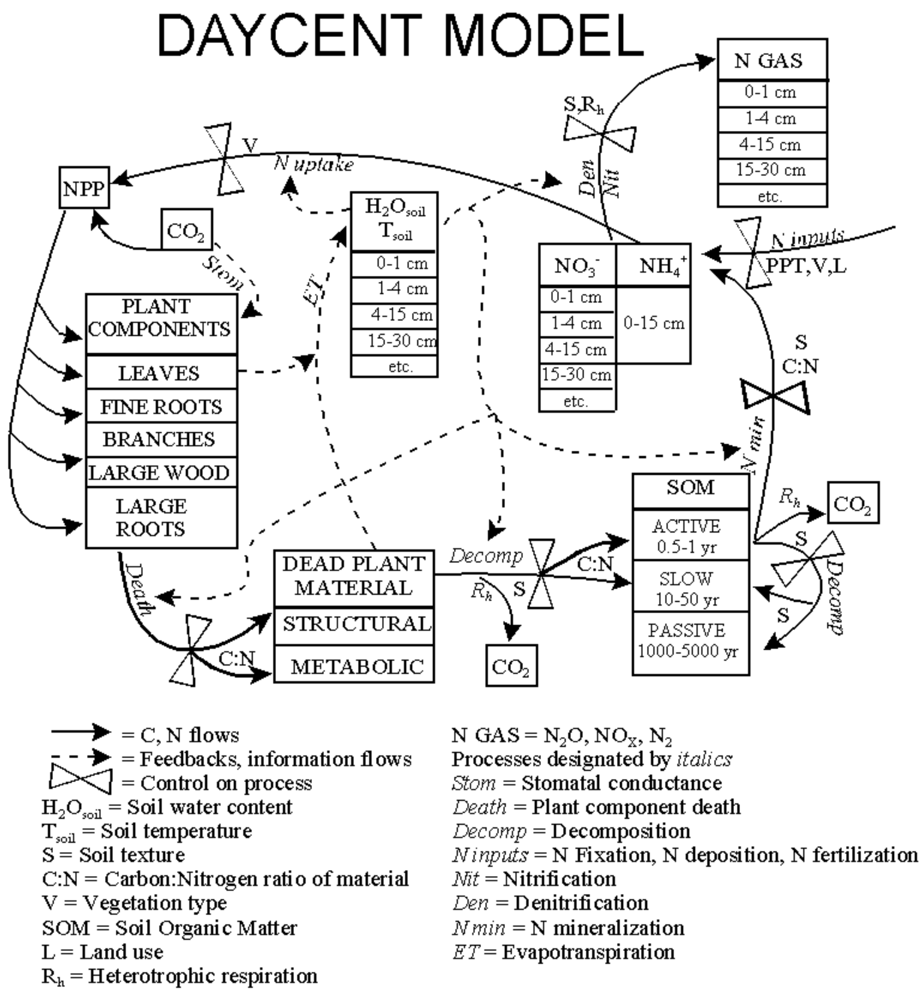

Figure 1.2: Flow diagram of the DAYCENT ecosystem model (Parton et al. 2001)

The Relationship between GIS and the CENTURY and DAYCENT Models is such that the CENTURY and DAYCENT models are point models, whereas carbon sequestration parameters are spatial in nature. GIS is spatial related software which is used to integrate non-spatial models such as CENTURY and DAYCENT. This enables the display of the model results spatially.

1.7 The Study Area

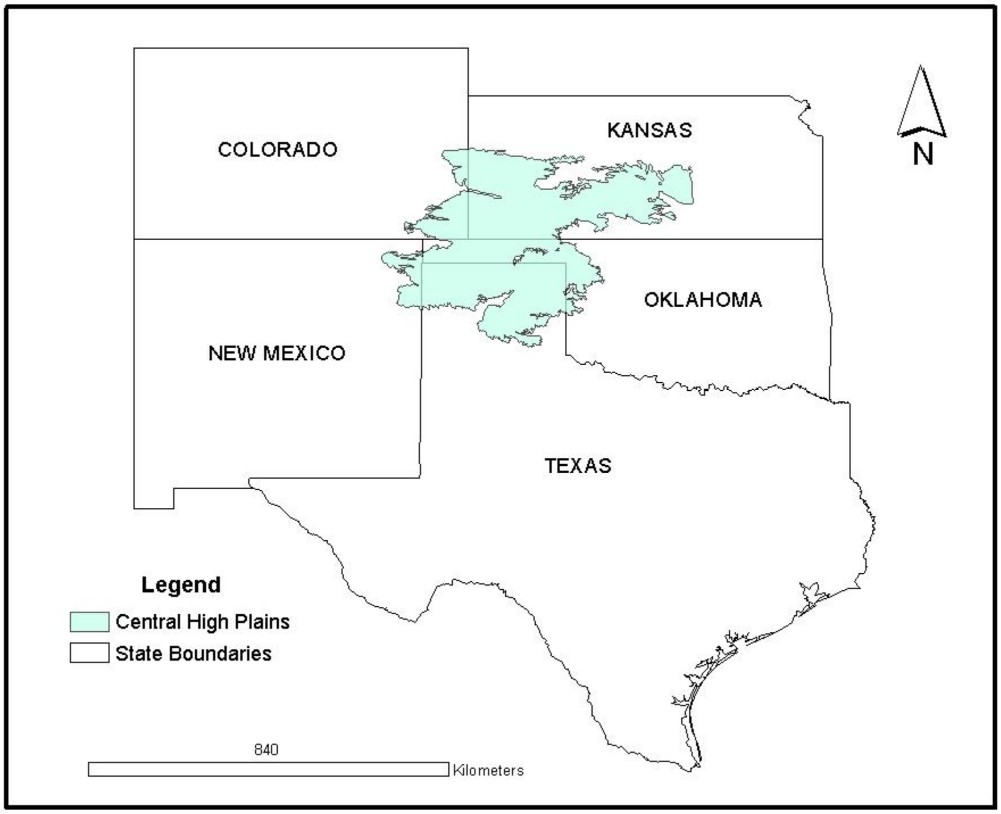

Figure 1.3: The Central High Plains Region

The CHP subregion (Figure 1.3) of the Great Plains in the central U.S; encompasses eastern Colorado, western Kansas, eastern New Mexico, northwestern Oklahoma, and northwestern Texas (Bailey 1980). The geomorphology of the region includes broad intervalley remnants of fluvial plains. Loess-mantled tablelands with gently rolling slopes and major valleys are bordered by steep slopes. Broad, level flood plains and terraces occur on major rivers and streams and elevation ranges from 2,625 to 3,950 ft (800 to 1,200 m) (Fenneman 1931).

The lithology and stratigraphy of the region follows state lines**.** The Colorado part is of Tertiary sandstones, siltstones, and conglomerates and Quaternary windblown dune sands and loess, with Cretaceous marine shales and Quaternary alluvium in the major drainages. The Kansas and Oklahoma part is mostly Quaternary windblown dune sands and loess, some Tertiary sandstones, shales, and conglomerates, and Cretaceous shales and limestones with Quaternary alluvium in stream valleys, while that of Texas and New Mexico are comprised of Paleozoic, Mesozoic, and Cenozoic aged sedimentary and volcanic rocks and alluvial deposits (Bailey, et al. 1994). Most Quaternary material was deposited by major rivers and streams flowing to the east and southeast across the region (Johnson 1971). Precipitation averages 16 to 21 in (400 to 530 mm). Temperature averages 50 to 57^{o}F (10 to 14^{o}C). The growing season lasts 140 to 185 days. This area has moderate temperature and moisture regimes. Soils include Mollisols, Entisols, and Alfisols, and the vegetation is mainly grama-buffalo grass prairie, bluestem-grama prairie, sandsage-bluestem prairie, and wheatgrass-bluestem-needlegrass prairie. The predominant vegetation is short grass prairie (Barbour and Billings 1988).

In terms of fauna**,** bison, wolves, and black-footed ferrets are historically associated with this region. Present large mammals include white-tailed deer, mule deer, and a small population of pronghorn antelope. Typical small mammals include the bobcat, red fox, jackrabbit, cottontail, and prairie dog. Year-round typical avifauna includes the introduced ring-necked pheasant, horned lark, northern bobwhite, Cooper's hawk, and prairie falcon. Summer nesters include Swainson's hawk, blue-winged teal, and ruddy duck. The goshawk may be a rare winter resident. The goldeneyes and common merganser are other winter residents. Herpetofauna include snapping turtle, Great Plains toad, western hognose snakes, rattlesnakes and the western garter snake (Grant and Birney 1979).

The North and South Platte Rivers and their tributaries flow through the CHP. Ground water is scarce and of poor quality where shale bedrock is near the surface. In much of the area, sand and gravel yield adequate amounts of ground water (Karl 1983). Fire, insects, and disease are predominant disturbance regimes in the region (Collins 2000; Fowler and Konopik 2007).

Agriculture in the form of cattle ranching and cultivation is the primary economic activity in the region; some areas have significant petroleum and natural gas deposits. Nearly all of this area is in farms and ranches; about 60 percent is cropland. This is a major dry farming area. Irrigation occurs along major rivers and also utilizes ground water sources (USDA National Agricultural Statistics Service 2002).

The CHP is part of the Ogallala Aquifer, also known as the High Plains Aquifer, which is a vast yet shallow underground water table aquifer located beneath the Great Plains in the U.S. Being soft and porous, the Ogallala easily soaks up rainfall which have resulted in a few well-developed drainage systems across the formation and the unit is an excellent aquifer for fresh groundwater throughout the High Plains (Johnson 1971).The Ogallala is one of the world's largest aquifers that covers about 174,000 mi^2 (450,000 km^2) in portions of the eight states of South Dakota, Nebraska, Wyoming, Colorado, Kansas, Oklahoma, New Mexico, and Texas. It was named in 1899 by N. H Darton near the town of Ogallala, Nebraska. About 27 percent of the irrigated land in the United States overlies this aquifer system, which yields about 30 percent of the nation's ground water used for irrigation. In addition, the aquifer system provides drinking water to 82 percent of the people who live within the aquifer boundary (Diffendal 1984).

In order to put the research problem, methodology and study objectives in context, literature relevant to the study were reviewed in chapter two.

CHAPTER II

2.0 BACKGROUND LITERATURE

Carbon sequestration in soil and grassland conservation programs has been extensively studied. The integration of different modeling frameworks is indeed relevant for carbon sequestration because of divergent tillage and conservation practices (Mitchel et al. 1996). In order to obtain and derive appropriate data collection and analysis procedures for carbon sequestration in the study area, it is pertinent to review relevant literature related to soil management practices, environmental and mineral cycling, GIS-based models, and carbon sequestration mitigation procedures. The review is based on nutrient cycling and SOC/carbon sequestration, land use/land cover and SOC/carbon sequestration, and environmental and GIS-based models and SOC/carbon sequestration.

2.1 Nutrient Cycling and SOC/Carbon Sequestration

Soil organic matter is a key component of all terrestrial ecosystems, and any variation in its composition and abundance has important effects on many of the processes that occur within the system (Batjes and Sombroek 1997). As observed by Delgado and Follett (2002) the continuing world population growth is increasing pressure on soil and water resources.

Productive soils are being affected by erosion and nutrient losses via surface transport and/or leaching. Baligar et al. (2001) reported that even though the use of nitrogen (N), phosphorus (P), and potassium (K^+) is increasing across the world, their use efficiencies are still about 50, 10, and 40%, respectively. Additionally, anthropogenic activities are contributing to higher atmospheric concentrations of carbon dioxide ($CO_{2)}$, nitrous oxide (N_2O), nitric oxide (NO), methane ($CH_{4)}$, and to global warming (IPCC 1994). Accordingly, Delgado and Follett (2002) have suggested that carbon management should be an integral part of nutrient management plans based on its potential contribution to the conservation of the biosphere. According to Delgado and Follett (2002) carbon management has tremendous potential to increase sustainability and productivity since it improves soil fertility and nutrient use efficiency.

Several authors have discussed in detail the significant impacts of soil carbon on physical, chemical, and biological properties (Stevenson 1982; Doran and Jones 1996; Paul et al. 1997; Lal 1995; Lal et al. 1997; Lal 1999). These studies have found that carbon can contribute positively to soil quality by improving porosity, available water holding capacity (AWHC), and cation exchange capacity (CEC), reducing toxicity from certain elements, helping increase yields, and bringing economical returns to farmers. And as noted by Dabney et al. (2001) soil organic matter serves as a storage form of N, P and sulfur (S) and helps in the cycling of essential nutrients. They contend that plant litter and animal products have a significant amount of nutrients that can be recycled and released slowly ensuring a higher nutrient uptake. For example, the concept of using winter cover crops (C3 crops) for soil and water conservation is based on their ability to scavenge nutrients, especially nitrate (NO_3), from lower depths and to recycle them back into the surface. Additionally, winter cover crops (WCCs) add organic C, cycle macro- and micronutrients, and conserve soil and water quality. In the same vein, Musvoto et al. (2000) reported that crop litter is used to supply N, P, S, and magnesium (Mg^{2+}), but needs to be incorporated two months before the period of higher demand to assure the needed time for proper residue mineralization and nutrient availability.

Follett et al. (2001) have summarized the role that soil plays in the global C cycle and states that there are two types of C pools in the pedosphere: soil organic carbon (SOC) and soil inorganic carbon (SIC). The SOC pool, according to them, is over twice as large as the atmospheric CO_2-C pool and 4.5 times larger than the C pool in land plants. In comparison, they found that the SIC pool is 1.1 times larger than the atmospheric pool and 1.4 times larger than the C pool in land plants. Together, the SOC and the SIC pools contain 3.2 times the C found in the atmosphere and 4 times the C found in terrestrial vegetation. By incorporating C into management plans, farmers benefit from the potential increase in sequestration and incorporation of atmospheric CO_2, significantly helping offset some of the effects of global warming (Lal et al. 1998). In line with this thought process, Parton et al. (1987) divided this large SOC pool in the pedosphere in three, according to dynamics and residence time. Based on their division, the active carbon pool is composed of mainly live microbes, microbial products, and SOM, with a short turnover time of one to five years. The slower pool of carbon is physically protected and is an organic form more resistant to decomposition (20 - 40 years). The passive pool, which is the recalcitrant and slower reactive carbon, has a turnover rate of 200 to 1500 years (Parton et al. 1987). Patton et al. (1987) used these categories and turnover times to develop and calibrate the CENTURY model that simulates C and N cycling and dynamics. This model has also been expanded to simulate P and S cycling.

The U.S. Department of Energy (DOE) opines that atmospheric greenhouse gas (GHG) concentrations have been increasing for about 2 centuries, mostly as a result of human (anthropogenic) activities, and now are higher than they have been for over 400,000 years. According to DOE (2005) about 6 billion tons (gigatons) of carbon are released into the air by human activity each year, three-quarters from the burning of fossil fuels and the rest from deforestation and other changes in land use, with a small amount from cement production. Although the effects of increased levels of CO_2 on global climate are uncertain, many agree that a doubling of atmospheric CO_2 concentrations, predicted for the middle of this CENTURY by the Intergovernmental Panel on Climate Change (IPCC 2007), could have a variety of serious environmental consequences (DOE 2005).

However, Kasting (1998) believes that there is roughly 750 gigatons (Gt. C) of carbon (in the form of CO_2) produced annually in the world from the burning of fossil fuels. Of that amount, approximately one quarter is taken up in the carbon cycle by forests and grasslands. He however, argues that grasslands are probably the least understood part of the global carbon cycle and are often managed by default. Obviously, a better understanding of the role of grasslands in the carbon exchange cycle could lead to grassland management practices that enhance this important environmental function.

It is pertinent to note that natural processes also contribute to the storage and cycling of carbon (Figure 2.1). The stability and sequestration of vast pools stored in oceanic and terrestrial environments depend, in part, on the microbial world. According to the American Society of Microbiology (King et al. 2001), "Microbes, responsible for transforming many of Earth's most abundant compounds, cannot be ignored in the search for scientific solutions to adverse global changes. Both the ubiquity of microbes and the delicacy of environmental balances contribute to (the planet's) sensitivity to disturbances in the microbial world."

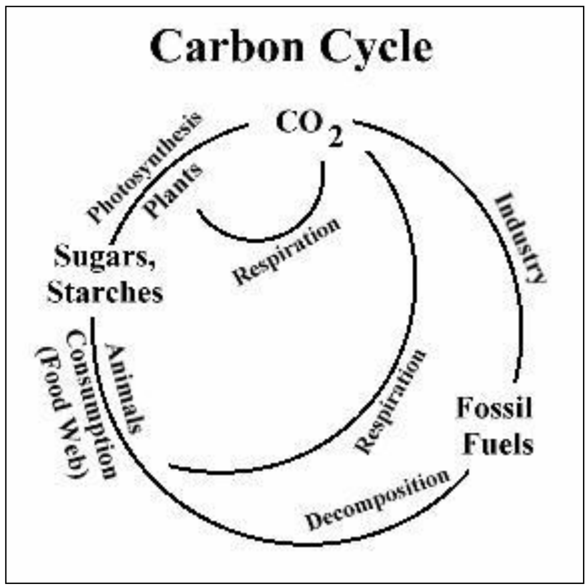

Figure 2.1: Simplified Global Carbon Cycle (adapted, King et al. 2001).

Also, Miller (2008) has observed that only about half of the CO_2 emissions from fossil-fuel combustion have remained in the atmosphere, with the other half being taken up by the land and ocean. In the face of increasing fossil-fuel emissions, according to him, this remarkably stable 'airborne fraction' has meant that the rate of carbon absorption by the land and ocean has accelerated over time. Miller (2008) maintains that seasonal cycles of atmospheric CO_2 are caused primarily by the terrestrial biosphere moving from being a net source of carbon to the atmosphere (mainly in winter) to becoming a net sink (mainly in summer), where net carbon uptake or release is determined by the balance between photosynthesis and respiration. Changes in the phasing therefore reflect changes in the timing of when the land is a net sink or source to the atmosphere.

2.2 Land Use/Land Cover and SOC/Carbon Sequestration

The importance of obtaining information on the potential for carbon sequestration in soils from the CRP has been stressed. Carbon sequestration in soils implies enhancing the concentrations/pools of soil organic matter and secondary carbonates (Lal et al. 2003). It is achieved through the adoption of recommended management practices (RMPs) on soils of agricultural, grazing, and forestry ecosystems and conversion of degraded soils and drastically disturbed lands to restorative land use (Lal et al. 2003).

Land management practices that are shown to increase C sequestration in terrestrial ecosystems include improved management of cropland by no tillage and application of organic fertilizer. Changes in land use caused by afforestation and grassing of arable land can also increase C storage. Regeneration of perennial vegetation may be more effective in sequestering C than the improved (fire, grazing, etc) management of arable soils (Paustian et.al. 1997; Smith et al. 2000). However, rates of soil C sequestration can vary greatly for different forest and grassland sites (Post and Kwon 2000).

Bowman and Anderson (2002) conducted two field studies in northeastern Colorado to quantify the SOC changes after various amounts of time in the CRP program. The study also sought to assess problems associated with converting CRP grass to cropland and the potential for loss of accrued SOC with different tillage systems. They found that of the six CRP sites assessed, three showed increased SOC content, while three showed no difference, but SOC loss was less with no-till (NT) and reduced till (RT). They then concluded that NT and RT systems designed to control perennial CRP grasses will enable producers to maintain some of the gains in SOC when CRP land is converted to cropland. In a similar study, Torbert et al. (2004) observed that although C can be sequestered in soil as a result of changes in land management, especially taking land out of cultivated agriculture, gains in soil C can be quickly eliminated with return to cultivation. Thus, in their study in central Alabama they examined the impact of converting land back into cultivated agricultural management on carbon sequestration within two different soil types. They collected soil samples from nine depths, and analyzed them for total N, organic C, and soil carbon-nitrogen ratio (C: N). They found that clay loam soil had higher capacity to sequester C than loamy sand soil, but observed little difference between forested soil and permanent pasture in the clay loam soil. Results, however, showed that clay loam soils, although having higher levels of C, lost 55% of its C after 2 years of cultivation, while the loamy sand soil showed little significant loss of C content within the same time period. Their conclusion was that the vulnerability of soil to lose sequestered C will likely depend on soil type. Chan et al. (2003) in a similar study in Australia also found differences in carbon sequestration and soil quality in conservation tillage soils. However, results indicate that the magnitude of difference was lower than that reported in the USA. Based on their results, Chan et al. (2003) speculate that the lack of positive response to the conservation tillage in Australia compared to the U.S was probably due to a number of factors, namely low crop yield due to low rainfall, and partial removal of stubble by grazing and high decomposition rate due to the high temperature.

In view of the importance of conservation measures in carbon sequestration, Antle et al. (2003) developed methods to investigate the efficiency of alternative contracts for C sequestration in cropland soils, considering the spatial heterogeneous nature of agricultural production systems, and the cost of implementing efficient contracts. They proposed per-ton contracts, rather than the per-hectare contracts for farmers and showed how to estimate the costs of implementing these more efficient contracts. Results show that per-hectare contracts are as much as five times more costly than per-ton contracts. Again, measurement costs to implement the per-ton contacts were found to be positively related to spatial heterogeneity. The finding implies that contracting parties could afford to bear a significant cost to implement per-ton contracts and achieve a lower total cost than would be possible with the less per-hectare contracts.

Although different approaches for determining the potential for C sequestration in CRP grassland ecosystems has been demonstrated, Kucharik et al. (2003) argue that the paired-site sampling approach traditionally used to quantify soil C changes has not been evaluated with robust statistical analysis. Thus, they assessed 14 paired CRP and cropland sites in Dane County, Wisconsin, to determine if the paired-site sampling design could detect statistically significant differences in mean soil organic C and total N storage using analysis of variance (ANOVA). Results indicate that CRP contributed to reducing soil bulk density by 13%, and increased SOC by 13% to 17%, and concluded that usage of statistical power analysis is essential to ensure a high level of confidence in soil C and N sequestration rates that are quantified using paired plots.

Several studies have shown the significant influence of soil tillage system on particulate organic matter (Cambardella and Elliott 1992; Bayer et al. 2002; Freixo et al. 2002), so that higher stocks and concentrations of this fraction were found in no-till than in conventionally tilled soils, because of the lower soil disturbance and decomposition rate due to no-till management (Balesdent et al. 2000). Furthermore, Wright et al. (2007) investigated the impacts of conventional tillage (CT), no tillage (NT) and wheat cropping sequences on the depth of dissolved organic carbon (DOC), SOC, and total N in central Texas. Soil samples were collected at different depths, ranging from 0-105 cm, and results show that the amount of carbon decreased with depth (Wright et al. 2007). This is an indication that carbon is found closer to the ground, largely in the top and subsoil horizons.

Land-cover change has significant influence on carbon storage and fluxes in terrestrial ecosystems. The southern United States is thought to be the largest carbon sink across the conterminous United States. However, the spatial and temporary variability of carbon storage and fluxes due to land-cover change in the southern United States remains unclear (Chen et al. 2006). In this study, Chen et al. (2006) first reconstructed the annual data set of land cover of the southern United States from 1860 to 2003 with a spatial resolution of 8 km. Then they used a spatially explicit process-based Terrestrial Ecosystem Model (TEM) 4.3 to simulate the effects of cropland expansion and forest regrowth on the carbon dynamics in this region. The study observed that the pattern of land-cover change in the southern United States was primarily driven by the change of cropland, including cropland expansion and forest regrowth on abandoned cropland. The TEM simulation estimated that total carbon storage in the southern United States in 1860 was 36.8 Pg C, which they admit, was likely overestimated, including 10.8 Pg C in the southeast and 26 Pg C in the south-central. Chen et al. (2006) also claim that during 1860–2003, a total of 9.4 Pg C, including 6.5 Pg C of vegetation and 2.9 Pg C of soil C pool was released to the atmosphere in the southern United States. The net carbon flux due to cropland expansion and forest regrowth on abandoned cropland, according to them was approximately zero in the entire southern region between 1980 and 2003. The study concluded that the temporal and spatial variability of regional net carbon exchange was influenced by land cover pattern, especially the distribution of cropland.

In a separate study, Navar-Chaidez (2008) has observed that information on carbon stock and fluxes resulting from land use changes in subtropical, semi-arid ecosystems are important to understand global carbon flux, yet little data is available. Working in the Tamaulipan thornscrub forests of northeastern Mexico, Navar-Chaidez (2008) estimated biomass components of standing vegetation from 56 quadrats (200 m^2 each). In the study, regional land use changes and present forest cover, as well as estimates of soil organic carbon from chronosequences, were used to predict carbon stocks and fluxes in this ecosystem. The study found that for the period of 1980–1996, the Tamaulipan thornscrub presented an annual deforestation rate of 2.27% indicating that approximately 600 km^2 of this plant community are lost every year and that 60% of the original Mexican Tamaulipan thornscrub vegetation has been lost since the 1950's. On the other hand, the study found that intensive agriculture, including introduced grasslands increased (4,000 km^2) from 32 to 42% of the total studied area, largely at the expense of the Tamaulipan thornscrub forests. Results of the study indicate that land-use changes from Tamaulipan thornscrub forest to agriculture contribute 2.2 teragram (Tg, 1 Tg=10^{12} grams) to current annual carbon emissions and standing biomass averages 0.24 ± 0.06 Tg, root biomass averages 0.17 ± 0.03 Tg, and soil organic carbon averages 1.80 ± 0.27 Tg. Furthermore, the study claims that land-use changes from 1950 to 2000 accounted for Carbon emissions of the order of 180.1 Tg. The study projected that land-use changes will likely contribute to an additional carbon flux of 98.0 Tg by the year 2100. The study concludes that practices to conserve, sequester, and transfer carbon stocks in semi-arid ecosystems are a means to reduce carbon flux from deforestation practices.

Houghton et al. (1999) looked at the contribution of land use change to the carbon budget of the U.S. by reconstructing the rates at which lands in the United States were cleared for agriculture, abandoned, harvested for wood, and burned from historical data for the period 1700-1990. The study used a terrestrial carbon model to calculate annual changes in the amount of carbon stored in terrestrial ecosystems, including wood products. Results from the study indicate that changes in land use released 27 ± 6 petagrams (Pg) of carbon to the atmosphere before 1945 and accumulated 2 ± 2 Pg of carbon after 1945, largely as a result of fire suppression and forest growth on abandoned farmlands. The study concluded that during the 1980s, the net flux of carbon attributable to land management offset 10 to 30 percent of U.S. fossil fuel emissions. Based on their research on the Blue Ridge ecoregion of North America, Liu et al. (2004) investigated carbon (C) sequestration using the General Ensemble Biogeochemical Modeling System (GEMS). GEMS was used to assimilate historical land use and land cover change

(LUCC) data within ten 20- km by 20-km sampling blocks in the ecoregion and performed biogeochemical C simulations for the period of 1973 – 2000. Results show that this ecoregion was a C sink during the simulation period. The sink averaged 100 – 120 g C m^{-2} yr^{-1} with a major portion (50-80%) attributed to living biomass and smaller portions attributed to soil and harvested C. Net primary productivity (NPP) in Blue Ridge ecoregion was about 600 to 800 g C m^{-2} yr^{-1}. Model simulations also indicated that LUCC played a significant role in determining the magnitude of carbon sink strength in the region, and conclude that without considering the dynamics of LUCC, the C sink strength would have been underestimated by 30 to 50 percent.

Pouyat et al. (2006) used data available from the literature and estimates from Baltimore and Maryland, to (i) assess inter-city variability of soil organic carbon (SOC) pools (1-m depth) of six cities (Atlanta, Baltimore, Boston, Chicago, Oakland, and Syracuse); (ii) calculate the net effect of urban land-use conversion on SOC pools for the same cities; (iii) use the National Land Cover Database to extrapolate total SOC pools for each of the lower 48 U.S. states; and (iv) compare these totals with aboveground totals of carbon storage by trees. The study shows that residential soils in Baltimore had SOC densities that were approximately 20 to 34% less than Moscow or Chicago. By contrast, park soils in Baltimore had more than double the SOC density of Hong Kong. Of the six cities, Atlanta and Chicago had the highest and lowest SOC densities per total area, respectively (7.83 and 5.49 kg m^{-2}). On a pervious area basis, the SOC densities increased between 8.32 (Oakland) and 10.82 (Atlanta) kg m^{-2}. In the northeastern United States, Boston and Syracuse had 1.6-fold less SOC post- than in pre-urban development stage. By contrast, cities located in warmer and/or drier climates had slightly higher SOC pools post- than in pre-urban development stage (4 and 6% for Oakland and Chicago, respectively). For the state analysis, aboveground estimates of C density varied from a low of 0.3 (WY) to a high of 5.1 (GA) kg m^{-2}, while belowground estimates varied from 4.6 (NV) to 12.7 (NH) kg m^{-2}. The ratio of aboveground to belowground estimates of C storage varied widely with an overall ratio of 2.8. Results suggest that urban soils have the potential to sequester large amounts of SOC, especially in residential areas where management inputs and the lack of annual soil disturbances create conditions for net increases in SOC. In addition, the study highlights the importance of regional variations of land-use and land-cover distributions, especially wetlands, in estimating urban SOC pools.

A sandy prairie remnant in the Lower Wisconsin River Valley, encroachment areas within the prairie, and an adjacent red pine (*Pinus resinosa* Aiton) plantation were studied by Scharenbroch et al. (2010) to determine the influence of woody cover on C dynamics. Field transects, aerial imagery, and a geographic information system were used to quantify encroachment from 1979 to 2002. A linear encroachment model predicted 100% encroachment of the 6.0-ha prairie in 50 years. Four field plots in each of pine, prairie, and encroachment areas were sampled and soils collected (0–18, 18–38, and 38–75 cm) in 2004 and 2008. Results show that total ecosystem C was greater in pine (126.6 Mg C ha^{-1}) and encroachment areas (71.8 Mg C ha^{-1}) than prairie (48.3 Mg C ha^{-1}).

Wu et al. (2008) determined the impact of long-term grazing exclusion (GE) on soil organic C and total N (TN) storage in the *Leymus chinensis* grasslands of northern China and estimated the dynamics of recovery after GE. The study investigated the aboveground biomass and soil organic C and TN storage in six contiguous plots along a

GE chronosequence comprising free grazing, 3-yr GE, 8-yr GE, 20-yr GE, 24-yr GE, and 28-yr GE. Grazing exclusion for two decades increased the soil C and N storage by 35.7% and 14.6%, respectively, in the 0- to 40-cm soil layer. The aboveground net primary productivity and soil C and N storage were the highest with a 24-yr GE and the lowest with free grazing. The storage increased logarithmically with the duration of GE; after an initial rapid increase after the introduction of GE, the storage attained equilibrium after a 20 yr period. Results suggest that by implementing GE, the temperate grasslands of northern China could facilitate significant C and N storage on a long-term scale and perhaps help in mitigating global climate change.

Recently, Zhao et al. (2010) quantified and evaluated the impact of land cover change databases at various spatial resolutions (250 m, 500 m, 1 km, 2 km, and 4 km) on the magnitude and spatial patterns of regional carbon sequestration in four counties in Georgia and Alabama using the General Ensemble Biogeochemical Modeling System (GEMS). Results indicated a threshold of 1 km in the land cover change databases and in the estimated regional terrestrial carbon sequestration. In addition, the overriding impact of inter-annual climate variability on the temporal change of regional carbon sequestration was unrealistically overshadowed by the impact of land cover change beyond the threshold. The implications of these findings directly challenge current continental to global-scale carbon modeling efforts relying on information at coarse spatial resolution without incorporating fine scale land cover dynamics.

2.3 The Role of Remote Sensing in Carbon Sequestration

Remote sensing also holds the potential for predicting the net ecosystem exchange (NEE) of carbon flux. This carbon flux can be partitioned into gross primary productivity (GPP) and respiration (R) which can be mapped spatially and temporally. This has obvious utility to estimate carbon sink and source relationships and to identify improved land management strategies for optimizing carbon sequestration (Wylie et al. 2003). 14-day average daytime CO_2 and nighttime CO_2 fluxes using Advanced Very High Resolution radiometer (AVHRR) were evaluated and predicted to determine Normalized Difference Vegetation Index (NDVI) during four growing seasons (1996-1999). Results show that NDVI was a strong predictor of daytime CO_2.

In their study on the calibration of remotely sensed data, Wylie et al. (2003) used the regression statistical technique to predict daytime CO_2 and found that cross-validation indicated that regression tree predictions of daytime CO_2 were prone to overfitting and that linear regression models were more robust. They concluded that multiple regression and regression tree models predicted nighttime CO_2 quite well with the regression tree model being slightly more robust in cross-validation.

Hunt Jr. et al. (2004) estimated carbon sequestration in a northern mixed-grass prairie site and a sagebrush–steppe site in southeastern Wyoming using an approach that integrates remote sensing, CO_2 flux estimates, and meteorological data from 1995-1999. Net ecosystem exchange (NEE) of CO_2 was estimated using aircraft and ground flux techniques and was linearly related to absorbed photosynthetically active radiation (APAR). The slope of this relationship is the radiation use efficiency (ε = 0.51 g C/MJ

APAR); which showed that there were no significant differences in the regression coefficients between the two sites. Using the Advanced Very High Resolution radiometer(AVHRR), Normalized Difference Vegetation Index (NDVI) and meteorological data, annual gross primary production and respiration were calculated from 1995 to 1999 for the two sites. Overall, the sagebrush–steppe site was a net carbon sink, whereas the northern mixed-grass prairie site was in carbon balance. The study found that there was no significant relationship between NEE and APAR for a coniferous forest site, indicating that this method for scaling up CO_2 flux data may be only applicable to rangeland ecosystems. The results of the study is also an indication that the combination of remote sensing with data from CO_2 flux networks can be used to estimate carbon sequestration regionally in rangeland ecosystems.

Because the integration of remote sensing and modeling produces spatially explicit information on carbon storage and flux, this integrated approach was employed by Turner et al. (2004) to compare carbon flux for the period 1992–1997 over two 165-km^2 areas in western Oregon. The Coast Range study area was predominantly private land managed for timber production, whereas the West Cascades study area was predominantly public land that was less productive but experienced little harvesting in the 1990s. In the Coast Range area, 17% of the land base was harvested between 1991 and 2000. Much of the area was in relatively young, productive-age classes that simulations indicate are a carbon sink. Mean annual harvest removals from the Coast Range were greater than mean annual net ecosystem production. On the West Cascades study area, a relatively small proportion (<1%) of the land was harvested and the area as a whole was accumulating carbon. The spatially and temporally explicit nature of this approach permits identification of mechanisms underlying land base carbon flux.

In their study, Wang et al. (2008) employed two methods, eddy covariance and chamber-based estimates, to measure the net ecosystem CO_2 exchange in a mature temperate mixed forest in 2003. The eddy covariance system was used as a reference, which was compared with the chamber-based method. Based on chamber fluxes, the ecosystem had a gross primary production of 1490 g C m^{-2} $year^{-1}$, 90% of which was released as efflux back into the air via respiration of the entire ecosystem. This was comprised of about 48% from soil surface CO_2 efflux, 31% from leaf respiration and 21% from stem and branch respiration. Net ecosystem exchange (NEE), estimated from the sum of daily component fluxes, was 146 g C m^{-2} $year^{-1}$. Ecosystem respiration (ER), estimated from the sum of daily ecosystem respiration, was 1240 g C m^{-2} $year^{-1}$. NEE was 9.8% of actual gross primary production (GPP). The eddy covariance estimates of NEE, ER and GPP were 188, 1030 and 1220 g C m^{-2} $year^{-1}$, respectively. The eddy covariance estimation of NEE was higher than that of the chamber-based estimation by 22.5%. On a daily basis, NEE of the scaled chamber estimates was in acceptable agreement with eddy covariance measurement data with R^2 values of 0.71. The discrepancy between the estimates of the two methods was greater in the non-growing season primarily due to the lack of spatial variability in the scaled chamber estimates and weak atmosphere turbulence by eddy covariance estimates. However, Wang et al. (2008) pointed out that there are many uncertainties for determination of absolute values of ecosystem component flux, and suggests that more detailed experiments and related theoretical studies are needed in the future.

2.4 Modeling and SOC/Carbon Sequestration

Computer models are important tools for assessing regional carbon sequestration and other environmental impacts on agricultural management practices. One of the most widely used simulation models for agricultural policy analysis is the Erosion Productivity Impact Calculator (EPIC) model (Williams 1990; Williams 1995), originally developed by the U.S. Department of Agriculture (USDA) and now maintained by the Texas A&M Backlands Research Center. EPIC is a field-scale model that can be adapted to a large range of crop rotations, management practices, and environmental conditions. Gassman et al. (2003) used EPIC to estimate regional soil carbon and other environmental indicators in the entire 12-state North Central region of the U.S. They found that EPIC is a robust tool for regional analyses of soil carbon changes, nutrient and erosion losses, and other environmental indicators in response to variations in management practices, cropping systems, climate inputs, and soil types.

Potter et al. (2003) analyzed net carbon flux predictions of 17 years in North America using the NASA-CASA model which was driven by vegetation cover properties derived from the Advanced Very High Resolution Radiometer (AVHRR) and radiative transfer algorithms that were developed for the Moderate Resolution Imaging Spectroradiometer (MODIS). The study found that although the terrestrial ecosystem sink for atmospheric CO_2 on the North American continent has been fairly consistent, inter-annual variability in net ecosystem production (NEP) fluxes can be readily identified at locations across the continent. Five major areas having the highest variability were detected: 1) along the extreme northern vegetated zones of Canada and Alaska, 2) the northern Rocky Mountains, 3) the central-western U.S. Great Plains and central farming region, 4) across the southern United States and Mexico, and 5) in coastal forest areas of the U.S. and Canada. According to them, analysis of climate anomalies over the 17-year time period suggests that variability in precipitation and surface solar irradiance could be associated with trends in carbon sink fluxes within regions of high NEP variability.

Ardo and Olsson (2003) used GIS and the CENTURY model to assess soil organic carbon in the Sudan, a semi-arid environment. They compiled a climate, land cover, and soil database and integrated it with the CENTURY ecosystem model. This enabled them to estimate historical, current and future pools of SOC as a function of land management and climate. They concluded that grassland and savannah SOC variations depend on grazing intensity and fire return interval, and that land management may affect future amounts of SOC in semi-arid areas thereby turning them from sources into sinks of carbon.

Ingrid et al. (1990) used the CENTURY model coupled to a GIS to simulate spatial variability in storage and fluxes of carbon and nitrogen within grassland ecosystems. The GIS contained information on driving variables required to run the model. These were soil texture, monthly precipitation and monthly minimum and maximum temperatures. They overlaid polygon maps of the above variables to produce a driving variable map of the study region. The final map had 768 polygons in 160 unique classes. The model was run to a steady state for each class and NPP, SOM, net N mineralization and trace gas emission were mapped back into the GIS for display. Variation in all of the above properties occurred within the region. NPP was primarily controlled by climate and patterns followed spatial variation in precipitation closely. Soil organic matter, in contrast, was controlled largely by soil texture within this climate range. Error associated with aggregation within the study area showed that spatial averages over the study area could be used to drive simulations of NPP, which is linearly related to rainfall. They concluded that more spatial detail was needed to be preserved for accurate simulation of SOM, which is non-linearly related to texture.

Using the CENTURY model, Smith el al. (2000) estimated the rate of SOC change in agricultural soils of Canada for the period 1970 to 2010. This estimation was based on the estimated SOC change for 15% of the 1250 agriculturally designated soil landscape of Canada (SLC) polygons. Simulations were carried out for two to five crop rotations and for conventional and no-tillage. The results indicate that the agricultural soils in Canada, whose SOC are currently very close to equilibrium, will stop being a net source of CO_2 and will become a sink by the year 2000. Rates of carbon change for the years 1970, 1990, and 2010 were estimated to be −67, − 39, and 11 kg C ha^{-1}. The results also revealed that the rate of decline in the carbon content of agricultural soils in Canada has slowed considerably in the 1990s as a result of an increase in the adoption of no-tillage management, a reduction in the use of summer fallowing, and an increase in fertilizer application. It was estimated that the proportion of agricultural land storing SOC will have increased from 17% in 1990 to 53% by the year 2000.

A simulation model of the grassland carbon cycle (CCGRASS) was developed by Dasselaar and Lantinga (1995) to evaluate the long-term effects of different management strategies and various environmental conditions on carbon sequestration in a loam soil under permanent grassland in the Netherlands. The model predicted that the rate of increase in the amount of soil organic carbon will be greatest at low to moderate application rates of nitrogen (100-250 kg N/ha per year). This, the authors argued was because the annual gross photosynthetic uptake of CO_2 in permanent grassland is hardly influenced by the level of N supply. Dasselaar and Lantinga (1995) claims that since N shortage stimulates the growth of the unharvested plant parts (roots and stubble) the carbon supply to the soil is highest at low to moderate N application rates. The rate of increase in soil organic carbon, according to them, will be greater under grazing than under mowing as a result of a greater amount of carbon added to the soil. Dasselaar and Lantinga (1995) further argue that increase of atmospheric CO_2 concentration may induce an increase in decomposition rate of soil organic matter due to simultaneously increased temperatures. At the same time, plant productivity and thus carbon supply to the soil will be stimulated due to the CO_2-fertilization effect. Assuming a temperature increase of 3^o C; when the present atmospheric CO_2 concentration doubled, the model predicted that the combined effect of elevated CO_2 and temperature will slightly reduce the rate of increase in the amount of organic carbon in grassland soils compared to that under unchanged environmental conditions. The study concluded that there was 2% less carbon sequestration by grassland at the end of a 100 year period as a result of these changes in environmental conditions. The separate effects of increased temperature or elevated CO_2 were 10% less and 10% more carbon storage after 100 years, respectively.

Mikhailova et al. (2000) used the CENTURY model to simulate the soil organic matter dynamics after conversion of native grassland to long-term continuous fallow for 50 years. The model was simulated such that the parameters are adjusted to the pre-management scenario. The results of the simulations corresponded to the results of the soil organic carbon that was obtained before the fallow. This shows that the use of models to simulate soil organic carbon fluxes is valid. Also, Grace et al (2006) developed a model called SOCRATES to predict long-term changes in soil organic carbon in terrestrial ecosystems. This they argued was because the maintenance of soil organic carbon in terrestrial ecosystems was critical for long-term productivity. They contend that simulation models of SOC dynamics are valuable tools in predicting the dynamics of carbon storage and developing management strategies for the mitigation of greenhouse gas emission. However, they observed that the utility of using models is generally reduced due to need for specific data.

Zhang et al. (2007) also used a modeling approach to evaluate and compare gross primary production (GPP) estimates for the Northern Great Plains grasslands of the U.S. They used an empirical pairwise regression (PWR) model from flux tower estimates and compared that with the MODIS-GPP model. They found that the MODIS-GPP model estimated lower values compared to the PWR model. This disparity in results may be connected to the fact that the global MODIS GPP model may have some limitation, which includes responding to dry years (seasonal variations of climate), differentiating between different types of grasses, such as C2 and C4, and problems with the separation of mixed cropland and grassland pixels. One of the usefulness of a study such as this, however, is that it can be used to explore the influence of soil and ecosystems characteristics on the modeling of grassland production.

Models have also been used to monitor and quantify carbon fluxes. For example, Coops et al. (2007) developed a physiological, principle, predicting growth from satellite (3PGS) model to predict GPP from a MODIS 8-day image, using local meteorology and canopy characteristics. They also used canopy characteristics from the MODIS fraction of photosynthetically active radiation (fPAR) algorithm to predict GPP. This is important because vegetation indices play a very prominent role in determining GPP and NPP which can tell us something about the amount of carbon in the vegetation. Remote sensing can also retrieve leave area index (LAI) and fPAR from vegetation.

Del Grosso et al. (2001) simulated the interaction of carbon dynamics and nitrogen trace gas fluxes using the DAYCENT model. The authors used this model to compare the effects of land management on SOM, nitrogen oxide (N_2O) emissions, plant production, and NO_3 leaching for a Great Plain soil that has been used for wheat fallow rotations and for a Midwestern soil used for corn/winter wheat/pasture rotations. Results of their study show that some type of agriculture can dramatically reduce soil C levels from what they were in the native condition, and that the loss can be reversed by perennial cropping, N fertilizer, irrigation, organic matter additions, no-till cultivation, and reversion to the native condition. According to Del Grosso et al. (2001) DAYCENT simulations suggest that soils that are depleted in SOM can temporarily compensate for greenhouse gas emissions by changing land management, but observed however, that net carbon sequestration will not continue for more than 10 to 50 years, under such conditions.

The DAYCENT ecosystem model (a daily version of CENTURY) and an emission factor (EF) methodology used by the Intergovernmental Panel on Climate Change (IPCC) were used to estimate direct and indirect N_2O emission for major cropping systems in the USA (Del Grosso et al. 2005). Results of a comparison of mean annual soil N_2O flux estimated by DAYCENT and an EF with estimated data for different cropping systems according to the authors, yielded r^2 values of 0.74 and 0.67, and mean deviations of −6 and +13%, respectively. The authors also found that at the national scale, DAYCENT simulation of total N_2O emission was ~25% lower than estimated using EF. For both models, N_2O emission was highest in the central USA followed by the northwest, southwest, southeast, and northeast regions. However, the models simulated roughly equivalent direct N_2O emission from fertilized crops, but EF estimated greater direct N_2O emission than DAYCENT for N-fixing crops. DAYCENT simulations were also performed for no tillage cropping, pre-1940 crop management, and native vegetation. Results suggest that conversion to no tillage at the national scale could mitigate ~20% of USA agricultural emission or ~1.5% of total USA emission of greenhouse gases.

Yongqiang et al. (2007) examined carbon dynamics of grasslands on the Qinghai-Tibetan Plateau and the roles it may play in regional and global carbon cycles. They used the CENTURY model to examine temporal and spatial variations of SOC in grasslands on the Plateau for the period from 1960 to 2002. According to the authors, the model successfully simulated the dynamics of aboveground carbon and soil surface SOC at the soil depth of 0–20 cm and the simulated results agreed well with the estimates. Some outcomes of their study reveal that an examination of SOC for eight typical grasslands shows different patterns of temporal variation in different ecosystems in 1960–2002. The extent of the temporal variation according to the study increased with the increase of SOC in the ecosystem. They found that SOC increased first and then decreased quickly during the period from 1990 to 2000. Spatially however, SOC density obtained for the equilibrium condition declined gradually from the southeast to the northwest on the plateau and showed a high heterogeneity in the eastern plateau. The results suggest that (i) SOC density in the alpine grasslands showed remarkable response to climate change during the 42 years, and (ii) that net carbon exchange rate between the alpine grassland ecosystems and the atmosphere increased from 1990 to 2000.

2.5 Summary of Literature Review

From the literature reviewed it is clear that soil management techniques, land use and land cover change, satellite imagery and GIS and remote sensing techniques, statistical techniques, and modeling are critical in the estimation of carbon flux in agricultural (till) and non-agricultural (no-till) lands. However, not very many studies have investigated the benefits of the conservation reserve program (CRP) in carbon sequestration as evident from a myriad of research articles on the subject. Whereas, several studies have been conducted in relation to carbon sequestration in the CHP region of the U.S., most of these studies adopted regional approaches which have generally been on smaller (coarser) scales. This study thus adopted an integrated modeling framework to examine the spatial tradeoffs of carbon sequestration benefits at a finer (larger) scale in the CHP, USA, as a case study.

Methods of data collection and analyses used for this study were adopted, and in some cases with modifications from the reviewed literature as presented in chapter three.

CHAPTER III

3.0 METHODOLOGY

This chapter has three sections: the first part is a description of data sources, nature and types; the second part illustrates the methodology of how the data were collected, and the last part describes the characteristics of the proposed environmental models and analyses within the context of the aims of this research.

3.1 Types and Sources of Data

Three types of data sets are needed for running the integrated CENTURY model. These are: (1) physical data with spatial characteristics, such as precipitation, temperature, elevation and soil types; (2) baseline carbon data; and (3) management data, such as land use, CRP, cropland, tillage and conservation practices and organic manure managements. The data were acquired from governmental agencies including the United States Department of Agriculture (USDA), Natural Resource Conservation Service (NRCS), Farm Service Agency (FSA), National Aeronautical Space Agency (NASA), Land Processes Distributed Active Archive Center (LPDAAC), and Daily Meteorological Data (DAYMET).

Global Positioning System (GPS) data were collected in the field using a Trimble AH grade GPS unit (Trimble 2006) to collect location points on selected CRP tracts.

Table 3.1: Types and Sources of Data

DATA TYPE	DESCRIPTION	SOURCE
Weather	Precipitation & Temperature	DAYMET U.S. Data Center
Soil	Physical and Chemical Properties	USDA-NRCS
Carbon	Baseline Carbon Data	USDA State Offices
LULC	Land Use/Land Cover	USDA-NRCS
CLU	Common Land Units	USDA-NRCS
Cropland Data Layer (CDL)	Cropland Classification	USDA-NRCS
CRP	Conservation Reserve Program	Derived using GIS
MGMT	Management Data	USDA-FSA and field work
VIs	Vegetation Indices	NASA-LPDAAC
NAIP Imagery	Aerial Photography	USDA-NRCS
Boundary File for the CHP	Boundary File	USGS

Note: ***USDA****: United States Department of Agriculture*

NRCS*: Natural Resource Conservation Service*

FSA*: Farm Service Agency*

DAYMET*: Daily Meteorological Data*

NASA*: National Aeronautical Space Agency*

LPDAAC*: Land Processes Distributed Active Archive Center*

USGS*: United States Geologic Survey*

3.2 Preprocessing of Spatial Data

The spatial data presented in table 3.1 were obtained from different sources at different resolutions with different projections. The first task was to ensure that the data were all in the same projection system, thus, the different data layers were reprojected to Albers Equal Area projection. The reprojections of the vector Data as well as the Cropland Data Layer (CDL) were done using ArcToolbox in ArcMap GIS (ESRI 2006). The MODIS Data, which are raster in nature were, however, reprojected to GeoTiff using the MODIS reprojection tool (MRT) (LP DAAC 2007). The reprojected MODIS data were further reprojected from the GeoTiff projection to Albers Equal Area projection to conform to the other data layers.

The National Agricultural Imagery program (NAIP), Moderate Resolution Imaging Spectroradiometer (MODIS), and the Cropland Data Layer (CDL) imagery were obtained and used for the study. NAIP data provides digital ortho photography imagery to governmental agencies and the general public as base layers for GIS programs (USDA 2006). The 2005 NAIP imagery acquired has a spatial resolution of 2 meters and a natural color (RGB) spectral resolution, and was used as the base data for classifying the MODIS data into land cover classes; as well as for validating the CDL data.

MODIS, a NASA satellite that captures data in 36 spectral bands comes at 250 m, 500 m, and 1000 m spatial resolutions, along with two vegetation indices (Vis); Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI). The MODIS data acquired for this study was the 250 m spatial resolution imagery with a temporal resolution of two days. In spite of a coarse spatial resolution, the MODIS imagery was chosen for the landscape metrics land cover classification because of its spectral and temporal resolution advantages, as well as the fact that it is free. The CDL which is a crop-specific land cover raster data, is produced from the Indian Remote Sensing RESOURCESAT-1 (IRS-p6) satellite at a spatial resolution of 30 meters. This imagery also provides acreage information for major commodities for states in the U.S. In this study, the CDL was used to extract CRP tracts in the CHP region of the U.S. (USDA 2006). A summary of the characteristics of the imagery used is presented in table 3.2).

Table 3.2: Characteristics of Classification Imagery

Imagery	Resolution			Time Acquired (Year)			
	Spatial (m)	Spectral	Temporal	2001	2003	2005	2008
NAIP	2	RGB				2005	
MODIS	250	36	2 days	2001	2003	2005	
CDL	30				2006	2007	2008

The data preparation also involved reclassification of the CDL. The output of the reclassified CDL was used as the input land cover for the post-CRP scenario for running the simulation. The procedure for obtaining the classification and reclassification outputs are presented in Figure 3.1, and the boundary of the study area is shown in Figure 3.2.

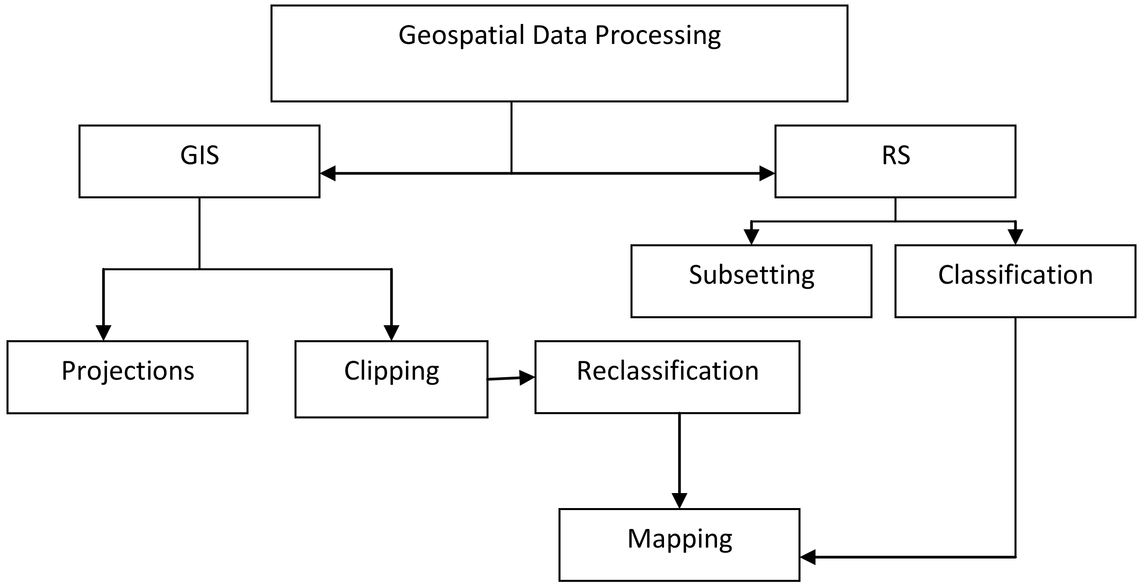

Figure 3.1: Schematic diagram of the Data Preprocessing phase

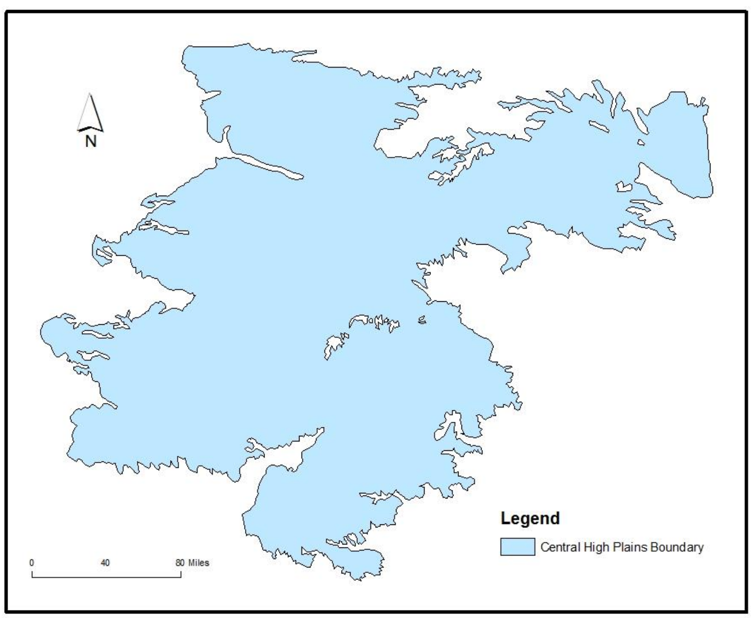

Figure 3.2: Boundary of the study area - Central High Plains

The preprocessing phase of the data analysis involved subsetting, mosaicking, data conversion, and resolution of coordinate systems and scales. Imagery Data were acquired for a much larger area than the study area. Subsetting utility functions in ERDAS IMAGINE (Leica Geosystems 2008) were therefore used to extract area of interest (AOI) for only the study area (see Figure 3.2). Earlier, a shapefile of the AOI (study area) had been created from shapefiles of the five states within which the study area lay. The initial boundary of the CHP region was obtained from USGS, and the shapefiles for the counties from the five states that constitute the CHP region were digitized using ArcMap (ESRI 2006) functionality. This shapefile (AOI) was used as analysis mask for the subsetting operations. The resulting output layer (Study area) saved storage space and reduced any spatial ambiguity from the data to be processed and analyzed. The study area is comprised of parts of 5 states, which have different spatial characteristics. A large portion of the subsetted imagery data also appeared as single band. To make composite wholes, these data were stacked in ERDAS IMAGINE and the different pieces were mosaicked together.

3.3 CRP Extraction from the CDL Data

Since the main objective of this study was to estimate long-term carbon sequestration on CRP tracts, obtaining the CRP tracts from the FSA was imperative. However, the FSA is reluctant to release the CRP data due to privacy issues. This was a problem for the research since the estimation and mapping of carbon sequestration was based on the CRP tracts. To get around this problem, CRP was derived from Cropland Data Layer (CDL) using spatial analysis tools in ArcMap. Texas County, Oklahoma was selected as a training site to test for the viability and accuracy of using the common land unit (CLU) and the CDL to extract CRP tracts. Texas County was selected because it was the only county in the study area whose CLU data contained CRP attributes, as well as an existing CRP layer for validation (available to the researcher). The CRP tracts were dissolved based on their feature IDs preparatory for the validation exercise.

After the data had been preprocessed (see section 3.2); the CLU and CDL data were clipped to the boundaries of Texas County (training site). The CLU data is a vector layer comprised of polygons, and came as a shapefile. The CDL on the other hand, is a raster dataset with a spatial resolution (cell size) of 30 meters. In order to proceed with the CRP extraction operation, the CLU and CDL layers needed to be in the same data format. Thus, the CLU was converted to a raster layer, with the cell size set at 30 meters to coincide with that of the CDL data. The rasterized (converted) CLU layer was then reclassified such that cells that contained CLU data were coded as 1 and non-CLU data coded as 0. Using the 'AND' (multiplication) operation in ArcMap, the CLU layer was multiplied by the CDL layer, and the resultant output layer showed areas of commonality.

The goal of this analysis was to determine the proportion of CRP in the cropland layer. Using the number of cells (count), the proportion of CRP and other grass cover types such as idle cropland and fallow land was determined to be about 48% of the cropland layer. To find the proportion of CRP in each zone, the zonal variety tool in ArcMap was used to determine the number of cover types in each CLU zone. Furthermore, the 'calculate zonal area' tool was used to calculate the proportion of each variety in the zone, as a percentage of the total area occupied by each cover type in the zone. For example, if a zone contains 4 different cover types, the zone variety will indicate 4, along with the corresponding area covered by each of the 4 cover types.

Although there were many land cover classes contained in the CDL data, two of the dominant ones were the land covers with a value of 61 (idle cropland/Fallow/CRP and a value of 62 (Grass, Pasture/Range/Non-ag/Was). The majority rule was adopted to determine the land cover type to be assigned for each zone based on the percentage of the area covered by the variety in the zone. Therefore, zones that had CRP as the majority in terms of area coverage were extracted as CRP tracts. After extracting the CRP tracts (land cover value 61) from the CDL layer, the accuracy of the operation needed to be verified. In order to do this, ground truth data was required, a task that set the stage for field data collection.

3.4 Field Data Collection

The field data collection which involved mainly the collection of GPS points and grass types is divided into 3 phases: pre-data collection phase, indoor preparation phase and the data collection phase (Figure 3.3). The field data collected for Texas County was conducted in the summer of 2008 from July 16-18, while field data collection for New Mexico, Colorado and Texas took place in the summer of 2009 from June 22-26.

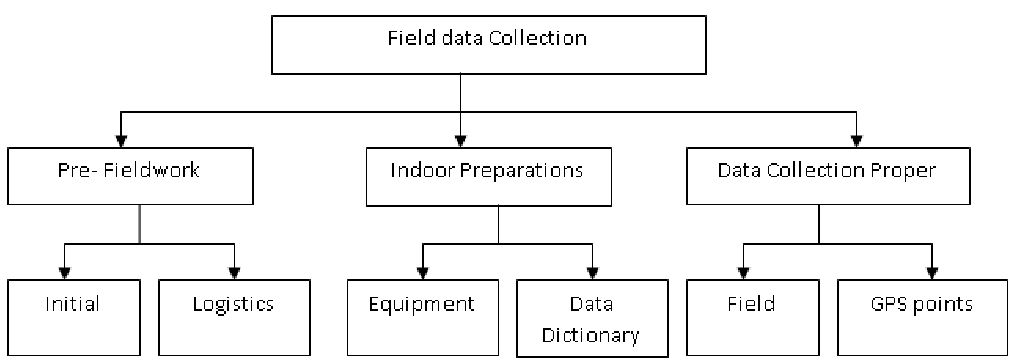

Figure 3.3: Field data Collection Phase

***3.4.1 Pre-Field Work Stage*:** This was the initial preparations for the data collection that involved contacting the executive directors of the Farm Service Agency (FSA) for the affected counties in Oklahoma, New Mexico, Colorado and Texas. During these communications which were both by phone and email, arrangements regarding time and nature of visit were discussed. The FSA officials agreed to provide CRP field guide maps for their respective counties, and also granted field interviews. This phase of the field work also involved other logistic arrangements such as the hiring of field assistants, renting of a vehicle and the reservation of accommodation.

***3.4.2 Indoor Preparations Stage*:** Once the travel and accommodation arrangements had been completed, indoor preparations began. This involved the acquisition of Geo XT GPS unit (Trimble 2006) from the Department of Geography at OSU. A data dictionary was set up to collect point features, grass types and a description of stand density of the grass in the field with Wide Area Augmentation System (WAAS) enabled, using the TerraSync and Pathfinder Office software. Whereas the TerraSync software provides mission planning in the field and data dictionary creation and editing, the GPS Pathfinder Office works with the TerraSync to provide advanced mission planning and data dictionary creation, data transfer, data import and export, as well as postprocessing operations such as differential correction.

***3.4.3 Sampling Design*:** Based on a CRP map divided into quadrats of township maps and sections, which were provided by the FSA offices in Oklahoma, New Mexico, Colorado, and Texas, a systematic random sampling technique was initially proposed for field data collection. However, physical access restrictions to a large number of the fields compelled a reconstruction of data collection method. And because a probability sample was not feasible in this case, and although nonprobability sampling methods are usually not recommended for quantitative research, Schutt (2009) argues that nonprobability sampling methods can be used in quantitative studies when researchers are unable to use probability methods. Consequently, an availability sampling technique was adopted to avoid possible legal problems that may have amounted to trespassing since many of the fields were fenced, and all the fields are private property. For instance, law enforcement agents (Police and Sheriff Deputies) in some counties in Oklahoma and Colorado stopped field data collection on unrestricted (not fenced) fields on 4 different occasions. The introduction letter obtained from the States' FSA offices, official identity cards (IDs) of field assistants, and copious explanation of the study and its goals, however, convinced the officers to allow data collection to continue. Data collection did not take place in Kansas because permission to go to the field was not granted by state and county officials, citing privacy rights and fear of litigation by landowners as the reason for the denial.

***3.4.4 Data Collection Phase**:* The field data was needed for this study to verify location information pertaining to CRP tracts, as well as obtaining ground truth data for land cover classification and accuracy assessment determination. The field data collected was mainly Global Positioning System (GPS) points and pictures of grass type at each location. A total of 105 GPS points were collected representing different CRP tracts in Colorado, New Mexico, Oklahoma and Texas as presented in Figure 3.4. The number of GPS points collected in each state is presented in Table 3.3.

Table 3.3: Number of GPS Points Collected by State

State	County	GPS Points
Colorado	Baca	30
New Mexico	Union	12
Oklahoma	Texas	32
Texas	Dallam	31

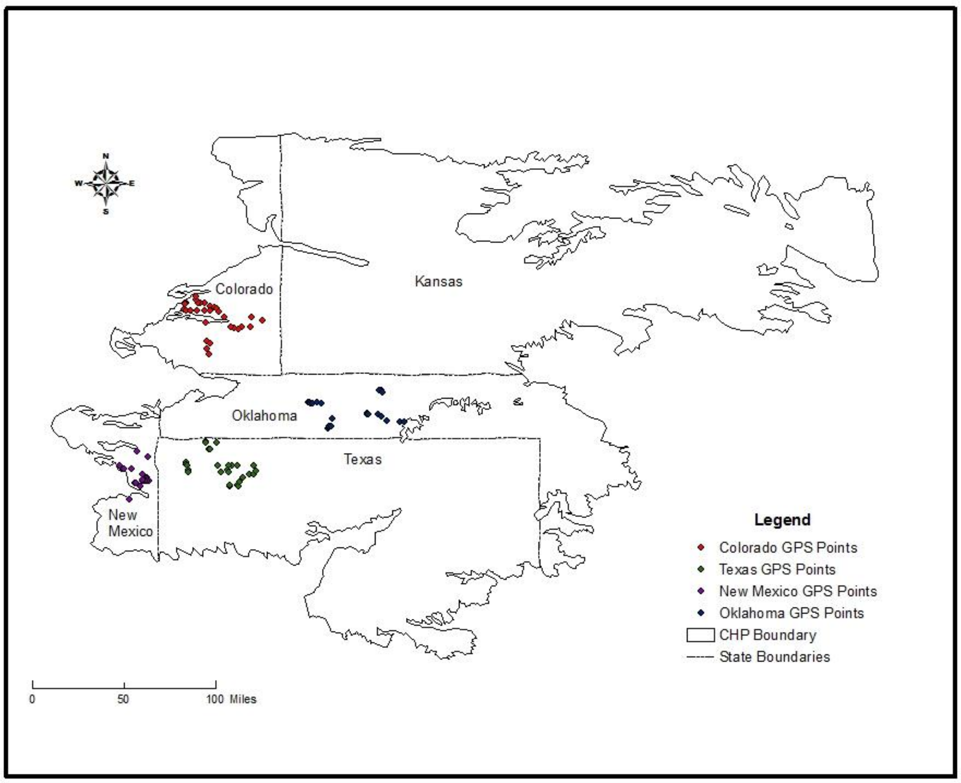

Figure 3.4: Global Positioning System (GPS) sample points

3.4.5 GPS Data Processing**:** The GPS data collected in the field were processed in the computer laboratory. The laboratory data preparation and processing was done in 3 phases: data transfer, differential correction and data export (Figure 3.5).

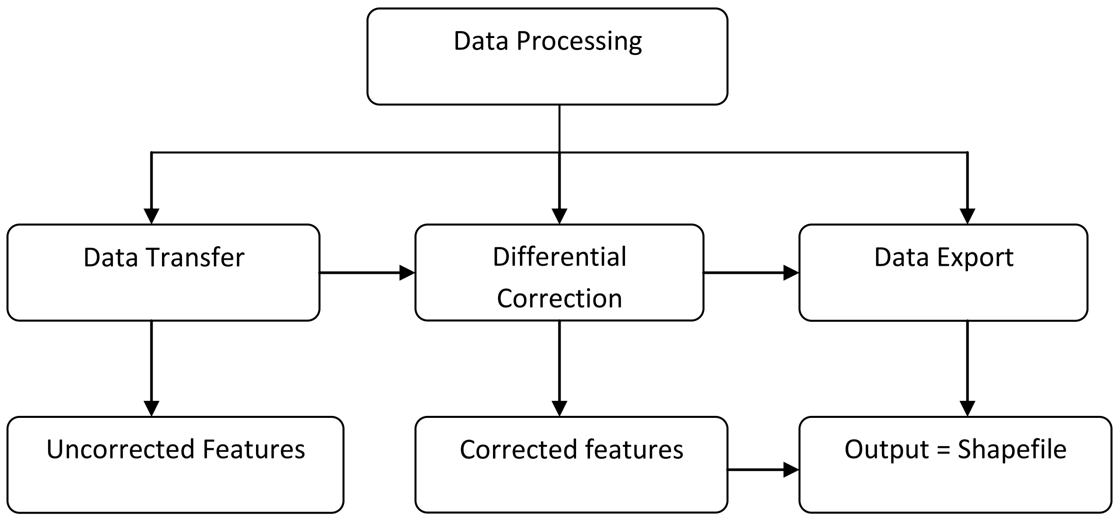

Figure 3.5: Laboratory GPS Data Processing

The collected field data were transferred from the GPS unit to the computer. This was done by first establishing a connection with the computer using a Windows CE's program called Microsoft Sync. This program allows the mobile device (GPS unit) to communicate with the computer. Once a connection has been established, the Data were transferred from the GPS unit to the computer, and differentially corrected using the GPS Pathfinder Office software.

The differentially corrected files were exported as shapefiles so that they could be displayed in a GIS. Using the GPS pathfinder office, the corrected files (with .cor extension) were exported by choosing the sample ArcView shapefile option from the export option. The exported data were then displayed in ArcMap and draped on the CRP tracts for Texas County, Oklahoma. Texas County was used as a training site to test for the accuracy (the field data collected with the help of FSA were used to extract CRP tracts after the training site results proved successful) of the classification because it was the only county that had CRP tracts obtained from the FSA (see Figure 3.6).

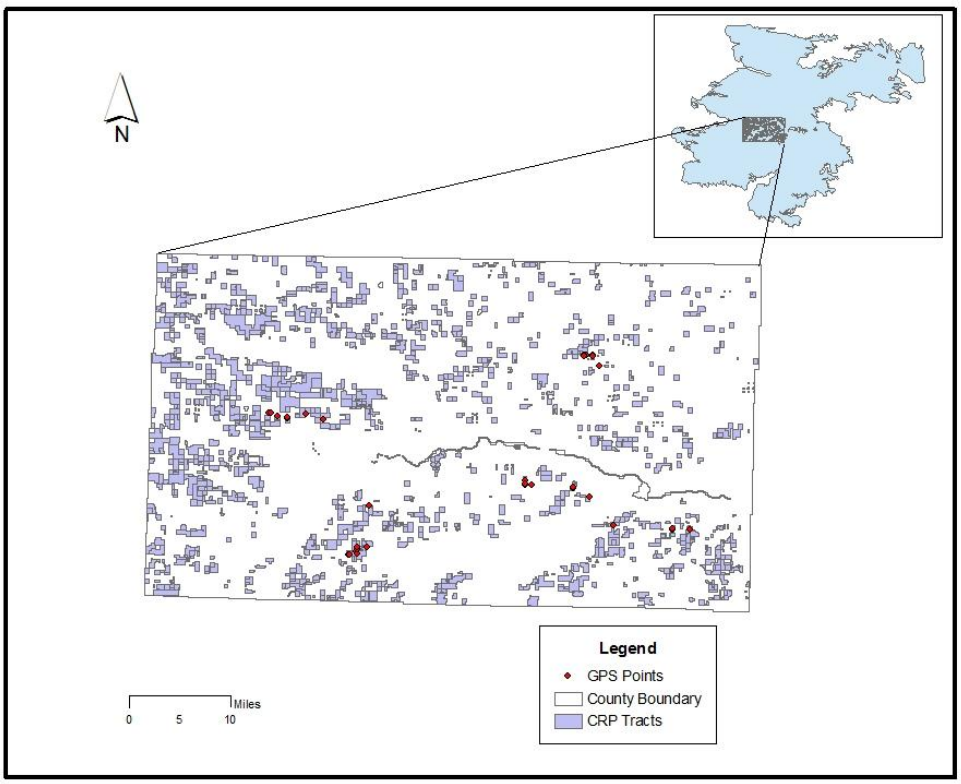

Figure 3.6: GPS points draped on Texas County CRP Tracts

Of the 32 GPS points collected for Texas County (training site), Oklahoma (figure 3.6), 28 GPS points fell inside CRP tracts. This means that about 90% of the points collected in the field in Texas County fell in CRP tracts. The fact that most of the GPS points collected in the field in Texas County actually fell in CRP tracts provided the basis for collecting the GPS points in other counties to be used as ground truth data for the extraction of CRP tracts in those areas in the absence of existing CRP tracts.

The remaining 10% were mainly other fallow grasslands which were very difficult to distinguish from CRP tracts. By all intent and purposes, these fields look similar except that the land owners for CRP tracts receive a pay check. This is the main distinction between a CRP field and a non-CRP field; otherwise they are similar in their spectral signatures when viewed from satellite imagery as well as their appearance in the field. This is why the spectral classes tend to overlap and moreover, most of the fields have a similar grass type particularly those fields that are planted with native grasses. This is another reason why it is difficult to distinguish between CRP and other grass cover types. According to the FSA Directors (personal communication), most grasses planted prior to 2002 and some in 1986 were Old World Bluestem (*Bothriochloa spp*). After 2002, most CRP fields have been planted with native grass such as Blue Grama (*Bouteloua gracilis*), Big Bluestem (*Andropogon gerardii*), Sand Bluestem (*Andropogon hallii*), and Black Grama (*Bouteloua eriopoda*) among others. It should be noted however that in spite of the effort to plant native grass, survival rate has been minimal at best as Old Bluestem still dominates and accounts for more acres in the study area. From field observations, and visual inspection of the grass coverage, exotic grasses planted on CRP fields appear to have higher stand densities compared to the native grass species. The exotic grasses for the most part have been very successful and grown well, protecting the soil in the process, but have been criticized for being less supportive of grassland animals compared to the native grasses (Lloyd and Martin 2005).

***3.4.6 Field Interview*:** The field data collection included a field interview. One of the objectives of this study was to evaluate management strategies by farmers pertaining to carbon sequestration of CRP fields. The FSA offices hold periodic meetings with landowners and farmers' associations, and the intent of the interview portion was to obtain such management information from the farmers directly or from the FSA officials. One interview was conducted in each County. These interviews were pre-planned with the FSA directors since the field visits did not coincide with the periodic meetings with the farmers. These and other information pertaining to the future of the CRP program in general were obtained during the interview process and are discussed in chapter 4 of this study.

3.5 Estimation and Verification of Carbon Sequestration

CENTURY and DAYCENT models were used in conjunction with GIS to map the spatial and temporal distributions of the amounts and variations of carbon in the study area. Statistical analyses were also conducted (see chapter 4) to find correlations between simulated carbon sequestration values and factors that influence carbon sequestration such as temperature, weather data and soil data in the study area.

3.5.1 Estimation of Carbon Sequestration: The estimation of carbon sequestration involved terrestrial carbon sequestration which includes carbon stored in vegetation and soil. The estimates were determined by running the CENTURY and DAYCENT models. Using the spatial analyst tool in ArcMap, CRP polygons extracted from the CDL layer were converted to points to determine the centroids of the locations representing the CRP tracts. The 'calculate area tool' in ArcMap was also used to calculate the area of each polygon (CRP tracts). Since the calculated model results were for one point (centroid) in the polygon (CRP tract), the estimated amount of carbon sequestered for that polygon was determined by multiplying the estimated amount at that point by the area of the polygon (CRP tract). Initially Kriging and Inverse Distance Weighting (IDW) were to be used to estimate the amount of carbon sequestration in areas where points were not sampled, but since the objective of the study was to measure carbon sequestration in CRP tracts, these techniques were not used. The results of the simulations from the models are presented in chapter 4.

3.5.2 Determination of Carbon Sequestration Potential in Grasslands: The determination of carbon sequestration potential was done using the CENTURY and DAYCENT models. The procedure started by collecting the relevant site data, including weather, land cover, and soil data. The parameters were prepared to be compatible with the models using a .100 file for the site specific parameters which include latitude and longitude of site, fraction of sand, silt, and clay in the soil, bulk density of soil, and the number of soil layers to simulate. Site specific event options such as CROP.100, CULT.100, FIRE.100, GRAZ.100 and HARV.100 were created. The next step was the creation of schedule files which determined the order and types of events that were included in the simulation and, the simulation was run. Finally, the model outputs were examined for accuracy. This is because if the net primary productivity (NPP) that the model is predicting for the site is not correct, then none of the other model outputs can be expected to be representative of the conditions at the site. Thus, the simulated NPP values were compared with the carbon baseline data obtained for Texas County, and simulation results from literature.

In this study, detailed mechanistic understanding and modeling of below-ground flux components, pool sizes and turnover rates were extracted from model results to adequately predict long-term, net C storage in ecosystems. This process required the estimation of carbon sequestration in terms of biomass and soil organic carbon. The amount of biomass was determined based on the estimation of above ground and below ground NPP. The model estimates NPP in terms of standing dead carbon (STDEDC), above ground live carbon (AGLIVC), and below ground live carbon (BGLIVC).

3.5.3 Rates of Carbon Sequestration and Management Strategies:

(a) Rates of Carbon sequestration: The CENTURY and DAYCENT models were used to estimate the rates of carbon sequestration in each CRP tract. These rates were determined based on passive, active and slow turnover rates for each CRP tract. Because plant and SOM residues are assumed to be decomposed from microbial respiration, the decomposition of the active pool increases when the soil becomes sandier (Parton 1992). The rates generally measure the lignin content of the soil in terms of these decomposed products which flow to the surface microbe pool of carbon (SOM1C(1)). The decomposition rate may potentially be reduced due to temperature and moisture within a soil depth of 0-30 centimeters (cm). The active organic carbon pool (SOM1C(2)), which has a turnover time of 0-2 years is a function of soil texture with sandy soils having higher rates, while the slow organic carbon pool, (SOM2C) with a turnover time of 20-50 years is higher in soils that have very high clay content. The passive organic carbon pool, (SOM3C) on the other hand is resistant to decomposition and has a turnover time of 400-2000 years. The proportion of decomposed products entering the passive pool is also accelerated when the soil has high clay content, and leached carbon (STREAM(5)),

which is lost organic matter from the decomposition of the active pool of SOM (Metherell et al. 1993).

(b) Management strategies and policy: Terrestrial ecosystems, including forests, pastures, grasslands, croplands, etc. offer significant short term and low-cost when compared to conservation options such as emission reduction through carbon trading to sequester carbon. These lands can, however, contribute to emissions through normal operations, such as tillage practices, fertilizer use, fires, and the use of pesticides. (Lee et al. 2005). Policy analysis was conducted focusing on four potential options for effecting C sequestration: 1) public land management policies such as burns, grazing and the planting of biofuel crops and the return of such lands to cultivation, especially focusing on tillage practices and fertilizer application. The return of CRP lands to production for instance could lead to loss in carbon sequestration, but burns could kill the grass completely such that the gains in carbon sequestration could be offset considering that most CRP fields are in marginal lands; 2) government incentives and regulations on private lands was based on payments made to farmers for enrolling in the CRP program. The analysis focused on whether the monetary incentive provided by government has actually improved carbon sequestration or not. This incentive was viewed from the perspective of the number of farmers who aspire to enroll in the program and those who are willing to re-enroll. The government regulation was analyzed on the basis of the number of landowners who wish to enroll in the CRP program, but who otherwise do not meet the basic requirements to qualify to enroll in the program; 3) private sector initiatives was an attempt to see if there was any private sector involvement in the endeavor to supplement government effort in resource conservation. This was centered on the private sector involvement in the

cultivation of alternative energy crops that help in climate change mitigation efforts by sequestering carbon in soils and biomass; and 4) research, education and technical assistance. The attempt here is to see how much research is focused on carbon sequestration both by government agencies, private sector and universities. This was analyzed based on research outputs in terms of publications and technical reports related directly to carbon sequestration on CRP fields. The impacts of these policy options are discussed in chapter 4 of this study. It should be pointed out that the current research did not assess budget impacts of implementing sequestration practices. The policy implementations were evaluated based on different scenarios reflecting the management practices as simulated using the CENTURY and DAYCENT models to see the effects of these management practices on carbon sequestration. The management practices information was obtained from FSA offices during field interviews from outcomes of their meetings with landowners and farmers' associations, and FSA and USDA reports that were posted online and referred to by the agency officials as reported by landowners who are beneficiaries of the CRP program.

3.5.4 Comparison of pre-CRP and post-CRP Carbon Sequestration: One of the main objectives of the study was to compare Pre-CRP and Post-CRP carbon sequestration in the study area. Based on this, two scenarios were developed, one before the area was converted to CRP (pre-CRP) and the other after the area was converted to CRP (post-CRP). And because the comparison pertains to the effect of land cover change in carbon sequestration, the creation of the scenarios hinged on land cover information. The Post-CRP land cover data was extracted from the CDL layer as CRP tracts. These CRP tracts were verified through ground truth information of GPS points collected in the field. The locations of these tracts were determined by converting the polygons to points and the centroids were used to determine their latitude and longitude. Therefore, the land cover type for the post-CRP for each location was CRP.

The pre-CRP scenario was aimed at reconstructing the land cover to what it was before the conversion of those fields to CRP tracts. Ideally, each CRP plot needs to be accounted for in terms of its pre-CRP land cover characteristics. To determine pre-CRP plots, the actual land cover characteristics of each plot would need to be obtained for each of the previous years that the study hoped to cover. This would require interviewing each CRP plot owner for land cover information for the number of years preceding the CRP or obtaining already collected or stored data. The first scenario is improbable for two reasons, 1) the High Plains is a vast area (area coverage) and the number of CRP plots is very large (number of plots). Interviewing individual farmers on specific details of land characteristics for each of their plots over the years is difficult to accomplish; 2) even if it were possible to obtain interview schedules for each farmer, it is improbable that the farmers will recall specifics of the land cover characteristics of each plot for the 25 years before CRP enrollment except if they have the data stored elsewhere. In the improbable situation that such data is available, there may be issues with changes in ownership of plots over the years and many gaps will still abound in the data that can be simulated. Furthermore, the researcher was unable to obtain any such data while on the field.

The creation of this scenario thus, required information on land use/land cover prior to the introduction of the CRP in 1985. Such data could not be obtained because the National Agricultural Statistics Service (NASS) data only provides statistics on crops grown, and information related to yield without specific location information, while the

NAIP and CDL data which would have provided such information only came into being in 2003 and 2006 respectively (USDA 2006).

To overcome this significant hurdle, the pre-CRP land cover characteristics for plots were obtained using ‘Spin’ operation in the CENTURY and DAYENT models. Spin uses a schedule file to tell the model what to simulate throughout the course of the model run. First, the model consists of 2 land cover files which consist of location information and covers the entire study area from the periods 1900-2010 (for the version of model being used). These land cover information are stored according to States and Counties. The first land cover file consists of land uses such as forests, grasslands, etc. (vveg.csv). The second file deals with cropping land cover types such as barley, corn, cotton, durham wheat, rice, soybeans, hay,etc. (crop.100). Second, the model requires exact location on each CRP plot. Using this data the model identifies each land cover file with the necessary land cover and selects the land cover type for the plot based on the year. In circumstances where the exact land cover characteristics could not be retrieved, the model assigns the most probable land cover type to the location based on the general area of its location.

The management simulations were run for 39 years from 2011-2050. The three management scenarios were for grazing, fire and biofuel. The weather data required for the simulation are minimum and maximum temperature as well as total precipitation. Soil parameters such as sand, silt, clay, bulk density, pH, and number of layers (soil depth) were also used for the simulation, along with location information (lat/long). In addition, land cover and management information were also used for the simulation. The management (treatments) options included grazing, fires, tillage (Till), fertilizers and manure.

Table 3.4: Simulation Parameters

Simulation	Land Cover	Site Parameters	Simulation time	Treatment
Pre-CRP	Crop, Pasture, Forest	Tmin, Tmax, PPT, Sand, Silt, Clay, Bulk Density, soil Layer, pH, Lat/long	1959-1984	Till., fire, grazing, fert., manure, irrigation
Post-CRP	CRP	Tmin, Tmax, PPT, Sand, Silt, Clay, Bulk Density, soil Layer, pH, Lat/long	1985-2010	None
Grazing	CRP	Tmin, Tmax, PPT, Sand, Silt, Clay, Bulk Density, soil Layer, pH, Lat/long	2011-2050	Grazing (low, medium, high)
Fire	CRP	Tmin, Tmax, PPT, Sand, Silt, Clay, Bulk Density, soil Layer, pH, Lat/long	2011-2050	Fire (low, medium, high)
Biofuel	Crop (Alfalfa, Corn)	Tmin, Tmax, PPT, Sand, Silt, Clay, Bulk Density, soil Layer, pH, Lat/long	2011-2050	Till., fert., manure, irrigation

The parameters listed in Table 3.4 for weather and site parameters are the basic parameters that must be entered in order to run the simulations for both CENTURY and DAYCENT models. For the most part, the same parameters used for running CENTURY are used by DAYCENT. There are a few additional input parameters that are used only by DAYCENT such as a description of the soil layer structure (SOIL.IN), additional site information (SITEPAR.IN), and weekly and/or daily ASCII output files (OUTFILES.IN) to work with the smaller time step used in DAYCENT as compared to monthly CENTURY. The DAYCENT model also requires additional weather parameters such as solar radiation, relative humidity, and wind speed input parameters contained in the daily weather file. Other parameters that are used for the simulation include field capacity of soil layer, evaporation coefficient of soil layer, percentage of roots in soil layer, organic matter in soil, and saturated hydraulic conductivity (Ksat) of the soil.

The soil physical (percent sand silt, clay,BD and Ksat) and chemical (pH, CEC, OM) properties were manually extracted from the STATSGO soil database using the location information created from the CRP centroids. These were used to create the input files for the model runs using the event file utility. The weather data and other soil parameters (field capacity, evaporation coefficient, percentage of roots in the soil and organic matter in soils) were automatically derived by the models. CRP tracts were extracted from the CDL data as raster. The raster data were converted to vector to create polygons. The polygons were used to create centroids (location) for the CRP tracts. This location information was used to match the loations of the input parameters for the model runs. The simulation outputs were in binary format and the LIS utility in the model was used to extract the results in text format. The ASCII (text) files were exported to a spreadsheet using the export functionality in Excel. This was done for the calculation of averages, percentages and the creation of tables. Using the unique location information, the simulation outputs were linked to the CRP information through simple join operations in ArcMap.

The general procedure for running the model is as follows:

The first step is collecting the site data (location and soil), and entering the site specific parameters into a <site>.100 file. The second step is the creation of site specific event options (crop, cultivation, fertilizer, fire, grazing, etc) in the Event.100 file, and step 3 is the creation of the schedule file (which determines the order and types of events) using the event.100 utility. The final step is to run the simulation. Figure 3.7 is a schematic diagram of the input files needed for running the simulation.

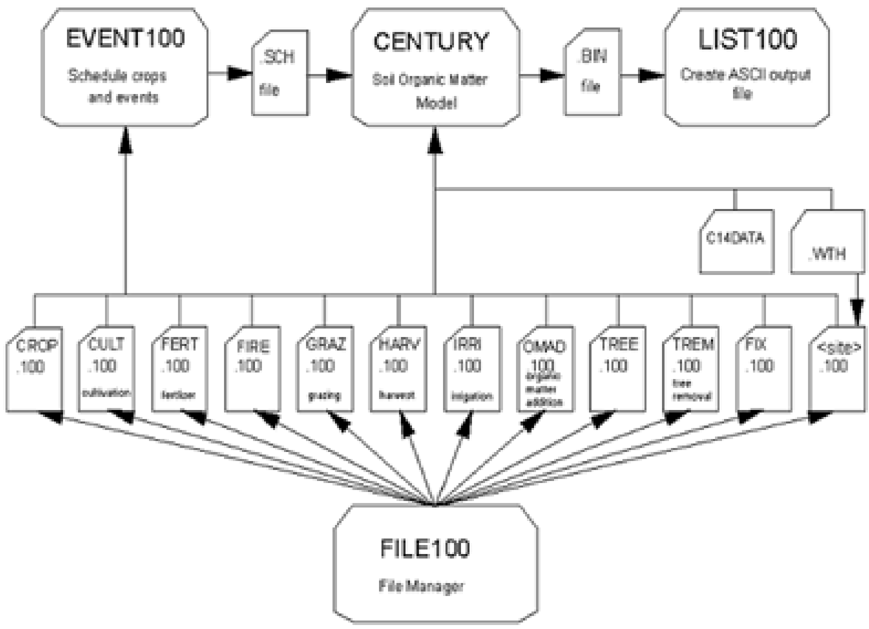

Figure 3.7: Schematic Diagram of Input files for running the CENTURY model (Adapted from Metherell et al. 1993).

The spin was used to run the Pre-CRP scenario to equilibrium from 1900-1984, a total of 84 years. The model outputs were however extracted for 1959-1984 (25 years) as the base years in order to compare with the Post-CRP simulation that was run from 1985-2010, a period of 25 years.

The simulation outputs come in one of three forms: 1) state variables, that represent the state of the system at the time that they were written to the output file; 2) annual accumulator variables that are set to zero at the end of the growing season, and 3) production variables which take the value of the annual production accumulator variables at the end of the growing season. These variables are set back to zero at the end of the year if no production occurred.

In this study, the production output variables (Table 3.5) were extracted for analyzing carbon sequestration potential in the CHP region, the study area. These simulation outputs were exported to a spreadsheet and tables and charts were created to compare the results. Details of these results are presented and discussed in chapter 4 of this study.

Table 3.5: Model Production Output Variables

OUTPUT VARIABLE	DESCRIPTION
STDEDC	Standing Dead Carbon
AGLIVC	Aboveground Live carbon
BGLIVC	Belowground Live Carbon
STRUCC(1)	Surface Structural Carbon
METABC(1)	Surface Metabolic Carbon
STRUCC(2)	Belowground Structural Carbon
METABC(2)	Belowground Metabolic Carbon
SOM1C(1)	Surface Microbe Carbon
SOM1C(2)	Active Organic Carbon
SOM2C	Slow Organic Carbon
SOM3C	Passive Organic Carbon
STREAM(5)	Leached Carbon

3.5.5 Trends and spatial distribution of carbon sequestration: The estimated carbon sequestration values obtained from the CENTURY and DAYCENT models in terms of the amount of carbon stored in grasslands and soils, rates of carbon sequestration and management strategies, as well as the comparison of pre-CRP and post-CRP outputs were tabulated and exported to ArcMap and mapped to display the spatial distribution of carbon sequestration as they relate to these scenarios. The centroids (which contain the actual simulation estimates) were displayed in ArcMap using graduated symbols to show the spatial distribution of carbon sequestration. Also the generated tables from the compared pre and post-CRP values were exported to ArcMap and mapped to display the temporal variation of carbon sequestration for the two scenarios. The geostatistical tool in ArcMap was used to perform trend analysis to identify trends of carbon sequestration as well as local and global outliers in the data. The GIS analysis for the conversion of polygons to centroids is presented in Figure 3.8.

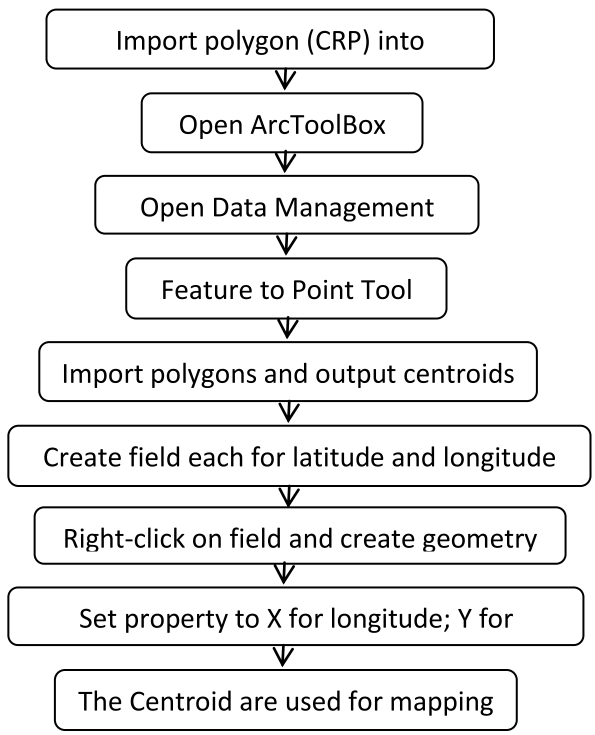

Figure 3.8: GIS Procedure for Exporting Centroids

3.5.6 Verification: The results obtained from the carbon models were subjected to verification and validation to establish model reliability and credibility and to reduce the risk of inappropriate simulation use (Philip and Watson 1982). Baseline information such as empirical carbon data and ground truthing information such as GPS location data and grass type information were collected from the Oklahoma USDA State office and field GPS sampling respectively to validate the model results. Results of past studies on carbon sequestration were obtained from existing literature to compare with results from simulations in the current study. This was aimed at helping to confirm and/or refute results of past studies, but importantly situate the study within the context of progress being made in carbon sequestration and CRP studies. Several data exploratory analytical techniques were employed to examine possible relationships between CRP characteristics and carbon sequestration. These techniques include multiple correlations, and Moran's Index (Moran's I).

Correlations between carbon sequestration (NPP) and CRP tracts characteristics allowed for inferences to be made on factors that influence carbon sequestration in CRP tracts. The use of correlation analysis also allowed for approximation of the correctness and accuracy of simulation models being used based on model error, accuracy and precision:

Error (absolute) = value (modeled) – value (estimated or expected)

Moran's index (Moran's I) was calculated in GeoDa (Anselin et al. 2006) to determine covariance between CRP tracts characteristics and carbon sequestration. Variables with high covariance were excluded from final analysis to reduce redundancy in the regression model.

Geographically Weighted Regression (GWR) was used to regress NPP, the dependent variable with various controlling variables including, temperature, precipitation, soil texture, soil reaction (pH),soil bulk density, soil slope, soil organic matter, soil saturated hydraulic conductivity (Ksat), and soil depth. Results of the exploratory data and regression analyses are presented and discussed in chapter 4. GWR establishes spatial relationships between the dependent and independent variables and importantly, allows for mapping of these relationships. It is therefore possible to identify spatial locations (here, counties) that have significant relationships between the dependent and independent variables, and others where relationships are weak or insignificant. The main advantage of the GWR is the disaggregation of relationships by spatial location, which enables an in-depth investigation into variables that significantly influence carbon sequestration in CRP.

3.6 The Integrated Modeling Framework

A GIS-based modeling framework was used to implement the conceptual framework (Figure 3.9). Within the framework two versions of soil organic matter models, CENTURY 4.5 (Parton et al. 1992) and DAYCENT 4.5 (Parton et al. 1998; Kelly et al. 2000), are used to simulate carbon sequestration and retention at different locations. Then a GIS-based interface was used to spatially target SOC in CRP tracts. The procedure for the empirical application is described below.

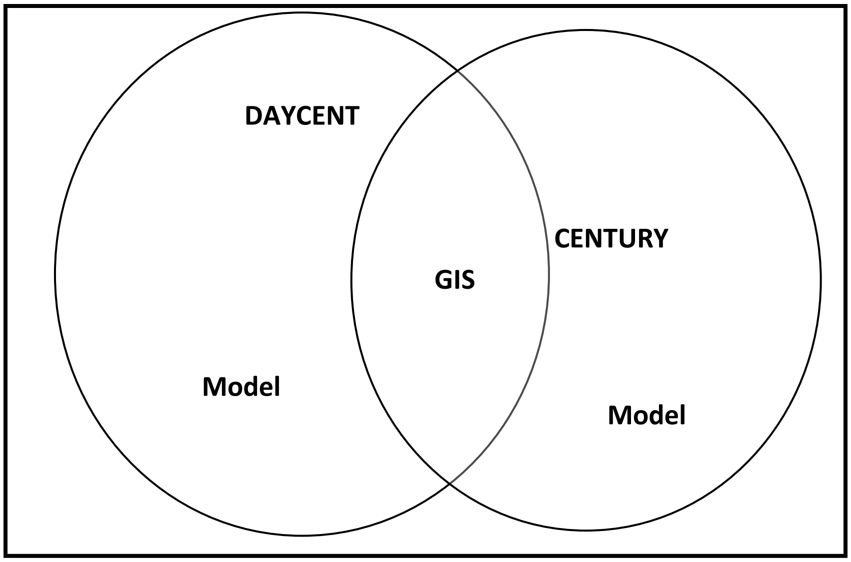

Figure 3.9: The GIS-Based modeling framework for estimating SOC

The basis for model integration is to define common spatial units for different models. The data required, such as soil type, weather, vegetation cover and tillage practices factor can be assumed as homogeneous in each CRP tract (Mankin et al. 2003).

The data for running CENTURY model, which include weather data, lignin content of plant material, plant Nitrogen (N), Phosphorus (P) and Sulphur (S) content, as well as soil texture, soil pH, soil bulk density and land cover are not very restricted, ranging in resolution from one km^2 to a couple of hundreds km^2, as long as accurate monthly average precipitation and temperature can be obtained (Mankin et al. 2003). Since CENTURY model can accept larger grid sizes without losing necessary accuracy, the CENTURY grid system was determined based on the various sizes of the CRP tracts.

Following the study framework, the simulation models were run independently and their outputs were incorporated into a GIS. The model outputs were produced in binary form. The simulation outputs were then extracted as text files using the ASCII conversion utility in the CENTURY and DAYCENT models. The text files were then exported into a

Spreadsheet and summarized by summations, averages and percentages, from which tables and charts were created.

Several processes were required to display the simulated outputs. First, the CRP tracts were converted from raster to vector format in ArcMap. Second, the centroids of the polygons were extracted as point features to represent each polygon. This step was essential because location information is required for the model runs. Third, tables of simulated output were joined to the centroids such that each polygon had the exact simulation output generated for it in the model runs by a simple join based on unique IDs. This allowed for mapping the spatial distribution of the model outputs. Further, using the joined point data with the simulated carbon output, a trend analysis was conducted using Geostatistical tools in ArcMap. This is a data mining process that provided exploratory information on inconspicuous patterns in the data.

CHAPTER IV

4.0 RESULTS, ANALYSES AND DISCUSSION

4.1 Introduction

The results obtained from the calibration and model runs using the CENTURY and DAYCENT models are presented and discussed in this chapter. These analyses pertain to the estimation of long term trends in carbon sequestration, as well as climatic and soil physical and chemical factors that are considered relevant in explaining the pre-CRP and post-CRP estimation of above and below ground carbon sequestration in the Central High Plains region of the U.S. These environmental factors of the CHP were discussed as they relate to carbon sequestration. The results of the analyses have been presented in the form of tables and charts using Microsoft Excel and the maps have been prepared using ArcMap. Trends in carbon sequestration were determined using the trend analysis tool in ArcMap and results presented as 3-dimensional charts. The presentation of results and discussion in this chapter has been designed such that answers to the research questions and objectives of this study are provided. The postulated hypotheses have also been tested and decisions made based on Z test results.

4.2 Presentation of Results

Results of the analyses conducted for this study mainly from simulations using the CENTURY and DAYCENT models are presented in this section. Due to differences in variables such as land use, soil, elevation and management practices among the five states (Colorado, Kansas, New Mexico, Oklahoma and Texas) that constitute the study area (CHP), the presentation of results have been done state by state. The results have been presented to depict the estimation of carbon sequestration potential based on the pre-CRP and post-CRP scenarios for each state as well as the future of carbon sequestration pertaining to management scenarios of grazing, fire and the cultivation of biofuel crops, especially alfalfa in the study area. Similarities and/or differences among the states are highlighted in the discussion section.

4.2.1 Colorado Carbon Sequestration Estimates:

Table 4.1: Net Primary Productivity (NPP) for Colorado

	Stdedc (Kt)	**Aglivc (Kt)**	**Bglivc (Kt)**	**NPP (Kt)**
Pre-CRP (CENTURY)	257.25	389.73	1530.82	2177.79
Pre-CRP (DAYCENT)	152.06	201.90	1670.29	2024.25
Post-CRP (CENTURY)	682.68	570.89	6097.15	7350.72
Post-CRP (DAYCENT)	433.19	385.043	2864.54	3682.77

Table 4.1 presents the results for Colorado for standing dead carbon (Stdedc), above ground live carbon (Aglivc), and below ground live carbon (Bglivc) for both CENTURY and DAYCENT models. The summation of the three categories (stdedc, aglivc, bglivc) constitutes the net primary productivity (NPP). The two models have

predicted the NPP slightly differently with CENTURY estimating higher values than DAYCENT. While the disparity between the two models in estimating the pre-CRP values appears to be relatively small (154 Kt.), that of the post-CRP is large (3667 Kt). Despite these differences, both models indicate that there was an increase in carbon sequestration with the introduction of the CRP, and that carbon sequestered progressively increased from standing dead to below ground. This means that carbon is sequestered more below ground than above ground in Colorado.

Given that the total area covered by CRP land in Colorado is 1293.35 Km^2, the average carbon sequestration is 0.23 kt per Km^2 per year for CENTURY and 0.11 kt per Km^2 per year for DAYCENT. It is not clear why there is this discrepancy between CENTURY and DAYCENT with regard to the estimation of the post-CRP for the study area. The DAYCENT model is considered a finer model in terms of scale since it runs on a daily time step as opposed to the monthly time step of the CENTURY model. Thus, we expect the simulation estimates to be more accurate than the CENTURY. However, the CENTURY model has been tested and validated more extensively than the DAYCENT model.

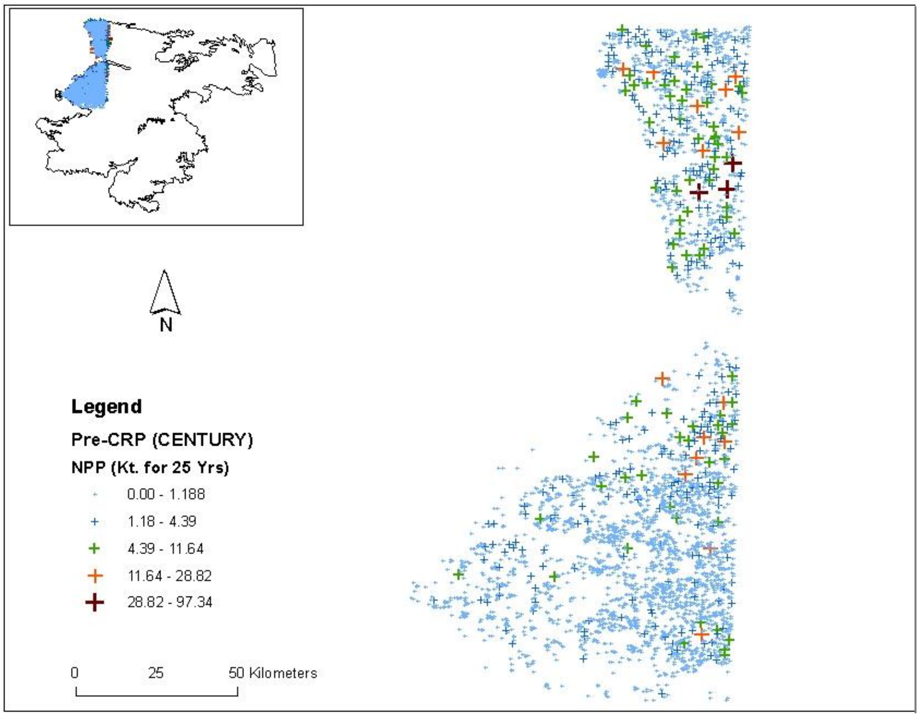

Figure 4.1: Colorado Spatial Distribution of NPP (pre-CRP CENTURY)

The spatial distribution of the Net Primary Productivity (NPP) for Colorado (Figure 4.1) shows that higher amounts of carbon sequestration are recorded in the northern part of the state where the highest values range from 28.82 to 97.34 kt of carbon sequestered per year. Since there appears to be a concentration of carbon sequestered in the northern part of the state, there was need to explore the existence of clusters. Moran's I value for Pre-CRP was 0.0242 and 0.0535 for Post-CRP for CENTURY. The Moran's I values as calculated using NPP estimation by CENTURY indicate that the distribution of carbon sequestration in Colorado is random.

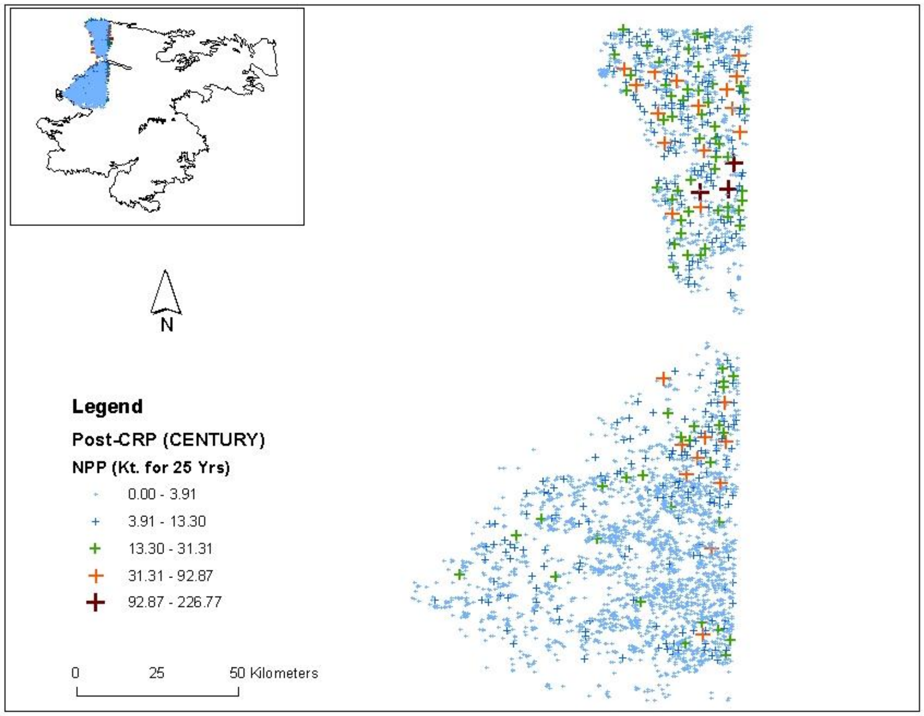

Figure 4.2: Colorado Spatial Distribution of NPP (post-CRP CENTURY)

The DAYCENT estimation of NPP shows a similar trend as that of CENTURY where clustering appears to be observable more in the northern part of the state compared to the southern part (Figures 4.3 and 4.4).

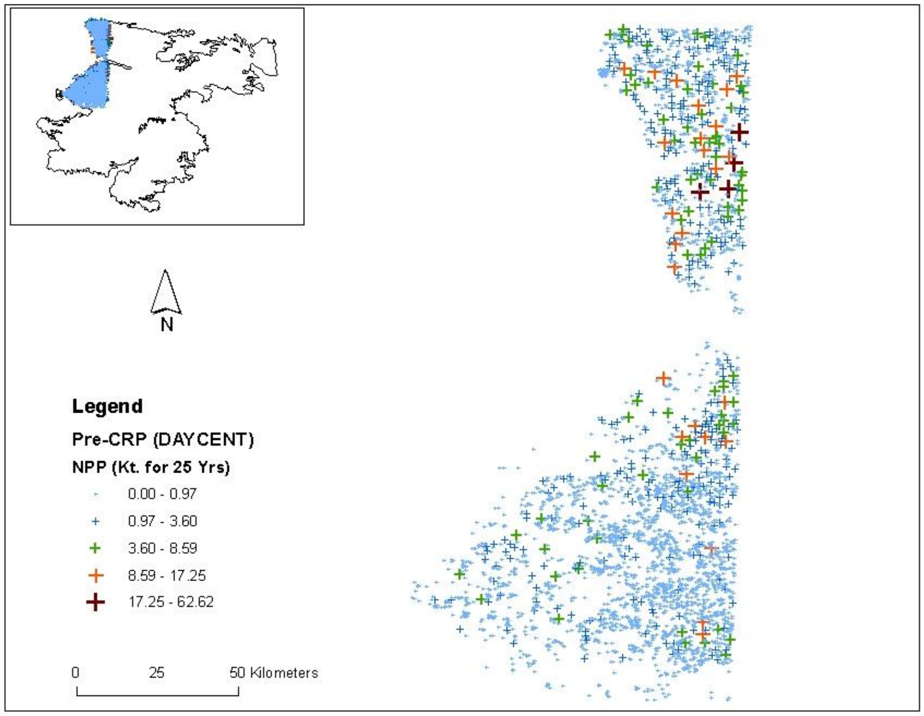

Figure 4.3: Colorado Spatial Distribution of NPP (pre-CRP DAYCENT)

Figure 4.3 presents results for the spatial distribution of pre-CRP NPP for Colorado predicted by the DAYCENT model. Based on the estimates, the NPP values ranged from 0-0.87 Kt. to 17.25-62.62 Kt. of carbon in the 25 years of simulations. A determination of Moran's I for DAYCENT shows a Moran's I value of 0.517. This value shows that the DAYCENT model suggests that there is an observed pattern in pre-CRP NPP for Colorado. These clusters are observed in the northern part of the state (Figure 4.3) where most of the values from 8.59 to 62.62 Kt. appear to be concentrated.

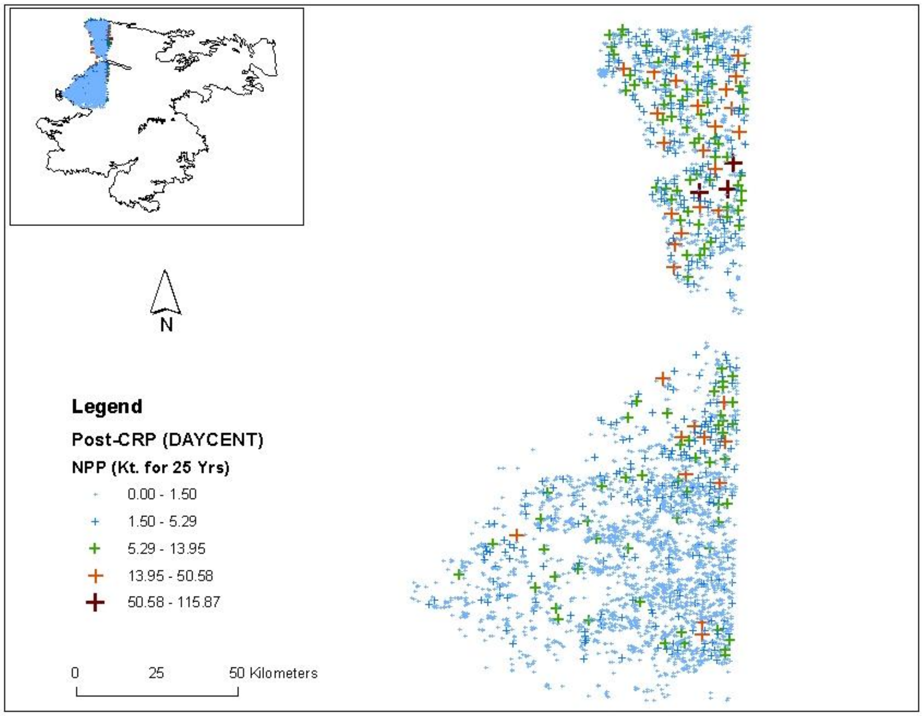

Figure 4.4: Colorado Spatial Distribution of NPP (post-CRP DAYCENT)

The post-CRP NPP estimates shown in Figure 4.4 predict a 45.86 percentage increase in the amount of NPP in Colorado from pre-CRP to post-CRP during the entire simulation period (25 years). A test of spatial autocorrelation shows a Moran's I value of 0.0488 for the post-CRP NPP in Colorado. This means that the spatial distribution of NPP in Colorado is occurring by chance (not spatially autocorrelated) for post-CRP while patterns are observed for the pre-CRP based on estimates by the DAYCENT model.

4.2.2 Temporal Distribution of Carbon Sequestration in Colorado:

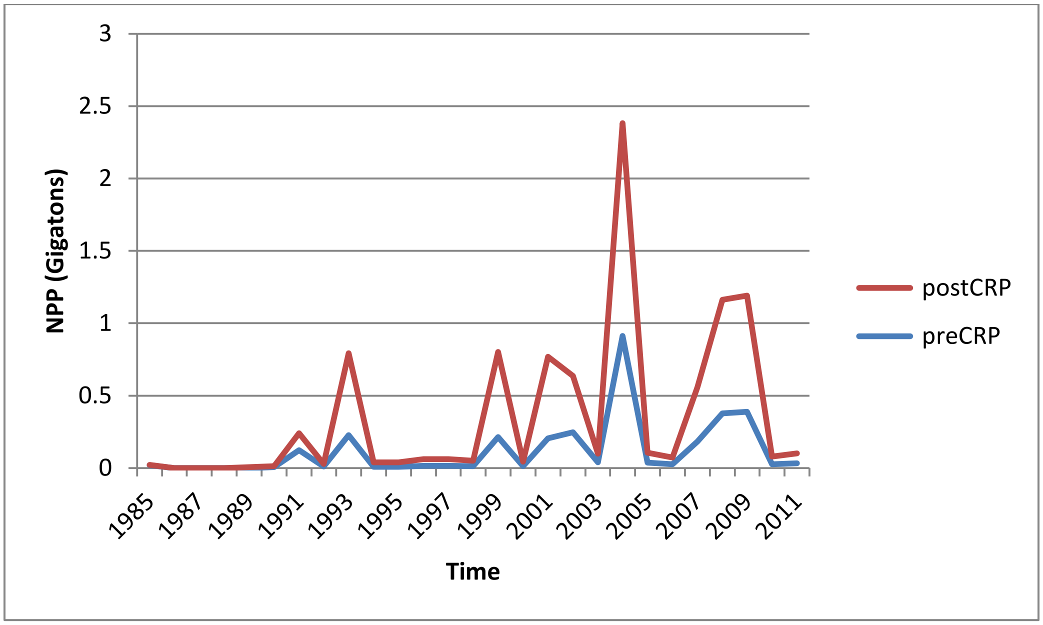

Figure 4.5: Colorado NPP Temporal Distribution

A change in NPP over time is shown in figure 4.5. The results are presented for pre-CRP and post-CRP scenarios. Results show that the amount of carbon sequestration has increased in Colorado since the inception of the CRP program in 1985. The increase in carbon sequestration here has followed a similar trend for the pre-CRP environment, except at a lower rate. There was one exception in 2000 with no increase in carbon sequestration with CRP, and 1994-1997 when the rate of increase was minimal. There was an exceptionally high amount of carbon sequestration in 2004, as well as 2007-2009. It is not clear why the increase in 2004 but it can be speculated that the 2007-2009 increase may be attributed to the re-enrollment and extension program (REX) which was authorized in 2006 for contracts expiring in 2007, 2008 or 2009. In general though, the results in Colorado seem to suggest that the longer the period of the CRP the more the amount of carbon that is sequestered. This will appear logical since under such conditions, the soil is covered which will in turn reduce the rate and amount of soil erosion and therefore limit the amount of carbon dioxide that will be released back into the atmosphere. The less the amount of carbon that is converted back into carbon dioxide, the more carbon is sequestered both above and below ground.

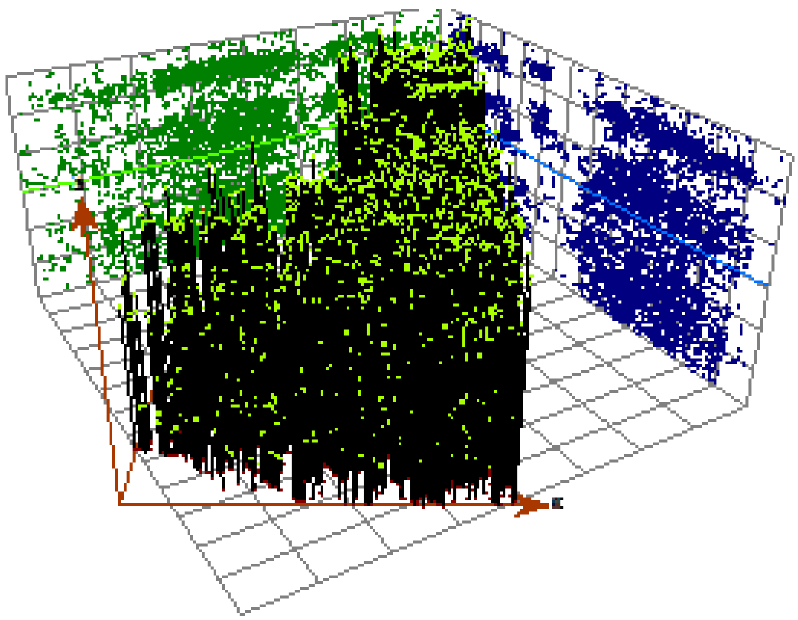

Figure 4.6: Colorado Pre-CRP NPP Trend Analysis

Figure 4.6 shows the Pre-CRP carbon sequestration trend for Colorado. The east-west direction (represented by the green line) indicates a slight eastward direction of carbon sequestration in the pre-CRP period. This trend may have been influenced by local outliers. There are seemingly no global outliers noticeable here. However, the most points tend towards the eastern direction as depicted by the trend line. In the north-south direction (represented by the blue line), there is no apparent trend since the trend line appears to be flat, although there is a slight inclination towards the north. The implication is that in the pre-CRP period, there has been a slightly higher degree of carbon sequestration in the eastern and northern CRP areas in Colorado. The northward trend observed here seems to support the results presented in Figures 4.1-4.4.

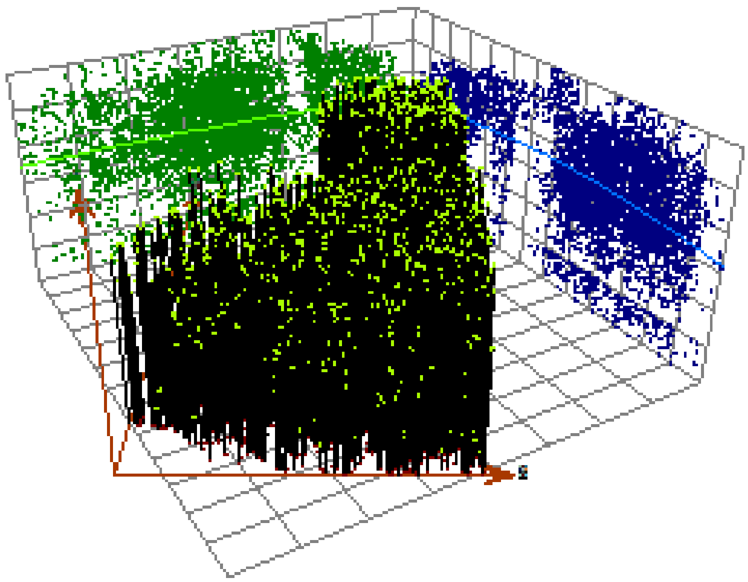

Figure 4.7: Colorado Post-CRP NPP Trend Analysis

In terms of the post-CRP carbon sequestration trend for Colorado (Figure 4.7), the east-west direction (represented by the green line) indicates a slight eastward direction as was the case with the pre-CRP period observed in Figure 4.6. The slight rise in carbon sequestration in the eastward direction may also have been influenced by the local outliers evident in the eastward direction. Again, the most points tend towards the eastern direction as depicted by the trend line. In the north-south direction (represented by the blue line), the trend line shows a stronger inclination towards the north compared to what was observed in the pre-CRP scenario. As observed in the trends for the pre-CRP, higher carbon sequestration rates in Colorado are trending toward the west to east and south to north directions.

4.2.3 Rates of Carbon Sequestration in Colorado**:** The turnover rates were estimated in terms of structural and metabolic rates for both the CENTURY and DAYCENT models for pre-CRP and post-CRP scenarios. Results as presented in Figure 4.8 show that the structural rates are higher than the metabolic rates as estimated by the two models. The rates are generally higher for post-CRP than pre-CRP scenarios for both models, and the predictions are comparable for the two models, except for strucc(2) where the CENTURY model estimated about 1000 kt compared to 800 kt by the DAYCENT in 25 years.

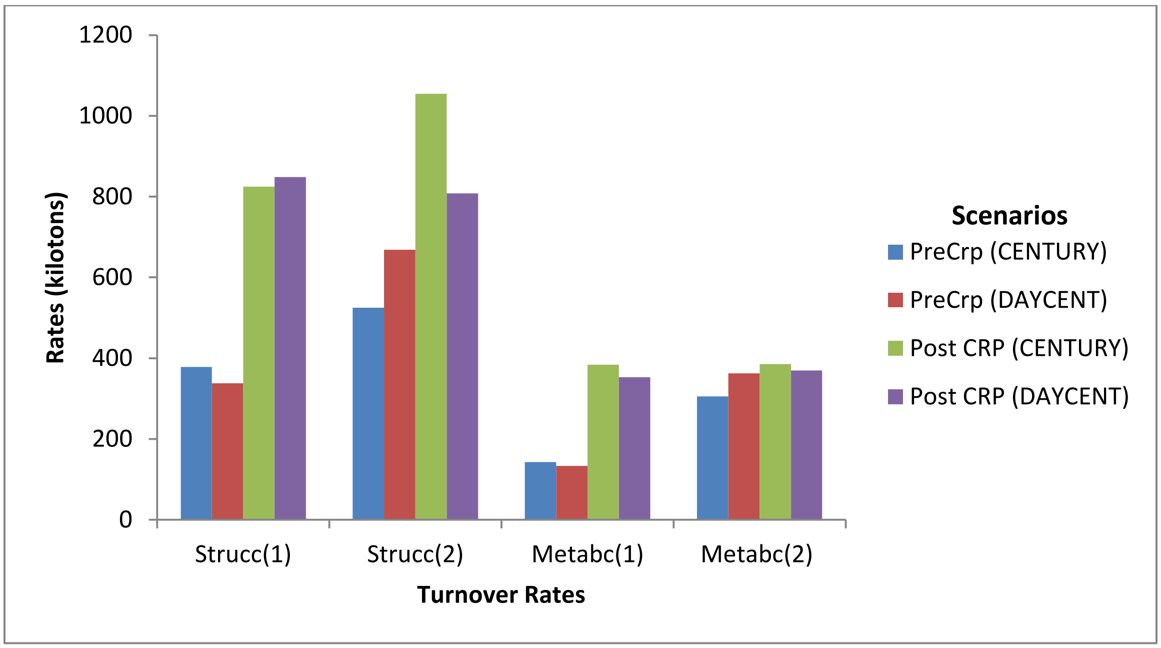

Figure 4.8: Structural and Metabolic Turnover Rates for Colorado

The turnover rates in terms of active (som1c(2), passive (som2c) and slow (som3c) are presented in Figure 4.8. The turnover rate depicted by som1c(1) is the litter level, whereas the som1c(2) represents the active turnover rate which is between 2-5 years, and the som2c is the slow turnover rates that reaches 50 years. The passive rate which is depicted by som3c can reach up to 200 years. Indeed, both models (Figure 4.9) have predicted very low rates (0-100 Kt) of the litter level carbon sequestration, and a higher rate (0-250 Kt) of the slow turnover rates. Generally speaking, the DAYCENT model estimated slightly higher values than the CENTURY model for both the active and slow rates, but the two models estimated the same values for the passive turnover rates. Figure 4.9 also shows that apart from the passive rates, both models have estimated higher turnovers for post-CRP compared to pre-CRP scenarios for the active and slow rates.

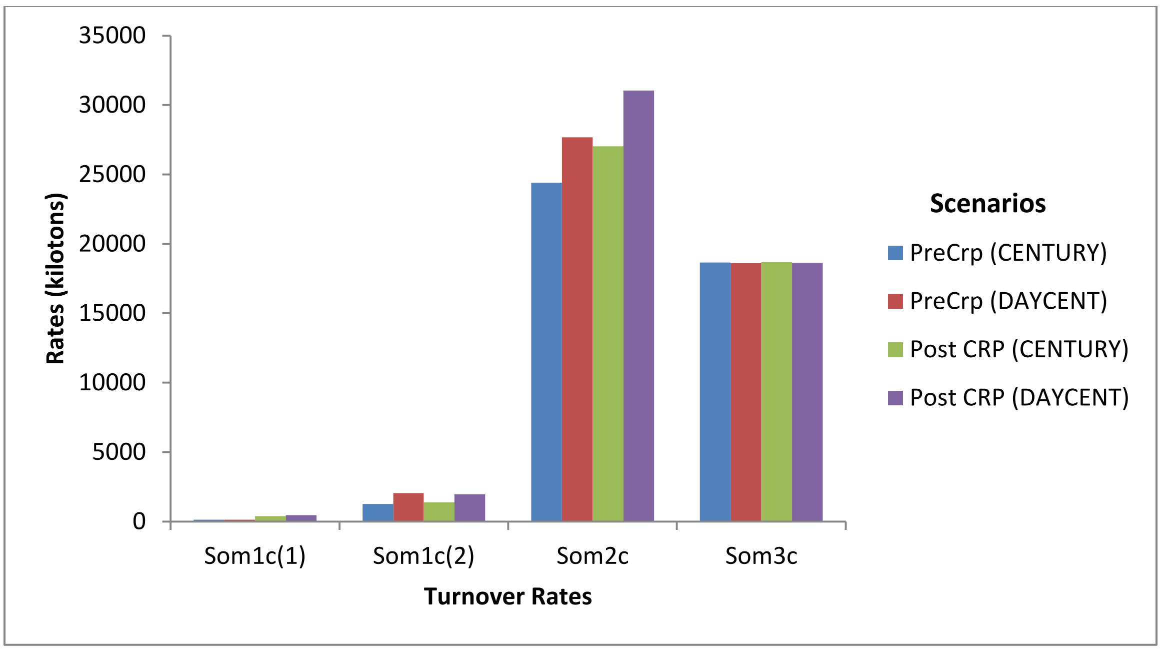

Figure 4.9: Active, slow and Passive turnover Rates for Colorado

4.2.4 Management Scenarios for Carbon Sequestration: Colorado: In order to determine the effects of management on carbon sequestration, three management scenarios, grazing, fire and the planting of biofuel crops were created and fed into the two models, CENTURY and DAYCENT. Results for NPP show that above ground carbon sequestration increased more than below ground carbon sequestration with the introduction of management practices on CRP tracts (see Figure 4.10). The two models as presented in Figure 4.10 reveal that estimates of both the standing dead and above ground NPP are negligible when management scenarios are applied to sequester carbon on CRP tracts, but that more carbon is sequestered below ground. The two models suggest that fire has a greater impact in sequestering carbon than grazing and biofuel in that order.

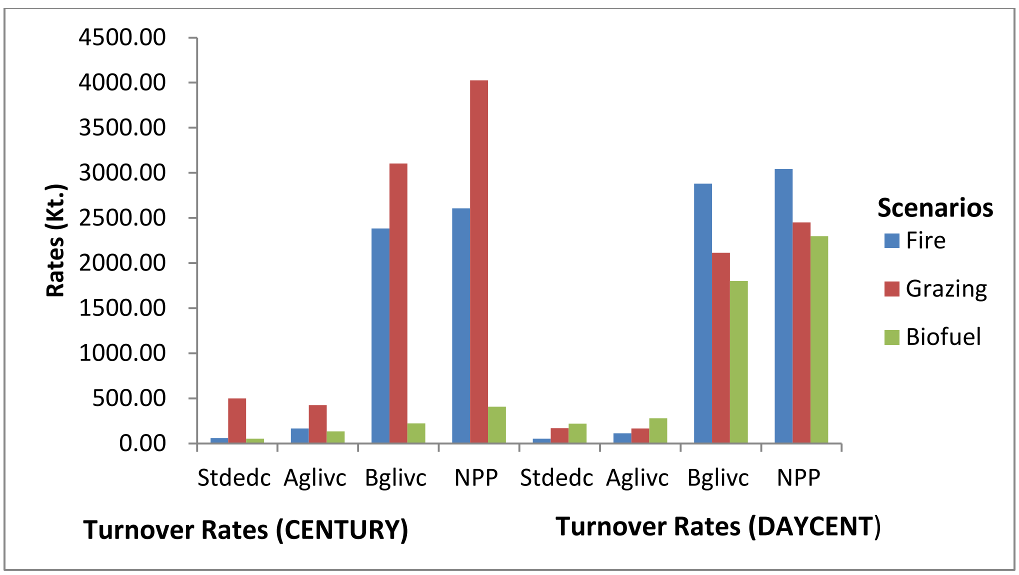

Figure 4.10: Management Scenarios for NPP for Colorado

In terms of the structural and metabolic rates (Figure 4.11) of carbon sequestration, however, the results show that the three management scenarios have less effect on carbon sequestration rates in Colorado. The highest amount of carbon that could be sequestered using the fire, grazing and biofuel management systems is about 900 Kt. in a 25-year period. The only exception is the value predicted by the DAYCENT model for strucc(2) which stands at about 3,850 Kt. of carbon. It is unclear why this value is this high, but it will be considered an outlier compared with the remaining estimates.

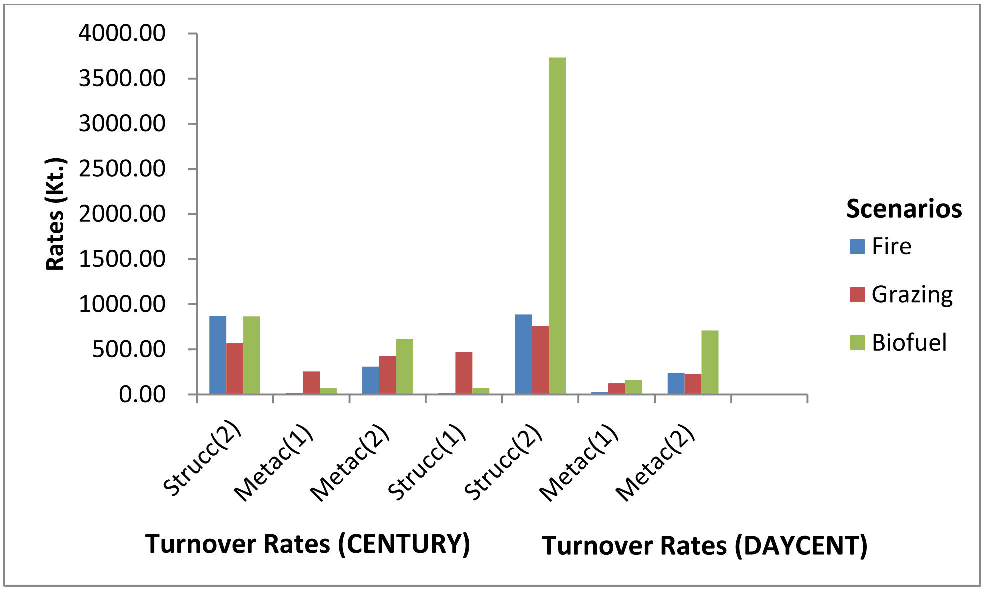

Figure 4.11: Management Scenarios for Structural and Metabolic Carbon Rates: Colorado

Regarding the turnover rates of active, slow and passive (see Figure 4.12), the results suggest that the implementation of the three management practices will boost the slow and passive carbon sequestration in the study area especially if considered in combination. Figure 4.12 reveals that the amount of active carbon sequestration based on the management scenarios is about 80 Kt. (3.2 Kt. per year), while that of the slow and passive range from 2000-2900 Kt. (80-116 Kt per year). Interestingly, though, both models have predicted almost equally in this regard showing that grazing, fire and biofuel will influence carbon sequestration in order of magnitude for the slow rate in that order.

The values for the passive rate, however, show that the use of fire will sequester more carbon than both grazing and biofuel which show equal effects for carbon sequestration.

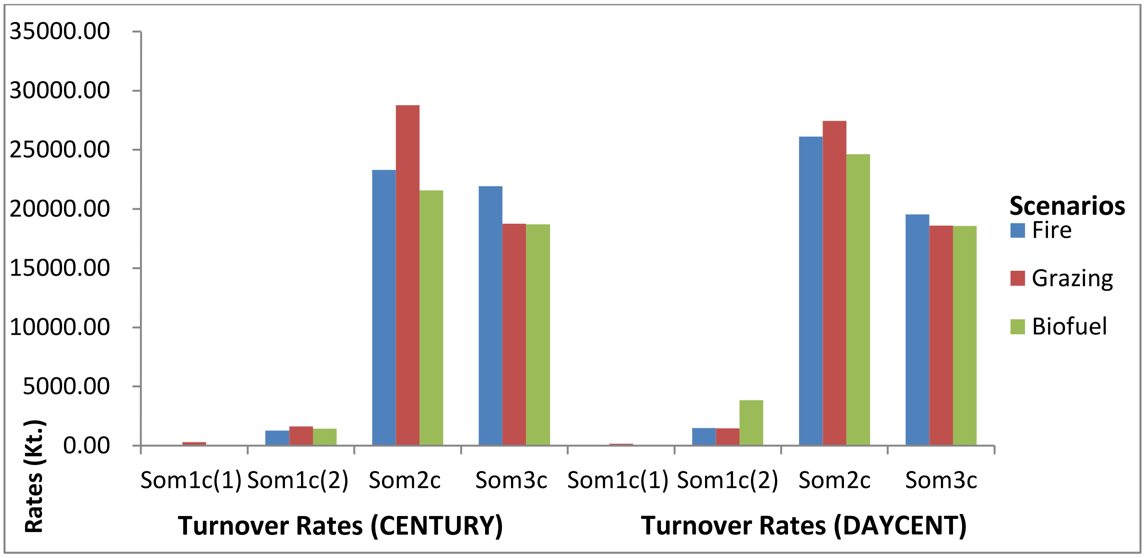

Figure 4.12: Management Scenarios for Active, Slow and Passive Turnover rates: Colorado

4.3.1 Kansas Carbon Sequestration Estimates:

Table 4.2: Net Primary Productivity (NPP) for Kansas

Scenario	Stdedc (kt)	Aglivc (kt)	Bglivc (kt)	NPP (kt)
Pre-CRP (CENTURY)	1179.00	1681.05	5833.24	8693.29
Pre-CRP (DAYCENT)	1516.61	2417.06	13991.09	17924.77
Post-CRP (CENTURY)	3172.71	2554.70	22869.88	28597.29
Post-CRP (DAYCENT)	4416.34	3895.60	23550.14	31862.08

Table 4.2 presents the results of the NPP for Kansas for pre-CRP and post-CRP as estimated by CENTURY and DAYCENT models. Whereas there is an apparent

significant difference in the estimates of pre-CRP carbon sequestration between the two models, the estimates for post-CRP carbon sequestration are rather close. The CENTURY model predicts a 23% increase in carbon sequestration from pre-CRP to post-CRP; while the DAYCENT model predicts a 21% increase. The CENTURY model predicts an average amount of NPP for pre-CRP to be 0.06 Kt. of carbon per Km^2, with a post-CRP value of 0.20 Kt. per Km^2 per year. The average values estimated by DAYCENT are 0.11 Kt. and 0.20 Kt. per Km^2 per year for pre-CRP and post-CRP respectively. This shows that the post-CRP estimates for the two models are the same. Table 4.2 also shows that carbon is sequestered more below ground (Bglivc) than above ground (Aglivc), and that the carbon sequestered in leaves and stems is greater than standing dead carbon (Stdedc).

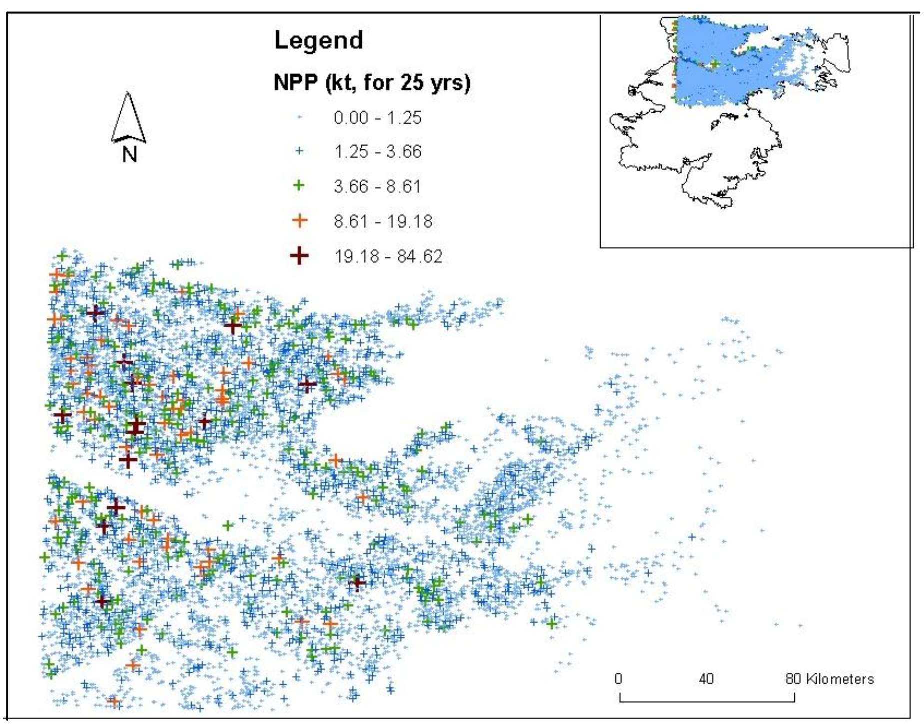

Figure 4.13: Spatial Distribution of NPP in Kansas (pre-CRP, CENTURY)

The results of the spatial distribution of pre-CRP NPP in Kansas using *CENTURY (Figure 4.13) show that the western part of Kansas has higher carbon* sequestration values compared to the east. The lowest values of NPP estimated by the CENTURY model for pre-CRP range from 0 to 3.59 Kt. of carbon and the highest values range from 38.76 to 240.56 Kt..

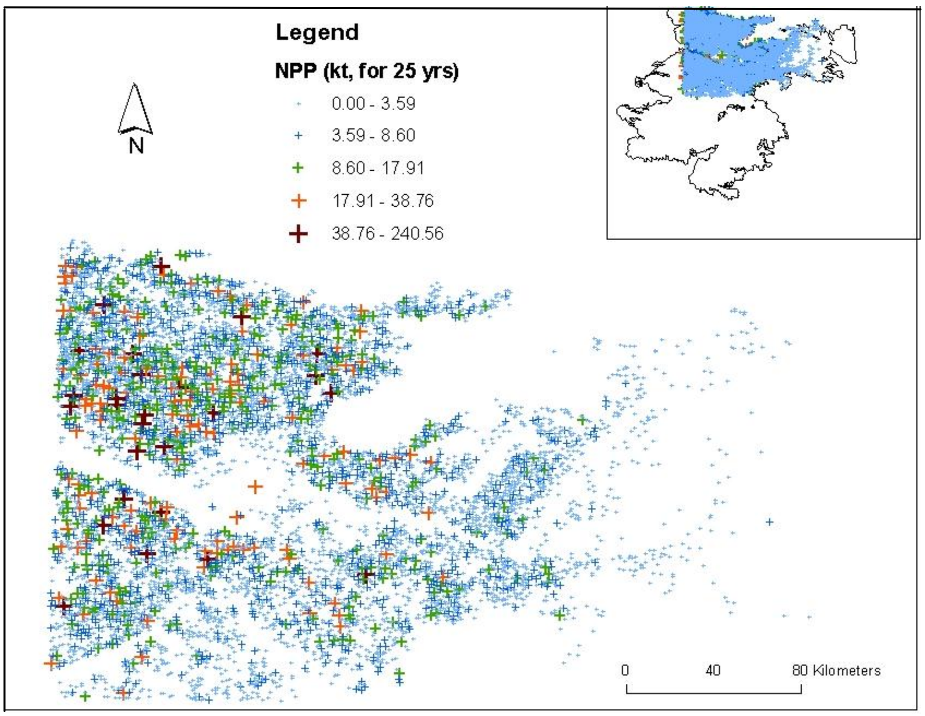

Figure 4.14: Spatial Distribution of NPP for Kansas for post-CRP (CENTURY)

The post-CRP distribution of NPP estimated by the CENTURY model follows a similar pattern to the pre-CRP distribution. More carbon is sequestered in the western part than the eastern part of the state (see Figure 4.14). However, the values for the post-CRP are 0 to 3.59 Kt. of carbon; and 38.76 to 240.56 Kt. of carbon for lowest and highest ranges, respectively. This is an indication of a significant increase (of between 57.89 to 63.33%) in carbon sequestration in the study area after the introduction of CRP.

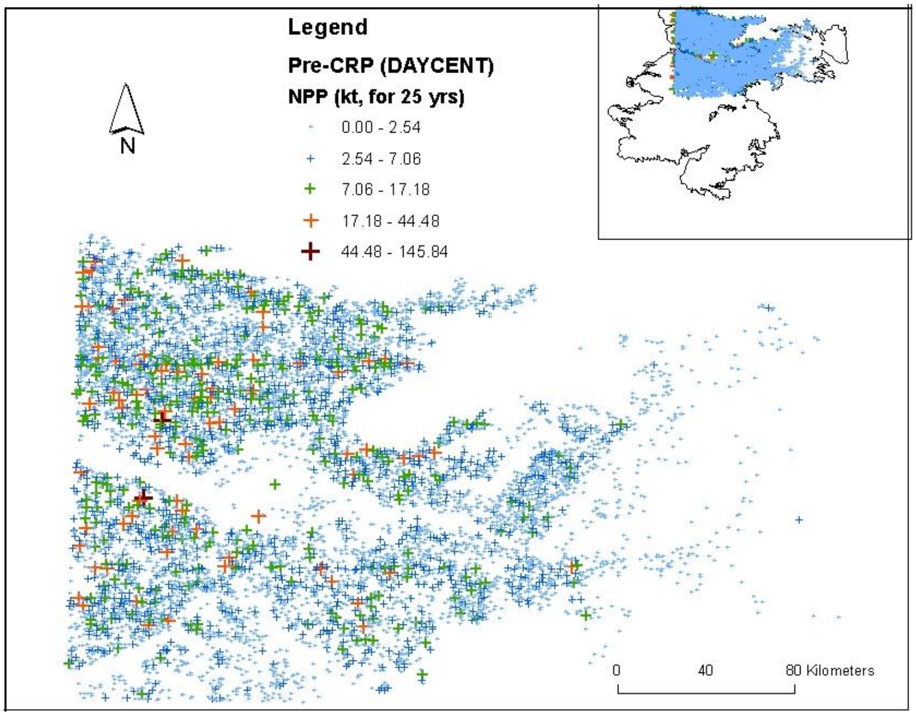

Figure 4.15: Spatial Distribution of NPP for Kansas for pre-CRP (DAYCENT)

The spatial distribution of the pre-CRP NPP estimated by the DAYCENT model for Kansas follows the same pattern with that of the CENTURY model with higher concentrations of carbon sequestration in the western part of the state. The results show that the DAYCENT model has estimated higher pre-CRP carbon values than the CENTURY model for the same area. Generally, the DAYCENT model is predicting a 53.45 % increase in carbon sequestration from pre-CRP to post-CRP.

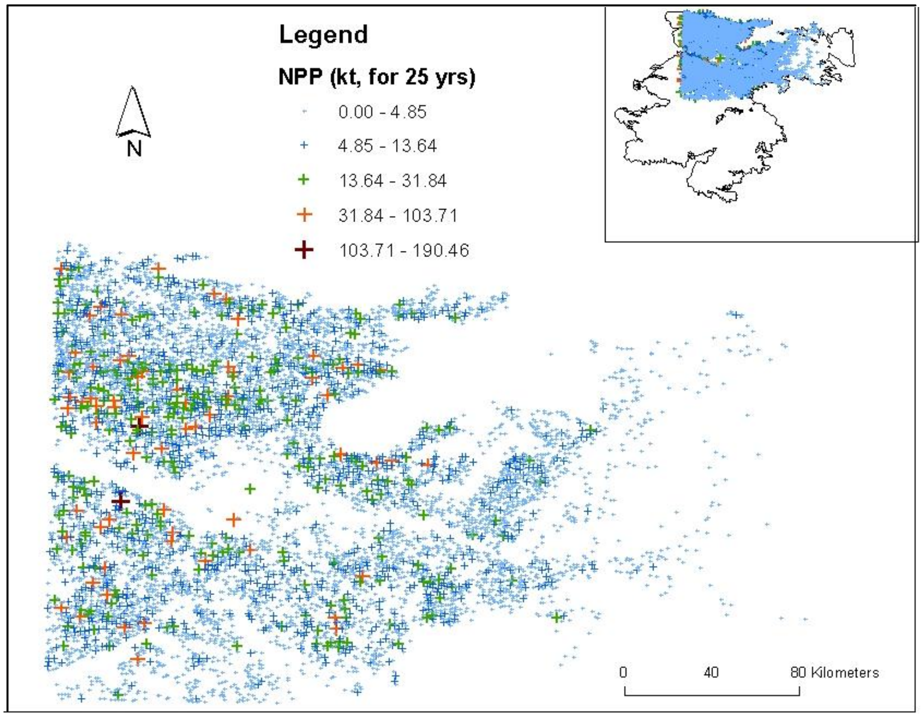

Figure 4.16: Spatial Distribution of NPP for Kansas using DAYCENT (post-CRP)

Moran's I tests were conducted to determine spatial autocorrelation in the area and results show values of 0.0476 and 0.0652 for pre-CRP and post-CRP for CENTURY respectively. The value of the Moran's I for the DAYCENT model were 0.0766 for pre-CRP and 0.0977 for post-CRP. The two models by these results have indicated that the distribution of NPP in Kansas depicts random permutations.

4.3.2 Temporal Distribution of Carbon Sequestration in Kansas:

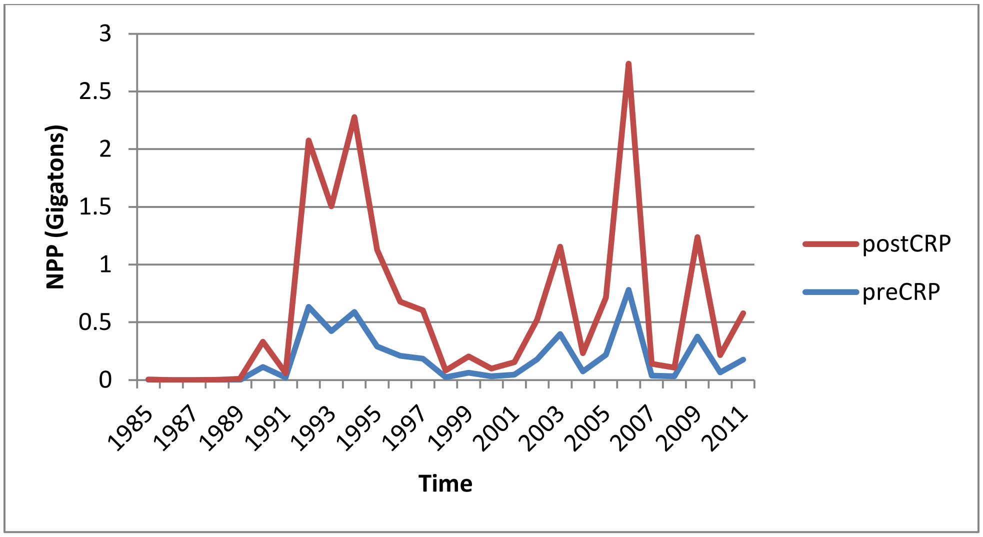

Figure 4.17: Kansas Temporal Distribution of Carbon Sequestration (Pre-CRP and post-CRP)

The results of the temporal distribution (Figure 4.17) indicate that carbon sequestration has increased with the introduction of the CRP program. The high increases from 1992-1998 do not seem to have any clear explanation, but may be pointers to the fact that increases in carbon sequestration are attributable to other factors (such as soil physical quality) other than CRP alone; because if CRP was the only factor, a steady increase in carbon sequestration would have been observed with time from the inception of the program. It may be speculated that the increases in 2006 and 2009 could be tied to the REX program (already discussed elsewhere in this study) which was instituted during this time. These high values coincide with clusters that showed very high rates of carbon sequestration in the study area as depicted by the spatial distribution of carbon sequestration in Kansas.

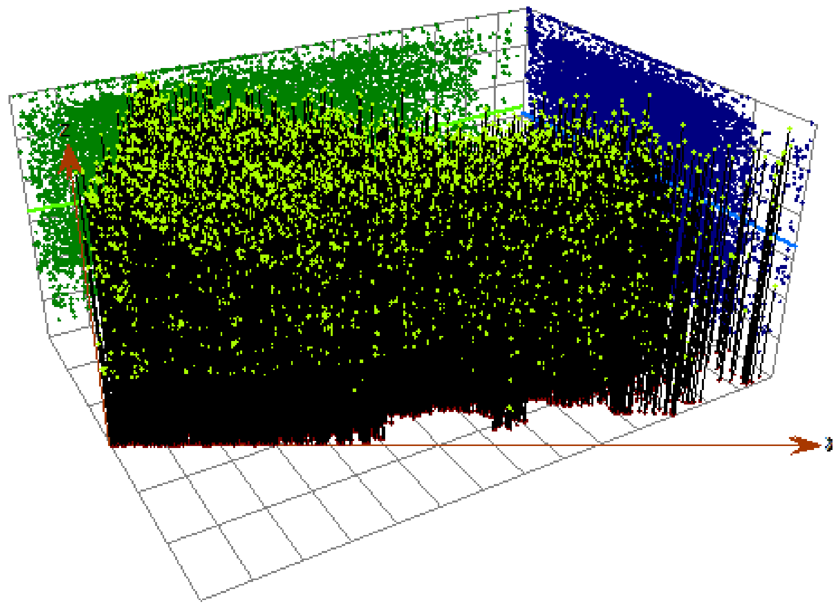

Figure 4.18: Kansas Pre-CRP NPP Trend Analysis

Figure 4.18 suggests that carbon sequestration trends from east to west in Kansas in the pre-CRP period. The slight rise in carbon sequestration in the eastward direction may have been influenced by the global outliers that are firmly in the western direction. The local outliers are generally in the continuum between the western and eastern sections. However, most points trend towards the eastern direction as depicted by the trend line. In the north-south direction (represented by the blue line), the trend line shows an inclination towards the north where there appears to be a concentration of global outliers. The implication is that in the pre-CRP period, there has been a slightly higher degree of carbon sequestration in the eastern and northern CRP areas in Kansas. Other factors that could have influenced this trend include grass types and stand density, climatic factors, and soil conditions, among other factors.

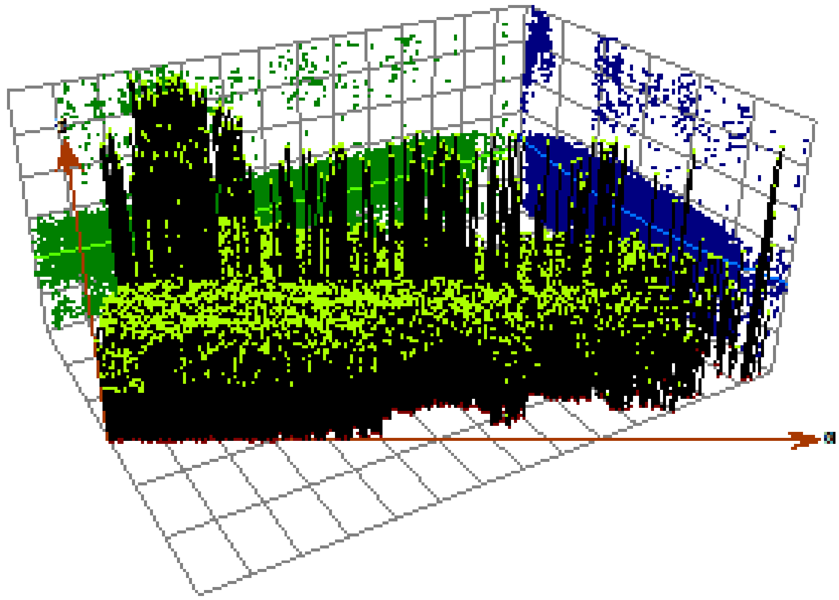

Figure 4.19: Kansas Post-CRP NPP Trend Analysis

Post-CRP carbon sequestration trend for Kansas show a west to east direction (represented by the green line). The global outliers are firmly in the western direction, which accounts for slight rise in carbon sequestration in the eastward direction. The local outliers generally fall within the western and eastern sections. In the north-south direction (represented by the blue line), the trend line shows an inclination towards the north where there appears to be a concentration of global outliers. Consequently, as is the case with the pre-CRP period, there has been a slightly higher degree of carbon sequestration in the eastern and northern CRP areas in Kansas.

4.3.3 Rates of carbon sequestration in Kansas: The rates of carbon sequestration were determined based on turnovers, including passive, active and slow. The turnover rates were estimated in terms of structural and metabolic rates for both the CENTURY and DAYCENT models for pre-CRP and post-CRP scenarios. Results presented in Figure 4.20 show that the structural rates (strucc(1); struck(2)) are higher than the metabolic rates (metabc(1); metabc(2)) as estimated by the two models. The rates are of course higher for post-CRP compared to pre-CRP scenarios for both models and the predictions are comparable for the two models. And while the CENTURY model estimates lower values for pre-CRP and post-CRP than DAYCENT for strucc(1), it estimates slightly higher values for strucc(2) for pre-CRP and post-CRP. For metabc(1), CENTURY model values are lower than those of DAYCENT model, but the values are about the same for metabc(2). There appear to be an anomaly in strucc(1) where the CENTURY model estimated about 4000 kt of carbon per year compared to 800 kt by DAYCENT for the same area.

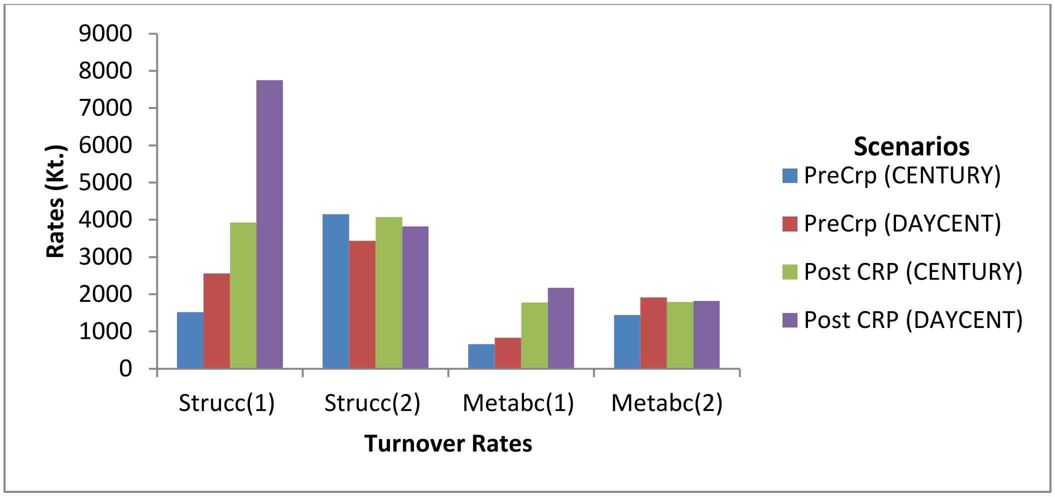

Figure 4.20: Structural and Metabolic Turnover Rates for Kansas

The turnover rates in terms of active, passive and slow are presented in Figure 4.21. The turnover rate depicted by som1c(1) is the litter level, whereas the som1c(2) represents the active turnover rate which is between 2-5 years; and the som2c is the slow turnover rate that reaches 50 years. The passive rate which is depicted by som3c can reach up to 200 years. Indeed, Figure 4.21 shows that both models have predicted very low rates of the litter level of carbon sequestration, and higher amounts of the slow turnover rates. As observed from Figure 4.21, the DAYCENT model has estimated slightly higher values than the CENTURY model for both the active and slow rates, but the two models estimated the same values for the passive turnover rates. Figure 4.21 also shows that apart from the passive rates, both models have estimated higher turnovers for post-CRP compared to pre-CRP scenarios for the active and slow rates.

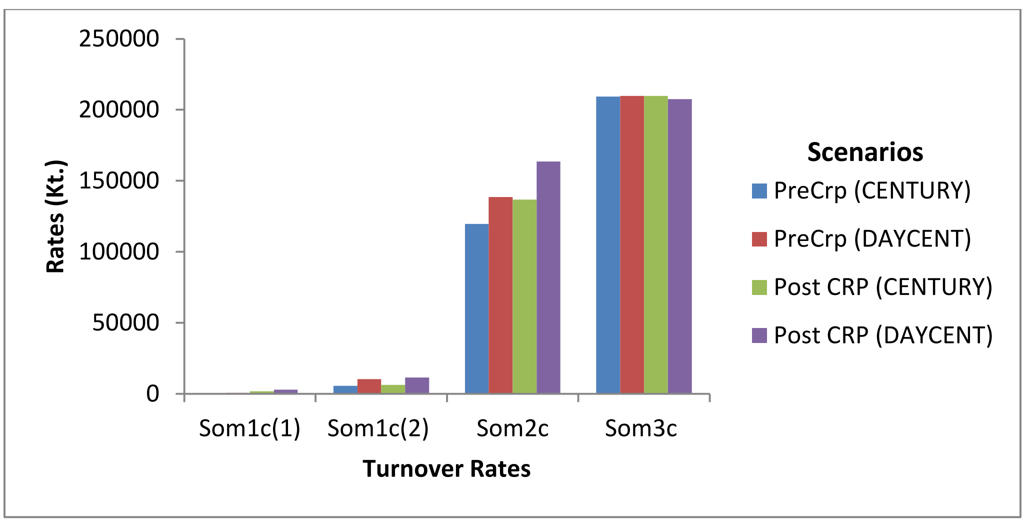

Figure 4.21: Active, Slow and Passive Carbon Turnover rates for Kansas

4.3.4 Management Scenarios for Carbon Sequestration: Kansas: Figure 4.22 summarizes the results of CENTURY and DAYCENT model simulations (2011-2050). NPP results do not seem to indicate that the introduction of management on CRP tracts will increase the amount of carbon sequestered when compared with post-CRP values. However, the results (Figure 4.22), show that the below ground carbon is greater (about 71%) than the above ground carbon. The two models presented in Figure 4.22 reveal that both the standing dead and above ground NPP is negligible when management scenarios are applied to sequester carbon on CRP tracts, but that substantive amounts of carbon are sequestered below ground. Whereas, the CENTURY model predicts that fire would sequester more carbon, than grazing, and biofuels; the DAYCENT model's figures suggest that biofuel sequesters more carbon at the litter and active levels than grazing and fire respectively.

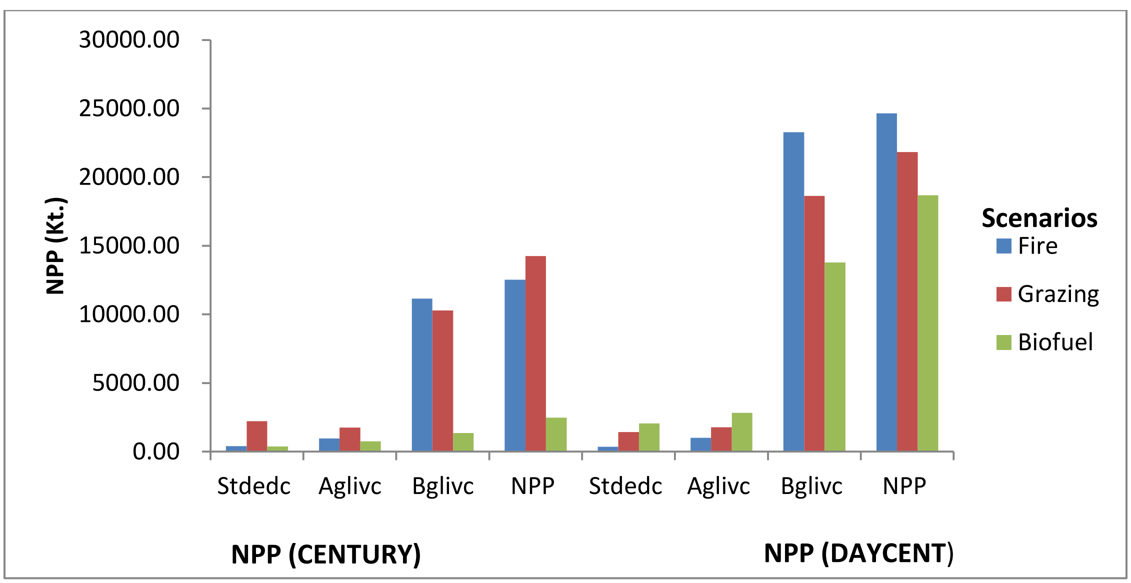

Figure 4.22: Management Scenarios NPP Carbon Rates for Kansas

Structural and metabolic carbon rates presented in Figure 4.23 suggest that the implementation of the three management practices had minimal effects on carbon sequestration in the study area. Figure 4.23 reveals that for stucc(1) only grazing showed any sign of increasing carbon sequestration based on the management scenarios at about 500 Kt. Carbon sequestration for strucc(2) shows that all three management scenarios will sequester about 600 Kt. of carbon in 39 years. The values for the DAYCENT model are not any better except for strucc(2) which shows that biofuel will increase the rate of carbon sequestration to about 18,000 Kt., a 93% increase over the CENTURY model within this 39-year period.

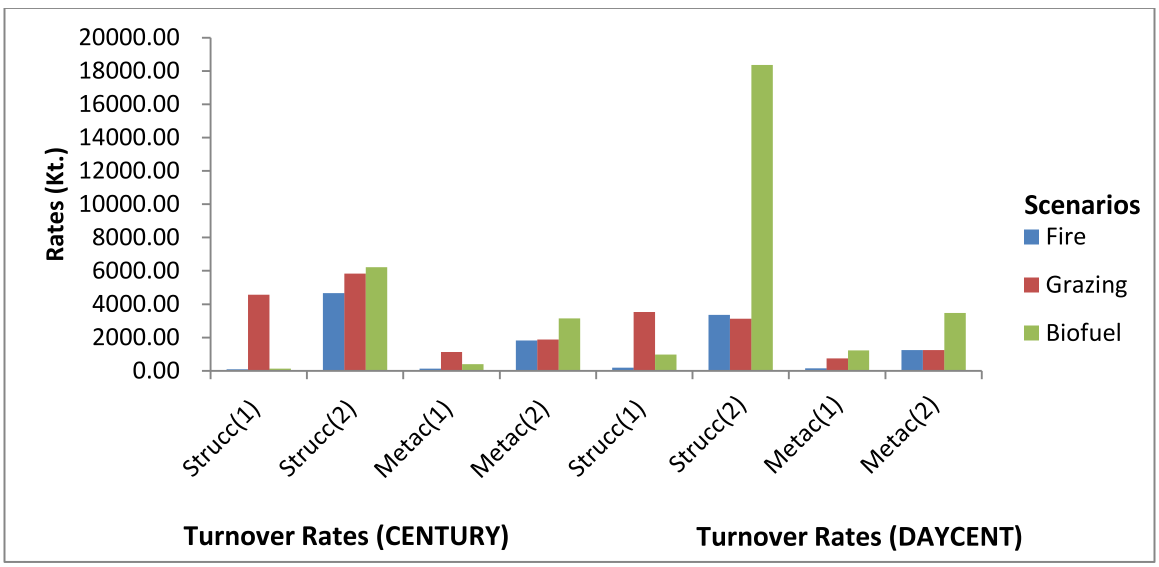

Figure 4.23: Management Scenarios for Structural and Metabolic Carbon Rates for Kansas

In terms of the turnover rates of active, slow and passive (see Figure 4.24), the results suggest that the implementation of the three management practices will increase the slow and passive carbon sequestration in the study area. Figure 4.24 reveals that the amount of active carbon sequestration based on the management scenarios is negligible while that of the slow and passive range from 100,000 to 230,000 Kt. of carbon. It should be noted that both models have equally predicted in order of magnitude that grazing, fire and biofuel will influence carbon sequestration for the slow rate. The values for the passive rate, however, show that the use of fire will sequester slightly more carbon than grazing or biofuel which show equal effects for carbon sequestration estimated by the two models.

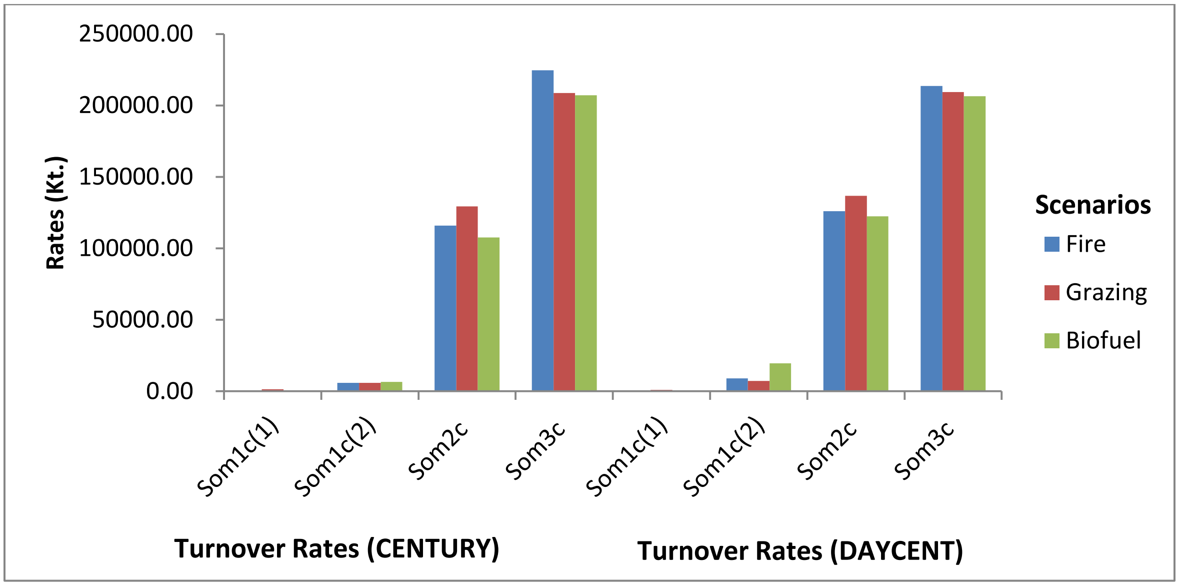

Figure 4.24: Management Scenario for Active, Slow and Passive Turnover Rates of Carbon for Kansas

4.4.1 New Mexico Carbon Sequestration Estimates:

Table 4.3: Net Primary Productivity (NPP) for New Mexico

Scenarios	Stdedc (Kt)	Aglivc (Kt)	Bglivc (Kt)	NPP (Kt)
Pre-CRP (CENTURY)	1.274	0.75	4.97	6.99
Pre-CRP (DAYCENT)	0.75	0.73	8.21	9.69
Post-CRP (CENTURY)	3.71	1.45	19.89	25.05
Post-CRP (DAYCENT)	3.63	3.78	17.25	24.67

Table 4.3 is a summary of the results for the NPP estimated for New Mexico and shows that the CENTURY model predicted lower NPP values than the DAYCENT model (difference is 2.7 Kt.) for Pre-CRP. The post-CRP estimates, however, are the reverse of what was observed in the pre-CRP environment because the CENTURY model had higher predictions (56.37% increase in carbon sequestration), compared to 44% by the DAYCENT model.

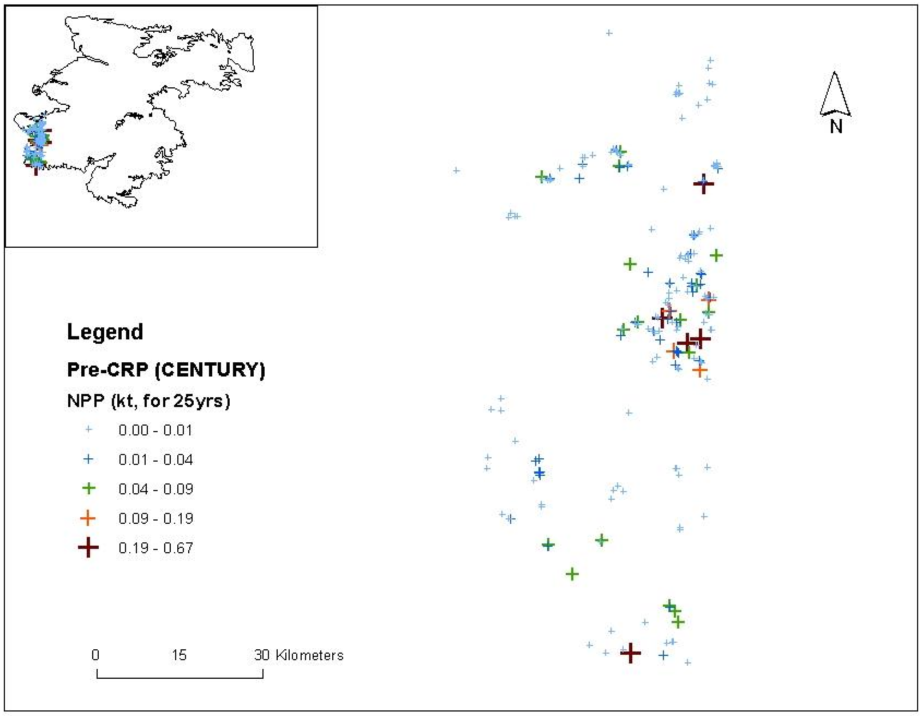

Figure 4.25: New Mexico Spatial Distribution of NPP (pre-CRP,CENTURY)

The spatial distribution of the NPP for New Mexico (Figure 4.25) shows pockets of high amounts of carbon sequestration across the state where the highest values range from 0.19 to 0.67 kt of carbon and lower values 0 to 0.01 Kt. of carbon. Moran's Index (Moran's I) was run for NPP using GeoDa (Anselin 2006), and the values for Pre-CRP were - 0.0176 and -0.0171 for Post-CRP for CENTURY. On the other hand, DAYCENT shows a Moran's I of -0.0041 and 0.0147 for pre-CRP and post-CRP respectively. Based on the Moran's I values for New Mexico, NPP shows no observed pattern.

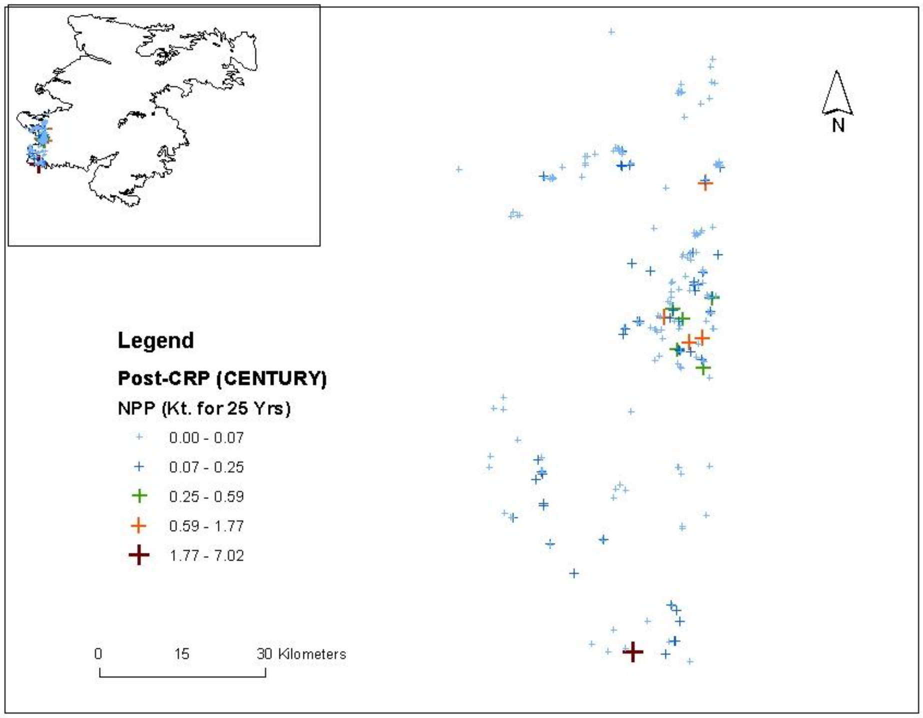

Figure 4.26: Spatial Distribution of NPP for New Mexico for post-CRP (CENTURY)

The spatial distribution of the NPP presented in Figure 4.26 for post-CRP using the CENTURY model estimates values for post-CRP ranging from 0.0 to 0.07 Kt. of carbon. It shows an increase of 66.10% in carbon sequestration from pre-CRP to post-CRP in New Mexico.

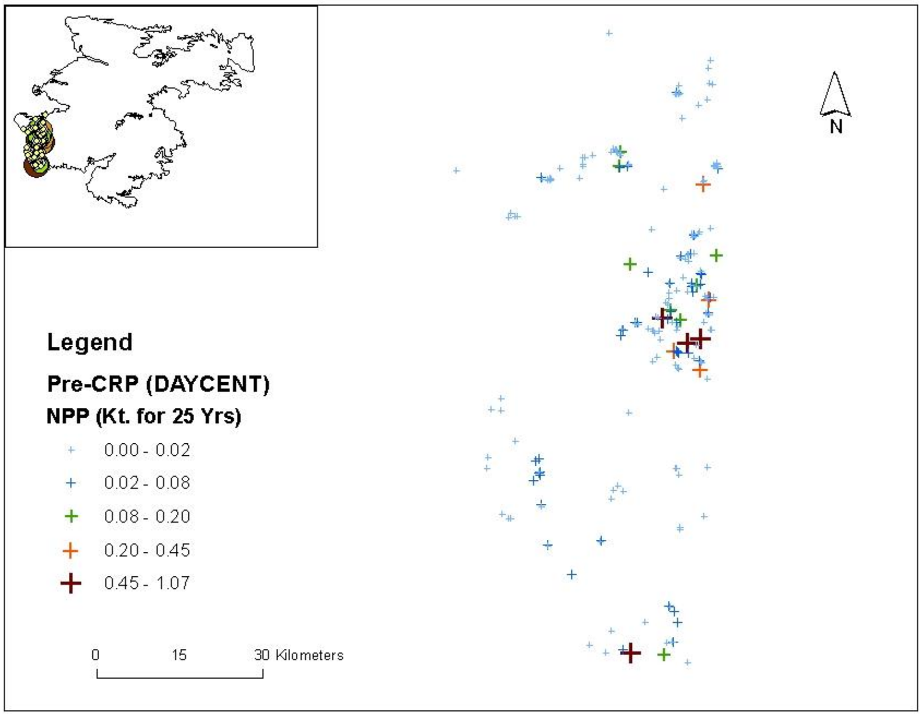

Figure 4.27: Spatial Distribution of NPP for New Mexico for pre-CRP (DAYCENT)

The estimation of pre-CRP NPP by the DAYCENT model for New Mexico (Figure 4.27) follows a similar pattern with that of the CENTURY model (Figure 4.26) where pockets of higher concentrations of carbon sequestration are observed in different parts of the state. The results depicted in Figure 4.27 show that the DAYCENT model has estimated higher pre-CRP carbon values than the CENTURY model for the same area. Similarly, the post-CRP spatial distribution estimated by the DAYCENT model presented in Figure 4.28 shows an 85.99% increase in carbon sequestration from pre-CRP to post-CRP compared to about 66% predicted by the CENTURY model over a 25-year period.

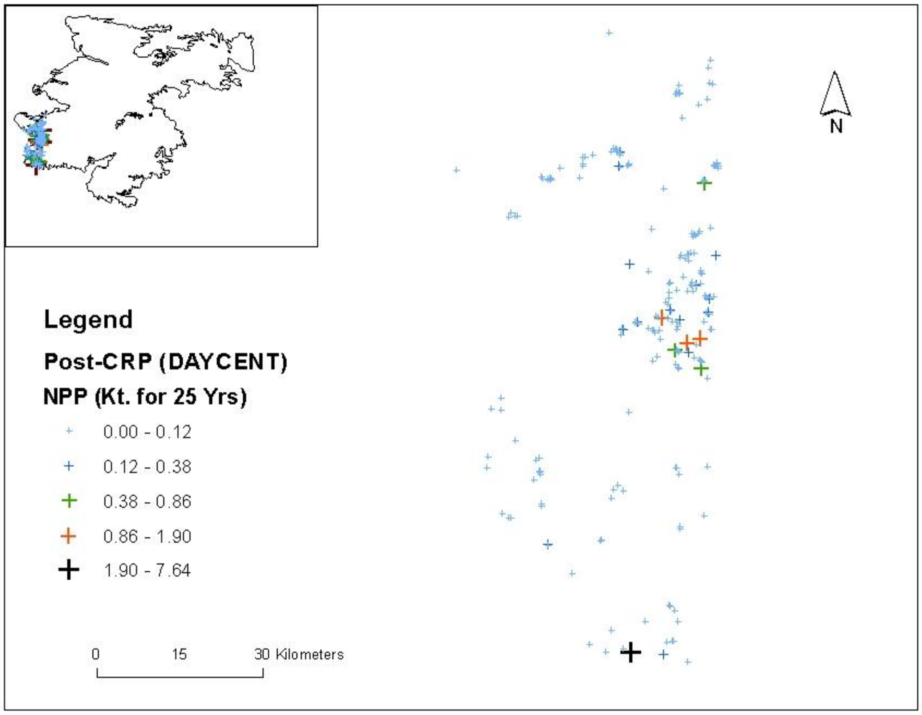

Figure 4.28: Spatial Distribution of NPP for New Mexico using DAYCENT (post-CRP)

4.4.2 Temporal Distribution of Carbon Sequestration in New Mexico:

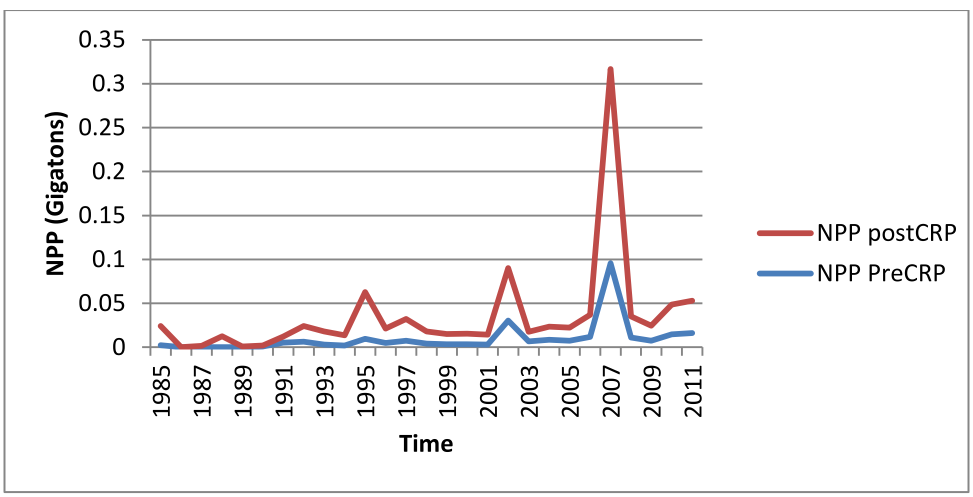

Figure 4.29: NPP Temporal Distribution for New Mexico

The temporal distribution of carbon sequestration in New Mexico appears to suggest an increase with age of grass (Figure 4.29). The only exception to this rule would be the period from 2007-2008 in which there is dramatic increase in carbon sequestration in the study area. As noted elsewhere in the study, this extraordinary increase in carbon sequestration can be speculated to be as a result of the REX program, which came into effect in 2006. However, apart from the initial years of the CRP program, there has been an increase in carbon sequestration post-CRP compared to pre-CRP (Figure 4.29). The amount of carbon sequestration in general also appears to be greater with longer periods of enrollment in CRP in New Mexico.

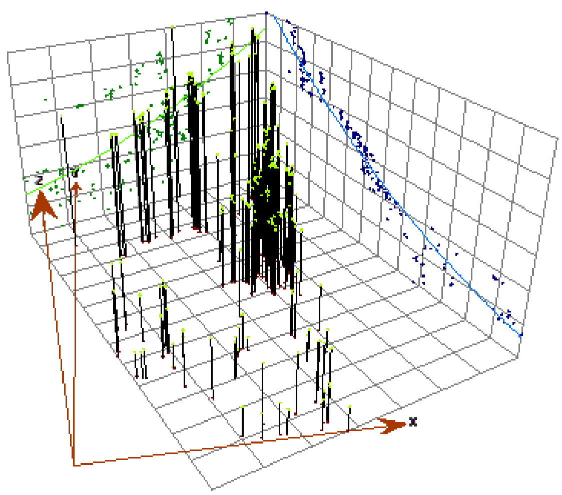

Figure 4.30: Pre-CRP NPP Trend Analysis for New Mexico

In New Mexico (Figure 4.30) Pre-CRP carbon sequestration shows an east-west trend. The sharp rise in carbon sequestration in the eastward direction is depicted by the trend line (represented in green). The few global outliers in the continuum between the western and eastern sections do not seem to have affected the trend here in New Mexico.

The north-south direction (represented by the blue line), on the other hand, shows a trend with an inclination towards the north, although neither local nor global outliers are evident. This implies that in the pre-CRP period, higher degree of carbon sequestration is trending in the eastern and northern CRP areas in New Mexico.

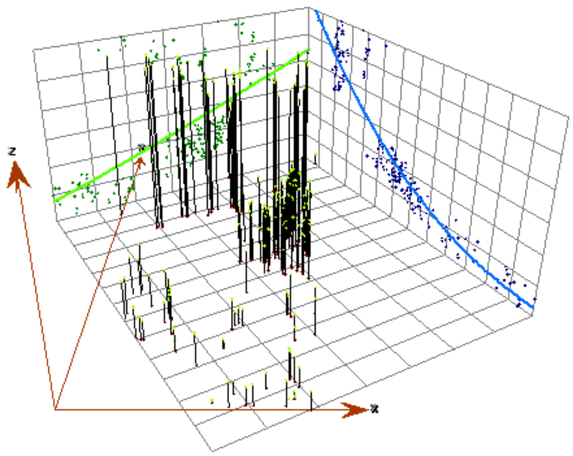

Figure 4.31: Post-CRP NPP Trend Analysis for New Mexico

As revealed by Figure 4.31, the Post-CRP carbon sequestration trend for New Mexico is similar to the pre-CRP period, in that the east-west direction (represented by the green line) is trending in the eastward direction. However, the rise in carbon sequestration in the eastward direction appears to have been influenced by local rather than global outliers. In the north-south direction (represented by the blue line), the trend line shows an inclination towards the north.

4.4.3 Rates of carbon sequestration in New Mexico: Estimated results by both models (Figure 4.32) show that in general, the structural rates are higher than the metabolic rates. The rates are higher for post-CRP than pre-CRP scenarios for both models, and the predictions are comparable for the two models, except for strucc(2) where estimates for the CENTURY model are higher than those of the DAYCENT model.

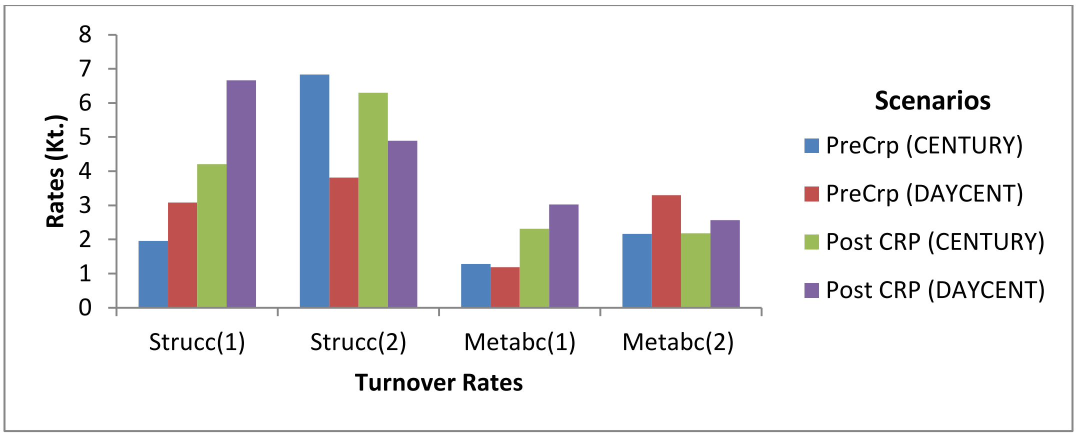

Figure 4.32: Structural and Metabolic Carbon Turnover Rates for New Mexico

Both models have predicted very low rates of the litter level carbon sequestration, and a higher rate of the slow turnover rates (Figure 4.33). There are no marked differences between the values estimated by the CENTURY model and the DAYCENT model. Figure 4.33 also shows that apart from the passive (som3c) rates (which show no change), both models have estimated higher turnovers for post-CRP compared to pre-CRP scenarios for the active (som1c(2) and slow rates (som2c) respectively.

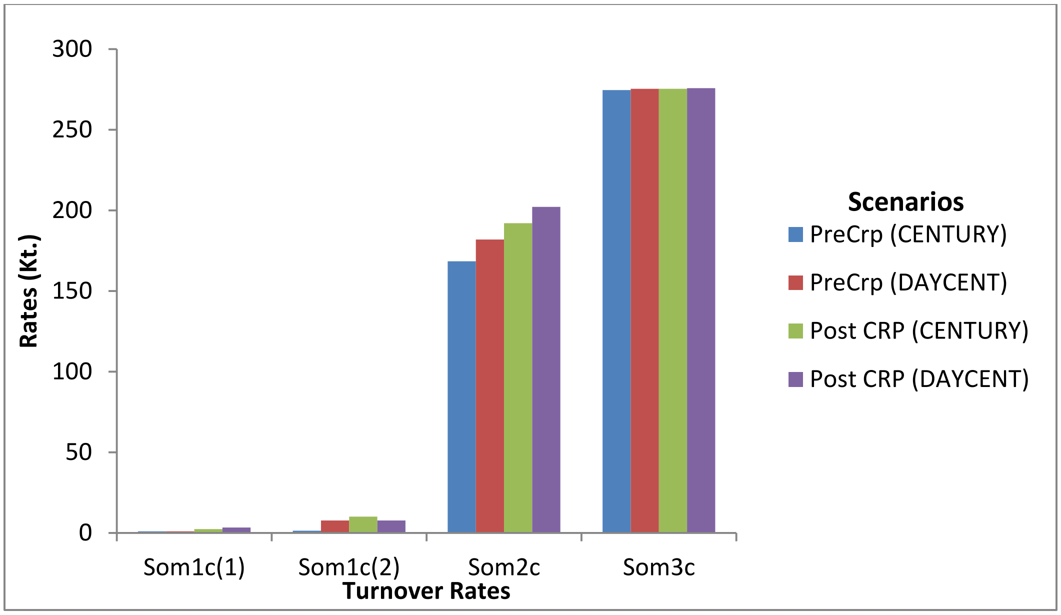

Figure 4.33: Active, Slow and Passive Rates for New Mexico

4.4.4 Management Scenarios for Carbon Sequestration: New Mexico: DAYCENT results for NPP show that the introduction of management on CRP tracts will increase the amount of carbon sequestered, with the below ground carbon being more by about 76% (see Figure 4.34). The two models reveal that both the standing dead and above ground NPP are not very significant when management scenarios are applied to sequester carbon on CRP tracts, but that more carbon is sequestered below ground than above ground (Figure 4.34). It is observed from Figure 4.34 that the CENTURY model estimates fire to sequester more carbon, followed by grazing, with biofuels being rather insignificant; and the DAYCENT model figure suggests a similar trend where fire sequesters more carbon followed by grazing and biofuel.

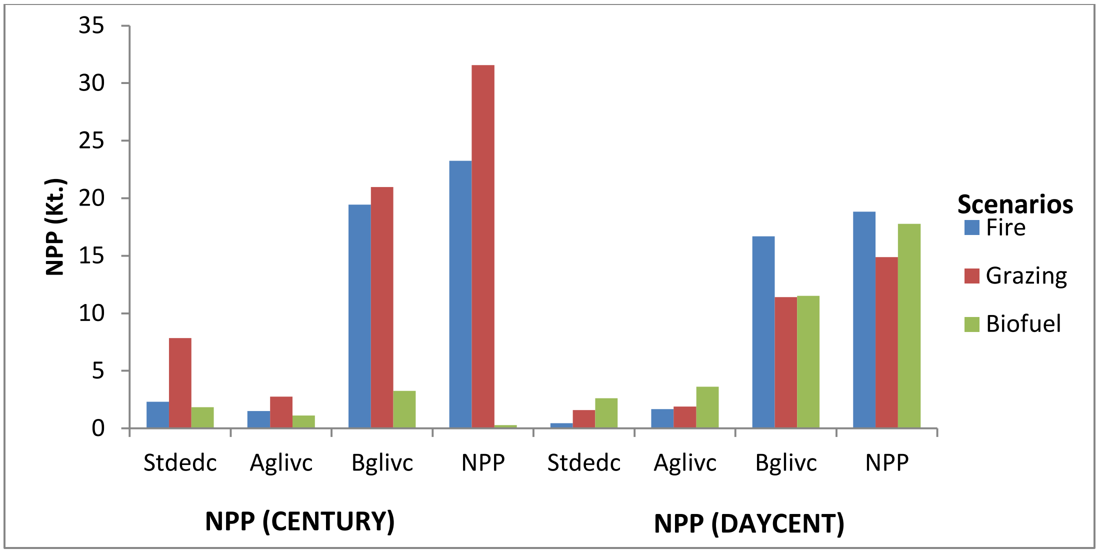

Figure 4.34: Management Scenarios for NPP for New Mexico

With respect to the structural and metabolic turnover rates (see Figure 4.35), the results suggest that the implementation of the three management practices has a mixed outcome for carbon sequestration. Figure 4.35 reveals that grazing and biofuel will enhance carbon sequestration, while fire's role appears limited for strucc(1); and that the important players for strucc(2) are the fire and grazing scenarios. The effects of these management systems appear to be modest for the rest of the structural and metabolic carbon sequestration rates in New Mexico. One important thing of note here, though, is that the highest numbers for strucc(1) and strucc(2) were estimated by the CENTURY model only for those two instances, but the remaining predictions were similar to those of the DAYCENT model.

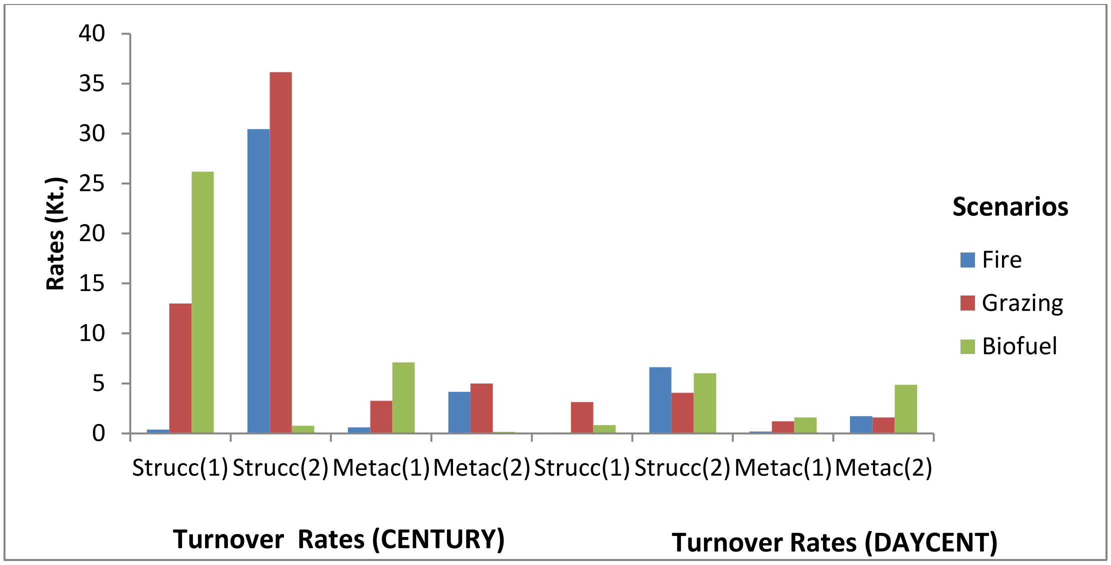

Figure 4.35: Management Scenarios for Structural and Metabolic Carbon Rates for New Mexico

In the case of the turnover rates of active, slow and passive (see Figure 4.36), the results suggests that the implementation of the three management practices (grazing, fire and planting of biofuel crops) will help in increasing the slow and passive carbon sequestration in the study area. Figure 4.36 reveals that the amount of active carbon sequestration based on the management scenarios will increase from 180 Kt. to about 280 Kt. into the slow and passive rates within a 39-year period. Breaking down the contribution of these management scenarios by model indicate that both surface and active carbon sequestration will increase only slightly using the three management choices. Both CENTURY and DAYCENT estimates higher effects of the management systems on slow and passive carbon sequestration in New Mexico, but while both models consider grazing to have the most impact for the slow rate, CENTURY predicts grazing to play a less significant role in determining the passive rate of carbon sequestration in the study area. The DAYCENT on the other hand gives all the three management scenarios almost an equal chance of influencing the passive carbon sequestration rate in the study area.

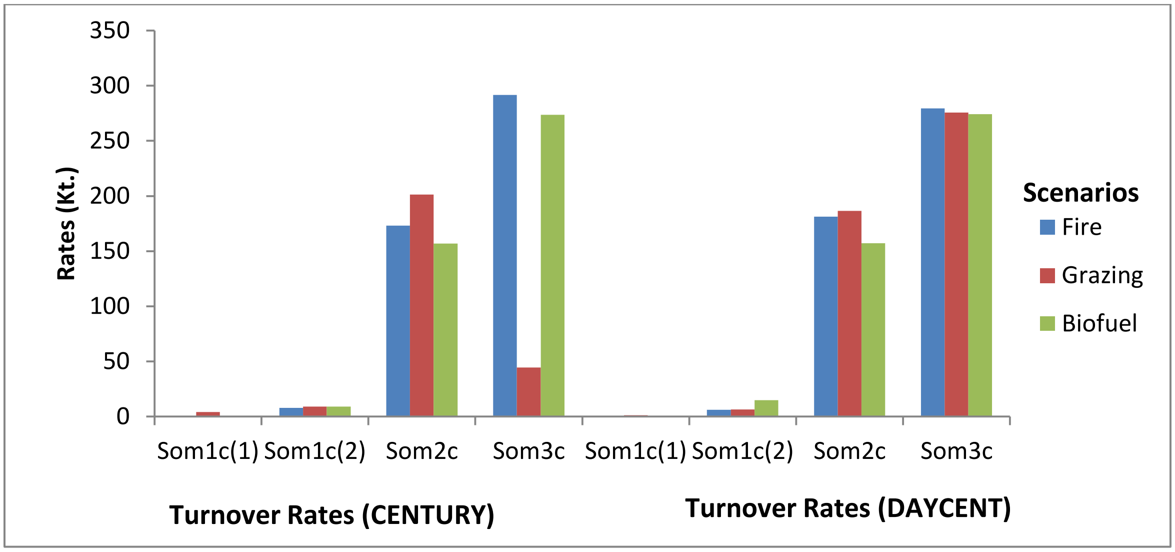

Figure 4.36: Management Scenarios for Active, Slow and Passives Rates for New Mexico

4.5.1 Oklahoma Carbon Sequestration Estimates:

Table 4.4: Net Primary Productivity (NPP) for Oklahoma

Scenario	Stdedc	Aglivc	Bglivc	NPP
Pre-CRP (CENTURY)	84.41	96.96	355.99	537.37
Pre-CRP (DAYCENT)	132.34	695.60	915.94	1743.88
Post-CRP (CENTURY)	168.56	1619.05	2019.07	3806.68
Post-CRP (DAYCENT)	238. 60	1205.95	1718.26	3162.80

Once again, the CENTURY model estimates of both pre-CRP and post-CRP periods are lower than estimates from the DAYCENT model. As observed in table 4.4, while the CENTURY model predicts a 75.26 % increase in carbon sequestration from pre-CRP to post-CRP, the DAYCENT model estimates a 28.92 % increase.

Based on the total area covered by CRP land in Oklahoma (344.99 Km^2), the average carbon sequestration estimated by the CENTURY model are 0.04 Kt.and 0.44 Kt per Km^2 per year for pre-CRP and post-CRP respectively. The averages for the DAYCENT model for pre-CRP and post-CRP are 0.2 kt and 0.37 kt per Km^2 per year in that order.

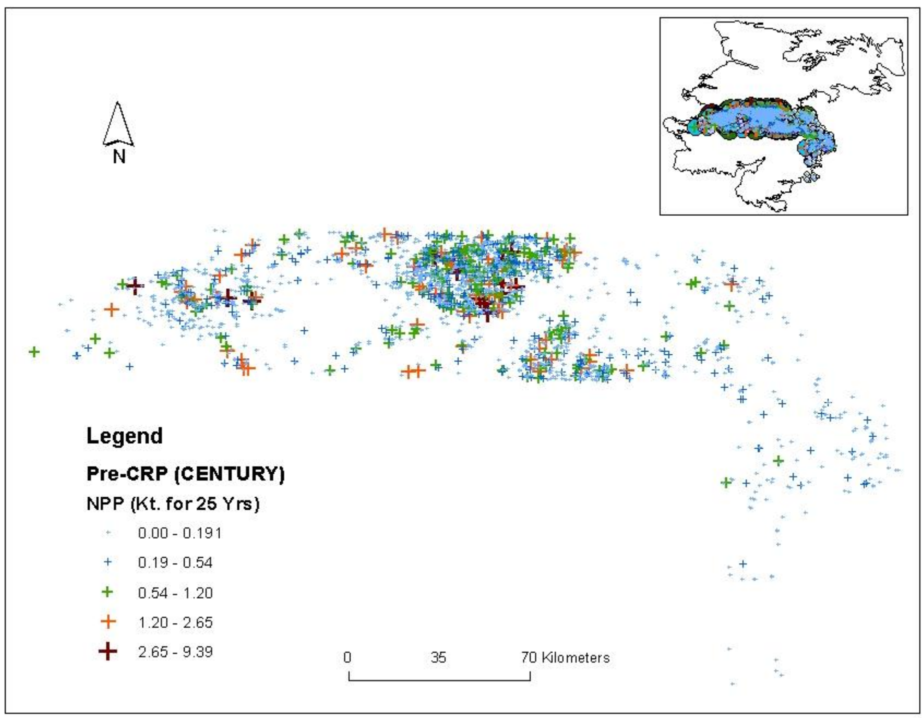

Figure 4.37: Oklahoma Spatial Distribution of NPP (pre-CRP, CENTURY)

The spatial distribution of NPP for Oklahoma (see Figure 4.37) for pre-CRP carbon sequestration estimates by the CENTURY model shows that the highest values range from 2.66- 9.39 kt of carbon sequestered. Values at the lower end of the spectrum span from 0 to 0.19 kt of carbon. Moran's I was used to test for patterns in NPP for CENTURY. The value for Pre-CRP was 0.0163 and 0.0260 for Post-CRP. On the other hand, DAYCENT shows a Moran's I of 0.0324 and 0.0260 for pre-CRP and post-CRP respectively. These values suggest that the distribution of NPP in Oklahoma is random.

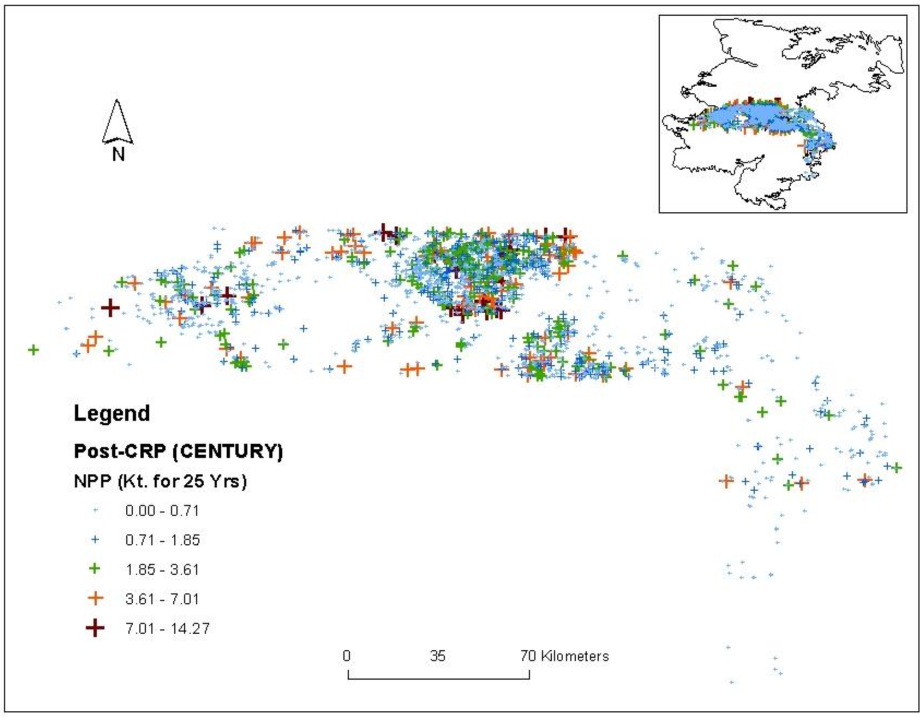

Figure 4.38: Spatial Distribution of NPP for Oklahoma for post-CRP (CENTURY)

The spatial distribution of the NPP as estimated for post-CRP using the CENTURY model follows a similar pattern to the pre-CRP (see Figure 4.38). The lower values range from 0 to 0.71 Kt. of carbon per year, with higher values of 7.01 to 14.27 Kt. of carbon. Results here show a 28.48% increase in carbon sequestration in the study area after the introduction of CRP.

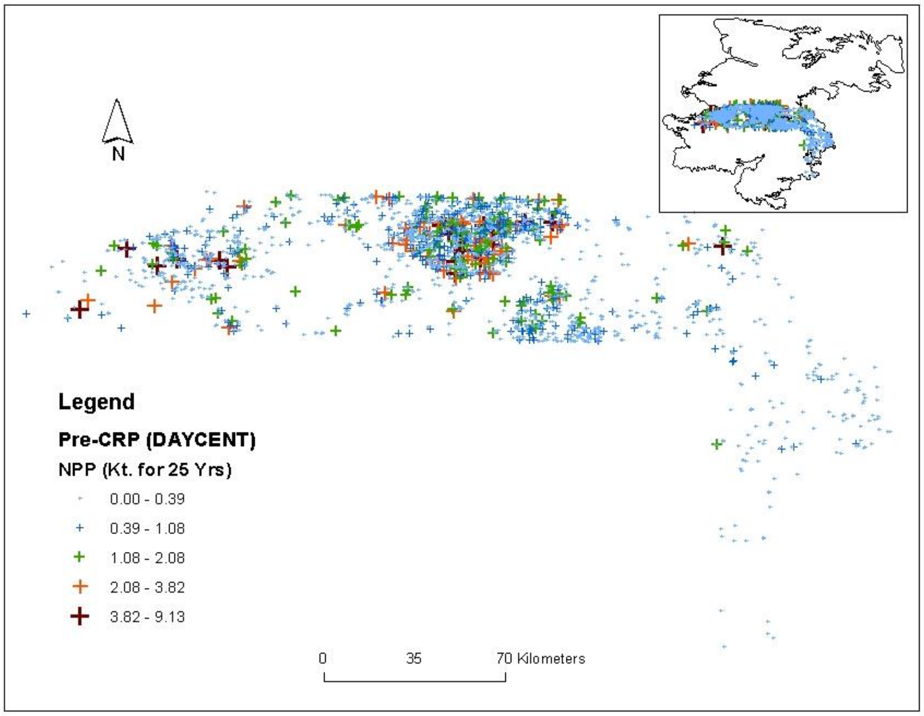

Figure 4.39: Spatial Distribution of NPP for Oklahoma for pre-CRP (DAYCENT)

Figure 4.39 presents the spatial distribution of the pre-CRP NPP as estimated by the DAYCENT model for Oklahoma. It follows the same pattern with that of the CENTURY model with higher concentrations of carbon sequestration in the western part of the state. The pre-CRP estimates of the DAYCENT model are 53% higher than those predicted by the CENTURY model. Conversely, the CENTURY model predicted carbon sequestration to be 9.28% higher than DAYCENT.

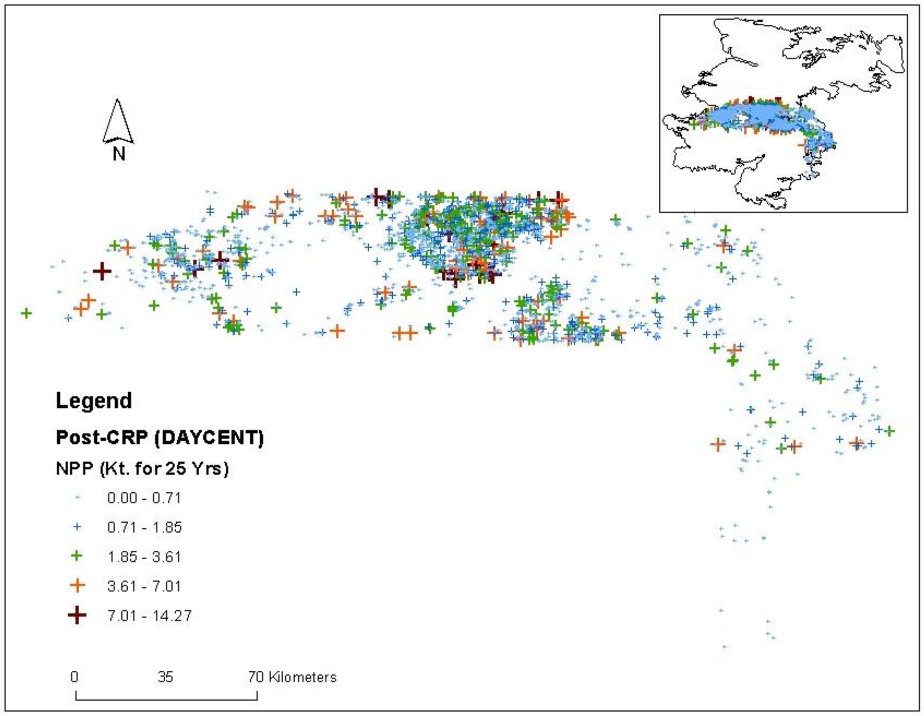

Figure 4.40: Spatial Distribution of NPP for Oklahoma using DAYCENT (post-CRP)

In the same vein, the post-CRP spatial distribution estimated by the DAYCENT model presented in Figure 4.40 shows that the higher values of carbon sequestration are found in areas with higher CRP enrollment in the state. Here, the DAYCENT model is predicting a 36.02% increase in carbon sequestration from pre-CRP to post-CRP in Oklahoma.

4.5.2 Temporal Distribution of Carbon Sequestration in Oklahoma:

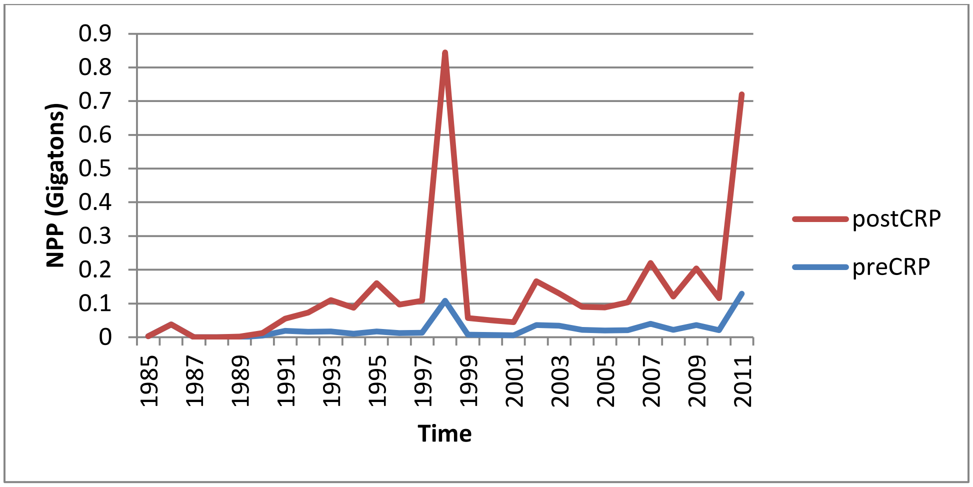

Figure 4.41: Oklahoma NPP Temporal Distribution

Carbon sequestration in Oklahoma shows an increasing trend from pre-CRP to post-CRP. This is indicated in Figure 4.41 which reveals that there has been a steady increase in carbon sequestration since the introduction of CRP in the study area in 1985. There is however, a sudden increase observed in 1998 and 2010 where the rates of carbon sequestration have been exceptionally high.

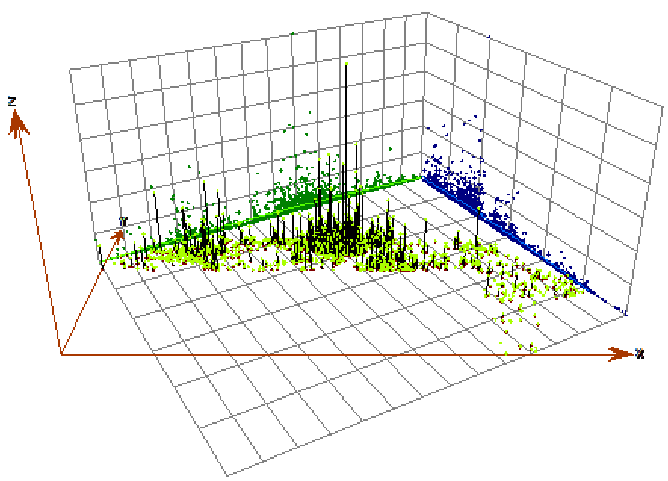

Figure 4.42: Oklahoma Pre-CRP NPP Trend Analysis

Figure 4.42 shows the Pre-CRP carbon sequestration trend for Oklahoma. There is no trend for carbon sequestration in the east-west direction. This is because the trend line is completely flat, although some scattered local and global outliers can be seen. We observe a similar trend in the north-south direction (represented by the blue line). Here again, the trend line is flat indicating that there is no trend for carbon sequestration in the pre-CRP period for Oklahoma

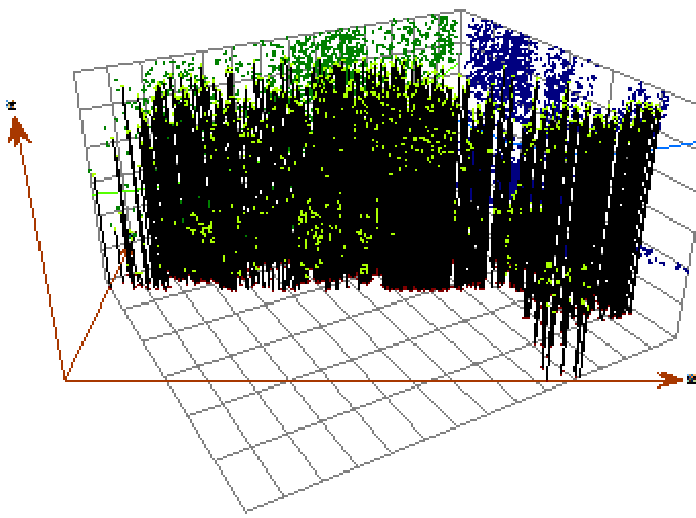

Figure 4.43: Oklahoma Post-CRP NPP Trend Analysis

The Post-CRP carbon sequestration trend for Oklahoma (Figure 4.43) shows some trending. The east-west direction (represented by the green line) indicates a slight westward direction of carbon sequestration in the post-CRP period. The slight rise in carbon sequestration in the westward direction has remained in spite of the presence of global outliers which are in the eastern direction. In fact, most points trend towards the western direction as depicted by the trend line. The north-south direction (represented by the blue line), however shows an inclination towards the south where there appears to be a concentration of global outliers in the north. In the post-CRP carbon sequestration period for Oklahoma, increase in the degree of carbon sequestration is trending in the western and southern parts of CRP areas.

4.5.3 Rates of Carbon Sequestration in Oklahoma: The turnover rates were estimated in terms of structural and metabolic rates for both the CENTURY and DAYCENT models for pre-CRP and post-CRP scenarios. Results presented in Figure 4.44 show that the structural rates are modestly higher than the metabolic rates as estimated by the two models. The rates are of course higher for post-CRP than pre-CRP scenarios for both models. The predictions for the two models are generally close, except for the pre-CRP estimates which are lower than those of the post-CRP by about 26%.

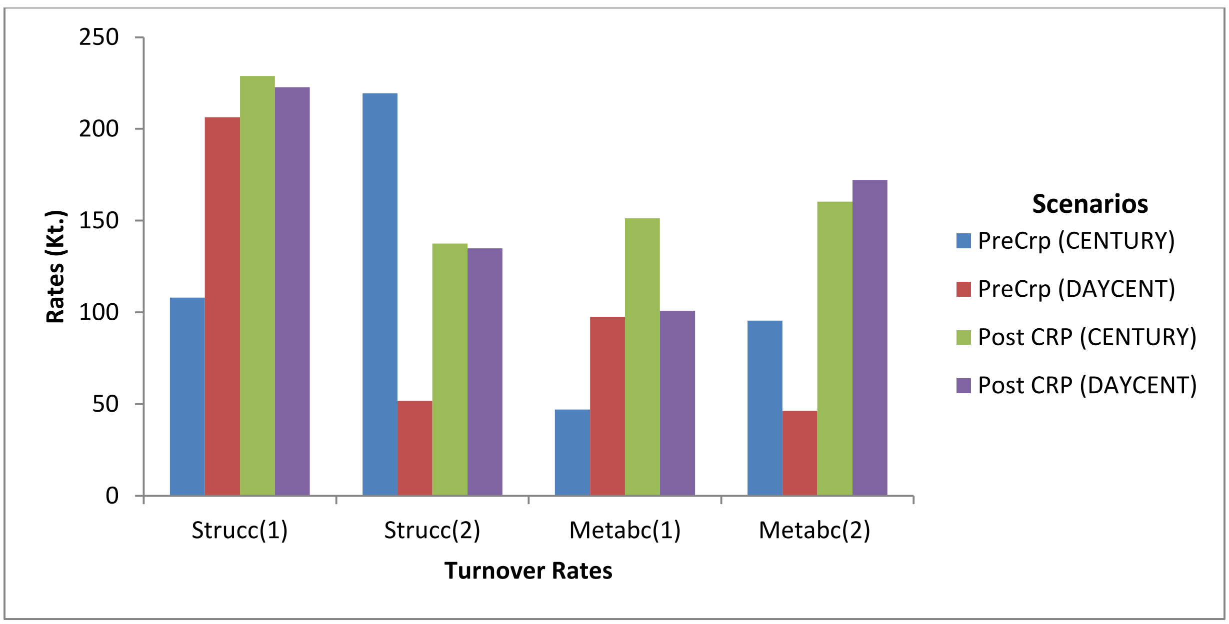

Figure 4.44: Structural and Metabolic Turnover Rates for Oklahoma

Figure 4.45 highlights the active, passive and slow turnover rates of carbon in Oklahoma. Visual inspection of Figure 4.45 shows that the pre-CRP value for

CENTURY for som3c is unusually much higher than the post-CRP for both the CENTURY and DAYCENT models. Apart from the passive rates whose values are variable, both models have estimated higher turnovers for post-CRP compared to pre-CRP scenarios for the active and slow rates.

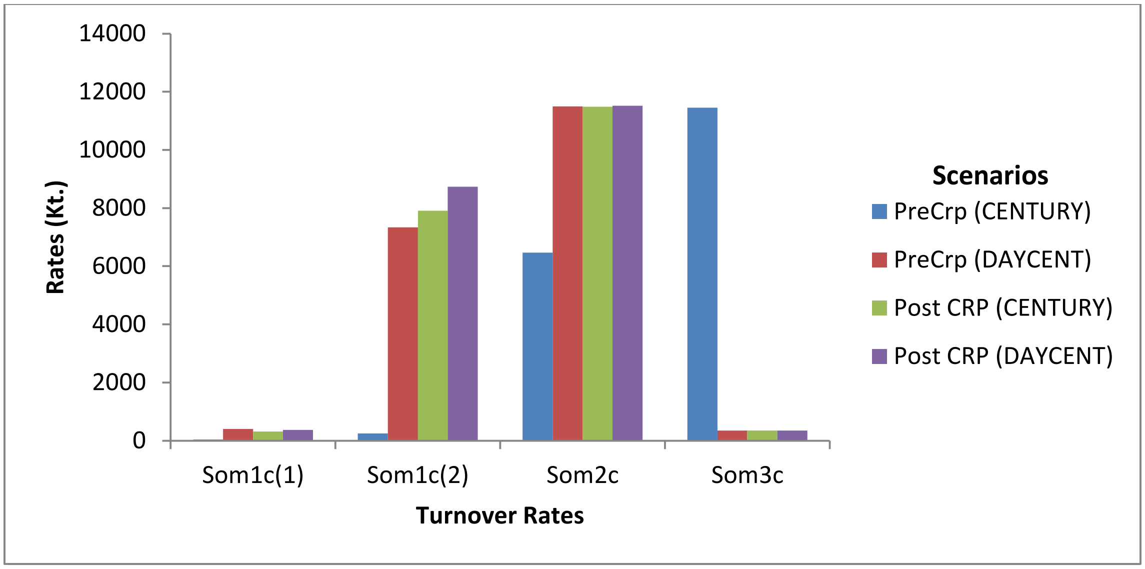

Figure 4.45: Active, Slow and Passive Carbon Rates for Oklahoma

4.5.4 Management Scenarios for Carbon Sequestration: Oklahoma: Results of the three management scenarios of grazing, fire and the planting of biofuel crops for the CENTURY and DAYCENT with respect to NPP suggests an increase in carbon sequestration (see Figure 4.46). Results from the two models reveal that these management scenarios seem to have little effect on both the standing dead and above ground NPP. The estimates from the CENTURY model suggest that grazing and fire would play a greater role in sequestering more carbon, in Oklahoma, with biofuels considered as being rather insignificant. The DAYCENT model figures on the other hand, suggest that grazing and biofuel will play greater roles in this endeavor, while that of fire would almost be non-existent. Judging from the predictions by the two models, grazing would seem to be the most consistent management option that would enhance carbon sequestration in Oklahoma.

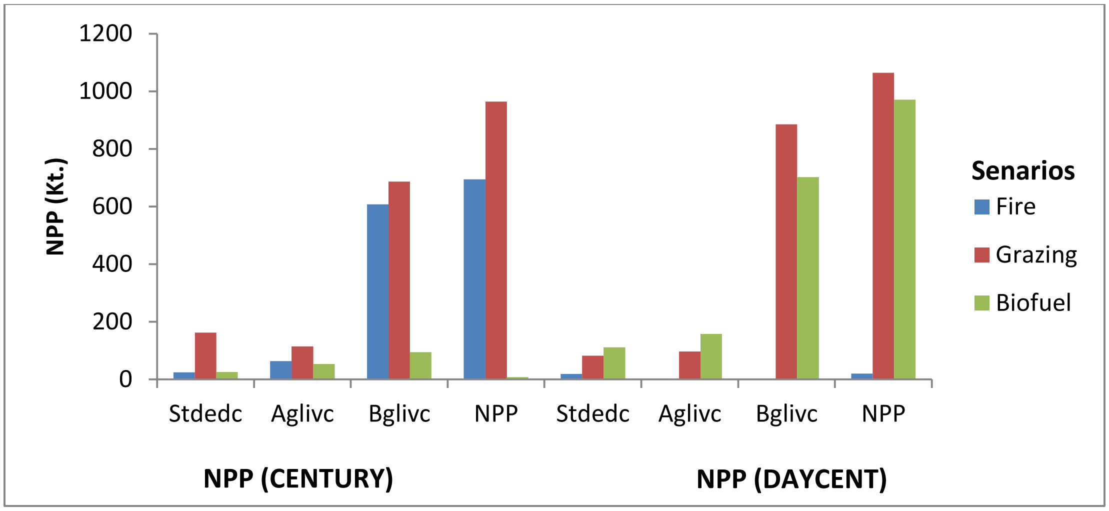

Figure 4.46: Management Scenarios for NPP Carbon Rates for Oklahoma

With regards to structural and metabolic carbon sequestration rates (see Figure 4.47), the results suggest that grazing and biofuel are the main management scenarios in enhancing carbon sequestration in the study area. Figure 4.47 reveals that biofuel and grazing have influenced the sequestration of strucc(1) while grazing and fire appear to be important for the sequestration of strucc(2). The only other instance in which fire has shown some importance is in the sequestration of metac(2), but for the rest of the rates, it is biofuel and grazing that have proven the most relevant.

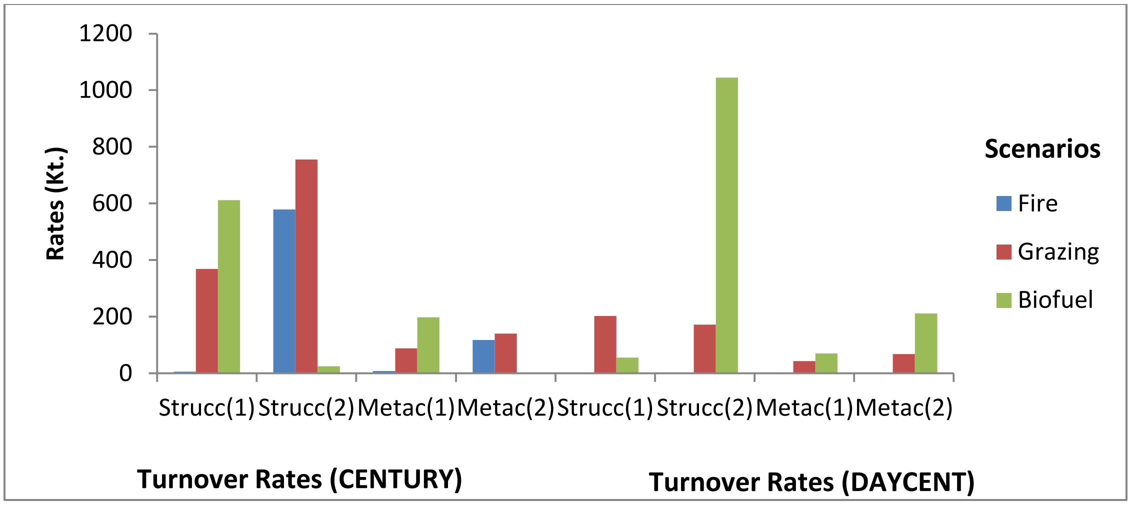

Figure 4.47: Management Scenarios for Structural and Metabolic Carbon Rates for Oklahoma

When the three management practices are implemented for the active, passive, and slow turnover rates, only the passive and slow carbon sequestration lead to large increases. Figure 4.48 reveals that the amount of active carbon sequestration based on the management scenarios is very small, while that of the slow and passive rates range from 800 to 1300 Kt. of carbon. It is only som1(2) that shows that biofuel will increase the rate of active carbon sequestration (see Figure 4.48). Whereas the CENTURY model indicates that fire, grazing and biofuel are important contributors to carbon sequestration, the DAYCENT model predicts that the important players are grazing and biofuel, indicating that fire does not play a role.

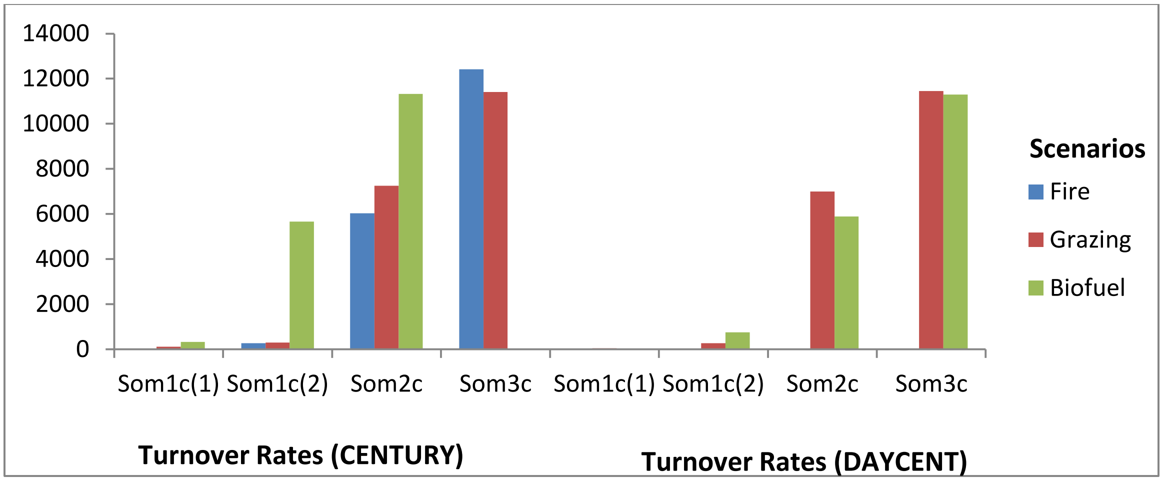

Figure 4.48: Management Scenarios for Active, Slow, and Passive carbon Rates for Oklahoma

4.6.1 Texas Carbon Sequestration Estimates:

Table 4.5: Net Primary Productivity (NPP) for Texas

Scenario	Stdedc	Aglivc	Bglivc	NPP
Pre-CRP (CENTURY)	78.19	98.79	365.62	542.59
Pre-CRP (DAYCENT)	80.16	125.79	649.20	855.15
Post-CRP (CENTURY)	191.49	139.076	1360.11	1690.68
Post-CRP (DAYCENT)	261.35	232.29	1202.09	1695.73

Table 4.5 presents the NPP simulation results for Texas. Results reveal a carbon sequestration increase of 51.4% from pre-CRP to post-CRP for the CENTURY model; while the DAYCENT model estimates a 33% increase.

The total area covered by CRP land in Texas is 378.90 Km^2. Thus the average pre-CRP carbon sequestration is 0.06 kt per Km^2 per year and the post-CRP carbon sequestration estimate is 0.18 Kt. per Km^2 per year for CENTURY. The pre-CRP value is 0.09 kt per Km^2 per year, and a post-CRP value of 0.18 Kt. per Km^2 per year for DAYCENT. In this simulation run, both models predicted the same post-CRP annual increase in carbon sequestration per unit area in Texas (1690 Kt and 1695 Kt) for CENTURY and DAYCENT, respectively.

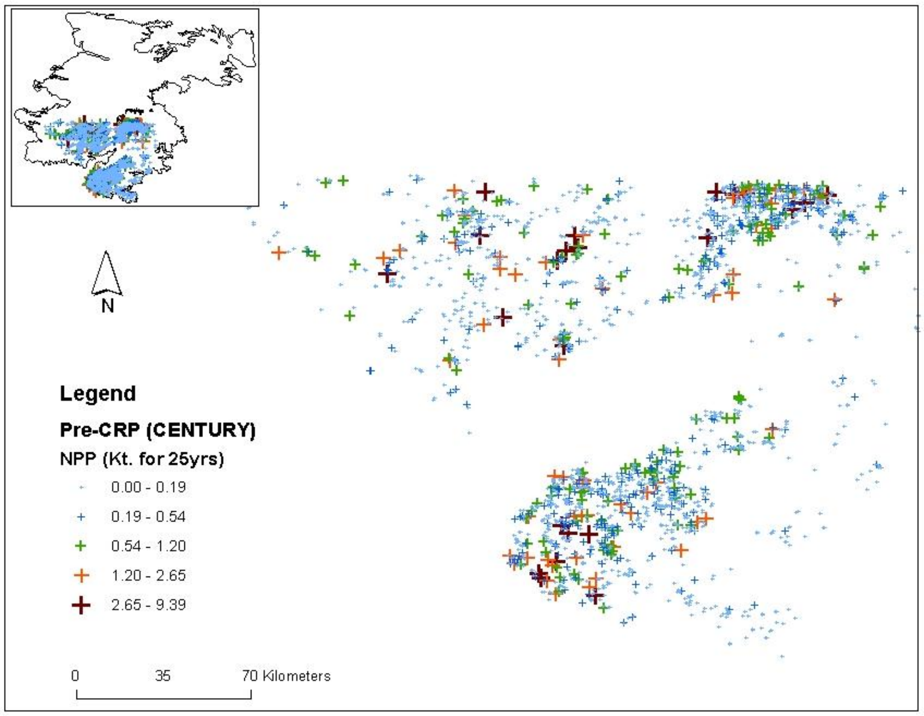

Figure 4.49: Texas Spatial Distribution of NPP (pre-CRP, CENTURY)

The spatial distribution of the Net Primary Productivity (NPP) for Texas (see Figure 4.49) shows that the lower range of carbon sequestration is 0 to 0.24 Kt. and the highest values range from 3.75 to 7.13 kt of carbon sequestered per year for the CENTURY model. The test for autocorrelation shows that the Moran's I value for Pre-CRP was 0.0020 and 0.0011 for Post-CRP for CENTURY. On the other hand, DAYCENT shows a Moran's I of 0.0115 and 0.0052 for pre-CRP and post-CRP respectively. This signifies chance occurrence of NPP on CRP tracts in Texas.

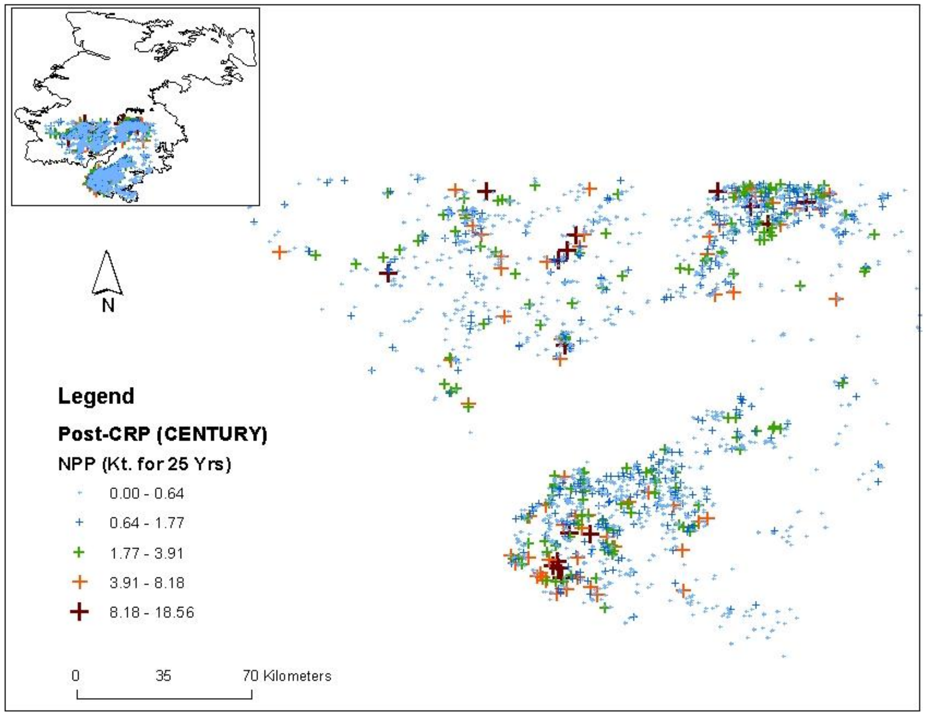

Figure 4.50: Spatial Distribution of NPP for Texas for post-CRP (CENTURY)

The spatial distribution of the NPP estimated for post-CRP using the CENTURY model is presented in Figure 4.50. The values for the post-CRP show a lower range of 0-0.56 Kt. of carbon per year, with higher values of 8.18-18.56 Kt. of carbon per year. This is an indication that there was an increase in carbon sequestration in the study area after the introduction of CRP. It shows a 61.58% increase in carbon sequestration from pre-CRP to post-CRP based on estimates from the CENTURY model.

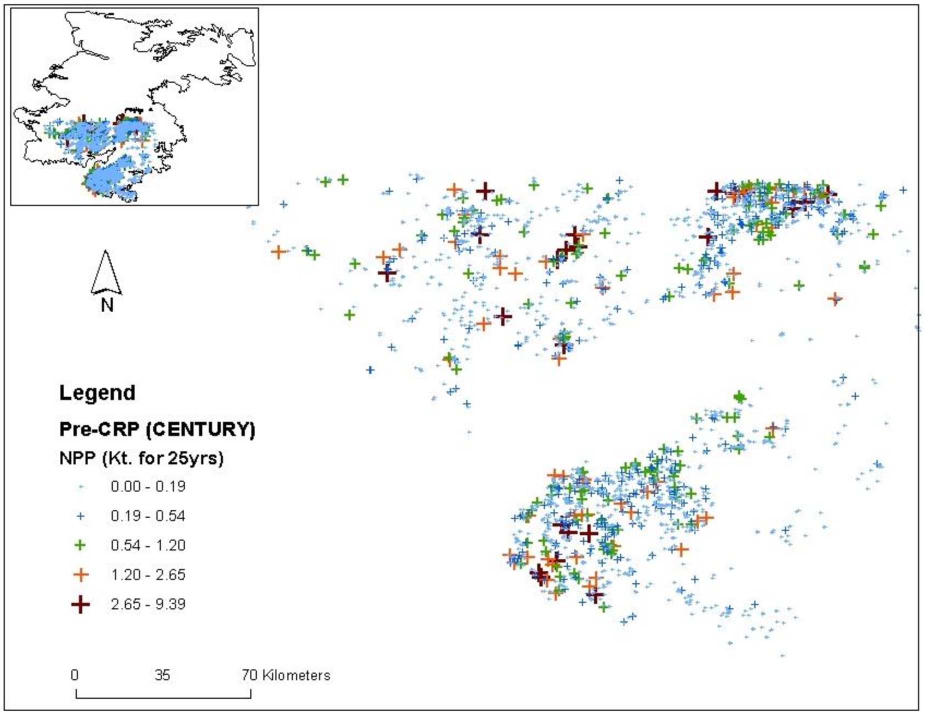

Figure 4.51: Spatial Distribution of NPP for Texas for pre-CRP (DAYCENT)

The pre-CRP estimates by the DAYCENT model (Figure 4.51), on the other hand, are slightly higher than those of the CENTURY model with a prediction of 66.58% increase in carbon sequestration from pre-CRP to post-CRP.

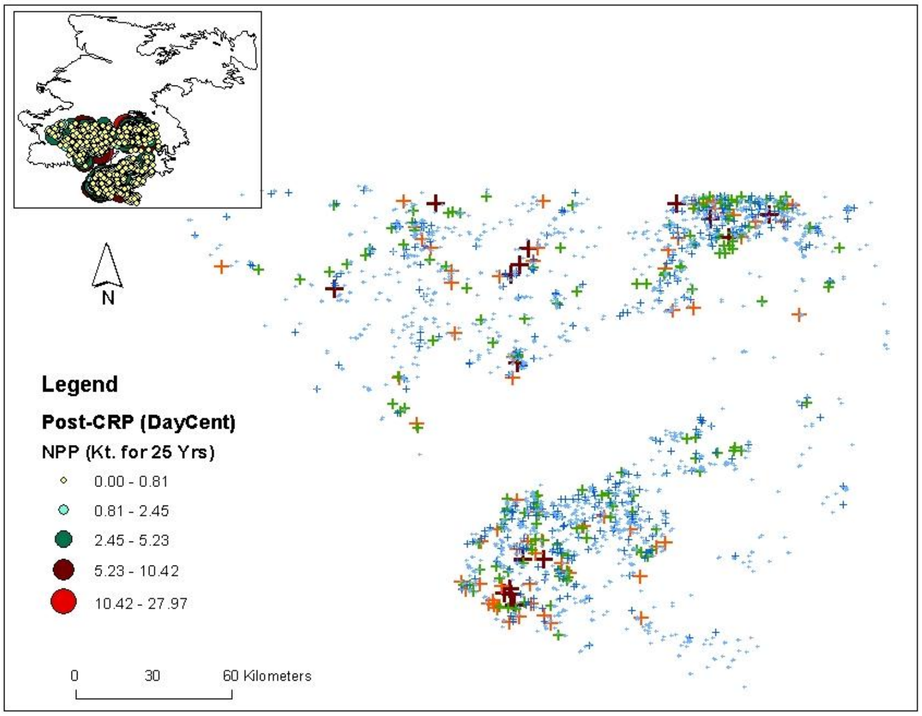

Figure 4.52: Spatial Distribution of NPP for Texas using DAYCENT (post-CRP)

4.6.2 Temporal Distribution of Carbon Sequestration in Texas:

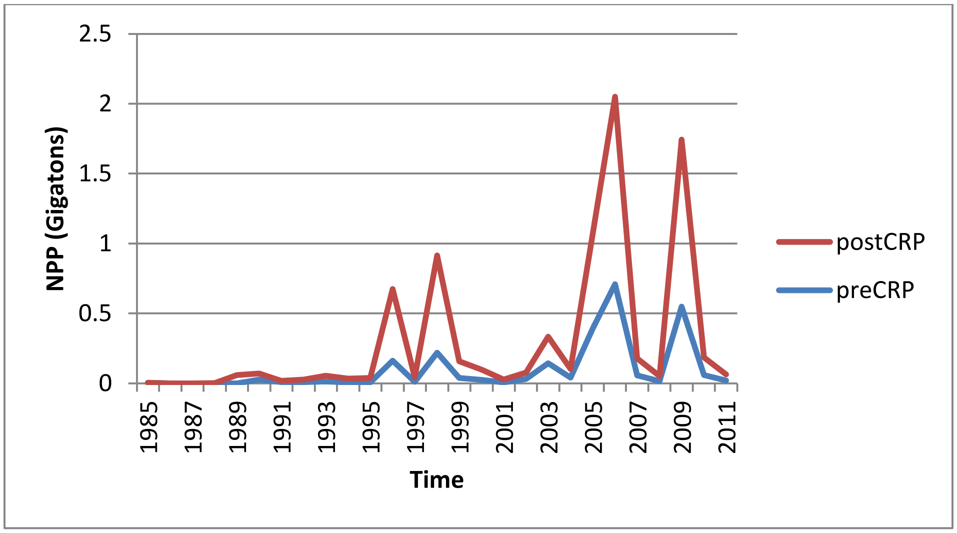

Figure 4.53: Texas NPP Temporal Distribution

Carbon sequestration in Texas has followed a similar temporal path with other states in the CHP region where rates of carbon sequestration have increased with the introduction of the CRP. These results are seen in Figure 4.53, and details show that the highest increases were recorded in the periods 2006 and 2009. Similar observations which have been speculatively attributed to the REX program initiated in 2006 appear to be in play here as well. The only exception here is in 2008 where carbon sequestration rates seem to flatten.

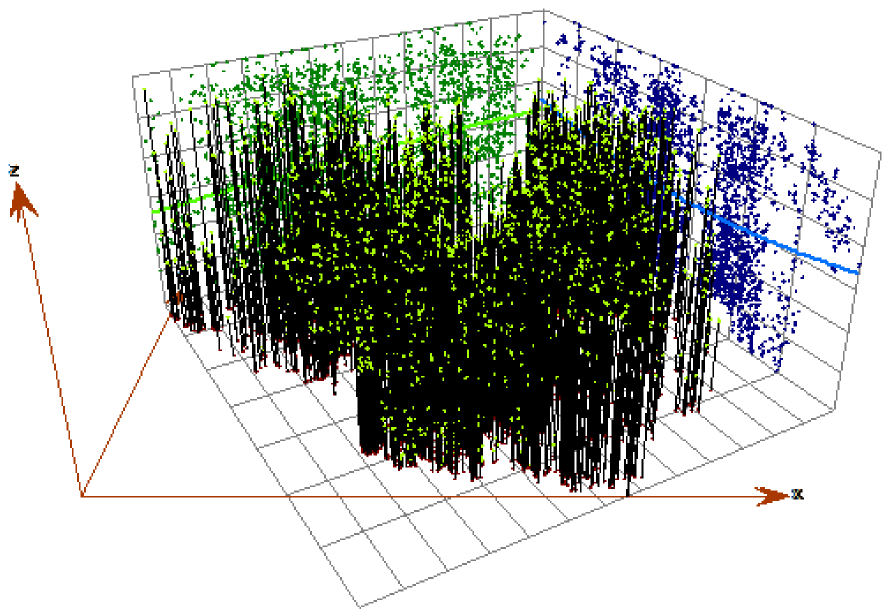

Figure 4.54: Texas Pre-CRP NPP Trend Analysis

The Pre-CRP carbon sequestration trend for Texas is presented in Figure 4.54. Carbon sequestration trends here are similar to those observed for other states in the region were the trends are east-west, and south-north. As observed in Figure 4.54, the appearance of both global and local outliers may have aided a change in the trend trajectory for the pre-CRP.

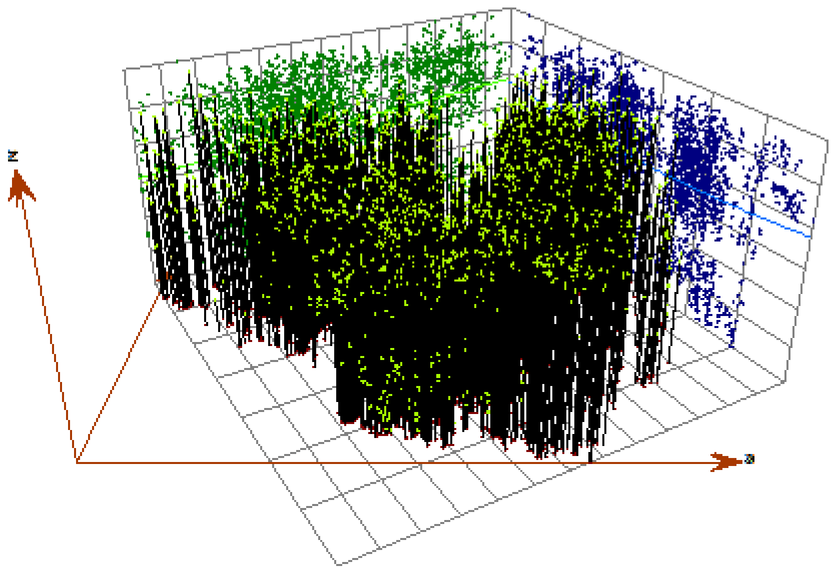

Figure 4.55: Texas Post-CRP NPP Trend Analysis

In the post-CRP carbon sequestration period in Texas (Figure 4.55), the influence of global outliers appear to be minimal in determining the trend direction due in part to the fact that most of the points trend towards the eastern direction as depicted by the trend line. In the north-south direction, the trend line shows an inclination towards the north where there appears to be a concentration of local outliers as well. This visual inspection of the post-CRP period of carbon sequestration indicates a slightly higher degree of carbon sequestration in the eastern and northern parts in Texas.

4.6.3 Rates of Carbon Sequestration in Texas: Estimated results presented in Figure 4.56 show that the structural rates are higher than the metabolic rates as predicted by the two models. The rates show higher values for post-CRP than pre-CRP scenarios for both models. The predicted values for both models are comparable, except for strucc(1) where the CENTURY model estimated about 450 kt per of carbon compared to 120 kt by the DAYCENT model.

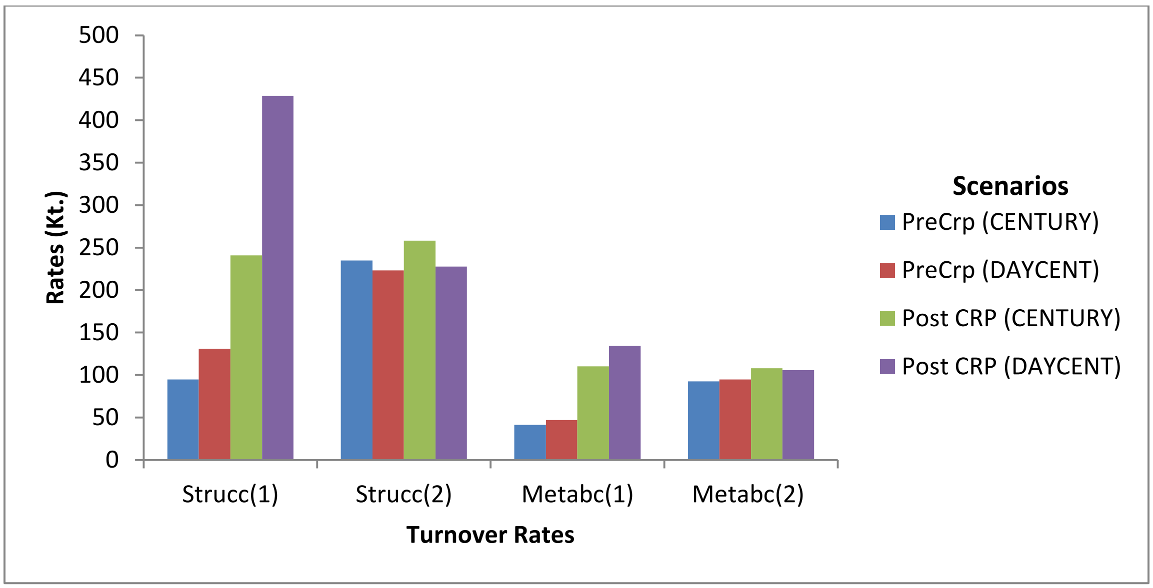

Figure 4.56: Structural and Metabolic Turnover Carbon Rates for Texas

The turnover rates estimates for the two models are almost equal. Strucc(1) values for post-CRP estimated by the DAYCENT model is the only high value. Unlike other cases, there is largely no difference between pre-CRP and post-CRP estimates.

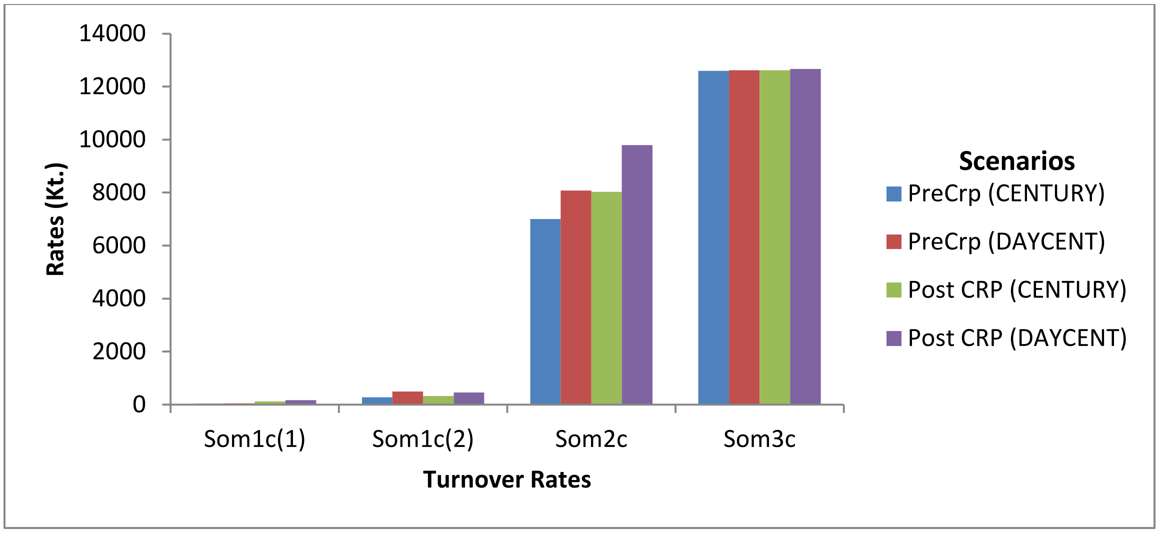

Figure 4.57: Active, Slow and Passive Carbon Rates for Texas

4.6.4 Management Scenarios for Carbon Sequestration: Texas: The effects of management on carbon sequestration were determined through three management scenarios, grazing, fire and the planting of biofuel crops simulated in CENTURY and DAYCENT. Results for NPP show that the introduction of management on CRP tracts is predicted to only increase belowground carbon sequestration (see Figure 4.58). Results from the two models reveal that both the standing dead and above ground NPP are low when management scenarios are applied to sequester carbon on CRP tracts. In fact, both the CENTURY and DAYCENT models suggest that fire would sequester more carbon, followed by grazing, and biofuels. The favorable consideration of fire as a management strategy in Texas is the reverse of what was predicted for Oklahoma where grazing appeared more favorable.

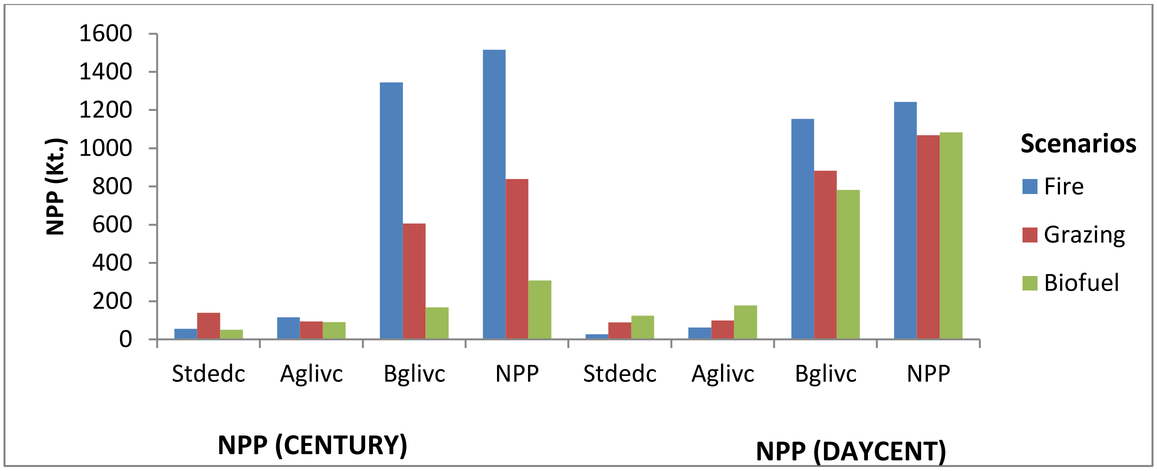

Figure 4.58: Management Scenarios for NPP for Texas

The structural and metabolic turnover rates presented in Figure 4.59 reveal that biofuel has an important effect on carbon sequestration for strucc(2) for both CENTURY and DAYCENT with values ranging from 800 kt. for CENTURY to 1000 Kt. for DAYCENT. Fire appears to be an important management tool in enhancing structural carbon sequestration for CENTURY compared to metabolic carbon sequestration.

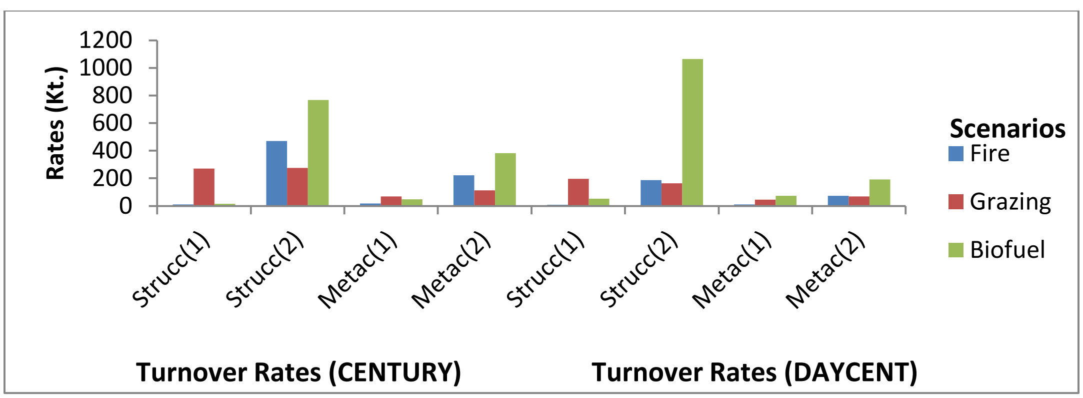

Figure 4.59: Management Scenarios for Structural and Metabolic Carbon Rates for Texas

Based on active, slow and passive turnover rates (see Figure 4.60), the results suggest that the implementation of the three management practices will increase the slow and passive carbon sequestration in the study area. Figure 4.60 reveals that the amount of active carbon sequestration based on the management scenarios is about 80 Kt. per year while that of the slow and passive rates range from 1200 to 2900 Kt. per year for CENTURY, and 600 Kt. to 1200 Kt. for DAYCENT. Both models estimate that carbon is sequestered much more below ground than above ground, and that there is more post-CRP carbon sequestration than pre-CRP carbon sequestration.

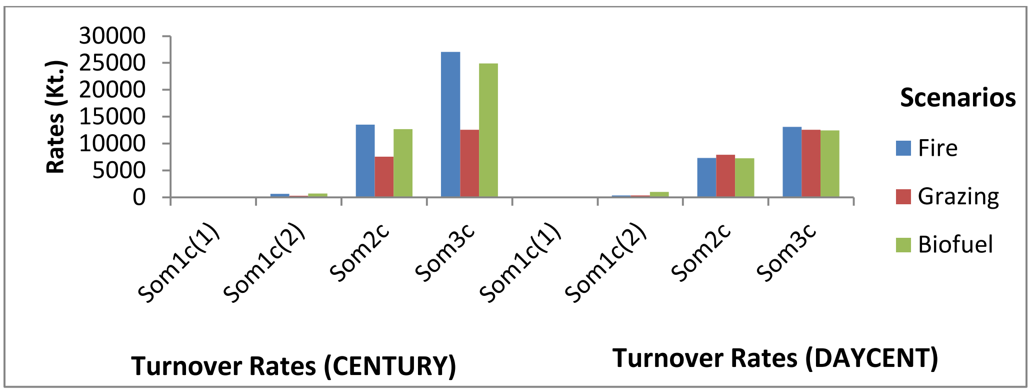

Figure 4.60: Management Scenarios for Active, Slow, and Passive Carbon Rates for Texas

4.7 Discussion of Results

The model results estimated carbon (C) as Net Primary Productivity (NPP). The estimates for both CENTURY and DAYCENT models were based on standing dead carbon (STDEDC), above ground live carbon (AGLIVC), and below ground live carbon

(BGLIVC). Results of model runs for pre-CRP are estimated in Kilotons (Kt) of NPP (Table 4.6), where 1 Kt is equivalent to 1000 metric tons.

Table 4.6: Pre-CRP NPP for CENTURY Model

State	stdedc (kt)	aglivc (kt)	bglivc (Kt)	NPP (Kt)	Area (Km^2)	%
Colorado	257.24	389.73	1530.82	2177.79	1293.35	18.21
Kansas	1179.00	1681.05	5833.24	8693.29	6298.71	72.70
New Mexico	1.27	0.75	4.97	6.99	0.01	0.06
Oklahoma	84.41	96.96	356.00	537.37	344.99	4.49
Texas	78.19	98.79	365.61	542.60	378.90	4.54
Totals	1600.11	2267.28	8090.65	11958.04	8315.96	100.00

The CHP region covers an area of 8315.96 Km^2, which means that the CENTURY model estimated the annual average carbon sequestered for the region as 478.32 Kt. This translates to an average of 0.06 Kt. per Km^2 per annum. The totals by state indicate that Kansas has the largest carbon sequestered and New Mexico has the least. These totals are related to CRP enrollments in the CHP sections of the respective states. According to FSA (2010), Texas ranks first (3,473.97 Km^2) in enrollment, followed by Colorado (2,992.52 Km^2), Kansas (2,504.62 Km^2), Oklahoma (918.13 Km^2) and New Mexico (44.80 Km^2) respectively. The total enrollment (area) for each state is presented in Table 4.6.

Table 4.7: Pre-CRP NPP for DAYCENT Model

State	stdedc (Kt)	aglivc (Kt)	bglivc (Kt)	NPP (Kt)	Area (Km^2)	%
Colorado	152.06	201.90	1670.29	2024.25	1293.35	9.32
Kansas	1516.61	2417.06	13991.09	17924.76	6298.71	82.49
New Mexico	0.75	0.73	8.21	9.69	0.01	0.04
Oklahoma	87.99	132.34	695.60	915.94	344.99	4.22
Texas	80.16	125.79	649.20	855.15	378.90	3.94
Totals	1837.57	2877.83	17014.39	21729.80	8315.96	100.00

The DAYCENT pre-CRP NPP estimates (Table 4.7) are higher than those predicted by the CENTURY model by 29%. The DAYCENT model estimates show that the average yearly pre-CRP output predicted by the DAYCENT is 869.19 Kt. This means that an average of 0.15 kt of carbon was sequestered per Km^2 per year for the CHP region. Parton et al. (2001) had estimated between 530 to 680 Kt per year for the grassland region of the U.S. This means that the two models overestimated the accumulation of carbon by about 12%.

Generally, the DAYCENT model estimates a higher amount of carbon sequestered in the region than the CENTURY model. However, there are seemingly significant discrepancies in some of the estimated quantities by states. Distributed quantities of sequestered carbon can be classified into two: large and small quantities. Estimates by both models for New Mexico, Oklahoma and Texas are similar and fall within the range of 0.04 and 4.54%. Both models had relatively large estimates for Colorado and Kansas. This is where the disparity in estimates by the models is more appreciable. The CENTURY model estimate is almost twice the quantity estimated by the DAYCENT model for the State of Colorado; and DAYCENT's estimate for Kansas is about 12% higher than estimated by the CENTURY model.

There appears to be a linear association between the area of CRP by states and both the percentage of carbon sequestered and the disparity in results of carbon sequestration by the two models. The larger the area of CRP in the region the larger the disparity in model estimates of carbon sequestration. It may be speculated that the modeling environments in both models treat area coverage differently, and that the CENTURY model may have a greater premium placed on the role of area coverage on carbon sequestration, as it continually returns higher estimates as area coverage increases than the DAYCENT model appears to. A more plausible explanation may lie in the fact that the DAYCENT model's predictions might be more accurate due to its finer scale and the utilization of more input variables for simulations than CENTURY.

Table 4.8: Post-CRP NPP for CENTURY Model

State	stdedc (Kt)	aglivc (Kt)	bglivc (Kt)	NPP (Kt)	Area (Km^2)	%
Colorado	682.68	570.89	6097.15	7350.72	1293.35	18.52
Kansas	3172.71	2554.70	22869.88	28597.29	6298.71	72.06
New Mexico	3.71	1.45	19.89	25.04	0.01	0.06
Oklahoma	231.45	168.56	1619.05	2019.07	344.99	5.09
Texas	191.49	139.08	1360.11	1690.68	378.90	4.26
Totals	4282.04	3434.67	31966.09	39682.80	8315.96	100.00

Tables 4.8 and 4.9 present the results of Post-CRP estimates for NPP by the CENTURY and DAYCENT models follow a similar trend as in the pre-CRP estimates.

Table 4.9: Post-CRP NPP for DAYCENT Model

State	stdedc (Kt)	aglivc (Kt)	bglivc (Kt)	NPP (Kt)	Area (Km^2)	%
Colorado	433.19	385.04	2864.54	3682.77	1293.35	9.45
Kansas	4416.34	3895.60	23550.14	31862.08	6298.71	81.73
New Mexico	3.62	3.80	17.25	24.67	0.01	0.06
Oklahoma	273.72	238.60	1205.95	1718.26	344.99	4.41
Texas	261.34	232.29	1202.10	1695.73	378.90	4.35
Totals	5388.22	4755.33	28839.97	38983.52	8315.96	100.00

In percentage contribution, the CENTURY model estimates twice as much as the DAYCENT model does for Colorado, while the DAYCENT model estimates about 12% higher carbon sequestration for Kansas than the CENTURY model. Estimates for New

Mexico, Oklahoma and Texas are still small with a range of 0.06 to 5.09% for both models.

The average carbon sequestration estimated by the CENTURY model for the post-CRP period is 0.19 Kt per Km^2 per year, and 0.18 Kt. per Km^2 per year for the DAYCENT model. This is a projected increase of 54% in NPP in the post-CRP period over the pre-CRP period by the CENTURY model; and, 28% gain in NPP in the post-CRP period over the pre-CRP period as estimated by DAYCENT model within the 25 years of simulation runs. The CENTURY model appears to have underestimated the pre-CRP NPP, which may have led to the perceived higher percentage of increase in carbon sequestration in the region. This is because the post-CRP prediction by the CENTURY model was only 0.8% higher than that of the DAYCENT model, compared with the 25% difference in the pre-CRP estimations. Considering that the DAYCENT model has shown relatively better consistency in results than the CENTURY model, it may be safe to assume that the DAYCENT model predictions are more accurate than the CENTURY model.

The results show that carbon is sequestered more below ground than above ground. The results indicate that standing dead carbon is more than above ground live carbon for all the states as estimated by the DAYCENT model except for New Mexico where the above ground live carbon (3.80kt per year) is larger than the standing dead carbon (3.62kt per year).

A comparison of the two models shows that both models estimated the percentages represented by each state to be very close, except of course Kansas and

Colorado where the disparity is about 50%. The CENTURY model estimates 18% while the DAYCENT estimates 9% for Colorado and 72% and 81% for Kansas, respectively.

For the 25-year period, though, the two models' estimates are close. Whereas the CENTURY model estimates an accumulation of 39,682.80 kt of carbon, the DAYCENT model estimates an accumulation of 38,983.52 kt. In terms of the average per unit area, the CENTURY model estimates 0.19 Kt. per Km^2 per year and the DAYCENT model's estimates of 0.18 Kt. per Km^2 per year are close. Both estimates fall within the range of results of studies by previous researchers. For example, the estimates are much higher than those returned by Follett (2001) (0.04 Kt. per Km^2 per year) and Schunabel et al. (2001) (0.08 Kt. per km^2 per year) but lower than Succhi et al.'s (2001) estimates of 0.35 Kt per Km^2 per year. The CENTURY and DAYCENT model results fall within the estimated ranges of 0.04 to 0.38 Kt per Km^2 per year (Lal et al., 2001) and 0.31 to 1.95 Kt per Km^2 per year estimated by Gassman et al. (2003) and Lichter et al. (2005). These results all point to an increase in carbon sequestration in the post-CRP period, which is corroborated by the present study in the CHP region. The significance of the increase in average carbon sequestration will help in mitigating the greenhouse effect, as SOM accumulation will act as a sink for carbon. These estimated carbon rates are pointers to the worthiness of the CRP program regarding future enrollments.

4.7.1. Environmental Factors and Carbon Sequestration in the CHP: Soil and weather data were acquired and processed as inputs for the simulation runs. These environmental factors contain the same latitude and longitude information as the CRP tracts. Simple join operations in ArcMap were conducted to join the weather and soil data to the CRP tracts. Several GIS operations were employed to determine the relationship between environmental factors and carbon sequestration in the CHP region. The location information (latitude and longitude) that was derived from centroids of the CRP tracts was used to extract soil and weather information for those locations. New fields were created in the attribute table of the CRP tracts and the data on soil and weather conditions were then added and displayed as map layers. The CRP carbon sequestration distribution layers were overlayed on the environmental factors layer and the intersect were extracted using the "intersect" tool in Geoprocessing toolbar of ArcMap. The relationship between the environmental factors and carbon sequestration are then extracted from the attribute table of the intersect layer.

High carbon sequestration values in the different states do not appear to be driven by the same factors in terms of importance, although some of the factors appear to be consistent in explaining higher rates of carbon sequestration across the states. For instance, in all the 5 states, higher carbon sequestration appears to be associated with lower ranges of precipitation. Areas that show higher amounts of carbon sequestration in Colorado are areas with relatively low precipitation ranging from 0.5-2.5 inches per month, in spite of the fact that precipitation in Colorado range from 0.5-10.5 inches per month. Similar trends are observed in Kansas, where high carbon sequestration values are associated with precipitation in the region of 0.5-2.5 inches per year, even though precipitation goes as high as 5.5 inches per month. The situation is similar in New Mexico, Oklahoma and Texas where higher values of carbon sequestration are not associated with high precipitation. This is unexpected, but Derner and Schuman (2007) contend that carbon sequestration decreases with increasing mean annual precipitation for both the 0 to 30 cm soil depths. According to them, the threshold for the positive to negative change in carbon sequestration occurs between 440 (17 in) to 600 mm (24 in) of precipitation.

The lowest temperature that will not inhibit an increase in carbon sequestration in Colorado is 5^{o}F and the highest temperature is 77^{o}F (Metherell et al. 1993). Temperatures here range from -7-97^{o}F. Values below or higher than this range appear to result in lower rates of carbon sequestration in the state. In Kansas, however, the lowest temperature is 15^{o}F and the highest is 91^{o}F. The temperatures in Kansas range from a low of 13^{o}F to a high of 97^{o}F. The temperature range for New Mexico that is associated with high carbon sequestration is 7-85^{o}F, but the overall range of temperature in the study area is7-95^{o}F. Oklahoma and Texas have favorable temperature ranges that are 21-89^{o}F and 19-91^{o}F for low to high temperatures respectively. And whereas Oklahoma generally experiences temperatures as low as 17^{o}F, Texas' low is about 19^{o}F. The higher spectrum of temperatures for Oklahoma and Texas are 99^{o}F and 103^{o}F respectively. Higher carbon sequestration values appear to be associated with mild temperature conditions in the CHP region of the United States.

Soils appear to play a significant role in that most areas with high carbon sequestration tend to favor sandy loam soils. All across the CHP region, similar observations are made. In Colorado for example, high sequestration rates are found in locations with 51% sand, 27% silt and 25% clay, while Kansas favors 37% sand, 42% silt and 35% clay on average. The situation in New Mexico is 56%, 42% and 25% for sand, silt and clay respectively. Oklahoma on the other hand favors 66% of sand, 40% silt and 25% clay, while Texas records 70%, 45%, and 30% sand, silt and clay in that order. These values show that apart from Kansas whose high carbon sequestration values are associated with loamy soils, the four other states seem to favor sandy loam soils judging by the numbers (Bird et al. 2001; Metherell et al. 1993).

Initial organic matter in the soil does not seem to have an effect in the amount of carbon sequestration produced in the CHP region. This is evident in the fact that all the five states recorded low values in locations with higher rates of carbon sequestration. The initial organic matter values associated with high carbon sequestration for Colorado, Kansas and Texas range from 0-0.75, and that of New Mexico is 0.2-1.25. Oklahoma's values range from 1.0-3.5. This appears to support the results of the regression analyses for all the states in which initial organic matter in the soil was not statistically significant. Soil bulk density (BD) is a measure of how dense and tightly packed a sample of soil is. The BD of a soil is a function of its structure and the composition of its soil particles. In general, soil BD ranges from 0.5 g/mL or less in organic soils with many pore spaces, to as high as 2.0 g/mL or greater in very compact mineral soil horizons. In the CHP, BD ranges from 1.02-1.98 g/mL, signifying that the soils are largely moderate to tightly packed mineral soils. A close observation of BD in the study area suggests that higher carbon sequestration values are found in locations with BD ranging from 1.11-1.52g/mL. This means that values much lower than the low end of the spectrum would be too porous to hold enough water and locations at the extreme end of the spectrum would be too compact to allow for water seepage.

Saturated hydraulic conductivity (ksat) is an important soil factor that is related to moisture retention capacity of the soil, thereby affecting vegetation growth and distribution. Ksat is a quantitative expression of the soil's ability to transmit water under a given hydraulic gradient. It can be thought of as the ease with which pores of a saturated soil permit water movement. Studies have shown that, where hydraulic gradients are the same, soils with higher conductivity have higher water flux (Soil Survey Staff, 1993). Ksat in the CHP region of the U.S. recorded low values in three of the five states that constitute the region. These states include Kansas, Oklahoma and Texas. Whereas the ksat values for Kansas range from 0.01-141.15, those associated with high carbon sequestration values were 0.01-4.0. The ksat values for Oklahoma range from 0.21-91.74 overall, but locations with high carbon sequestration recorded values from 4.23-42.33; while the values for Texas range from 0.005-92.0, but those associated with high carbon sequestration values range from 2.7-28.0. The situation is however different for Colorado and New Mexico where ksat ranges from 0.21-141.0 and 0.21-91.74 respective, and the values related to high carbon sequestration also range from 10.5-141.0 and 2.82-91.74 in that order. If these results are considered on their face value this will mean that ksat did not appear to play a major role in determining carbon sequestration in Kansas, Oklahoma and Texas because low ksat values would mean low soil water movement which in turn would inhibit plant growth. In the same vein, we would expect Colorado and New Mexico to have more rapid vegetation growth due to the ease with which water moves in the soil. Belyea and Malmer (2004) have observed a rapid decline in carbon sequestration with increasing surface gradient as a result of reduced water seepage.

Cation exchange capacity (CEC) is the capacity of the soil to exchange nutrients in ionic form between the soil and soil solution. This measure is related to soil fertility and nutrient retention capacity of soils, as such, it is an important soil factor that affects plant growth. When a soil has high CEC it indicates that the soil has a greater capacity to hold cations, and low CEC values mean that the soil is only capable of holding fewer nutrients and will likely be subject to leaching of mobile anion nutrients. In terms of soil management, high CEC would therefore, require higher rates of fertilizers or lime to change the soil. It should be pointed out that the particular CEC of a soil is neither good nor bad, but knowledge of the CEC in the soil is a valuable management tool since it tells you the amount of fertilizer or lime to apply in order to change the condition of the soil for an intended purpose, especially for agricultural production. The CEC values in the CHP range from 0.0-65.0 milliequivalents per 100 grams of soil (meq/100g). In Colorado CEC values range from 2.5-65.0 meq/100g, with those of Kansas, New Mexico, Oklahoma and Texas ranging from 0.0-40.2 meq/100g, 0.5-30 meq/100g, 1.0-55 meq/100g, and 2.5-45 meq/100g respectively. It should be pointed out here that CEC values of 0-3 meq/100g have no agronomic significance. But from the CEC values presented here, it shows that locations in the CHP with low values would be susceptible to the leaching of mobile anions. CEC values for locations with high rates of carbon sequestration in Kansas and Oklahoma range from 7.3-18.1 meq/100g, and 11.0-16.0 meq/100g respectively; while those of Colorado, New Mexico and Texas range from 0.5-21.0 meq/100g. This shows that soils in Kansas and Oklahoma would be easier to manage based on their CEC values since they appear to be moderate compared to seemingly more extreme cases observed in Colorado, New Mexico and Texas.

There is a relationship between CEC and soil reaction (pH). Soil pH is a measure of the soil acidity or alkalinity and is sometimes called the soil "water" pH. This is because it is a measure of the pH of the soil solution, which is considered the active pH that affects plant growth. For instance, Park et al (2011) have observed that alfalfa grows best in soils having a pH of 6.2 - 7.8, while soybean grows best in soils with a pH between 6.0 and 7.0. Peanuts grow best in soils that have a pH of 5.3 to 6.6. Many other crops, vegetables, flowers and shrubs, trees, weeds and fruit are pH dependent and rely on the soil solution to obtain nutrients. In the CHP pH values range from 5.8-9.0. The range of pH values in locations that have recorded high carbon sequestration rates is 6.7-7.6 in Colorado, 5.9-7.5 in Kansas, and 7.2-7.9 in New Mexico. The values for Oklahoma and Texas are 6.7-7.6 and 6.8-7.7 respectively. The pH values throughout the CHP region show that carbon sequestration prefers basic rather than acidic soils.

Soil slope in the CHP region ranges from 0.0-50^o, with values for Colorado being 1-34^o, and those of Kansas, New Mexico, Oklahoma and Texas being 0-33^o, 0.5-55^o, 0.5-44^o, and 0.0-50^o respectively. Slope is an important soil factor because it is related to soil stability. The steeper the slope, the less stable is the soil. As observed in the CHP region, higher carbon sequestration rates are found in locations where the slope form ranges from 1.0-3.0^o for Colorado, and 0.0-2.0^o for Kansas. The values for New Mexico, Oklahoma and Texas are 0.5-3.0^o, 0.5-4.5^o, and 0.0-4.0^o respectively. This is an indication that high carbon sequestration rates are found in locations with gentle gradients in the CHP where the soils are stable. Stable soils would be expected to have higher depths, and deep soils would have bigger capacities to retain soil water which will in turn affect plant growth. Soil depth in the CHP region ranges from 3-269 inches. The deepest soils which are in excess of 200 inches are found in Colorado, Kansas, Oklahoma and Texas. Only New Mexico has the deepest soils of 165 inches. However, soil locations associated with high carbon sequestration in Colorado are from 3-53 inches, and those of Kansas are 34-107 inches. High carbon sequestration rates are found in locations with soil depths of 3-30 inches, 5-86 inches and 33-71 inches for New Mexico, Oklahoma and Texas in that order. Locations with deeper soils appear to have higher below ground carbon sequestration compared to relatively shallow soils. It should be noted however, that this claim is not exclusive because so many factors are in play in the determination of carbon sequestration rates in the CHP region of the U.S.

4.7.2. Rates of Carbon Sequestration: Rates of carbon sequestration in the CHP are higher for the structural than metabolic rates, and post-CRP rates being higher than pre-CRP rates. These rate differentials could be attributed to the fact that the metabolic rates have to do with decomposition and so some of the carbon is easily converted back to CO_2. In terms of numbers, the rates of carbon in the CHP region show that rates of carbon sequestration are higher in CRP land than on the land under different management systems of grazing, prescribed burns and the planting of biofuel crops such as alfalfa. The results obtained reaffirm that notion that more carbon is sequestered below ground than above ground. This is important and significant because above ground carbon sequestration can easily be lost and be converted back to CO_2 once the land is stripped of its vegetation and the soils exposed to erosion. The below ground carbon sequestration on the other hand has a longer lifespan since the passive carbon sequestration can stay in the soil for more than 200 years. The implication of this is that if more of the slow and passive carbon is sequestered, then the amount of CO_2 that escapes to the atmosphere will be less.

The slow rates of carbon sequestration estimates for the CHP are 15,873 and 15,593 Kt. per year for CENTURY and DAYCENT models, respectively. These values are lower than Schuman et al. (2001)'s estimates of 20,000 to 30,000 Kt. per year for the grassland region of the U.S. The passive rate estimates for the CHP by the CENTURY and DAYCENT models are 236,300 and 435,000 Kt. per year, respectively. These estimates are consistent with the predictions of Parton et al. (2001) who estimated 349, 000 to 529,000 Kt. per year. It would seem that the CENTURY model underestimated the carbon sequestration rates because estimated values by this model fell short of the lower ends of both Schuman et al. (2001) and Parton et al's (2001) lower ranges. The estimate of the DAYCENT for the passive rate on the other hand, is consistent with the estimates of Parton et al. (2001). However, the high values of carbon sequestration simulated underscores the important role that grasslands play in carbon sequestration, especially in relation to the speed with which grasses grow and their ability to provide cover for soils, which in turn reduces the rate and intensity of soil erosion. The continuous vegetal cover does not only reduce the amount of carbon that could be re-converted to CO_2, but also provides habitat for numerous wildlife as well as improving water quality since there would be less sediment yield migrating to surface and ground water sources.

4.7.3. Policy Strategies and Management Practices for Carbon Sequestration: The importance of grazing and fires as conservation and management strategies in grassland ecosystems have been observed by many researchers including Fuhlendorf et al. (2006) and Hickman et al. (2004). Policy analysis was conducted based on different scenarios that reflect different management practices. The scenarios which include grazing, fires and the planting of biofuel crops on CRP lands were conducted to ascertain their impacts on carbon sequestration in the CHP region of the U.S. The results of the management scenarios as presented for each of the five states that constitute the CHP indicate that these management options have rather limited effects in increasing the rate of above ground carbon sequestration in the CHP region of the U.S. Results obtained for both the CENTURY and DAYCENT models have similar conclusions. The management scenarios of grazing, fire and biofuel however, appear to be more significant in increasing below ground rates of carbon sequestration with grazing having the most effects followed by biofuel and then fire. The positive effects of these management scenarios are seen more in the slow and passive rates of carbon sequestration, and very little with regards to the active rate which is about 2-5 years. The implication of this is that the introduction of management options such as grazing, fire and the planting of biofuel crops has a longer-term benefit for carbon sequestration in the study area and should form part of the policy making process for not only the conservation effort of policy makers in the region, but also the long-term policy making for the greater goal of global climate change mitigation efforts in the region.

As part of field data collection, field interviews were administered to the FSA directors in Texas County, Oklahoma, Union County, New Mexico, Baca County, Colorado and Dallam County in Texas. The purpose of the interview portion of the field trip was to obtain information on the CRP program in the Central High Plains region as they relate to policy making. Preconceived questions were drafted by the researcher including questions such as: (i) what happens to the CRP tracts when contracts expire (ii) are farmers concerned about their contracts, and are they coming to ask questions? (iii) are farmers asking questions about bio-fuels and possible return to production? (iv) what is the status of the re-enrollment and extension (REX) program? (v) what is the status of CRP with regards to grazing, and (vi) the 2008 Farm Bill; what is its status and how similar or different is it from the previous one? Answers to these and other questions that were addressed during the interview session are summarized here.

It was gathered from the discussions that farmers are concerned about their contracts, especially those whose contracts were nearing their expiration dates. From all indications, farmers want to stay in the CRP. The reason for this is not farfetched. Looking at the demographics of the farmers, they are mostly the elderly and retirees who are paid money for not cultivating their fields. Based on personal communication with the FSA Directors in the four states visited, most of the farmers are not interested in returning to production. In fact, they revealed that only about 10% of the farmers have indicated any willingness to return to production at the expiration of their contracts. The reasons for this low percentage in spite of the high price of crops such as corn and alfalfa could be attributed to the fact that most of the farmers are old as well as the fact that there are a high percentage of absentee land owners in the study area, particularly Texas County, Oklahoma. The 10% that indicated interest in returning to production indicated they would produce livestock or crops. One can only speculate here that these farmers are likely to be those that are already corn producers. It was surprising though, to note that many of the farmers were not enthusiastic about bio-fuels, and the Directors indicated that very few of them were asking questions in this direction. Even when the bio-fuel question was raised, there were little or no interests on the part of the farmers in this regard. But this is rapidly changing with new incentive programs to promote bioenergy crops such as switch grass and mescanthus.

As for the 90% who said they would not return to production after the expiration of their contracts, most of them cited other problems apart from age as their reasons.

These problems include the cost of land preparation and equipment. Some farmers said that their lands were marginal to start with that was why they put it into CRP. Their argument is that if the land ceases to be in the CRP it will not be economical for them to put it into production. The problem of water availability was another reason raised as putting the land back into production will most likely require irrigation. Again, one can only speculate here that the age factor may be in part, responsible, since the farmers are not prepared or willing to return to production irrespective of the circumstances. The low percentage of farmers willing to put their land back into production after the expiration of CRP contracts was also attributed to absentee land owners who Miranda said was a big problem in Texas county, Oklahoma because it affected participation of farmers in activities that the FSA organizes and coordinates.

In terms of grazing the CRP fields, the Directors revealed that CRP has always been available for grazing under emergency situations only. As a matter of policy this practice was continuing. What this means is that grazers would be allowed to graze the CRP field only when there was a drought, fire, flood or any other natural disaster. The issue of a 3-year rotational grazing also came up as it was suggested by some farmers but the idea was rejected out rightly by wildlife groups.

The field interview also revealed that, due to the cut in CRP acreage enrollment as contained in the new farm bill from 39 million acres to 32 million acres nation-wide, no new contracts were scheduled to be signed in most of the counties in the study area. The drop in CRP acreage enrollment has also been attributed in part to pressure to convert CRP areas to corn for the production of ethanol. This policy decision has become a contentious political issue in which there is the issue of alternative fuel (bio-fuel) on the one hand and that of environmental conservation on the other.

The re-enrollment and extension program (REX) which was authorized in 2006, was meant to address contract issues that were expiring. Under this program, any contract that was to expire in 2007, 2008, or 2009 was granted an extension of between 2, 3, 4, 5 or a re-enrollment of 10 years. The decision to extend or re-enroll depended on the environmental score of the farmer. The higher the score, the more likely was a farmer to be granted a re-enrollment into the program. It was revealed that no burning of any sort is allowed or encouraged in the CRP fields in the study area. This is simply because the area is too dry and fire incidences may easily get out of control.

4.8. Statistical Analysis and Hypotheses Testing

The statistical analyses presented in this section were based on the simulation results from the CENTURY and DAYCENT models. The statistical analyses started with data exploration and multiple correlation analyses were performed in excel while tests for autocorrelation which were performed using GeoDa (Anselin et al. 2006). Multiple regression analyses were also performed using Geographically Weighted Regression (GWR) by Fotheringham et al. (2007).

4.8.1. Descriptive Data Analysis: This was done to provide a general description of the data used for this study. The measures of central tendency were described through the determination of means, while spread was determined through standard deviation. Also covered in this section were the determination of correlations and measures of autocorrelation (Moran's I) for NPP (the dependent variable) for pre-CRP and post-CRP.

Colorado had a pre-CRP average of 0.398 kt per year of carbon and a post-CRP mean of 1.343 kt of carbon. The values for the standard deviation were 2.268 and 6.135 for pre-CRP and post-CRP respectively. The mean above ground carbon for pre-CRP and post-CRP for Colorado were 0.071 and 0.104, standard deviations of 0.620 and 0.679 respectively. The average below ground carbon values in Colorado are 0.278 and 1.114 for pre-CRP and post-CRP; while their standard deviation values are 1.480 and 5.057.

A multiple correlation analysis for Colorado (Appendix B (i)) shows that NPP (the dependent variable) is weakly but negatively correlated with slope. In the same vein, pH and CEC also show weak but negative correlations with NPP. This means that as slope angle increases, the amount of NPP decreases in Colorado. It also shows that an increase in pH and CEC will result to a decrease in NPP. Sand and CEC, as well as ksat and clay exhibit strong negative relationships, while CEC and clay show a strong positive relationship. The implication of this is that as the amount of clay increases in the soil, CEC and ksat decreases.

The mean NPP values for Kansas in the pre-CRP and post-CRP eras are 0.361 and 1.186, with standard deviation values of 1.247 and 3.477 respectively. The above ground and below ground mean carbon values are 0.069 and 0.106 for pre-CRP and post-CRP, with standard deviation values of 0.302 and 0.457 in that order. The below ground mean and standard deviation values for pre-CRP and post-CRP for Kansas are 0.242 and 0.949; and 0.828 and 2.764 respectively.

In terms of correlation (Appendix B (ii)), while CEC and bulk density are negatively correlated with NPP, slope and pH have positive but weak relationships. Again, whereas sand and clay have strong negative correlations with CEC, CEC and clay show strong positive relationship.

In New Mexico, pre-CRP and post-CRP average carbon values are 0.034 and 0.122, with standard deviation values of 0.088 and 0.529 respectively. The mean above ground carbon values for pre-CRP and post-CRP in New Mexico are 0.004, and 0.007; with standard deviation values of 0.009 and 0.020. The average and standard deviation below ground carbon values are 0.024 and 0.097; and 0.066 and 0.406 for pre-CRP and post-CRP in that order.

The relationship among variables in New Mexico (Appendix B (iii)) is such that slope, pH and CEC have weak negative correlation with NPP. On the other hand, bulk density and clay are strongly but negatively correlated and organic matter and soil depth are also strongly but negatively correlated. This means that as the percentage of clay content in the soil increases, the value of bulk density decreases. In the same vein, with an increase in soil depth, the amount of organic matter reduces.

The pre-CRP mean NPP value in Oklahoma is 0.177 with a standard deviation of 0.434, while the post-CRP mean value is 0.664 with a standard deviation of 1.281. For the above ground carbon averages, pre-CRP has 0.0318, with a standard deviation of 0.105; and post-CRP values of 0.055 and 0.148 for mean and standard deviation respectively. Mean above ground pre-CRP and post-CRP carbon are 0.117 and 0.533; and standard deviation values of 0.279 and 1.031 respectively.

The variables in Oklahoma (Appendix B (iv)) show that while slope, pH and CEC have weak but positive relationships with NPP, ksat shows a negative but weak correlation. However, ksat and sand have a strong positive relationship, but also a strong but negative correlation with silt. This means that as the percentage of sand increases, saturated soil conductivity (ksat) also increases, but when the percentage of silt in the soil increases, ksat decreases.

Descriptively, the pre-CRP and post-CRP mean NPP values for Texas are 0.158 and 0.494, and standard deviation values of 0.448 and 1.185. In terms of above ground carbon, the pre-CRP and post-CRP means are 0.029 and 0.041, with standard deviation values of 0.102 and 0.129 respectively. Above ground pre-CRP and post-CRP averages are 0.107 and 0.397, with 0.294 and 0.960 standard deviation values respectively.

The correlation analysis for Texas (Appendix B (v)) show that temperature is negatively correlated with carbon rates, but there is a strong positive relationship between carbon rates and CRP area. NPP also shows weak negative correlations with ksat, pH and slope, while CEC and clay show a very strong positive correlation, but a strong but negative correlation between ksat and silt. This means that as the clay content of the soil increases, there is an increase in cation exchange capacity (CEC) of the soil, whereas there is an inverse relationship between ksat and silt.

4.8.2. Regression Analysis: The regression analysis for this study was conducted using Geographic Weighted Regression (GWR). The choice of GWR stems from the fact the data for determining carbon sequestration is spatial in nature and standard regression techniques assumes the data to be constant over space, which means one model fits all. In this kind of situation the same stimulus may provoke a different response in different parts of the study region, thereby creating a spatial nonstationarity. Again, because the process here is based on global models, the processes are assumed to be stationary and therefore, are location dependent. And so, when we apply a typical linear regression model to spatial data we assume a stationary process depicted in equation 1 (Fortheringham et al. 2007).

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \beta_n x_{ni} + \varepsilon_i \quad \ldots\ldots\ldots\ldots \quad 1$$

In this case, the parameter estimates obtained in the calibration of such a model are constant over space as indicated by equation 2.

$$\boldsymbol{\beta' = (X^T X)^{-1} X^T Y} \quad \ldots\ldots\ldots\ldots \quad 2$$

Where X is a matrix of independent variables; and Y is a vector of observations on the dependent variable.

The implication of this is that, any spatial variations in the processes being examined can only be estimated by the error term. In order to account for any spatial variation in the parameter estimates using the ordinary least square (OLS) method, we might map the residuals from the regression to determine whether there are any spatial patterns, or compute an autocorrelation statistic or even try to ‘model’ the error dependency with various types of spatial regression models.

Instead of adopting these long processes to correct for spatial variations in the parameter estimates, we can address the issue of spatial nonstationarity directly and allow the relationships we are measuring to vary over space. This is where Geographically

Weighted Regression (GWR) becomes relevant, and that is why it has been used in this study. GWR is a statistical technique that allows for the modeling of processes that vary over space (Charlton et al. 2006). It uses local models which are spatial disaggregations of global models, whose results are location-specific, not location dependent. This situation is captured in the equation:

$$y(g) = \beta_0(g) + \beta_1 (g)\, x_1 + \beta_2 (g)\, x_2 + \ldots\ \beta_n (g)\, x_n + \varepsilon (g) \quad \ldots\ldots\ldots\ldots \quad 3$$

where (g) refers to a location at which estimates of the parameters are obtained. Using this estimation method therefore, weights can be assigned to each location.

$$\boldsymbol{\beta' = (X^T W(g)\, X)^{-1} X^T W(g)\, Y} \quad \ldots\ldots\ldots\ldots \quad 4$$

where **W(g)** is a matrix of weights specific to location g such that observations nearer to g are given greater weight than observations further away. The basis of this assertion is rooted in the “First Law of Geography”: everything is related with everything else, but closer things are more related (Tobler 1970). Therefore, the weights are assigned as follows:

Table 4.10: Weight Matrix: W(g) …………………………………... 5

Weights	w_{g1}	w_{g2}	w_{g3}	w_{gn}
w_{g1}	w_{g1}	0	0	0
w_{g2}	0	w_{g2}	0	0
w^{g3}	0	0	w_{g3}	0
w_{gn}	0	0	0	w_{gn}

where w_{gn} is the weight given to data point n for the estimate of the local parameters at location g. It should be noted that nnumerous weighting schemes can be used. They can either be **fixed** or **adaptive**. Two examples of a fixed weighting scheme are the Gaussian function (Fotheringham et al. 2007).

$$w_{ij} = \exp[-(d_{ij}^2 / h^2)/2] \quad \text{..........} \quad 6$$

where h is known as the bandwidth and controls the degree of distance-decay ,d and the bisquare function:

$$w_{ij} = [1-(d_{ij}^2 / h^2)]^2 \quad \text{if } d_{ij} < h = 0 \quad \text{..........} \quad 7$$

In this study the spatially adaptive weighting function was used. This function is given by:

$$w_{ij} = \exp(-R_{ij} / h) \quad \text{..........} \quad 8$$

where R is the ranked distance

or $w_{ij} = [1-(d_{ij}^2 / h^2)]^2$ if j is one of the Nth nearest neighbours of i 9

In terms of calibration, the results of GWR appear to be relatively insensitive to the choice of weighting function as long as it is a continuous distance-based function (Fotheringham et al. 2007). Regardless of whichever weighting function is used, the results will, however, be sensitive to the degree of distance-decay. Therefore an optimal value of either h or N has to be obtained. This can be found by minimising a cross-validation score or the Akaike Information Criterion (AIC).

$$CV = \sum_i [y_i - y_{\neq i}' (h)]^2 \quad \ldots\ldots \quad 10$$

where $y_{\neq i}'$ (h) is the fitted value of y_i with data from point i omitted from the calibration, and

$$AIC = 2n \ln(\sigma') + n \ln(2\pi) + n[n + Tr(\mathbf{S})] / [n - 2 - Tr(\mathbf{S})] \quad \ldots\ldots \quad 11$$

where n is the number of data points, σ' is the estimated standard deviation of the error term, and Tr(**S**) is the trace of the hat matrix.

The regression results for Colorado (Appendix A (i) show that using the global model, the coefficient of determination, was 0.8373, with an adjusted R^2 of 0.8369. In contrast, the GWR estimation had a coefficient of determination of 0.8464, and an adjusted R^2 of 0.8457. The results for Colorado show that there is a slight improvement from the global model to the local model. The results indicate that 84% of carbon sequestration in Colorado is accounted for by the 11 independent variables that were considered (Table 4.11).

Results from Table 4.11 show that of the 12 independent variables under consideration, only two were statistically significant. Cation exchange capacity (CEC) with a p-value of 0.02 is significant at 5% level, while minimum temperature with a p-value of 0.00 is significant at 0.1% level. The fact that only two variables are statistically significant does not imply that the other variable have not contributed to carbon sequestration in Colorado. As Table 4.11 shows, bulk density (BD) and slope appear to be very strong variables owing to their p-values of 0.07 and 0.25 respectively, even though they are not statistically significant.

The regression results for Kansas (Appendix A(ii) on the other hand show a global coefficient of determination of 0.94728 with an R^2 of 0.94725. Two variables, Tmin (0.0100) and slope (0.0300) were the only ones that were statistically significant. The GWR estimation for Kansas has a coefficient of determination value of 0.94767 and R^2 values of 0.94763. This means that the controlling variables have explained about 95% of the response variable in Kansas. The remaining 5% is explained by factors other than the ones listed in Table 4.11.

Table 4.11 show that of the 12 independent variables considered in the determination of carbon sequestration in Kansas, only two were statistically significant. The two statistically significant variables are minimum temperature with a p-value of 0.01, significant at 1% level, and slope with p-value of 0.03 significant at 5% level. Table 4.22 shows that bulk density (BD) and cation exchange capacity (CEC) were strong contenders with p-values of 0.24 and 0.28 respectively. Again, it should be pointed out that simply because a variable is not statistically significant does not mean that it does not play a role in explaining the response variable.

In New Mexico, a coefficient of determination value of 0.87347 and an adjusted R^2 value of 0.86694 was recorded for the global regression model; while a coefficient of determination of 0.98045 and an adjusted R^2 of 0.9782 was estimated by GWR (Appendix A (iii). The implication of these results is that there was a significant improvement from the global estimation to the local estimation of carbon sequestration in New Mexico. Whereas in the global model, 87% of carbon sequestration in New Mexico is explained by the 9 independent variables that were considered, the global model indicates that these variables actually accounted for 98% of carbon sequestration in New

Mexico. Table 4.17 shows that only one of the variables, metabc(2) with p-value at 0.04 is statistically significant.

Table 4.11 show that only metabc(2) which is an initial metabolic below ground carbon is statistically significant in determining carbon sequestration in new Mexico.

The regression analysis for Oklahoma (Appendix A (iv) shows that the coefficient of determination is 0.87939 and the adjusted R^2 value is 0.878876 for the global model; while GWR estimated a coefficient of determination value of 0.911355, and an R^2 of 0.907898. This indicates that while the global model show that the independent variables explained about 88% of the dependent variable, the local model estimated by GWR suggests that about 91% of the independent variables have explained the dependent variable. A Monte Carlo test of significance shows that only som2c and som3c, which are both below ground initial carbon are statistically significant (Table 4.11). Of the 12 independent variables considered precipitation, bulk density and slope were close to being statistically significant.

Table 4.11: Monte Carlo Significance Test for Oklahoma, Texas, New Mexico. Kansas and Colorado

Parameter	P-value				
Parameter	Oklahoma	Texas	Kansas	NMexico	Colorado
Intercept	0.72000 n/s	0.99000 n/s	0.37000 n/s	0.07000 n/s	0.26000 n/s
strucc(2	0.53000 n/s	0.36000 n/s	0.23000 n/s	0.04000 *	0.30000 n/s
metabc(2	0.54000 n/s	0.05000 *	0.41000 n/s	0.98000 n/s	0.94000 n/s
som2c	0.01000 **	0.10000 n/s	0.55000 n/s	0.22000 n/s	0.74000 n/s
som3c	0.01000 **	0.10000 n/s	0.79000 n/s	0.85000 n/s	0.49000 n/s
PPT	0.10000 n/s	0.0000***	0.60000 n/s	0.85000 n/s	0.74000 n/s
Tmin	0.24000 n/s	0.83000 n/s	0.01000 **	0.96000 n/s	0.00000 ***
Depth	0.81000 n/s	0.65000 n/s	0.55000 n/s	0.98000 n/s	0.25000 n/s
BD	0.26000 n/s	0.90000 n/s	0.24000 n/s	0.11000 n/s	0.07000 n/s
Ksat	0.81000 n/s	0.16000 n/s	0.78000 n/s	0.22000 n/s	0.42000 n/s
CEC	0.75000 n/s	0.77000 n/s	0.28000 n/s	0.56000 n/s	0.02000 *
pH	0.52000 n/s	0.93000 n/s	0.79000 n/s	0.46000 n/s	0.83000 n/s
Slope	0.13000 n/s	0.45000 n/s	0.03000 *	0.56000 n/s	0.25000 n/s

*** = significant at .1% level
** = significant at 1% level
* = significant at 5% level

The regression analysis for Texas (Appendix A (v) reveals a global coefficient of determination value of 0.775 with an adjusted R^2 of 0.7743; while the GWR estimates a coefficient of determination value of 0.8193 and an R^2 value of 0.8168. This shows that the local model has improved the predictive power of estimating the response variable (NPP) over the global model by about 4%.

As Table 4.11 indicates, of the 12 independent variables used to explain the dependent variable of NPP, only metabc(2), p-value 0.05, and precipitation, p-value 0.00 are statistically significant. This means that although the 12 variable have explained 77% (global) and 82% (GWR) of the dependent variable, only two of them are statistically significant.

4.8.3. Hypothesis Testing: In chapter 1 of this study, several research objectives were considered, and a number of research questions were raised to address these stated objectives. Consequently, two hypotheses were stated, and the testing of these hypotheses was employed to help in decision making regarding the data collected for the study. We had hypothesized that CRP lands would lead to increases in carbon sequestration compared to non-CRP lands, such as lands under cultivation; and that CRP lands would sequester more carbon than lands under management systems such as grazing, fire and biofuel. This second hypothesis was drawn because CRP lands are completely unmanaged, and we set out to see if there would be any change in carbon sequestration if any form of management is employed as part of policy change.

The two hypotheses are directional, and also because the sample data are large, a one-tailed Z test was used to test for these hypotheses. In order to make the hypothesis testing clearer, the hypotheses have been represented in the form of Null (H_o) and alternative (H_1) hypotheses.

H_o: there is no difference in the amount of carbon sequestration between non-CRP (pre-CRP) and CRP (post-CRP) land.

H_1: CRP (pre-CRP) land actually sequesters more carbon than non-CRP (pre-CRP) lands.

This hypothesis was tested using the Z test using NPP values for pre-CRP and post-CRP. The results of the test as presented in Table 4.12 show the calculated Z scores for the various states that form the CHP region of the U.S. Table 4.26 shows that because the p_values are all significant. This means that the Null hypothesis is hereby rejected and the alternative hypothesis that CRP (post-CRP) sequesters more carbon than non-CRP (pre-CRP) land is accepted.

Table 4.12: Mean (Z) Test for Pre-CRP and Post-CRP

Colorado	Kansas	New Mexico	Oklahoma	Texas
-70.05*	-148.4894***	-9.877*	-40.1644***	-29.5977***

Note: *=significant at 5%; **=significant at 1%; ***=significant at 0.1%; ‘=not significant

The second hypothesis was also tested using a one-tailed Z test because it is also directional. Stating this is a Null and alternative hypotheses.

H_o: there is no difference in the amount of carbon sequestered between unmanaged (CRP) land and managed (grazing, fire, and biofuel) lands in the CHP region of the U.S.

H_1: Unmanaged (CRP) lands sequester more carbon than managed (grazing, fire, and biofuel) lands in the CHP region of the U.S.

This hypothesis was tested using post-CRP NPP values and NPP values obtained for the grazing, fire and biofuel scenarios and the calculated Z values are presented in Table 4.27. Results presented in Table 4.13 indicate that there is not enough evidence to reject the Null hypothesis. As such, we cannot categorically make a decision as to whether an unmanaged land sequesters more carbon than managed lands. The only exception, though, is biofuel for Kansas which is significant. But on the strength of that result alone, we may speculate that there might have been some outlier values that may have impacted the results.

Table 4.13: Mean (Z) Test for Post-CRP and Grazing, Fire and Biofuel

Scenario	Colorado	Kansas	New Mexico	Oklahoma	Texas
Grazing	-0.176-06^	-0.411-06^	-0.889-10^	-0.425-06^	0.989-06^
Fire	-0.1579-07^	0.2225-06^	-0.315-09^	-0.161-05^	-0.108-05^
Biofuel	0.809-07^	-58.7471***	0.680-10^	-0.1175-06^	-0.664-07^

Note: *=significant at 5%; **=significant at 1%; ***=significant at 0.1%; ^=not significant

These results show that while we can conclude with a 95% confidence that a land use change from agriculture to CRP will result in an increase in carbon sequestration (Table 4.12); we do not have enough evidence to conclude that land under management systems such as grazing, prescribed burns and the planting of biofuel crops such as alfalfa will sequester less carbon than unmanaged lands such as under CRP (Table 4.13).

CHAPTER V

5.0 SUMMARY AND CONCLUSIONS

5.1 Introduction

This chapter presents a summary of the findings of the study as well as some suggestions on areas of further research. The main thrust of this study has been on the long-term trends in carbon sequestration, as well as a comparative estimation of potential pre-CRP and post-CRP carbon sequestration in the CHP region of the U.S. This study was carried out using an integrated modeling and GIS approach whereby two models, CENTURY and DAYCENT were used to simulate carbon pools and the results integrated to a GIS for further analyses and mapping.

5.2 Summary of Findings and Conclusions

The threat of global climate change has prompted policy makers to consider ways of offsetting greenhouse gas emissions through carbon sequestration projects which help remove CO_2 from the atmosphere (Kucharik 2004). And because global climate change, including warmer temperatures, higher CO_2 concentrations, increased nitrogen deposition, increased frequency of extreme weather events, and land use change, affects soil carbon inputs (plant litter), and carbon outputs (decomposition); capturing and storing carbon in biomass and soil in the agricultural sector has gained widespread acceptance as a potential greenhouse gas mitigation strategy (Feng et al. 2004). Consequently, research attention is increasingly focused on understanding the mechanisms by which various land use practices can sequester carbon, including the introduction of cover crops on fallow land, the conversion of conventional tillage to conservation tillage, and the retirement of land from active production to a grass cover or trees (Feng et al. 2004; Mitchel et al. 1996).

As Lal et al. (1995) has observed, the pool of organic carbon in soils plays a key role in the carbon cycle and has a large positive impact on the greenhouse effect. According to Post et al. (1990), soils contain an estimated 1.5 x 10^{15} g of carbon, or twice as much as the atmosphere and three times the level held in terrestrial vegetation. In addition, soil carbon plays a key role in determining long-term soil fertility necessary to sustain profitable long-term agricultural production (Mitchel et al. 1996). Therefore, the ability to sequester carbon in soils by proper tillage and erosion management provides enough and long-term justification for soil conservation programs, including the Conservation Reserve Program (CRP).

CRP is the largest land retirement program in the U.S. It enrolls about 10% of all cropland and accounts for more than 85% of all federal conservation expenditure. CRP was initiated to encourage farmers to remove highly erodible land from production and plant native grasses or other protective vegetation for 10-15 years. Carbon sequestration emerged as a co-benefit to the original objectives of soil erosion control and improved water quality, and has attracted lots of studies since then.

The main goal of this research was to examine long term trends in carbon sequestration in Conservation Reserve Program (CRP) tracts in the Central High Plains (CHP) region of the U. S. The second goal was to examine the amount of carbon sequestered on the same tracts before they were converted to CRP and compare the two. In short, the aim was to estimate pre-CRP and post-CRP carbon sequestration in the CHP region. To achieve these goals, the following objectives are considered:

1 To develop a Geospatial Database pertaining to soils, land cover, and climate for the CHP region.
2 To compare the estimated amount of carbon sequestered in the study area before and after conversion to CRP.
3 To evaluate rates of carbon sequestration and assess policy strategies and management practices for carbon sequestration in the study area.
4 To project future trends in carbon sequestration, and map the spatial and temporal distribution of carbon sequestration in the study area.

The Central High Plains (CHP) region is part of the Great Plains in Central USA. It comprises portions of 5 States, including Colorado, Kansas, New Mexico, Oklahoma and Texas. Agriculture in the form of cattle ranching and cultivation is the primary economic activity in the region. Nearly all of this area is in farms and ranches; about 60 percent is cropland. This is a major dry land farming area that utilizes a large groundwater reservoir of the Ogallala aquifer. Soil conservation is the principal environmental problem in the study area as soils are severely threatened by intensive farming. This has threatened biodiversity in the region and has significantly reduced the organic carbon (C) content and nutrient supply capacity of the soil. Several findings and conclusions can be deduced from the study, and are summarized thus:

1. The results indicate that within a 25-year period the CENTURY model estimated 11958.04 Kt and 39,682.8 kt for pre-CRP and post-CRP, respectfully; while the DAYCENT model estimated 21729.80 Kt and 38,983.52 kt. These estimates show that, whereas the CENTURY model projected a 54% increase in carbon sequestration, the DAYCENT model's predicted increase was 28%.
2. While the CENTURY model estimated an average per unit area pre-CRP rate of 0.06 kt C km^{-2}, and a post-CRP value of 0.20 Kt C km^{-2} per year, the DAYCENT model estimated 0.11 kt C km^{-2} and 0.19 Kt C km^{-2}per year for the CHP region of the U.S. It will be expected that the passive pool will steadily increase in the study area with prolonged management (CRP) since the soil is continuously under cover. The slow pool also increased with longevity in CRP, but active carbon pools are minimal due to decomposition rate that re-converts carbon into CO_2, released back into the atmosphere.
3. Land use change plays a very important role in carbon sequestration. This is demonstrated from the fact that the amount of carbon sequestered increased tremendously when the land use was changed from agriculture and ranching to CRP in the CHP region.
4. The study shows that more carbon is sequestered below ground than above ground. This is because CENTURY estimated that the above ground carbon accounts for 9.7% and the below ground accounts for the remaining 90.3% of the

carbon sequestered. DAYCENT on the other hand estimated 14% above ground and 86% below ground carbon.

5. The study shows that slope, minimum temperature, cation exchange capacity (CEC), bulk density, saturated soil conductivity (ksat) and a sandy loam texture are the most important factors controlling carbon sequestration in the CHP region of the U.S. Texture, minimum temperature and slope were the most important owing to their statistical significance in estimating carbon sequestration.
6. The distribution of NPP in the CHP region is random. This was based on Moran's Index determination which ranged from 0.01-0.05. Isolated areas that exhibited clustering were outliers. Results of trend analysis indicated that these outliers were both global and local in nature.
7. The Geospatial Database that was created from the study will serve as a reference tool for researchers, farmers, ranchers and policy makers in the CHP.
8. The use of the cropland data layer (CDL) data have shown to be effective in the extraction of CRP tracts in the Central High Plains (CHP) region. The study is an illustration of how GIS and modeling can be used to analyze temporal and spatial changes in carbon sequestration due to changes in land use.
9. Statistical analyses show that slope is inversely related to NPP, which means that as the gradient increases, the amount of carbon sequestration decreases. Precipitation did not seem to play an important role in carbon sequestration in the region. This is not surprising because Derner and Schuman (2007) have found a negative relationship between precipitation and carbon sequestration in the 0 to 30 cm soil depths.

10. Decisions on the effects of management practices of grazing, fire and biofuel in the CHP were inconclusive owing to high p_values which were higher than 0.05. . Derner and Schuman (2007) have observed a decrease in carbon sequestration with longevity in grazing as a land management practice. However, studies (Lal et al. 2001) have suggested that the use of these management systems in combination yields more carbon than if they were adopted singly.
11. Results pertaining to live plant biomass simulated by both CENTURY and DAYCENT models were generally low as expected since live plant biomass changes very rapidly; thus, accumulations are minimal.
12. Results obtained from the study has provided an indication of the potential contribution of carbon sequestration to the overall climate change mitigation strategy and conservation management practices of the CHP region and may be a strong basis upon which subsequent policy on future enrollments in CRP contracts will be based.

Soil, weather, cropland, and elevation data were pre-processed using ArcGIS and ERDAS Imagine software. The processed data were used to create input files for running the CENTURY and DATCENT models. The CENTURY model version 4.5 which runs on a monthly time-step and the DAYCENT model version 4.5 which runs on a daily time-step were used to simulate potential carbon sequestration. The SPIN functionality in the models was used to run the pre-CRP scenario to equilibrium from 1900 to 1984; and the post-CRP scenario was simulated from 1985 to 2010 (25 years). Simulation results from the pre-CRP model run were extracted for the period 1959-1984 for comparison with the post-CRP scenario. Simulations were also run from 2011-2050 (40 years) to determine the effects of management (grazing, fire and biofuel) on potential carbon sequestration in the CHP.

This study attempts to quantify potential carbon sequestration in CRP tracts in the CHP region of the U.S. in terms of above and below ground live carbon. The soil organic matter pools determined were active, slow and passive. The active pool represents soil microbes and microbial products and has a turnover time of 2-5 years. The slow pool includes resistant plant material with a turnover time of 20-50 years, and the passive pool is very resistant to decomposition and includes physically and chemically stabilized soil organic matter (SOM), with a turnover time of 400-2000 years. ArcGIS was used to produce maps showing the spatial distribution of simulated results pertaining to carbon sequestration in the study area.

This study also attempted the determination of the pre and post-CRP estimates of carbon sequestration in the study area, to help in explaining the temporal variability and spatial distribution of carbon sequestration in the CHP. The spatial distribution of CRP tracts and the related carbon sequestration from the maps produced, gives this study a firm geographic perspective. It is anticipated that the simulated estimates derived from the study will enhance our understanding of environmental benefits of carbon sequestration. And since the geographic distribution of co-benefits varies significantly, the results of the study will provide information to policy makers, the agricultural sector, the scientific community and the general public on the benefits of carbon sequestration which can have very important implications for both environmental conditions and income distributions to farmers in the study area. The results of this study, apart from contributing to the body of literature pertaining to the effect of land use change on carbon sequestration, can also be replicated elsewhere, in terms of quantifying and verifying carbon sequestration potentials especially in the grassland region of developing countries like Nigeria.

5.3 Recommendations and Suggestions for Further Research

1. The models used for this study are point models. It takes a lot of time and effort to parameterize these models. A complete integration of these models with a GIS will greatly enhance its effectiveness and accuracy especially when dealing with spatial data.

2. The original intent of the study was to simulate carbon on the basis of grazing intensities in terms of low, medium and high, but these were not very clear in the model. The same can be said of fire in which the original intent was to look at the effect of fire based on time and intensity. The models could still be developed to produce more clarity in output that will allow for discernment of the effects of land use intensities on carbon sequestration. These laudable objectives are achievable by other means and methods and it is important that future studies devise objective methods to achieve them.

3. The CENTURY and DAYCENT models should be developed such that raster data can be used. This way, outputs can be mapped on a cell level. This will allow for finer scale and more accurate simulation outputs.

4. The processes of obtaining CRP data from the FSA were tedious. Although the data was available, it was not accessible due to privacy concerns. The thrust of this research was dependent on the availability of such data, and when that did not happen, it made the study much more difficult and challenging. To get around this problem, we had to devise

a method of deriving the CRP data from the cropland data layer (CDL) using the spatial analytical techniques in GIS. The only actual CRP data obtained and used were for Texas and Oklahoma. The availability of the CRP data from the Farm Service Agency (FSA) would have improved the accuracy and reliability of the findings of this research. It behooves the necessary authorities and agencies to make such important data accessible for research purposes, while at the same time ensuring anonymity of owners. It is important to examine the successes and potentials of large policies such as the CRP program in which a lot of public resources have been invested.

5. The CENTURY and DAYCENT models should include plant species changes which will help in simulating live plant biomass better. This is because as noted by Parton el at. (1993), changes in species composition from C3 and C4 vegetation or structural changes resulting from shifts between grasslands and savannas affect nutrient dynamics, water utilization, biomass allocation and other characteristics which modify plant production and seasonality of plant growth. Modeling these changes would improve the reliability of inferences and conclusions that may be derived from these studies.

The following areas are hereby recommended for further research:

1. Comparative analysis of carbon sequestration in temperate grassland vs. tropical grassland ecosystems
2. Implications of carbon sequestration and climate change initiatives and policy
3. Comparative analysis of the benefits and implications of natural and anthropogenic methods of carbon sequestration for croplands

4. Determining the effects of land use dynamics and intensity on carbon sequestration rates.
5. Deriving accurate CRP data from a combination of sources such as CDL, Landsat, NAIP and MODIS.
6. The impact of landscape structure on carbon sequestration and biodiversity.

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APPENDICES

Appendix A (i): Colorado with Monte Carlo Significance test

```
*************************************************
*       Geographically Weighted Regression      *
*               Release 3.0.1                   *
*            Dated: 06-vii-2003                 *
*                                               *
*       Martin Charlton, Chris Brunsdon         *
*            Stewart Fotheringham               *
*     (c) University of Newcastle upon Tyne     *
*************************************************
Program starts at: Thu Jan 27 15:18:16 2011

** Program limits:
** Maximum number of variables.....     52
** Maximum number of observations..  80000
** Maximum number of fit locations.  80000

COPrCmodel2
** Observed data file:        F:\Dissertation Analyses Layers\Colorado
** Prediction location file:  Estimation at sample point locations
** Result output file:        F:\Dissertation Analyses Layers\Colorado

** Variables in the data file...
 ID       XCoord   YCoord   Area     time     stdedc   aglivc   bglivc
 NPP      strucc(1 strucc(2 metabc(1 metabc(2 som1c(1) som1c(2) som2c
 som3c    stream(5 PPT      Tmin     Tmax     Depth    Sand     Silt
 Clay     OM       BD       Ksat     CEC      pH       Slope    Elevatio

** Dependent (y) variable..........NPP
** Easting  (x-coord) variable.....XCoord
** Northing (y-coord) variable.....YCoord
** No weight variable specified
** Independent variables in your model...
 strucc(1 metabc(1 som2c    som3c    Tmin     OM       BD       Ksat
 CEC      pH       Slope
** Kernel type:  Adaptive
** Kernel shape: Bi-Square
** Bandwidth selection by AICc minimisation
** Use all regression points
** No calibration history requested
** No prediction report requested
** Output estimates to be written to .txt file
** Monte Carlo significance tests for spatial variation
```

```
** No casewise diagnostics requested

*** Analysis method ***
*** Geographically weighted multiple regression
** Cartesian coordinates: Euclidean Distance
**************************************************************
*                                                            *
*        GEOGRAPHICALLY WEIGHTED GAUSSIAN REGRESSION         *
*                                                            *
**************************************************************
 Number of data cases read: 5475
 Observation points read...
Dependent mean=  397769536.
 Number of observations, nobs= 5475
 Number of predictors,   nvar= 11
 Observation Easting extent:   1.13589561
 Observation Northing extent:  1.88773668
*Finding bandwidth...
  ... using all regression points
 This can take some time...
 *Calibration will be based on  5475 cases
*Adaptive kernel sample size limits:     273   5475
 *AICc minimisation begins...
       1880.506407990000      245936.546516040950
       2874.000000000000      245747.011840515710
** Convergence after     8 function calls
** Convergence: Local Sample Size=   4716

*********************************************************
*           GLOBAL REGRESSION PARAMETERS                *
*********************************************************
Diagnostic information...
Residual sum of squares.........********************
Effective number of parameters..          12.000000
Sigma..........................    915911709.393659
Akaike Information Criterion....      241509.394736
Coefficient of Determination....           0.837313
Adjusted r-square...............           0.836955

Parameter              Estimate              Std Err                    T
---------          ------------         ------------         ------------
Intercept  80107428.297079369000 419381435.260469080000         0.191013291478
 strucc(1         0.545889673291         0.086030855347         6.345277786255
 metabc(1         0.560399899529         0.184562910517         3.036362409592
 som2c           -0.139146680524         0.009448598820       -14.726699829102
 som3c            0.308007765369         0.011191749011        27.520967483521
 Tmin       -539551.062776322010   2185639.977279597000        -0.246861815453
 OM         5792407.854625900300  23114377.896441363000         0.250597596169
 BD      -128345401.293454960000 204815197.930145080000        -0.626640021801
 Ksat       -305800.188865121860    578067.710200675300        -0.529004096985
 CEC       -3001122.846403075800   2197977.052610978900        -1.365402221680
 pH         9458374.594644194500  31965539.101754032000         0.295892864466
 Slope     -3334911.572837857100   2691707.099163733900        -1.238957881927


*********************************************************
*                GWR ESTIMATION                         *
*********************************************************
 Fitting Geographically Weighted Regression Model...
 Number of observations............ 5475
 Number of independent variables... 12
  (Intercept is variable 1)
 Number of nearest neighbours...... 4716
 Number of locations to fit model.. 5475

Diagnostic information...
Residual sum of squares.........********************
```

```
Effective number of parameters..         25.078095
Sigma..........................   890907244.454984
Akaike Information Criterion....     241219.528764
Coefficient of Determination....          0.846443
Adjusted r-square...............          0.845736
 ** Results written to .txt file

**********************************************************
*                      ANOVA                             *
**********************************************************
        Source                        SS        DF              MS              F
OLS Residuals   **********************     12.00
GWR Improvement **********************     13.08*****************
GWR Residuals   **********************   5449.92*****************       24.7768


**********************************************************
*          PARAMETER 5-NUMBER SUMMARIES                  *
**********************************************************
   Label       Minimum  Lwr Quartile        Median  Upr Quartile       Maximum
-------- ------------- ------------- ------------- ------------- -------------
Intrcept*********************************************************************
strucc(1      0.365127      1.215890      2.041865      2.074873      2.112249
metabc(1     -0.310044      0.118895      0.423367      0.629557      2.199238
som2c        -0.181677     -0.136146     -0.107419     -0.099494     -0.092338
som3c         0.194238      0.206268      0.217065      0.300200      0.371912
Tmin     ************** 776629.8487871105476.1063461178685.6740141226846.996731
OM       **************1827769.6968548630810.251643****************************
BD       **************1435573.195569******************************************
Ksat     -973052.345000-339960.781924-226720.046466-180971.494879 -17822.498133
CEC      ******************************************-918617.450255-257512.886376
pH       **************1873395.6564389786875.820904****************************
Slope    ****************************-351336.274168-172707.982446 -18547.280142


        <------------------ LOWER ----------------><------------------ UPPER ------
----------->
   Label Far Out   Outer Fence Outside   Inner Fence   Inner Fence Outside   Outer
Fence Far Out
-------- ------- ------------- ------- ------------- ------------- ------- ---------
---- -------
Intrcept       0**************       0****************************
921**************      341
strucc(1       0     -1.361061       0     -0.072586      3.363349       0
4.651824       0
metabc(1       0     -1.413088       0     -0.647096      1.395548     179
2.161540       2
som2c          0     -0.246103       0     -0.191124     -0.044516       0
0.010463       0
som3c          0     -0.075527       0      0.065370      0.441098       0
0.581995       0
Tmin        1225-429537.626893      54 173546.1109471781769.411854
02384853.149694        0
OM           289**************     294****************************
0**************        0
BD          1268**************      39****************************
0**************        0
Ksat        1052-816928.643061      58-578444.712493  57512.435689       0
295996.366257        0
CEC          399**************     753**************1537322.939111
03993263.328478        0
pH           135**************     185****************************
0**************        0
Slope          0**************     408**************3935678.047352
08044064.077150        0

**************************************************
```

```
*                                              *
*   Test for spatial variability of parameters  *
*                                              *
************************************************

Tests based on the Monte Carlo significance test
procedure due to Hope [1968,JRSB,30(3),582-598]

Parameter                 P-value
----------      -----------------
Intercept           0.26000   n/s
strucc(1            0.30000   n/s
metabc(1            0.94000   n/s
som2c               0.74000   n/s
som3c               0.49000   n/s
Tmin                0.00000   ***
OM                  0.74000   n/s
BD                  0.07000   n/s
Ksat                0.42000   n/s
CEC                 0.02000   *
pH                  0.83000   n/s
Slope               0.25000   n/s

*** = significant at .1% level
**  = significant at 1% level
*   = significant at 5% level

Program terminates normally at: Thu Jan 27 19:08:23 2011
```

Appendix A (ii): Kansas with Monte Carlo

```
************************************************
*       Geographically Weighted Regression      *
*               Release 3.0.1                   *
*            Dated: 06-vii-2003                 *
*                                               *
*       Martin Charlton, Chris Brunsdon         *
*            Stewart Fotheringham               *
*      (c) University of Newcastle upon Tyne    *
************************************************
Program starts at: Sat Apr 16 00:48:08 2011

** Program limits:
** Maximum number of variables.....      52
** Maximum number of observations..  80000
** Maximum number of fit locations.  80000

Kansas_Monte Carlo
** Observed data file:         C:\Documents and Settings\elishad\Deskto
** Prediction location file:  Estimation at sample point locations
** Result output file:         C:\Documents and Settings\elishad\Deskto

** Variables in the data file...
 ID       UID      XCoord   YCoord   stdedc   aglivc   bglivc   NPP
 strucc(1 strucc(2 metabc(1 metabc(2 som1c(1) som1c(2) som2c    som3c
 Area (Km PPT      Tmin     Tmax     Depth    Sand     Silt     Clay
 OM       BD       Ksat     CEC      pH       Slope    Elevatio

** Dependent (y) variable..........NPP
** Easting  (x-coord) variable.....XCoord
** Northing (y-coord) variable.....YCoord
```

```
** No weight variable specified
** Independent variables in your model...
 strucc(1 metabc(1 som3c    PPT      Tmin     Clay     BD       Ksat
 CEC      pH       Slope
** Kernel type:  Adaptive
** Kernel shape: Bi-Square
** Bandwidth selection by AICc minimisation
** Use all regression points
** No calibration history requested
** No prediction report requested
** Output estimates to be written to .txt file
** Monte Carlo significance tests for spatial variation
** No casewise diagnostics requested

*** Analysis method ***
*** Geographically weighted multiple regression
** Cartesian coordinates: Euclidean Distance
**************************************************************
*                                                            *
*        GEOGRAPHICALLY WEIGHTED GAUSSIAN REGRESSION         *
*                                                            *
**************************************************************
 Number of data cases read: 24108
 Observation points read...

 Dependent mean=  1.32163715
 Number of observations, nobs= 24108
 Number of predictors,   nvar= 11
 Observation Easting extent:   4.71474743
 Observation Northing extent:  1.89690101
*Finding bandwidth...
  ... using all regression points
 This can take some time...
 *Calibration will be based on  24108 cases
*Adaptive kernel sample size limits:    1205  24108
 *AICc minimisation begins...
       8282.416236485000       65261.117358840289
      12656.500000000000       65001.637639077824
** Convergence after     8 function calls
** Convergence: Local Sample Size=  23470

*********************************************************
*           GLOBAL REGRESSION PARAMETERS                *
*********************************************************
Diagnostic information...
Residual sum of squares.........        20143.087803
Effective number of parameters..           12.000000
Sigma...........................            0.914304
Akaike Information Criterion....        64109.768674
Coefficient of Determination....            0.947285
Adjusted r-square...............            0.947259

Parameter              Estimate              Std Err                  T
---------          ------------          ------------          ------------
Intercept       -0.048295757779        0.117968470158       -0.409395486116
 strucc(1        3.760328981895        0.016008320226      234.898406982422
 metabc(1       -4.757760699153        0.047991879416      -99.136787414551
 som3c           0.061516593463        0.000591552062      103.991851806641
 PPT             0.002502621483        0.003973298248        0.629859983921
 Tmin            0.003010083749        0.002559204384        1.176179528236
 Clay            0.000284259235        0.001200213963        0.236840471625
 BD             -0.019355401569        0.058119307064       -0.333028763533
 Ksat           -0.000373282476        0.000301039830       -1.239977002144
 CEC            -0.002055599544        0.001668539771       -1.231975197792
 pH              0.008309491986        0.008021037329        1.035962224007
 Slope          -0.001210661686        0.001311756273       -0.922931909561
```

```
*********************************************************
*               GWR ESTIMATION                          *
*********************************************************
 Fitting Geographically Weighted Regression Model...
 Number of observations............ 24108
 Number of independent variables... 12
  (Intercept is variable 1)
 Number of nearest neighbours...... 23470
 Number of locations to fit model.. 24108
Diagnostic information...
Residual sum of squares.........       19994.118738
Effective number of parameters..          20.821677
Sigma...........................           0.911083
Akaike Information Criterion....       63948.483982
Coefficient of Determination....           0.947675
Adjusted r-square...............           0.947630
 ** Results written to .txt file

*********************************************************
*                     ANOVA                             *
*********************************************************
        Source                     SS        DF             MS             F
OLS Residuals                 20143.1     12.00
GWR Improvement                 149.0      8.82        16.8867
GWR Residuals                 19994.1  24087.18         0.8301       20.3436


*********************************************************
*          PARAMETER 5-NUMBER SUMMARIES                 *
*********************************************************
   Label       Minimum  Lwr Quartile        Median  Upr Quartile       Maximum
-------- ------------- ------------- ------------- ------------- -------------
Intrcept     -0.130325     -0.051053     -0.001282      0.042095      0.116376
strucc(1      3.517056      3.567916      3.743358      3.786531      3.823242
metabc(1     -4.926366     -4.799502     -4.697492     -4.388544     -4.220657
som3c         0.060523      0.060972      0.061434      0.062497      0.063461
PPT          -0.000966      0.001195      0.002100      0.003277      0.005583
Tmin         -0.003300     -0.002892      0.002209      0.004441      0.006554
Clay         -0.000682     -0.000276      0.000263      0.000480      0.000758
BD           -0.100744     -0.052450     -0.027366     -0.000148      0.038450
Ksat         -0.000682     -0.000470     -0.000397     -0.000353     -0.000248
CEC          -0.003640     -0.002809     -0.002335     -0.000952     -0.000256
pH            0.003008      0.007820      0.009440      0.010721      0.013763
Slope        -0.003019     -0.001935     -0.001192      0.000524      0.001731


        <------------------ LOWER ----------------><------------------ UPPER ------
----------->
   Label Far Out   Outer Fence Outside   Inner Fence   Inner Fence Outside   Outer
Fence Far Out
-------- ------- ------------- ------- ------------- ------------- ------- ---------
---- -------
Intrcept       0     -0.330497       0     -0.190775      0.181817       0
0.321539       0
strucc(1       0      2.912068       0      3.239992      4.114455       0
4.442379       0
metabc(1       0     -6.032376       0     -5.415939     -3.772108       0     -
3.155671       0
som3c          0      0.056398       0      0.058685      0.064785       0
0.067072       0
PPT            0     -0.005051       0     -0.001928      0.006400       0
0.009523       0
Tmin           0     -0.024890       0     -0.013891      0.015440       0
0.026440       0
Clay           0     -0.002545       0     -0.001410      0.001615       0
0.002749       0
```

```
BD             0     -0.209356       0     -0.130903      0.078304       0
0.156757       0
Ksat           0     -0.000820     370     -0.000645     -0.000178       0     -
0.000003       0
CEC            0     -0.008381       0     -0.005595      0.001834       0
0.004620       0
pH             0     -0.000882      59      0.003469      0.015073       0
0.019424       0
Slope          0     -0.009313       0     -0.005624      0.004213       0
0.007902       0

*************************************************
*                                               *
*   Test for spatial variability of parameters  *
*                                               *
*************************************************

Tests based on the Monte Carlo significance test
procedure due to Hope [1968,JRSB,30(3),582-598]

Parameter                  P-value
----------      ------------------
Intercept            0.37000   n/s
strucc(1             0.23000   n/s
metabc(1             0.41000   n/s
som3c                0.79000   n/s
PPT                  0.60000   n/s
Tmin                 0.01000   **
Clay                 0.55000   n/s
BD                   0.24000   n/s
Ksat                 0.78000   n/s
CEC                  0.28000   n/s
pH                   0.79000   n/s
Slope                0.03000   *

*** = significant at .1% level
**  = significant at 1% level
*   = significant at 5% level

Program terminates normally at: Sat Apr 16 22:42:06 2011
```

Appendix A (iii): New Mexico Post-CRP for CRP Model

```
*************************************************
*       Geographically Weighted Regression      *
*               Release 3.0.1                   *
*            Dated: 06-vii-2003                 *
*                                               *
*       Martin Charlton, Chris Brunsdon         *
*            Stewart Fotheringham               *
*     (c) University of Newcastle upon Tyne     *
*************************************************
Program starts at: Sun Jan 30 20:28:06 2011

** Program limits:
** Maximum number of variables.....      52
** Maximum number of observations..  80000
** Maximum number of fit locations.  80000

NMPoCmodel
** Observed data file:         F:\Dissertation Analyses Layers\New Mexi
** Prediction location file:  Estimation at sample point locations
** Result output file:         F:\Dissertation Analyses Layers\New Mexi
```

```
** Variables in the data file...
 ID       F_AREA   X_Coord  Y_Coord  time     stdedc   aglivc   bglivc
 NPP      strucc(1 strucc(2 metabc(1 metabc(2 som1c(1) som1c(2) som2c
 som3c    stream(5 PPT      Tmin     Tmax     Depth    Sand     Silt
 Clay     OM       BD       Ksat     CEC      pH       Slope    Elevatio
** Dependent (y) variable..........NPP
** Easting  (x-coord) variable.....X_Coord
** Northing (y-coord) variable.....Y_Coord
** No weight variable specified
** Independent variables in your model...
 metabc(2 PPT      Tmin     Depth    Silt     Clay     BD       pH
 Slope
** Kernel type:  Fixed
** Kernel shape: Gaussian
** Bandwidth selection by AICc minimisation
** Use all regression points
** No calibration history requested
** No prediction report requested
** Output estimates to be written to .txt file
** Monte Carlo significance tests for spatial variation
** No casewise diagnostics requested

*** Analysis method ***
*** Geographically weighted multiple regression
** Cartesian coordinates: Euclidean Distance
****************************************************************
*                                                              *
*        GEOGRAPHICALLY WEIGHTED GAUSSIAN REGRESSION           *
*                                                              *
****************************************************************
 Number of data cases read: 206
 Observation points read...

 Dependent mean=  119747104.
 Number of observations, nobs= 206
 Number of predictors,   nvar= 9
 ** Observation Easting extent:   0.570577443
 ** Observation Northing extent:  1.111588
*Finding bandwidth...
  ... using all regression points
 This can take some time...
 *Calibration will be based on  206 cases
 *Fixed kernel bandwidth search limits:   0.0285288719  0.570577437
 *AICc minimisation begins...
          0.299553154425        8511.565119926636
          0.403075218253        8562.934337749864
** Convergence after    10 function calls
** Convergence: Bandwidth=      0.23914

***********************************************************
*          GLOBAL REGRESSION PARAMETERS                   *
***********************************************************
Diagnostic information...
Residual sum of squares.........********************
Effective number of parameters..          10.000000
Sigma..........................    205325893.359973
Akaike Information Criterion....        8483.437537
Coefficient of Determination....           0.873473
Adjusted r-square...............           0.866984

Parameter               Estimate                Std Err                   T
---------           ------------           ------------        ------------
Intercept-170090106.564827740000 394012346.717840020000       -0.431687235832
 metabc(2        11.105291051772         0.310034796426       35.819499969482
 PPT      -17200287.384357005000  19522407.808391102000       -0.881053566933
 Tmin       3548962.246858361200   2556958.172470597100        1.387962579727
```

```
 Depth       134421.635293538890    298817.459059609620         0.449845314026
 Silt      -2932250.316430440200   1666567.615854639800        -1.759454727173
 Clay        778375.408979356060   1869826.356496954800         0.416282176971
 BD        13937250.446145700000 157629728.896761690000         0.088417649269
 pH        19918122.175500344000  39879197.303560957000         0.499461472034
 Slope      -173682.096184970050   1909139.114420101000        -0.090974040329

**********************************************************
*                GWR ESTIMATION                          *
**********************************************************
 Fitting Geographically Weighted Regression Model...
 Number of observations............ 206
 Number of independent variables... 10
  (Intercept is variable 1)
 Bandwidth (in data units).........  0.239138492
 Number of locations to fit model.. 206

Diagnostic information...
Residual sum of squares.........********************
Effective number of parameters..           21.085064
Sigma..........................     83087546.564859
Akaike Information Criterion....        8125.090451
Coefficient of Determination....           0.980453
Adjusted r-square...............           0.978212
 ** Results written to .txt file

**********************************************************
*                      ANOVA                             *
**********************************************************
        Source                       SS         DF              MS              F
OLS Residuals    8263109606877795300.0      10.00
GWR Improvement  6986542073981698000.0      11.09*****************
GWR Residuals    1276567727214233300.0     184.91*****************       91.2961


**********************************************************
*          PARAMETER 5-NUMBER SUMMARIES                  *
**********************************************************
   Label       Minimum  Lwr Quartile        Median  Upr Quartile       Maximum
-------- ------------- ------------- ------------- ------------- -------------
Intrcept**********************************************************************
metabc(2      1.948045      5.978865      8.080516      9.943391     13.360184
PPT     ***************************************** 24205.6290361735526.229666
Tmin     374188.5733621494879.4328132273542.8492762431972.0288592739950.317147
Depth    -10884.015666  62716.263454  94512.865650 101705.915721 113831.141571
Silt    *******************************************************-535983.968189
Clay    -748131.267127-289670.337034  15010.259718 791181.3552712470553.668591
BD      **********************************************************************
pH      ***************************************** 579972.335398**************
Slope   -445798.107674-287099.887160-217307.087511 438356.6777865076613.020643


        <------------------- LOWER ------------------><------------------- UPPER ------
----------->
   Label Far Out   Outer Fence Outside   Inner Fence   Inner Fence Outside   Outer
Fence Far Out
-------- ------- ------------- ------- ------------- ------------- ------- ---------
---- -------
Intrcept       0**************       0*****************************
0**************       0
metabc(2       0     -5.914712       0      0.032076     15.890179       0
21.836968       0
PPT            0**************       0*****************************
0**************       0
Tmin           0**************       0  89240.5387443837610.922928
05243249.816997       0
```

```
Depth          0 -54252.693349      10   4231.785052 160190.394123       0
218674.872524       0
Silt           0**************       0**************-678493.697452       6-
144321.407496       0
Clay           0**************       0**************2412458.893728
24033736.432186       0
BD             0**************       0****************************
0**************       0
pH             0**************       0****************************
32**************       0
Slope          0**************       0**************1526541.525207
112614726.372627       4

*************************************************
*                                               *
*   Test for spatial variability of parameters  *
*                                               *
*************************************************

Tests based on the Monte Carlo significance test
procedure due to Hope [1968,JRSB,30(3),582-598]

Parameter                 P-value
----------      ------------------
Intercept           0.07000   n/s
metabc(2            0.04000   *
PPT                 0.85000   n/s
Tmin                0.96000   n/s
Depth               0.98000   n/s
Silt                0.98000   n/s
Clay                0.22000   n/s
BD                  0.11000   n/s
pH                  0.46000   n/s
Slope               0.56000   n/s

*** = significant at .1% level
**  = significant at 1% level
*   = significant at 5% level

Program terminates normally at: Sun Jan 30 20:28:20 2011
```

Appendix A (iv): Oklahoma with Monte Carlo significance test

```
*************************************************
*       Geographically Weighted Regression      *
*               Release 3.0.1                   *
*            Dated: 06-vii-2003                 *
*                                               *
*       Martin Charlton, Chris Brunsdon         *
*            Stewart Fotheringham               *
*     (c) University of Newcastle upon Tyne     *
*************************************************
Program starts at: Thu Jan 27 00:09:09 2011

** Program limits:
** Maximum number of variables.....      52
** Maximum number of observations..  80000
** Maximum number of fit locations.  80000

OKPoDmodel
** Observed data file:         F:\Dissertation Analyses Layers\Oklahoma
** Prediction location file:  Estimation at sample point locations
** Result output file:         F:\Dissertation Analyses Layers\Oklahoma
```

```
** Variables in the data file...
 ID       XCoord   YCoord   Area     time     stdedc   aglivc   bglivc
NPP      strucc(1 strucc(2 metabc(1 metabc(2 som1c(1) som1c(2) som2c
 som3c    stream(5 PPT      Tmin     Tmax     Depth    Sand     Silt
 Clay     OM       BD       Ksat     CEC      pH       Slope    Elevatio

** Dependent (y) variable..........NPP
** Easting  (x-coord) variable.....XCoord
** Northing (y-coord) variable.....YCoord
** No weight variable specified
** Independent variables in your model...
 strucc(2 metabc(2 som2c    som3c    PPT      Tmin     Depth    BD
 Ksat     CEC      pH       Slope
** Kernel type:  Adaptive
** Kernel shape: Bi-Square
** Bandwidth selection by AICc minimisation
** Use all regression points
** No calibration history requested
** No prediction report requested
** Output estimates to be written to .txt file
** Monte Carlo significance tests for spatial variation
** No casewise diagnostics requested

*** Analysis method ***
*** Geographically weighted multiple regression
** Cartesian coordinates: Euclidean Distance
****************************************************************
*                                                              *
*        GEOGRAPHICALLY WEIGHTED GAUSSIAN REGRESSION           *
*                                                              *
****************************************************************
 Number of data cases read: 3040
 Observation points read...

 Dependent mean=  565216768.
 Number of observations, nobs= 3040
 Number of predictors,   nvar= 12
 Observation Easting extent:   3.72605467
 Observation Northing extent:  1.55054843
*Finding bandwidth...
  ... using all regression points
 This can take some time...
 *Calibration will be based on  3040 cases
*Adaptive kernel sample size limits:     152   3040
 *AICc minimisation begins...
       1044.441081560000      129329.309738692510
       1596.000000000000      129392.732475483890
** Convergence after    10 function calls
** Convergence: Local Sample Size=    784

***********************************************************
*           GLOBAL REGRESSION PARAMETERS                  *
***********************************************************
Diagnostic information...
Residual sum of squares.........********************
Effective number of parameters..           13.000000
Sigma..........................    413881368.962191
Akaike Information Criterion....      129276.084099
Coefficient of Determination....           0.879394
Adjusted r-square...............           0.878876

Parameter              Estimate              Std Err                  T
---------          ------------         ------------       ------------
Intercept-280610556.454413000000 213763831.064410000000       -1.312713027000
 strucc(2       -0.780486037713         0.094973061578       -8.217972755432
 metabc(2       -1.881985335814         0.257407983005       -7.311293601990
```

```
 som2c          0.415984045406        0.029228632033        14.232073783875
 som3c         -0.132638146069        0.022278097928        -5.953746318817
 PPT       5866796.468224552500   4648514.491911424300        1.262079834938
Tmin      4631331.842034529900   2403151.565863410900       1.927190899849
 Depth      -34641.446307052458    126295.771914455120       -0.274288237095
 BD      307979154.466180150000 101481525.035360140000        3.034829854965
 Ksat      -136932.262846588270    372489.139313102640       -0.367614120245
 CEC        662942.406615529090   1666801.572149365900        0.397733241320
 pH      -42720958.423109576000  15719993.458124261000       -2.717619419098
 Slope    -2422928.081049761300   1458356.642362073300       -1.661409854889


**********************************************************
*                GWR ESTIMATION                          *
**********************************************************
 Fitting Geographically Weighted Regression Model...
 Number of observations............ 3040
 Number of independent variables... 13
  (Intercept is variable 1)
 Number of nearest neighbours...... 784
 Number of locations to fit model.. 3040

Diagnostic information...
Residual sum of squares.........********************
Effective number of parameters..          114.232252
Sigma...........................    360914551.398950
Akaike Information Criterion....       128551.581811
Coefficient of Determination....            0.911355
Adjusted r-square...............            0.907893
 ** Results written to .txt file

**********************************************************
*                      ANOVA                             *
**********************************************************
        Source                     SS         DF              MS              F
OLS Residuals   **********************    13.00
GWR Improvement **********************   101.23*****************
GWR Residuals   **********************  2925.77*****************       10.4205


**********************************************************
*          PARAMETER 5-NUMBER SUMMARIES                  *
**********************************************************
   Label       Minimum  Lwr Quartile        Median  Upr Quartile       Maximum
-------- ------------- ------------- ------------- ------------- -------------
Intrcept**********************************************************************
strucc(2     -2.354242     -1.363638     -0.667916     -0.122337      1.410375
metabc(2    -13.248176     -2.219654     -1.104990      0.026481      2.848516
som2c        -0.400333      0.225826      0.418307      0.792968      1.235252
som3c        -0.716189     -0.426264     -0.137886      0.024193      0.463297
PPT     ****************************4476266.032831***************************
Tmin    ************** 207218.9222544943163.5223229395940.079718**************
Depth   -422616.103541-228109.022644 -90728.472593  38422.969333 475179.656019
BD      **********************************************************************
Ksat    **************-223412.597678 -86096.555722 195208.2272851297787.901584
CEC     **************************** 408831.8307243327623.5431627369166.382603
pH      **********************************************************************
Slope   *****************************************-209605.9706873604994.907125


        <------------------ LOWER ----------------><------------------ UPPER ------
----------->
   Label Far Out   Outer Fence Outside   Inner Fence   Inner Fence Outside   Outer
Fence Far Out
-------- ------- ------------- ------- ------------- ------------- ------- ---------
---- -------
```

```
Intrcept       0**************      0****************************
0**************       0
strucc(2       0     -5.087539      0     -3.225588      1.739614       0
3.601564       0
metabc(2     102     -8.958058    163     -5.588856      3.395682       0
6.764884       0
som2c          0     -1.475601      0     -0.624888      1.643681       0
2.494394       0
som3c          0     -1.777632      0     -1.101948      0.699877       0
1.375561       0
PPT            0**************      0****************************
37**************       0
Tmin           0**************      0****************************
0**************       0
Depth          0**************      0-627907.010609 438220.957298      18
838018.945263       0
BD             0**************      0****************************
0**************       0
Ksat           0**************    255-851343.835123 823139.464730
2311451070.702175       0
CEC            0**************      0**************9997521.538916
0**************       0
pH            18**************    145****************************
0**************       0
Slope        174**************    161**************4237764.125382
08685134.221451       0

*************************************************
*                                               *
*   Test for spatial variability of parameters  *
*                                               *
*************************************************

Tests based on the Monte Carlo significance test
procedure due to Hope [1968,JRSB,30(3),582-598]

Parameter                  P-value
----------      ------------------
Intercept            0.72000   n/s
strucc(2             0.53000   n/s
metabc(2             0.54000   n/s
som2c                0.01000   **
som3c                0.01000   **
PPT                  0.10000   n/s
Tmin                 0.24000   n/s
Depth                0.81000   n/s
BD                   0.26000   n/s
Ksat                 0.81000   n/s
CEC                  0.75000   n/s
pH                   0.52000   n/s
Slope                0.13000   n/s

*** = significant at .1% level
**  = significant at 1% level
*   = significant at 5% level

Program terminates normally at: Thu Jan 27 12:38:24 2011
```

Appendix A (v): Texas with Monte Carlo Significance Test

```
*************************************************
*       Geographically Weighted Regression      *
*               Release 3.0.1                   *
```

```
*            Dated: 06-vii-2003                *
*                                              *
*       Martin Charlton, Chris Brunsdon        *
*            Stewart Fotheringham              *
*     (c) University of Newcastle upon Tyne    *
************************************************
Program starts at: Thu Jan 27 12:45:46 2011

** Program limits:
** Maximum number of variables.....     52
** Maximum number of observations..  80000
** Maximum number of fit locations.  80000

TXPrCmodel
** Observed data file:        F:\Dissertation Analyses Layers\Texas\CR
** Prediction location file:  Estimation at sample point locations
** Result output file:        F:\Dissertation Analyses Layers\Texas\CR

** Variables in the data file...
 ID       XCoord   YCoord   Area     time     stdedc   aglivc   bglivc
 NPP      strucc(1 strucc(2 metabc(1 metabc(2 som1c(1) som1c(2) som2c
 som3c    stream(5 PPT      Tmin     Tmax     Depth    Sand     Silt
 Clay     OM       BD       Ksat     CEC      pH       Slope    Elevatio

** Dependent (y) variable..........NPP
** Easting  (x-coord) variable.....XCoord
** Northing (y-coord) variable.....YCoord
** No weight variable specified
** Independent variables in your model...
 strucc(2 metabc(2 som2c    som3c    PPT      Tmin     Depth    BD
 Ksat     CEC      pH       Slope
** Kernel type:  Adaptive
** Kernel shape: Bi-Square
** Bandwidth selection by AICc minimisation
** Use all regression points
** No calibration history requested
** No prediction report requested
** Output estimates to be written to .txt file
** Monte Carlo significance tests for spatial variation
** No casewise diagnostics requested

*** Analysis method ***
*** Geographically weighted multiple regression
** Cartesian coordinates: Euclidean Distance
**************************************************************
*                                                            *
*        GEOGRAPHICALLY WEIGHTED GAUSSIAN REGRESSION         *
*                                                            *
**************************************************************
 Number of data cases read: 3424
 Observation points read...

 Dependent mean=  158468768.
 Number of observations, nobs= 3424
 Number of predictors,   nvar= 12
 Observation Easting extent:   3.02248836
 Observation Northing extent:  1.7069
*Finding bandwidth...
  ... using all regression points
 This can take some time...
 *Calibration will be based on  3424 cases
*Adaptive kernel sample size limits:     171   3424
 *AICc minimisation begins...
       1176.232284735000      141138.519707114780
       1797.500000000000      141073.021133218890
** Convergence after     9 function calls
** Convergence: Local Sample Size=   2125
```

```
**********************************************************
*           GLOBAL REGRESSION PARAMETERS                 *
**********************************************************
Diagnostic information...
Residual sum of squares.........********************
Effective number of parameters..         13.000000
Sigma...........................   212651154.831647
Akaike Information Criterion....      141043.509941
Coefficient of Determination....          0.775187
Adjusted r-square...............          0.774330

Parameter                Estimate                Std Err                      T
---------            ------------           ------------           ------------
Intercept -66356829.964970231000 115251322.779868230000        -0.575757622719
 strucc(2          0.061153960717         0.033298914635         1.836515188217
 metabc(2         -1.391550449712         0.049471221527       -28.128482818604
 som2c             0.004931331114         0.004621982754         1.066929817200
 som3c             0.052284610275         0.002618886020        19.964447021484
 PPT          319858.995515662070   2411875.600293980400         0.132618367672
 Tmin          24682.870262987126    731352.529361473050         0.033749621361
 Depth        -62711.713324973178     60289.729098059004        -1.040172457695
 BD         47728549.151373535000  51202736.910811029000         0.932148396969
 Ksat        -162030.499408596140    217479.490332111400        -0.745038092136
 CEC          312784.250810612580    672616.593390661990         0.465026080608
 pH         -2127871.225652580100  10086118.803536413000        -0.210970267653
 Slope       1008656.912535976300    505907.175643112980         1.993758916855


**********************************************************
*                GWR ESTIMATION                          *
**********************************************************
 Fitting Geographically Weighted Regression Model...
 Number of observations............ 3424
 Number of independent variables... 13
  (Intercept is variable 1)
 Number of nearest neighbours...... 2125
 Number of locations to fit model.. 3424

Diagnostic information...
Residual sum of squares.........********************
Effective number of parameters..         47.714799
Sigma...........................   191574609.087795
Akaike Information Criterion....      140364.461263
Coefficient of Determination....          0.819399
Adjusted r-square...............          0.816846
 ** Results written to .txt file

**********************************************************
*                      ANOVA                             *
**********************************************************
        Source                     SS         DF              MS             F
OLS Residuals   **********************     13.00
GWR Improvement 30334698977595752000.0     34.71*****************
GWR Residuals   **********************   3376.29*****************       23.8094


**********************************************************
*          PARAMETER 5-NUMBER SUMMARIES                  *
**********************************************************
   Label       Minimum  Lwr Quartile        Median  Upr Quartile       Maximum
-------- ------------- ------------- ------------- ------------- -------------
Intrcept*********************************************************************
strucc(2     -0.445129     -0.212566     -0.109049      0.255073      0.532092
metabc(2     -2.891612     -2.051672     -1.596303     -0.744997     -0.668250
som2c        -0.119786     -0.076262      0.002885      0.037695      0.050321
som3c         0.023831      0.031036      0.057109      0.101396      0.128724
PPT     ***************************3539239.3592545289076.9324439104845.294998
```

```
Tmin     -666564.400183-455899.008406-223126.604531 482496.4690961090914.118021
Depth    -214967.493268-111033.004665 -62020.988677   9735.709978  35617.379397
BD       ***********************************************************************
Ksat     -738433.020863-542353.179965-228621.323301  48098.399218 353045.072795
CEC      **************-584383.701307 190052.523008 400390.289160 704310.560069
pH       ****************************1470237.2899475099113.715145**************
Slope    -683919.367619 511028.425599 789393.5921301195370.1994842034519.768869


        <------------------- LOWER ----------------><------------------- UPPER ------
----------->
   Label Far Out   Outer Fence Outside   Inner Fence   Inner Fence Outside   Outer
Fence Far Out
-------- ------- ------------- ------- ------------- ------------- ------- ---------
---- -------
Intrcept       0**************      74****************************
0**************       0
strucc(2       0     -1.615485       0     -0.914026      0.956533       0
1.657992       0
metabc(2       0     -5.971699       0     -4.011686      1.215017       0
3.175031       0
som2c          0     -0.418136       0     -0.247199      0.208632       0
0.379569       0
som3c          0     -0.180043       0     -0.074503      0.206936       0
0.312476       0
PPT            0**************       0*****************************
0**************       0
Tmin           0**************       0**************1890089.685351
03297682.901605       0
Depth          0-473339.148595       0-292186.076630 190888.781943       0
372041.853908       0
BD             0**************      18****************************
2**************       0
Ksat           0**************       0************** 933775.767993
01819453.136768       0
CEC            0**************       0**************1877551.274861
03354712.260562       0
pH             0**************       0*****************************
0**************       0
Slope          0**************      49-515484.2352282221882.860311
03248395.521138       0

*************************************************
*                                               *
*   Test for spatial variability of parameters  *
*                                               *
*************************************************

Tests based on the Monte Carlo significance test
procedure due to Hope [1968,JRSB,30(3),582-598]

Parameter                  P-value
----------       ------------------
Intercept            0.99000   n/s
strucc(2             0.36000   n/s
metabc(2             0.05000   *
som2c                0.10000   n/s
som3c                0.10000   n/s
PPT                  0.00000   ***
Tmin                 0.83000   n/s
Depth                0.65000   n/s
BD                   0.90000   n/s
Ksat                 0.16000   n/s
CEC                  0.77000   n/s
pH                   0.93000   n/s
Slope                0.45000   n/s
*** = significant at .1% level
```

```
**  = significant at 1% level
*   = significant at 5% level

Program terminates normally at: Thu Jan 27 14:28:18 2011
```

Appendix B (i) Colorado Correlation Analysis

	NPP	strucc(1)	strucc(2)	metabc(1)	metabc(2)	som1c(1)	som1c(2)	som2c	som3c	Area (Km2)	PPT	Tmin	Tmax	Depth	Sand	Silt	Clay	OM	BD	Ksat	CEC	pH	Slope	Elevation
NPP	1.000																							
strucc(1)	0.974	1.000																						
strucc(2)	0.908	0.899	1.000																					
metabc(1)	0.827	0.907	0.748	1.000																				
metabc(2)	0.897	0.950	0.792	0.924	1.000																			
som1c(1)	0.947	0.986	0.896	0.916	0.944	1.000																		
som1c(2)	0.957	0.975	0.893	0.904	0.937	0.981	1.000																	
som2c	0.976	0.990	0.895	0.908	0.956	0.986	0.990	1.000																
som3c	0.973	0.989	0.892	0.913	0.957	0.987	0.990	1.000	1.000															
Area (Km2	0.973	0.989	0.892	0.913	0.957	0.987	0.990	1.000	1.000	1.000														
PPT	-0.005	0.002	-0.011	0.010	0.006	0.001	0.001	-0.001	0.000	0.000	1.000													
Tmin	0.021	0.024	0.011	0.026	0.027	0.021	0.022	0.023	0.023	0.023	0.002	1.000												
Tmax	0.026	0.027	0.024	0.021	0.024	0.025	0.025	0.024	0.024	0.024	0.011	0.003	1.000											
Depth	0.011	0.009	0.002	0.015	0.008	0.012	0.015	0.011	0.012	0.012	-0.015	0.006	-0.019	1.000										
Sand	0.013	0.009	0.005	0.003	0.005	0.009	0.014	0.011	0.011	0.011	-0.010	0.005	0.004	0.141	1.000									
Silt	-0.006	-0.001	-0.003	0.001	0.001	-0.002	-0.009	-0.005	-0.004	-0.004	0.008	-0.004	0.002	-0.107	-0.927	1.000								
Clay	-0.020	-0.018	-0.005	-0.008	-0.012	-0.018	-0.018	-0.018	-0.017	-0.017	0.010	-0.005	-0.013	-0.149	-0.791	0.504	1.000							
OM	0.016	0.020	0.024	0.012	0.023	0.018	0.016	0.017	0.016	0.016	0.025	0.001	0.020	-0.562	-0.101	0.117	0.041	1.000						
BD	0.014	0.010	0.000	0.004	0.007	0.009	0.015	0.012	0.012	0.012	-0.017	-0.008	-0.008	0.199	0.898	-0.821	-0.729	-0.166	1.000					
Ksat	0.009	0.007	-0.003	0.005	0.005	0.008	0.011	0.008	0.008	0.008	-0.017	0.000	0.016	0.246	0.772	-0.628	-0.756	-0.159	0.756	1.000				
CEC	-0.011	-0.008	0.004	-0.002	0.000	-0.009	-0.009	-0.008	-0.008	-0.008	0.021	-0.003	0.000	-0.251	-0.647	0.373	0.882	0.272	-0.625	-0.634	1.000			
pH	-0.002	-0.005	0.001	0.003	-0.009	-0.003	-0.002	-0.003	-0.002	-0.002	-0.017	0.013	0.002	0.437	-0.243	0.199	0.235	-0.528	-0.212	-0.164	0.082	1.000		
Slope	-0.002	0.000	-0.012	0.003	0.002	-0.005	0.000	-0.001	-0.002	-0.002	0.023	0.004	-0.017	0.002	0.031	-0.024	-0.032	-0.018	0.030	0.031	-0.025	-0.012	1.000	
Elevation	0.017	0.021	0.018	0.027	0.012	0.020	0.022	0.018	0.019	0.019	-0.013	0.005	-0.006	-0.003	-0.003	0.015	-0.018	-0.022	-0.009	0.023	-0.019	0.045	0.157	1.000

Appendix B (ii): Kansas Correlation Analysis

	NPP	*strucc(1)*	*strucc(2)*	*metabc(1)*	*metabc(2)*	*som1c(1)*	*som1c(2)*	*som2c*	*som3c*	*Area (Km2)*	*PPT*	*Tmin*	*Tmax*	*Depth*	*Sand*	*Silt*	*Clay*	*OM*	*BD*	*Ksat*	*CEC*	*pH*	*Slope*	*Elevation*
NPP	1.000																							
strucc(1)	0.956	1.000																						
strucc(2)	0.793	0.772	1.000																					
metabc(1)	0.798	0.884	0.731	1.000																				
metabc(2)	0.844	0.850	0.816	0.831	1.000																			
som1c(1)	0.909	0.939	0.801	0.857	0.888	1.000																		
som1c(2)	0.518	0.474	0.517	0.485	0.607	0.712	1.000																	
som2c	0.912	0.897	0.873	0.863	0.934	0.936	0.633	1.000																
som3c	0.909	0.901	0.878	0.866	0.927	0.912	0.545	0.993	1.000															
Area (Km2	0.912	0.901	0.878	0.867	0.934	0.934	0.613	0.999	0.996	1.000														
PPT	-0.005	-0.006	-0.004	-0.005	-0.004	-0.008	-0.010	-0.006	-0.005	-0.006	1.000													
Tmin	0.000	0.000	-0.003	0.001	-0.007	-0.003	-0.007	-0.004	-0.003	-0.004	-0.002	1.000												
Tmax	0.001	0.000	-0.001	0.002	0.003	0.001	0.004	0.001	0.000	0.000	0.001	-0.008	1.000											
Depth	-0.008	-0.008	-0.007	-0.013	-0.005	-0.008	-0.008	-0.007	-0.006	-0.006	-0.009	-0.003	-0.001	1.000										
Sand	0.005	0.005	0.000	0.001	-0.001	-0.006	-0.023	0.002	0.006	0.003	0.014	-0.005	-0.004	0.058	1.000									
Silt	-0.003	-0.003	0.001	0.001	0.002	0.006	0.022	-0.001	-0.004	-0.002	-0.017	0.005	0.009	-0.093	-0.938	1.000								
Clay	-0.006	-0.006	-0.002	-0.005	-0.001	0.004	0.018	-0.004	-0.006	-0.004	-0.004	0.003	-0.004	0.017	-0.816	0.564	1.000							
OM	0.006	0.007	0.005	0.009	0.001	0.010	0.015	0.002	-0.001	0.001	0.002	0.000	0.003	-0.623	-0.347	0.375	0.200	1.000						
BD	0.000	0.001	-0.007	-0.006	-0.001	-0.008	-0.019	-0.006	-0.003	-0.005	0.009	0.001	-0.005	0.275	0.591	-0.610	-0.391	-0.419	1.000					
Ksat	0.006	0.006	0.005	0.002	0.005	-0.001	-0.013	0.004	0.006	0.004	0.004	-0.005	0.002	0.105	0.758	-0.640	-0.737	-0.296	0.394	1.000				
CEC	-0.006	-0.003	-0.004	-0.002	-0.005	0.006	0.018	-0.007	-0.009	-0.007	-0.004	0.004	-0.003	0.007	-0.717	0.492	0.886	0.187	-0.323	-0.683	1.000			
pH	0.016	0.013	0.013	0.013	0.013	0.012	0.009	0.016	0.016	0.015	-0.005	0.007	0.005	0.320	-0.259	0.244	0.209	-0.187	-0.133	-0.162	0.138	1.000		
Slope	0.012	0.014	0.013	0.013	0.015	0.012	0.001	0.012	0.013	0.013	0.003	0.008	0.011	0.009	-0.006	0.008	0.000	0.000	-0.006	-0.010	-0.004	0.006	1.000	
Elevation	-0.005	-0.007	0.010	-0.003	0.001	-0.008	-0.005	-0.002	-0.001	-0.001	0.009	0.029	0.001	-0.011	-0.066	0.062	0.054	0.043	-0.065	-0.047	0.039	0.026	0.118	1.000

Appendix B (iii): New Mexico Correlation Analysis

	NPP	strucc(1)	strucc(2)	metabc(1)	metabc(2)	som1c(1)	som1c(2)	som2c	som3c	Area (Km2)	PPT	Tmin	Tmax	Depth	Sand	Silt	Clay	OM	BD	Ksat	CEC	pH	Slope	Elevation
NPP	1.000																							
strucc(1)	0.940	1.000																						
strucc(2)	0.783	0.939	1.000																					
metabc(1)	0.778	0.909	0.944	1.000																				
metabc(2)	0.932	0.972	0.914	0.945	1.000																			
som1c(1)	0.870	0.982	0.976	0.940	0.959	1.000																		
som1c(2)	0.869	0.909	0.878	0.952	0.977	0.913	1.000																	
som2c	0.967	0.979	0.893	0.908	0.992	0.951	0.956	1.000																
som3c	0.969	0.979	0.891	0.906	0.991	0.950	0.955	1.000	1.000															
Area (Km2)	-0.162	-0.113	-0.020	-0.009	-0.100	-0.059	-0.044	-0.108	-0.111	1.000														
PPT	-0.016	0.003	0.007	0.029	0.006	0.009	0.019	-0.001	-0.001	0.061	1.000													
Tmin	0.078	0.043	-0.035	-0.010	0.039	0.005	0.008	0.042	0.044	-0.658	0.052	1.000												
Tmax	-0.024	0.018	0.083	0.052	0.014	0.049	0.025	0.009	0.007	0.385	0.081	-0.368	1.000											
Depth	0.040	-0.008	-0.038	-0.001	0.021	-0.025	0.039	0.024	0.025	0.013	-0.066	0.080	-0.063	1.000										
Sand	0.163	0.133	0.069	0.090	0.134	0.107	0.114	0.142	0.143	-0.317	-0.078	0.173	-0.071	-0.183	1.000									
Silt	-0.142	-0.094	-0.029	-0.045	-0.100	-0.064	-0.084	-0.111	-0.112	0.269	0.024	-0.138	0.036	0.115	-0.873	1.000								
Clay	-0.137	-0.136	-0.094	-0.112	-0.131	-0.122	-0.112	-0.133	-0.133	0.272	0.115	-0.159	0.089	0.203	-0.831	0.454	1.000							
OM	-0.003	0.044	0.077	0.044	0.015	0.058	-0.002	0.012	0.012	0.082	0.010	-0.114	0.089	-0.686	0.105	0.018	-0.211	1.000						
BD	0.018	-0.068	-0.127	-0.052	-0.009	-0.095	0.018	-0.006	-0.006	-0.113	-0.037	0.112	-0.041	0.424	0.201	-0.240	-0.095	-0.560	1.000					
Ksat	0.302	0.256	0.169	0.200	0.269	0.220	0.243	0.278	0.279	-0.394	-0.058	0.234	-0.012	-0.014	0.710	-0.571	-0.645	-0.026	0.359	1.000				
CEC	-0.132	-0.124	-0.074	-0.112	-0.131	-0.109	-0.117	-0.130	-0.130	0.295	0.100	-0.208	0.135	-0.046	-0.732	0.377	0.908	0.087	-0.267	-0.647	1.000			
pH	-0.105	-0.124	-0.112	-0.111	-0.118	-0.125	-0.094	-0.111	-0.111	0.153	0.041	-0.032	-0.054	0.303	-0.248	0.247	0.172	-0.396	0.046	-0.234	0.017	1.000		
Slope	-0.011	0.009	0.020	0.004	-0.004	0.021	-0.015	-0.005	-0.005	-0.001	0.110	0.012	-0.092	-0.051	-0.050	0.070	0.011	-0.022	-0.010	-0.046	0.003	0.110	1.000	
Elevation	0.070	0.067	0.050	0.051	0.057	0.049	0.043	0.058	0.059	-0.138	-0.008	0.109	-0.036	-0.014	0.020	0.079	-0.126	0.007	0.040	0.109	-0.107	-0.105	0.109	1.000

Appendix B (iv): Oklahoma Correlation Analysis

	NPP	strucc(1)	strucc(2)	metabc(1)	metabc(2)	som1c(1)	som1c(2)	som2c	som3c	Area (Km2)	PPT	Tmin	Tmax	Depth	Sand	Silt	Clay	OM	BD	Ksat	CEC	pH	Slope	Elevation
NPP	1.000																							
strucc(1)	0.953	1.000																						
strucc(2)	0.786	0.826	1.000																					
metabc(1)	0.737	0.851	0.747	1.000																				
metabc(2)	0.821	0.871	0.811	0.852	1.000																			
som1c(1)	0.928	0.976	0.854	0.838	0.892	1.000																		
som1c(2)	0.849	0.852	0.848	0.796	0.873	0.896	1.000																	
som2c	0.934	0.943	0.871	0.840	0.905	0.969	0.960	1.000																
som3c	0.931	0.944	0.869	0.844	0.905	0.973	0.952	0.999	1.000															
Area (Km2)	0.932	0.945	0.869	0.844	0.905	0.973	0.952	0.999	1.000	1.000														
PPT	0.031	0.033	0.031	0.023	0.014	0.035	0.016	0.027	0.029	0.029	1.000													
Tmin	0.020	0.031	0.030	0.018	0.014	0.028	0.004	0.012	0.013	0.013	-0.038	1.000												
Tmax	-0.005	-0.007	-0.001	-0.006	-0.005	-0.004	-0.014	-0.008	-0.008	-0.008	-0.025	0.072	1.000											
Depth	-0.014	-0.014	-0.022	-0.001	-0.010	-0.012	-0.013	-0.016	-0.016	-0.016	-0.017	-0.010	-0.023	1.000										
Sand	-0.005	-0.003	-0.009	-0.014	-0.018	-0.005	-0.014	-0.010	-0.010	-0.010	-0.064	0.058	0.013	0.069	1.000									
Silt	0.004	-0.001	0.009	0.014	0.017	0.000	0.018	0.010	0.009	0.009	0.058	-0.057	0.000	-0.098	-0.932	1.000								
Clay	0.005	0.007	0.007	0.009	0.014	0.013	0.003	0.007	0.008	0.008	0.051	-0.039	-0.032	0.006	-0.769	0.486	1.000							
OM	0.020	0.019	0.033	0.011	0.029	0.020	0.018	0.023	0.022	0.022	0.019	-0.054	-0.013	-0.518	-0.322	0.318	0.216	1.000						
BD	-0.010	-0.023	-0.033	-0.037	-0.032	-0.034	-0.034	-0.035	-0.036	-0.035	-0.038	0.043	0.009	0.367	0.248	-0.261	-0.138	-0.417	1.000					
Ksat	-0.014	-0.014	-0.006	-0.015	-0.025	-0.017	-0.015	-0.016	-0.016	-0.016	-0.058	0.037	0.009	0.080	0.744	-0.629	-0.685	-0.291	0.156	1.000				
CEC	0.008	0.012	0.006	0.012	0.017	0.017	0.004	0.012	0.014	0.014	0.052	-0.034	-0.039	-0.001	-0.705	0.456	0.897	0.265	-0.124	-0.652	1.000			
pH	-0.025	-0.038	-0.017	-0.005	0.004	-0.027	0.005	-0.008	-0.010	-0.010	0.040	0.012	0.048	0.225	-0.212	0.136	0.273	-0.195	-0.079	-0.169	0.187	1.000		
Slope	0.000	0.007	0.012	0.010	0.009	0.011	0.016	0.010	0.009	0.009	0.027	0.001	0.018	0.019	0.026	-0.014	-0.038	-0.032	0.009	0.050	-0.032	0.004	1.000	
Elevation	-0.017	-0.017	0.013	-0.005	-0.029	-0.016	-0.024	-0.024	-0.024	-0.024	0.020	0.022	0.028	0.007	0.046	-0.039	-0.041	-0.023	0.011	0.064	-0.044	-0.034	0.043	1.000

Appendix B (v): Texas Correlation Analysis

	NPP	strucc(1)	strucc(2)	metabc(1)	metabc(2)	som1c(1)	som1c(2)	som2c	som3c	Area (Km2)	PPT	Tmin	Tmax	Depth	Sand	Silt	Clay	OM	BD	Ksat	CEC	pH	Slope	Elevation
NPP	1.000																							
strucc(1)	0.943	1.000																						
strucc(2)	0.800	0.808	1.000																					
metabc(1)	0.758	0.885	0.723	1.000																				
metabc(2)	0.868	0.937	0.781	0.886	1.000																			
som1c(1)	0.923	0.984	0.811	0.862	0.941	1.000																		
som1c(2)	0.923	0.944	0.828	0.848	0.929	0.959	1.000																	
som2c	0.954	0.969	0.820	0.856	0.939	0.978	0.986	1.000																
som3c	0.951	0.968	0.813	0.857	0.939	0.979	0.983	0.999	1.000															
Area (Km2)	0.952	0.969	0.813	0.857	0.939	0.979	0.983	0.999	1.000	1.000														
PPT	0.028	0.032	0.019	0.025	0.025	0.035	0.030	0.031	0.031	0.031	1.000													
Tmin	-0.004	-0.016	-0.055	-0.026	-0.031	-0.020	-0.016	-0.016	-0.017	-0.017	-0.028	1.000												
Tmax	0.000	0.000	-0.006	0.006	0.015	0.002	0.007	0.003	0.002	0.002	-0.010	0.111	1.000											
Depth	0.015	0.008	0.009	0.004	0.013	0.011	0.013	0.013	0.014	0.014	0.008	0.009	0.024	1.000										
Sand	0.002	0.009	-0.011	0.024	0.002	0.004	-0.009	0.000	0.002	0.002	0.005	-0.022	-0.016	-0.077	1.000									
Silt	-0.005	-0.008	0.003	-0.021	-0.003	-0.003	0.003	-0.004	-0.005	-0.005	-0.012	0.003	-0.038	-0.046	-0.858	1.000								
Clay	0.000	-0.009	0.014	-0.019	-0.001	-0.005	0.013	0.003	0.001	0.001	0.009	0.038	0.066	0.180	-0.850	0.458	1.000							
OM	-0.029	-0.022	-0.023	-0.015	-0.025	-0.020	-0.023	-0.026	-0.027	-0.027	-0.005	0.006	-0.013	-0.552	-0.181	0.258	0.046	1.000						
BD	0.025	0.020	0.012	0.022	0.015	0.017	0.016	0.020	0.021	0.021	0.006	-0.006	-0.024	0.332	0.425	-0.308	-0.405	-0.365	1.000					
Ksat	-0.001	0.006	0.002	0.009	-0.002	0.004	-0.009	-0.002	0.000	0.000	-0.027	-0.028	-0.027	-0.078	0.759	-0.645	-0.651	-0.145	0.289	1.000				
CEC	0.004	-0.003	0.016	-0.013	0.000	-0.002	0.011	0.005	0.003	0.003	-0.016	0.020	0.063	0.080	-0.706	0.376	0.836	0.197	-0.434	-0.549	1.000			
pH	-0.013	-0.027	-0.035	-0.036	-0.021	-0.027	-0.020	-0.021	-0.021	-0.021	0.029	0.019	-0.026	0.297	-0.187	0.207	0.111	-0.233	0.078	-0.247	0.006	1.000		
Slope	-0.017	-0.009	-0.016	-0.007	-0.005	-0.005	-0.013	-0.009	-0.007	-0.007	-0.018	0.017	-0.021	-0.001	0.011	-0.011	-0.009	0.007	-0.023	0.005	-0.019	0.011	1.000	
Elevation	0.005	0.013	-0.011	0.002	-0.006	0.009	-0.004	-0.002	-0.002	-0.002	-0.051	0.050	-0.024	0.004	-0.001	-0.018	0.019	0.022	0.005	0.019	0.031	0.025	-0.110	1.000

VITA

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Scope and Method of Study: The main goal of this research is to examine long term trends in carbon sequestration in Conservation Reserve Program (CRP) tracts in the Central High Plains (CHP) region of the U. S. The second goal is to examine the amount of carbon sequestered in the CRP tracts before they were converted to CRP and compare the two. To achieve these goals, the following objectives are considered: To estimate the carbon sequestration potential in CRP in the CHP using an integrated model, CENTURY and GIS to evaluate rates of carbon sequestration and assess policy strategies and management practices for carbon sequestration in the study area; to compare the estimated amount of carbon sequestered in the study area before and after conversion to CRP; and to project future trends in carbon sequestration, and map the spatial and temporal distribution of carbon sequestration in the CHP.

Findings and Conclusions: CENTURY model estimated the total carbon sequestration for the pre-CRP period (1900-1984) as 11958.04 Kt and for the post-CRP period (1985-2010) as 39,682.8 kt; while estimates for same periods by DAYCENT are 21729.80Kt and 38,983.52 kt respectively. Between the pre-CRP and post-CRP periods, however, the CENTURY model indicates a 54% increase in carbon sequestration, while the DAYCENT model estimated only a 28% increase. The overestimation of carbon sequestration by the CENTURY model between the pre-CRP and post-CRP periods may be attributed to the fact that CENTURY runs on a monthly time step while DAYCENT runs on a daily time step. Similarly, the above ground carbon sequestered percentages are 9.7% and 14% for the CENTURY and DAYCENT models respectively; and 90.3% and 86% for below ground percentages for CENTURY and DAYCENT, respectively. The annual rates of carbon sequestration per unit area were also estimated for both models: CENTURY estimated 0.06 Kt per km^2 per yr (pre-CRP) and 0.20 kt per km^2 per yr (post-CRP); DAYCENT estimates were 0.11 Kt per km^2 per yr (pre-CRP) and 0.19 kt per km^2 per yr (post-CRP). In conclusion, estimates by the CENTURY and DAYCENT models indicate that the CRP program is effective in sequestering carbon in the CHP region.

ADVISER’S APPROVAL: Dr. Mahesh N. Rao