Theses and Dissertations

2016

Simulating the Impacts of Land-Use Land-Cover Changes on Cropland Carbon Fluxes in the Midwest of the United States

Zhengpeng Li
South Dakota State University

Recommended Citation

SIMULATING THE IMPACTS OF LAND-USE LAND-COVER CHANGES ON

CROPLAND CARBON FLUXES IN THE MIDWEST OF THE UNITED STATES

BY

ZHENGPENG LI

A dissertation submitted in partial fulfillment of the requirements for the

Doctor of Philosophy

Major in Geospatial Science and Engineering

South Dakota State University

2016

SIMULATING THE IMPACTS OF LAND-USE LAND-COVER CHANGES ON CROPLAND CARBON FLUXES IN THE MIDWEST OF THE UNITED STATES

This dissertation is approved as a creditable and independent investigation by a candidate for the Doctor of Philosophy in Geospatial Science and Engineering science degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

Shuguang Liu, Ph.D.
Dissertation Advisor   Date

Michael C.Wimberly, Ph.D.
Major Advisor   Date

Geoffrey Henebry, Ph.D.
Director, Geospatial Science Center of Excellence   Date

Dean, Graduate School   Date

To

My Dad, Qingshu Li, who did not have the opportunity to receive college
education but became a senior engineer by himself.

My Mom, Guihua Wang

Also to

My wife, Xuexia Chen

My son, Stone Li

My daughter, Jessica Li

ACKNOWLEDGEMENTS

CONTENTS

ABBREVIATIONS

C carbon

ha hectare

Mha million hectare

NEE net ecosystem exchange

NEP net ecosystem production

NPP net primary production

SD standard deviation

SOC soil organic carbon

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

SIMULATING THE IMPACTS OF LAND-USE LAND-COVER CHANGES ON

CROPLAND CARBON FLUXES IN THE MIDWEST OF THE UNITED STATES

ZHENGPENG LI

2016

Understanding the major drivers of the cropland carbon fluxes is important for carbon management and greenhouse gas mitigation in agriculture. Past studies found that agricultural land-use and land-cover (LULC) changes, such as changes in cropland production technologies, tillage practices, and planted crop species, could have large impacts on carbon fluxes. However, the impacts remain highly uncertain at regional to global scales.

Satellite remote sensing is commonly used to create products with geospatial information on LULC changes. This geospatial information can be integrated into biogeochemical models to simulate the spatial and temporal patterns of carbon fluxes.

We used the General Ensemble Biogeochemical Modeling System (GEMS) to study LULC change impacts on cropland carbon fluxes in the Midwest USA. First we evaluated the impacts of LULC change on cropland net primary production (NPP) estimates. We found out the high spatial variability of cropland NPP across the study region was strongly related to the changes in crop species. Ignoring information about crop species distributions could introduce large biases into NPP estimates.

We then investigated whether the characteristics of LULC change could impact the uncertainties of carbon flux estimates (i.e., NPP, net ecosystem production (NEP) and soil organic carbon (SOC)) using GEMS and two other models. The uncertainties of all three flux estimates were spatial autocorrelated. Land cover characteristics, such as cropland percentage, crop richness, and land cover diversity all showed statistically significant relationships with the uncertainties of NPP and NEP, but not with the uncertainties of SOC changes.

The impacts of LULC change on SOC changes were further studied with historical LULC data from 1980 to 2012 using GEMS simulations. The results showed that cropland production increase over time from technology improvements had the largest impacts on cropland SOC change, followed by expansion of conservation tillage.

This study advanced the scientific knowledge of cropland carbon fluxes and the impacts of various management practices over an agricultural area. The findings could help future carbon cycle studies to generate more accurate estimates on spatial and temporal changes of carbon fluxes.

CHAPTER 1. INTRODUCTION

Cropland provides necessary food supplies for human society and is an important component of the biosphere carbon cycle. Cropland is also under intensive management and has significant social and economic impacts. Climate disruptions to cropland production have increased in the past 40 years and are projected to increase over the next 25 years (Hatfield et al., 2014). A sustainable management plan on croplands should not only mitigate/adapt to the climate change but also meet the demands of human society. Such management plans can only be built with a good understanding of the carbon cycle on croplands and the mechanisms that drive it. Thus, it is important to quantify the spatial and temporal variations in the cropland carbon dynamics and investigate the major driving factors behind these variations.

Many efforts have been made to assess carbon dynamics in cropland during the past decade (Eve et al., 2002; Liu et al., 2011; Ogle et al., 2003; West et al., 2010; Zhu and Reed, 2012). The complex interplay of multiple factors such as climate, land cover, and management practices has made the estimation of carbon sinks and sources from regional to global scale very challenging. For example, the European carbon assessment found that satellite based models estimated lower cropland net primary production (NPP) (419 – 494 $gC\ m^{-2}\ yr^{-1}$) than process based model (585 $gC\ m^{-2}\ yr^{-1}$), and yield statistics (646 $gC\ m^{-2}\ yr^{-1}$) (Ciais et al., 2010). A recent comparison in the USA also found that cropland net ecosystem exchange (NEE) estimates from inventory based methods (-264.3 $TgC\ yr^{-1}$, negative values indicate carbon sinks and positive ones are carbon sources) were significantly different from the estimates of atmospheric inversion models (-136.8 $TgC\ yr^{-1}$) and terrestrial biosphere models (-94.6 $TgC\ yr^{-1}$) (Hayes et al., 2012). Although

some of the variations can be attributed to differences in model structure and model driver data, more research is needed to more precisely quantify the impact of model formulation and driver data on the uncertainties of the simulation outputs (Huntzinger et al., 2012).

1.1 BIOGEOCHEMICAL MODELS FOR CARBON CYCLE STUDIES

The understanding of ecosystem carbon cycles can be improved through both observations and modeling activities (Huntzinger et al., 2012; Michalak et al., 2011). Biogeochemical models have been developed since the 1970s to study carbon cycles on croplands, such as CENTURY (Parton et al., 1987), EPIC (Williams, 1990) , and STICS (Brisson et al., 2003) . These biogeochemical models were developed based on long term field studies and have been validated across multiple sites. The Intergovernmental Panel on Climate Change (IPCC, 2006) referred to these models as Tier 3 method to estimate soil organic carbon (SOC) changes in countries. Using these models for regional and global studies are likely to provide more precise and accurate results comparing with Tier 2 (country-specific emission factors) and Tier1 (global emission factors) methods (Smith et al., 2012). Bondeau et al. (2007) simulated the cropland use change from 1901 to 2000 using a dynamic global vegetation model integrated with the STICS model (Bondeau et al., 2007). Using DAYCENT and historical land use data, Hartman et al. (2011) simulated the impact of historical land-use changes on greenhouse emissions in 21 counties in the Great Plains (Hartman et al., 2011). Using the CENTURY model and the National Resources Inventory (NRI) data, Ogle et al. (2009) estimated that the SOC stock in croplands increased by 14.6 TgC yr^{-1} from 1990 to 1995 and 17.5 TgC yr^{-1} from 1995 to 2000 in the USA. Another study using the NRI data and EPIC model estimated the

SOC changes in croplands was much smaller, only increased 55.89 TgC in 30 years (Potter et al., 2009). Although these studies provided useful information across large extents, these researches did not include the land-use land-cover (LULC) change dynamics at an adequate temporal frequency and did not have enough spatial resolution.

1.2 SPATIAL LAND COVER DATA

Satellite-based land cover datasets have been developed since the 1980s. The biophysical variables measured from remotely sensed data can be used to produce land cover data across large region (Townshend et al., 1991). Several global land cover products were produced using the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) data, such as the International Geosphere–Biosphere Programme (IGBP) land cover, the IGBP Data and Information Systems, the University of Maryland (UMD) land cover layer and the MODIS land cover product (Friedl et al., 2010; Hansen et al., 2000; Loveland and Belward, 1997; Loveland et al., 2000). These global land cover products generally have the spatial resolution between 1 km and 1 degree. Many studies used these land cover data sets in biosphere models to study different ecosystem carbon fluxes globally and regionally (Cramer et al., 1999; Ito, 2011; Lobell et al., 2002; Zhao et al., 2006).

In the USA, higher resolution satellites, such as the Advanced Wide Field Sensor (AWiFS) and Landsat Thematic Mapper (TM) data have been used to generate LULC data sets that have spatial resolutions between 30 m to 56 m. These data sets include the National Land Cover Dataset (NLCD), USDA Cropland Data Layer (CDL), and North American Forest Dynamics Project (Boryan et al., 2011; Goward et al., 2008; Vogelmann,

2001). These data sets provide detailed information on LULC and have been used to estimate the spatial and temporal variations of carbon fluxes (Tan et al., 2006; West et al., 2008; Zhang et al., 2014; Zhao et al., 2009). Recent developments in carbon modeling make it possible to couple these high resolution datasets with biogeochemical models to simulate regional carbon dynamics (Causarano et al., 2008; Liu et al., 2011; Zhao et al., 2009; Zhu et al., 2010).

1.3 OBJECTIVES OF THE DISSERTATION RESEARCH

More precise and accurate estimates of carbon dynamics are needed to develop effective management plans (Michalak et al., 2011; Smith et al., 2012). Previous studies have demonstrated the importance of temporal interval and spatial details of LULC change information on estimating regional carbon dynamics in the southeastern United States (Zhao and Liu, 2014; Zhao et al., 2009, 2010). Without integrating the LULC data into carbon cycle studies, it would be impossible to accurately quantify the spatial distributions of carbon sources and sinks and understand the mechanisms behind them. A recent study, the USGS National Assessment of Ecosystem Carbon Sequestration and Greenhouse Gas Fluxes, has simulated the ecosystem carbon dynamics with spatially explicit LULC data and provided valuable information for policy makers and resource managers (Zhu et al., 2010; Zhu et al., 2011; Zhu and Reed, 2012). However, uncertainties in these assessment results remain high because of insufficient input data and inherent uncertainty related to the structure and the parameterization of the models used in the assessments (Zhu et al., 2010).

I will use the available LULC data sets and the General Ensemble Biogeochemical Modeling System (GEMS) in this study to simulate the spatial and temporal variations in carbon fluxes in croplands, assess the uncertainty of the model estimates, and find the mechanisms driving these variations in the Midwest USA. GEMS is an integrated modeling framework designed to simulate the spatial and temporal variations of ecosystem carbon fluxes using spatially explicit LULC data, as well as climate, soil and management information (Liu, 2009; Liu et al., 2004).

I address the following key science questions in this study:

Question 1: Since multiple crops can be planted on the cropland, can we estimate the cropland carbon fluxes accurately if the cropland is treated as a single crop types?

Hypothesis 1: Changes in the spatial patterns of planted crop types will not change the spatial patterns of cropland carbon fluxes.

Many process-based models studies still treat cropland as a single land cover type in simulating regional carbon fluxes. For example, in the 19 models compared in the NACP regional interim synthesis, 8 of them used land cover inputs from MODIS or IGBP land cover data sets, which only have one cropland cover type (Huntzinger et al., 2012). This approach ignores the fact that multiple crop species can be planted in croplands and crop species can be rotated annually.

I will use GEMS to simulate the carbon fluxes with the changes of the crop species in croplands. The results will be compared with the carbon fluxes estimates from other methods to test this hypothesis.

Question 2: Multiple models have been used to simulate cropland carbon fluxes in the past. What is the impact of the differences among cropland cover type on the uncertainties of the carbon fluxes estimates?

Hypothesis 2: The uncertainties of the carbon fluxes estimated from multiple models are randomly distributed across croplands.

How to quantify and reduce uncertainty is a high priority in the most recent US carbon cycle science plan (Michalak et al., 2011). A comparison between multiple terrestrial biosphere models at flux tower sites found the biome classification was the most important factor controlling the model-data mismatch of the estimated carbon fluxes (Schwalm et al., 2010). Another comparison of global NPP estimates from multiple biosphere models also found that different vegetation classifications partially caused higher NPP differences at the borders of vegetation types (Cramer et al., 1999). These earlier studies indicated the differences in the land cover type (with associated differences in model parameterization) could bring large uncertainty in carbon fluxes estimates.

It is important to study the influence of land cover characteristics on the uncertainties of the carbon fluxes estimates. The hypothesis I make here is a null hypothesis and will be tested using geospatial statistics. The carbon fluxes estimates from GEMS and other methods will be used to compute the uncertainties. Then the relationships between the uncertainties spatial distributions and the land cover inputs will be analyzed to test the hypothesis.

Question 3: Given the considerable LULC and management changes in the cropland from 1980 to 2012 in the Midwest temperate prairie, where are the major SOC sinks and sources in croplands and what are their magnitudes?

Hypothesis 3: Cropland is a major carbon sink from 1980 to 2012.

Since 1980s, changes in crop management practices in cropland were substantial in the Midwest USA. These changes include technology improvements (irrigation, fertilization, pest management, etc.), conversion from intensive tillage to conservation tillage, enhanced crop rotation and implementation of cropland conservation programs. The combination of these cultivation improvements has led to considerable enhancement in cropland production and cropland SOC (Hicke et al., 2004; Parton et al., 2007; Prince et al., 2001). For example, the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA) reported the yields of the three major crops (corn, soybean and wheat) increased about 40%, 33% and 16% respectively in 2000s from the basis of the 1980s (USDA, 2012). An analysis of NASS data showed that cropland area decreased by 4% while the average crop production increased by 40% from 1972 to 2001 in the USA, with large production increases occurring across the Great Plains and Midwest regions (Hicke et al., 2004). From 1989 to 2004, the percentage of cropland that used conservation tillage increased from 25% to 41.5% in the USA (CTIC, 2008). In addition to improved tillage practices, more than 13 Mha cropland were enrolled in Conservation Reserve Program (CRP) since 1986 (USDA, 2012). Eve et al. (2002) used Intergovernmental Panel on Climate Change (IPCC) methods to estimate the SOC sequestrated on planted cropland from 1982 to 1997 is about 15.1 TgC yr^{-1} in the USA. A later study gave a much lower estimate with consideration of the SOC loss in organic soil (Ogle et al., 2003). The land use and management practice changes on the cropland increased SOC in mineral soil by about 6.5 – 15.3 TgC yr^{-1} but decreased SOC in organic soil by 6.4 - 13.3 TgC yr^{-1} from 1982 to 1997 (Ogle et al., 2003). Using the

CENTURY model and NRI data, Ogle et al. (2009) found that SOC increased by 14.6

TgC yr^{-1} from 1990 to 1995 and 17.5 TgC yr^{-1} from 1995 to 2000. These studies

indicated that land use and management practices could result in significant changes in

the croplands carbon stocks. All these changes need to be fully assessed to find out

whether the cropland in the Midwest is a carbon sink or source. It also will be necessary

to find out the major driving factors of SOC dynamics in croplands and the mechanism

behind them.

Question 4: Among the major changes in land use and management practice recorded in

the region, what is the major driving factor in SOC changes?

Hypothesis 4: The increase of conservation tillage is the major driving factor of the SOC

changes from 1980 to 2012.

 Past research suggested that increase of conservational tillage on cropland has

sequestrated more SOC on the cropland than other practices (Eve et al., 2002; Lal et al.,

2007; West et al., 2008). But many field measurements showed the increase in soil

carbon under conservational practice would reach a balance after certain years (West et

al., 2002; Ogle et al. 2003). West and Post (2002) analyzed many field experiments and

concluded that carbon accumulation usually occurred over 15 to 20 years with maximum

SOC increase rate between 5 and 10 years. Environmental Protection Agency (EPA)

reported the annual net carbon flux on croplands was lower from 2005 to 2010 (4.3 – 5.0

TgC per year) than in1990 (8.0 TgC per year) (US-EPA, 2012). Since many croplands

switched to conservation tillage in 1990s, it is possible the tillage impact on these

cropland soils has reached the saturation level after 2000. As a result, the conservational

tillage could show smaller impact on SOC dynamics and become less important after 2000.

Ogle et al. (2005) synthesized the results from field experiments and evaluated different agricultural management impacts on SOC storage. Their study showed that increasing carbon input through cropping practices is as important as reducing tillage intensity. Studies have found the production in crops experienced large increase since 1980 (Hicke et al., 2004; Prince et al., 2001).The increase in crop production not only produced more residues but also increased the root biomass of the crop, both could bring more carbon inputs into the soil and potentially increase SOC (Follett, 2001; Lal et al., 2007). Given the large increase in crop production from 1980 to 2000, the increasing carbon inputs into the soil may become a major factor driving the SOC changes in croplands.

It will be necessary to find out the major driving factors of SOC dynamics in the Midwest croplands and the mechanism behind them. These findings will help to develop more effective carbon management plans.
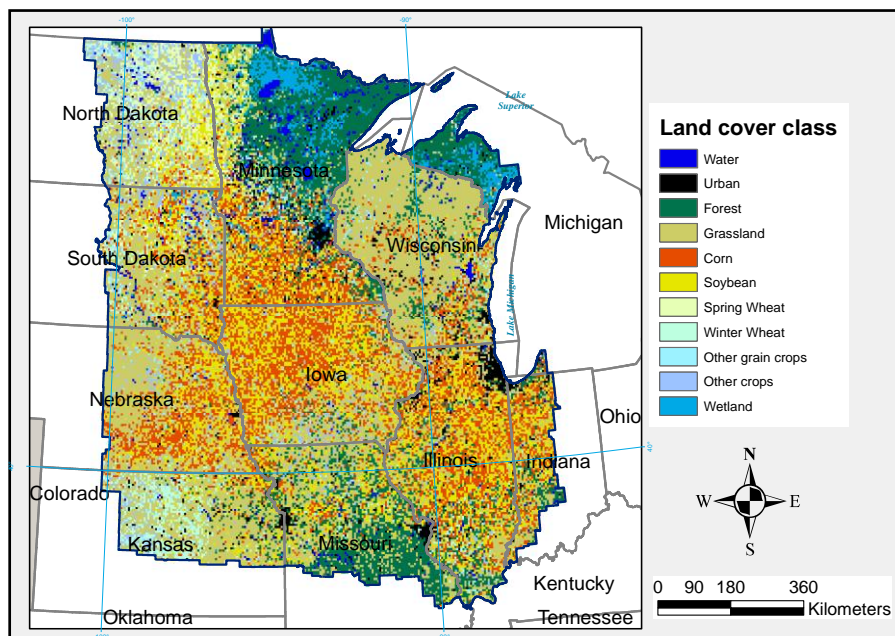
Figure 1.1 Mid-Continent Intensive Campaign region boundary and land cover class in 2001 (combined from National Land Cover Database 2001 and Cropland Data Layer)

The research areas I choose to study are both located in the Midwest. The first research area is the Mid-Continent Intensive Campaign (MCI) region of the National America Carbon Program (NACP) (Ogle et al., 2006). The MCI region encompasses 678 counties from 11 states in the Midwestern United States (Figure 1.1). The second research area is EPA ecoregion 9.2 Temperate Prairies in central and northern part of the Great Plains (Wiken et al., 2011). The northern part of this ecoregion is located in North Dakota, western Minnesota and eastern South Dakota (Figure 1.2). The central part includes the major portions of Iowa. The southern part of the region covers eastern Missouri, western Kansas and northern Oklahoma. Both areas cover multiple major land resource areas (MLRA) and have large variations in climate, soil, and cropping systems (USDA, 2006).
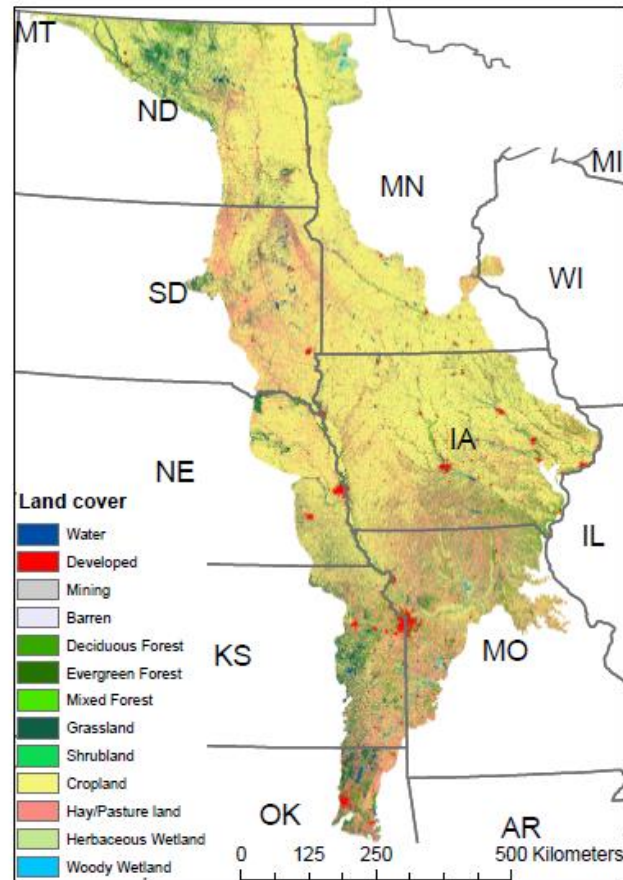
Figure 1.2. Land cover class in the Temperate Prairies (Ecoregion 9.2) from FORE-SCE model in 1992.

1.4 STRUCTURE OF THE DISSERTATION RESEARCH

Chapter 2 presents a study of LULC impacts on the cropland carbon flux estimates. The research in this chapter is to test the hypothesis 1. I compared three estimates of cropland NPP: the MODIS NPP product, crop inventory data and GEMS in the MCI region. Both GEMS and crop inventory estimates included crop species information while MODIS product did not. I analyzed the difference in the spatial and temporal

variability of NPP from the three methods. This paper was published in Ecological Modelling in 2014.

Chapter 3 presents the study of model uncertainties associated with land cover data in the MCI region. The research in this chapter is to test hypothesis 2: the model uncertainties between multiple models are randomly distributed on croplands. This study compared the NPP, NEP, and SOC change in 2007 and 2008 from three methods: crop inventory, EPIC and GEMS. In this paper, I used spatial statistical analysis method to study the spatial distributions of the uncertainties and investigated the relationships between uncertainties and the land cover characteristics. This paper was submitted to Ecological Modelling and accepted with moderate revision.

Chapter 4 presents a study of land use and management changes and their impacts on the SOC dynamics from 1980 to 2012 in the temperate prairies ecoregion 9.2. This study tests hypotheses 3 and 4: cropland is a major carbon sink from 1980 to 2012; and the increase of conservation tillage is the major driving factor of the SOC changes from 1980 to 2012.I used spatially explicit land use data and built multiple management scenarios to simulate historical impacts on cropland SOC and analyze the spatial patterns. This paper will be submitted to Ecological Modelling.

Chapter 5 reviews the results of all the studies presented, emphasizes the linkages between the studies, and highlights how the GEMS model was used with spatial land use data to advance the study of regional carbon dynamics in the Midwest USA.

1.5 REFERENCES

Bondeau, A., Smith, P.C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze-Campen, H., MÜLler, C., Reichstein, M., Smith, B., 2007. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Global Change Biology 13, 679-706.

Boryan, C., Yang, Z., Mueller, R., Craig, M., 2011. Monitoring US agriculture: the US department of agriculture, national agricultural statistics service, cropland data layer program. Geocarto International 26, 341-358.

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., 2003. An overview of the crop model STICS. European Journal of agronomy 18, 309-332.

Causarano, H.J., Doraiswamy, P.C., McCarty, G.W., Hatfi eld, J.L., Milak, S., Stern, A.J., 2008. EPIC modeling of soil organic carbon sequestration in croplands of Iowa. J. Environ. Qual. 37, 8.

Ciais, P., Wattenbach, M., Vuichard, N., Smith, P., Piao, S.L., Don, A., Luyssaert, S., Janssens, I.A., Bondeau, A., Dechow, R., Leip, A., Smith, P.C., Beer, C., Van Der Werf, G.R., Gervois, S., Van Oost, K., Tomelleri, E., Freibauer, A., Schulze, E.D., Carboeurope Synthesis, T., 2010. The European carbon balance. part 2: croplands. Global Change Biology 16, 1409-1428.

Cramer, W., Kicklighter, D.W., Bondeau, A., Iii, B.M., Churkina, G., Nemry, B., et al., The participants of the Potsdam NPP model intercomparison, 1999. Comparing global models of terrestrial net primary productivity (NPP): overview and key results. Glob. Change Biol. 5, 1–15.

CTIC, 2008. National crop residue management survey data. Conservation Technology Information Center.

Eve, M.D., Sperow, M., Paustian, K., Follett, R.F., 2002. National-scale estimation of changes in soil carbon stocks on agricultural lands. Environmental Pollution 116, 431-438.

Friedl, M.A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., Huang, X., 2010. MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote Sensing of Environment 114, 168-182.

Goward, S.N., Masek, J.G., Cohen, W., Moisen, G., Collatz, G.J., Healey, S., Houghton, R.A., Huang, C., Kennedy, R., Law, B., Powell, S., Turner, D., Wulder, M.A., 2008. Forest Disturbance and North American Carbon Flux. Eos Trans. AGU 89.

Hansen, M.C., Defries, R.S., Townshend, J.R.G., Sohlberg, R., 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. International Journal of Remote Sensing 21, 1331-1364.

Hatfield, J., G. Takle, R. Grotjahn, P. Holden, R. C. Izaurralde, T. Mader, E. Marshall, and D. Liverman, 2014: Ch. 6: Agriculture. Climate Change Impacts in the United States: The Third National Climate Assessment, J. M. Melillo, Terese (T.C.) Richmond, and G. W. Yohe, Eds., U.S. Global Change Research Program, 150-174. doi:10.7930/J02Z13FR.

Hartman, M.D., Merchant, E.R., Parton, W.J., Gutmann, M.P., Lutz, S.M., Williams, S.A., 2011. Impact of historical land-use changes on greenhouse gas exchange in the U.S. Great Plains, 1883–2003. Ecological Applications 21, 1105-1119.

Hayes, D.J., Turner, D.P., Stinson, G., McGuire, A.D., Wei, Y., West, T.O., Heath, L.S., de Jong, B., McConkey, B.G., Birdsey, R.A., Kurz, W.A., Jacobson, A.R., Huntzinger, D.N., Pan, Y., Post, W.M., Cook, R.B., 2012. Reconciling estimates of the contemporary North American carbon balance among terrestrial biosphere models, atmospheric inversions, and a new approach for estimating net ecosystem exchange from inventory-based data. Global Change Biology 18, 1282-1299.

Hicke, J.A., Lobell, D.B., Asner, G.P., 2004. Cropland area and net primary production computed from 30 years of USDA agricultural harvest data. Earth Interact. 8, 1-20.

Huntzinger, D.N., Post, W.M., Wei, Y., Michalak, A.M., West, T.O., Jacobson, A.R., Baker, I.T., Chen, J.M., Davis, K.J., Hayes, D.J., Hoffman, F.M., Jain, A.K., Liu, S., McGuire, A.D., Neilson, R.P., Potter, C., Poulter, B., Price, D., Raczka, B.M., Tian, H.Q., Thornton, P., Tomelleri, E., Viovy, N., Xiao, J., Yuan, W., Zeng, N., Zhao, M., Cook, R., 2012. North American Carbon Program (NACP) regional interim synthesis: Terrestrial biospheric model intercomparison. Ecological Modelling 232, 144-157.

IPCC, 2006, Generic methodologies applicable to multiple land use categories. In, 2006 IPCC Guidelines for National Greenhouse Gas Inventories (eds Eggleston H, Buendia L, Miwa K, Ngara T, Tanabe K). Intergovernmental Panel on Climate Change, Hayama, Kanagawa, Japan.

Ito, A., 2011. A historical meta-analysis of global terrestrial net primary productivity: are estimates converging? Global Change Biology 17, 3161-3175.

Liu, S., 2009. Quantifying the spatial details of carbon sequestration potential and performance, in: McPherson, B., Sundquist, E. (eds.), Carbon Sequestration and its Role

in the Global Carbon Cycle. American Geophysical Union, Washington, DC, pp. pp. 117-128.

Liu, S., Loveland, T.R., Kurtz, R., 2004. Contemporary carbon dynamics in terrestrial ecosystems in the southeastern plains of the United States. Environmental Management 33, S442-S456.

Liu, S., Tan, Z., Li, Z., Zhao, S., Yuan, W., 2011. Are soils of Iowa USA currently a carbon sink or source? Simulated changes in SOC stock from 1972 to 2007. Agriculture, Ecosystems & Environment 140, 106-112.

Lobell, D.B., Hicke, J.A., Asner, G.P., Field, C.B., Tucker, C.J., Los, S.O., 2002. Satellite estimates of productivity and light use efficiency in United States agriculture. Global Change Biology 8, 722-735.

Loveland, T.R., Belward, A.S., 1997. The IGBP-DIS global 1km land cover data set, DISCover: First results. International Journal of Remote Sensing 18, 3289-3295.

Loveland, T.R., Reed, B.C., Brown, J.F., Ohlen, D.O., Zhu, Z., Yang, L., Merchant, J.W., 2000. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. International Journal of Remote Sensing 21, 1303-1330.

Michalak, A.M., Jackson, R.B., Marland, G., Sabine, C.L., the Carbon Cycle Science Working Group, 2011. A U.S. carbon cycle science plan.

Ogle, S., Davis, K., Andrews, A., Gurney, K., West, T.O., Cooke, R.B., et al., 2006. Science plan: Mid-Continent Intensive Campaign of the North American Carbon Program. Greenbelt, MD.

Ogle, S.M., Jay Breidt, F., Eve, M.D., Paustian, K., 2003. Uncertainty in estimating land use and management impacts on soil organic carbon storage for US agricultural lands between 1982 and 1997.

Parton, W.J., Gutmann, M.P., Ojima, D., 2007. Long-term Trends in Population, Farm Income, and Crop Production in the Great Plains. BioScience 57, 737-747.

Parton, W.J., Schimel, D.S., Cole, C.V., Ojima, D.S., 1987. Analysis of factors controlling soil organic matter levels in great plains grasslands1. Soil Sci. Soc. Am. J. 51, 1173-1179.

Prince, S.D., Haskett, J., Steininger, M., Strand, H., Wright, R., 2001. Net primary production of U.S. Midwest croplands from agricultural harvest yield data. Ecological Applications 11, 1194-1205.

Schwalm, C.R., Williams, C.A., Schaefer, K., Anderson, R., Arain, M.A., Baker, I., Barr, A., Black, T.A., Chen, G., Chen, J.M., Ciais, P., Davis, K.J., Desai, A., Dietze, M., Dragoni, D., Fischer, M.L., Flanagan, L.B., Grant, R., Gu, L., Hollinger, D., Izaurralde, R.C., Kucharik, C., Lafleur, P., Law, B.E., Li, L., Li, Z., Liu, S., Lokupitiya, E., Luo, Y., Ma, S., Margolis, H., Matamala, R., McCaughey, H., Monson, R.K., Oechel, W.C., Peng, C., Poulter, B., Price, D.T., Riciutto, D.M., Riley, W., Sahoo, A.K., Sprintsin, M., Sun, J., Tian, H., Tonitto, C., Verbeeck, H., Verma, S.B., 2010. A model-data intercomparison of CO2 exchange across North America: Results from the North American Carbon Program site synthesis. Journal of Geophysical Research: Biogeosciences 115, G00H05.

Smith, P., Davies, C.A., Ogle, S., Zanchi, G., Bellarby, J., Bird, N., Boddey, R.M., McNamara, N.P., Powlson, D., Cowie, A., van Noordwijk, M., Davis, S.C., Richter, D.D.B., Kryzanowski, L., van Wijk, M.T., Stuart, J., Kirton, A., Eggar, D., Newton-Cross, G., Adhya, T.K., Braimoh, A.K., 2012. Towards an integrated global framework to assess the impacts of land use and management change on soil carbon: current capability and future vision. Global Change Biology 18, 2089-2101.

Tan, Z., Liu, S., Johnston, C.A., Liu, J., Tieszen, L.L., 2006. Analysis of ecosystem controls on soil carbon source-sink relationships in the northwest Great Plains. Global Biogeochemical Cycles 20.

Tan, Z., Liu, S., Johnston, C.A., Loveland, T.R., Tieszen, L.L., Liu, J., Kurtz, R., 2005. Soil organic carbon dynamics as related to land use history in the northwestern Great Plains. Global Biogeochemical Cycles 19, GB3011.

Townshend, J., Justice, C., Li, W., Gurney, C., McManus, J., 1991. Global land cover classification by remote sensing: present capabilities and future possibilities. Remote Sensing of Environment 35, 243-255.

United States Department of Agriculture (USDA), 2006. Major land resource regions custom report (USDA Agriculture handbook 296). USDA. http://soils.usda.gov/MLRAExplorer, accessed Oct 22nd 2012.

USDA, N., 2012. NRCS Geospatial Data Gateway.

US-EPA., 2012, Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2010.

Vogelmann, J.E., S.M. Howard, L. Yang, C. R. Larson, B. K. Wylie, and J. N. Van Driel,, 2001. Completion of the 1990's National Land Cover Data Set for the conterminous United States. Photogrammetric Engineering and Remote Sensing 67, 650-662.

West, T.O., Brandt, C.C., Baskaran, L.M., Hellwinckel, C.M., Mueller, R., Bernacchi, C.J., Bandaru, V., Yang, B., Wilson, B.S., Marland, G., Nelson, R.G., Ugarte, D.G.D.L.T., Post, W.M., 2010. Cropland carbon fluxes in the United States: increasing

geospatial resolution of inventory-based carbon accounting. Ecological Applications 20, 1074-1086.

Wiken, E., Jiménez Nava, F., Griffith, G., 2011. North American Terrestrial Ecoregions

Level III, in: Cooperation, C.f.E. (Ed.), Montreal, Canada, p. 149.

Williams, J.R., 1990. The Erosion-Productivity Impact Calculator (EPIC) Model: A Case History. Philosophical Transactions of the Royal Society of London B: Biological Sciences 329, 421-428.

Zhang, X., Sahajpal, R., Manowitz, D.H., Zhao, K., LeDuc, S.D., Xu, M., Xiong, W., Zhang, A., Izaurralde, R.C., Thomson, A.M., West, T.O., Post, W.M., 2014. Multi-scale geospatial agroecosystem modeling: A case study on the influence of soil data resolution on carbon budget estimates. Science of The Total Environment 479–480, 138-150.

Zhao, M., Running, S.W., Nemani, R.R., 2006. Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. Journal of Geophysical Research: Biogeosciences 111, G01002.

Zhao, S., Liu, S., 2014. Scale criticality in estimating ecosystem carbon dynamics. Global change biology 20, 2240-2251.

Zhao, S., Liu, S., Li, Z., Sohl, T.L., 2009. Ignoring detailed fast-changing dynamics of land use overestimates regional terrestrial carbon sequestration. Biogeosciences 6, 1647-1654.

Zhao, S., Liu, S., Li, Z., Sohl, T.L., 2010. A spatial resolution threshold of land cover in estimating terrestrial carbon sequestration in four counties in Georgia and Alabama, USA. Biogeosciences 7, 71-80.

Zhu, Zhiliang, ed., Bergamaschi, Brian, Bernknopf, Richard, Clow, David, Dye, Dennis, Faulkner, Stephen, Forney, William, Gleason, Robert, Hawbaker, Todd, Liu, Jinxun, Liu, Shuguang, Prisley, Stephen, Reed, Bradley, Reeves, Matthew, Rollins, Matthew, Sleeter, Benjamin, Sohl, Terry, Stackpoole, Sarah, Stehman, Stephen, Striegl, Robert, Wein, Anne, and Zhu, Zhiliang, 2010, A method for assessing carbon stocks, carbon sequestration, and greenhouse-gas fluxes in ecosystems of the United States under present conditions and future scenarios: U.S. Geological Survey Scientific Investigations Report 2010–5233, 188 p. (Also available at http://pubs.usgs.gov/sir/2010/5233/.)

Zhu, Zhiliang, ed., Bouchard, Michelle, Butman, David, Hawbaker, Todd, Li, Zhengpeng, Liu, Jinxun, Liu, Shuguang, McDonald, Cory, Reker, Ryan, Sayler, Kristi, Sleeter, Benjamin, Sohl, Terry, Stackpoole, Sarah, Wein, Anne, and Zhu, Zhiliang, 2011,

Baseline and projected future carbon storage and greenhouse-gas fluxes in the Great Plains region of the United States: U.S. Geological Survey Professional Paper 1787, 28 p. (Also available at http://pubs.usgs.gov/pp/1787/.)

CHAPTER 2. COMPARING CROPLAND NET PRIMARY PRODUCTION

ESTIMATES FROM INVENTORY, A SATELLITE-BASED MODEL, AND A

PROCESS-BASED MODEL IN THE MIDWEST OF THE UNITED STATES

Li, Z., Liu, S., Tan, Z., Bliss, N.B., Young, C.J., West, T.O., Ogle, S.M., 2014.

Comparing cropland net primary production estimates from inventory, a satellite-based

model, and a process-based model in the Midwest of the United States. Ecological

Modelling 277, 1-12.

2.0 ABSTRACT

Accurately quantifying the spatial and temporal variability of net primary production (NPP) for croplands is essential to understanding regional cropland carbon dynamics. We compared three NPP estimates for croplands in the Midwestern United States: inventory-based estimates using crop yield data from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS); estimates from the satellite-based Moderate Resolution Imaging Spectroradiometer (MODIS) NPP product; and estimates from the General Ensemble biogeochemical Modeling System (GEMS) process-based model. The three methods estimated mean NPP in the range of $469 – 687$ g C m^{-2} yr^{-1} and total NPP in the range of $318 – 490$ Tg C yr^{-1} for croplands in the Midwest in 2007 and 2008. The NPP estimates from crop yield data and the GEMS model showed the mean NPP for croplands was over 650 g C m^{-2} yr^{-1} while the MODIS NPP product estimated the mean NPP was less than 500 g C m^{-2} yr^{-1}. MODIS NPP also showed very different spatial variability of the cropland NPP from the other two methods. We found these differences were mainly caused by the difference in the land cover data and the crop specific information used in the methods. Our study demonstrated that the detailed mapping of the temporal and spatial change of crop species is critical for estimating the spatial and temporal variability of cropland NPP. We suggest that high resolution land cover data with species-specific crop information should be used in satellite-based and process-based models to improve carbon estimates for croplands.

2.1 INTRODUCTION

The cropland net primary production (NPP) is an important component in the cropland carbon cycle because it represents the ability of the cropland to fix atmospheric carbon as biomass. Accurately quantifying the changes of cropland NPP is necessary for understanding the carbon dynamics for croplands, securing food and energy needs, and mitigating the effects of climate change. However, the global and regional NPP estimates still have large uncertainties among different methods (Ciais et al., 2010; Cramer et al., 1999; Ito, 2011). A comparison of the global NPP estimates found that simulated NPP from multiple models ranges between 39.9 and 80.5 Pg C yr^{-1} for the terrestrial biosphere (Cramer et al., 1999). A recent study showed that the global NPP estimates from different methods are converging because more observational data are being used, especially spatial datasets generated from satellite remote sensing data (Ito, 2011). Differences among the global NPP estimates, however, are still about 8–9 Pg C yr^{-1} between 2000 and 2010 (Ito, 2011). The carbon balance study of European croplands found that cropland NPP estimates range from 490 to 846 gC m^{-2} yr^{-1} using different methods (Ciais et al., 2010). Such differences in NPP estimates are likely to bring more uncertainties in the regional carbon budget. In a recent study of North America carbon balance, the mean carbon sink for croplands estimated from multiple terrestrial biosphere models is much lower (-94.6 Tg C yr^{-1}) than with inventory-based estimates (-264.3 Tg C yr^{-1}) and atmospheric inversion models (-136.8 Tg C yr^{-1}) (Hayes et al., 2012). These large differences between the estimates of cropland carbon sink may be reduced by more accurate NPP estimates for croplands.

Ito (2011) classified the global NPP estimation methods into five major categories: inventory, empirical model simulation, biogeochemical model simulation, dynamic global vegetation model simulation, and remote sensing estimation. At the regional level, three methods are commonly used to estimate the cropland NPP: crop inventory, biogeochemical model simulation, and remote sensing estimation using a satellite-based model.

NPP equals the amount of biomass that vegetation assimilates over a certain time period (Jenkins et al., 2001; Prince et al., 2001; Scurlock et al., 2002). For crops, the growing season NPP can be estimated from the crop yield data in the crop inventory with allometric and biomass conversion factors such as harvest index, root /shoot ratio, and biomass-to-carbon ratio (Hicke et al., 2004; Prince et al., 2001; West et al., 2010). Because government agencies usually maintained crop inventory and regularly updated the crop yield data, the magnitudes and interannual changes of NPP for croplands can be estimated from these inventory data. Prince et al. (2001) estimated cropland NPP using the crop yield data from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) and found that county-level NPP varies from 200 gC m^{-2} yr^{-1} to over 850 gC m^{-2} yr^{-1} in the U.S. Midwest. Hicke et al. (2004) analyzed the national crop yield data from NASS and found that the NPP of U.S. cropland increased from 350 gC m^{-2} yr^{-1} in 1972 to 490 gC m^{-2} yr^{-1} in 2001. This approach is limited because the agricultural inventory data are usually reported based on political boundaries and lack spatial detail within the boundaries.

Remote sensing information of the vegetation can be used in satellite-based models to estimate NPP. Field experiments have shown that the carbon assimilation rates of crops are proportional to the intercepted solar radiation (Monteith and Moss, 1977; Monteith, 1972). The intercepted solar radiation by vegetation can be estimated from the Normalized Difference Vegetation Index (NDVI) from satellite remote sensing data (Goetz et al., 1999; Prince and Goward, 1995; Prince, 1991). Gross Primary Production (GPP) can be estimated from NDVI and the Photosynthetically Active Radiation (PAR) with a conversion efficiency factor ε (Running et al., 2004):

$$GPP = \varepsilon \times FPAR \times PAR \approx \varepsilon \times NDVI \times PAR, (1)$$

FPAR is the fraction of PAR that is absorbed by vegetation. The conversion factor ε is the light use efficiency (LUE) factor and its value is affected by biological and environmental factors (Prince and Goward, 1995). Many terrestrial biosphere models used this approach to estimate the GPP and study the carbon balance in large regions and at the global scale (Hayes et al., 2012; Prince and Goward, 1995; Running et al., 2004; Tian et al., 2010). NPP can be calculated as the difference between GPP and the Autotrophic Respiration (AR) (Chapin et al., 2006). The Moderate Resolution Imaging Spectroradiometer (MODIS) project used this approach to generate the global GPP and NPP datasets with the Biome-BGC model (Running et al., 2004; White et al., 2000; Zhao et al., 2005). The Carnegie-Ames-Stanford-Approach (CASA) model uses a similar approach to calculate NPP directly from photosynthesis without the calculation of GPP and AR (Potter et al., 2003).

Process-based models can simulate NPP based on the crop-specific characteristics and the environmental variables that constrain crop growth (Cramer et al., 1999). For example, crop-specific characteristics are represented in models by multiple crop parameters such as maximum growth rate, the shoot/root ratio and the carbon/nitrogen ratios in the crop components. These model parameters are derived from field observations and calibrated with site level biometric measurements. Environmental variables influencing growth, such as temperature, precipitation, and nutrient limits, are usually estimated from climate, soil, and management data. Multiple models are based on this approach: the CENTURY model developed by Parton et al. (1993); the Denitrification-Decomposition model developed by Li et al. (1997); the Environment Policy Integrated Climate model developed by Izaurralde et al. (2006); and the Erosion-Deposition-Carbon-Model (EDCM) developed by Liu et al. (2003).

In this study, we estimated NPP for croplands in the Midwest of the United States with three methods: crop inventory, a satellite-based model, and a process-based model. We assessed the estimates of cropland NPP per unit area and the total cropland NPP from these methods to answer three questions:

i) What is the NPP for croplands in the Midwest estimated from different methods in 2007 and 2008?

ii) What is the spatial and temporal variability of the NPP for croplands, and what are the major driving factors of this variability?

iii) What are the differences between the NPP estimated by each method and what are the causes of these differences?

2.2 MATERIALS AND METHODS

2.2.1 Study area

The study area is the Mid-Continent Intensive Campaign (MCI) region of the National America Carbon Program (NACP) (Ogle et al., 2006). The MCI region encompasses 678 counties from 11 states in the Midwestern United States (Figure 2.1). The MCI region covers multiple major land resource areas (MLRA) and has large variety in climate, soil and cropping system. A MLRA is a region that has similar climate, soil, and land use system as defined by the USDA (USDA, 2006).

The northwestern part of the MCI region including North Dakota and South Dakota is in the Northern Great Plains Spring Wheat Region (USDA, 2006). The mean annual precipitation varies from 355 to 535 mm and the mean annual air temperature from 5 to 7 °C. The dominant soil type is Mollisols and the major cropping system is dry-farmed spring wheat. The northeastern part of the MCI region including northern Minnesota, northern Illinois and most of Wisconsin is in the Northern Lake States Forest and Forage Region (USDA, 2006). This region has the mean annual precipitation from 660 to 865 mm and the mean annual air temperature from 4 to 7 °C. Histosols is the dominant soil type. Other major soil types include Alfisols, Spodosols, Entisols and Mollisols. There is large forest area in this region and the major cropping systems are corn and wheat.
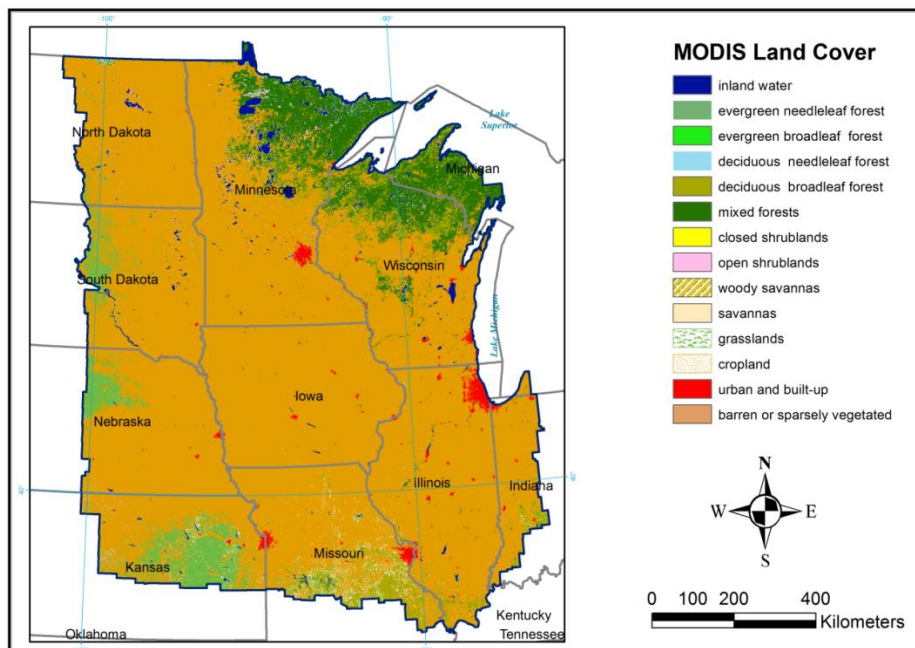
Figure 2.1. Mid-Continent Intensive Campaign (MCI) region boundary and spatial distribution of land covers extracted from University of Maryland global land cover product.

Most of the central part and large fraction of southwestern part of the MCI region is in the Central Feed Grains and Livestock Region. This includes south part of Minnesota, Iowa, Illinois and north part of Missouri (USDA, 2006). This area has the most favorable climate and soil for agriculture. The mean annual precipitation ranges from 815 to 990 mm and the mean annual air temperature ranges from 8 to 12 °C. Major soil types include Mollisols, Entisols, Alfisols, Entisols and Inceptisols. The major cropping systems are continuous corn and corn soybean rotation. This area provides most of the corn and soybeans in the U.S.

The western part of the MCI region including part of South Dakota, Nebraska is in the Western Great Plains Range and Irrigated Region (USDA, 2006). This region has the mean annual precipitation from 330 to 560 mm and the mean annual air temperature from 7 to 11 °C. The dominant soil types are Entisols and Mollisols. Pastureland grazing by cattle is a major land use in this region. The major cropping systems are irrigated corn and soybean, as well as some dry-farmed winter wheat. The irrigated croplands locate mainly along the streams and large amount of the water withdrawn is used for irrigation. The southwestern part of the MCI region including part of Nebraska and north Kansas is in the Central Great Plains Winter Wheat and Range Region (USDA, 2006). This region has the mean annual precipitation from 815 to 990 mm and the mean annual air temperature from 12 to 16 °C. The dominant soil type is Mollisols. The major land uses in this region include pastureland grazing by cattle, irrigated cropland planted with corn and soybean, and dry-farmed cropland planted with winter wheat.

Overall, the MCI region has a land area of about 124 million hectare (Mha), and over 40% of the land area is used for agriculture. Corn, soybean, spring wheat, and winter wheat are the four major crops planted in the MCI region and together they occupy more than 90% of the agricultural area. Over 30 Mha cropland area is used to plant corn and soybean and about 10 Mha cropland area is planted with small grains and other crops from 1990 to 2000 (West et al., 2008). Though conventional tillage and reduced tillage are the dominant tillage practices used in the MCI region, no-till practice has increased from 7% in 1990 to 19% in 2000 (West et al., 2008).

2.2.2 Methods for estimating NPP

2.2.2.1 Crop inventory

The USDA crop inventory database contains the crop yields data derived from farm census records (USDA, 2009). USDA state and county-scale crop yields data both are available from 2000 to 2008 through the NASS quick stats website (NASS, 2011).

We downloaded the county-level crop yield data for all the crops in 2007 and 2008 to estimate the NPP for croplands. The crop yields data were converted to NPP using the method published by Prince et al. (2001). The crop NPP (g C m^{-2} yr^{-1}) is calculated from the crop yield data by first converting the yield to the harvested carbon and then to the crop NPP as follows:

$$C_{harvest} = Yield_{unit} \times f_{mass} \times f_{dry} \times f_{carbon} \text{, (2)}$$

$$NPP = \frac{C_{harvest}}{HI} \times (1 + RS) \text{ , (3)}$$

where $C_{harvest}$ is the harvested carbon of the crop (g C m^{-2} yr^{-1}), Yield is the estimated crop yield in report unit (bushel, ton, pound, etc.) per acre per year, f_{mass} is a factor to convert the yield report unit to a standard unit of biomass (kg per bushel, kg per ton, etc.), f_{dry} is a factor to convert the mass to dry biomass, f_{carbon} is a carbon content factor to convert the dry biomass to carbon (450 gC per kg) (Hicke et al., 2004; Prince et al., 2001) , HI is defined as the ratio of yield to the harvestable biomass, and RS is a factor to estimate the total biomass of the crop. For crops harvested with aboveground biomass, such as corn and soybean, RS is the root/shoot ratio. For crops harvested with belowground biomass, such as potato and sugar beets, RS is the shoot/root ratio. The

conversion factors used in this study are taken from West et al. (2010) and provided in

Table 2.1.

Table 2.1. Factors used to estimate cropland Net Primary Production (NPP) from USDA

National Agricultural Statistics Service (NASS) county yield data.

Crop	Reporting Units	mass per Unit (kg)	Conversion to Dry Matter	Harvest Index	Root:Shoot Ratio
barley	bushel	21.8	0.9	0.5	0.5
beans	hundredweight	50.8	0.76	0.46	0.08
corn grain	bushel	25.4	0.87	0.53	0.18
corn silage	ton	907.2	0.26	1	0.18
oats	bushel	14.5	0.92	0.52	0.4
peanuts	pounds	0.45	0.91	0.4	0.07
potatoes	hundredweight	50.8	0.2	0.5	0.07
rye	bushel	25.4	0.9	0.5	1.02
sorghum grain	bushel	25.4	0.87	0.44	0.08
sorghum silage	ton	907.2	0.26	1	0.18
soybean	bushel	27.2	0.92	0.42	0.15
sugarbeets	ton	907.2	0.15	0.4	0.43
sunflower	pound	0.453	0.93	0.27	0.06
wheat	bushel	27.2	0.89	0.39	0.2

The county-level cropland NPP on a unit per area is calculated as the area weighted

mean of all the crop NPP in the county with the following equation:

$$\overline{NPP_{USDA}} = \frac{\sum_{i=1}^{m} NPP(i) \times Area(i)}{\sum_{i=1}^{m} Area(i)} , (4)$$

where m is the number of crop species in the county, NPP (i) is the NPP calculated from

crop yield data for crop species (i), and Area (i) is the harvested area of the crop species

(i). These county-level NPP are presented in Figure 5 and Figure 6 to compare with the

NPP estimates from the satellite-based model and the process-based model.

The mean and the standard deviation (SD) of the NPP for croplands are calculated for

the MCI region with the following equations:

$$\overline{NPP_{USDA}} = \frac{\sum_{j=1}^{n} \sum_{i=1}^{m} NPP(i,j) \times Area(i,j)}{\sum_{j=1}^{n} \sum_{i=1}^{m} Area(i,j)}, (5)$$

$$SD = \sqrt{\frac{\sum_{j=1}^{n} \sum_{i=1}^{m} (NPP(i,j) - \overline{NPP_{USDA}})^2 \times Area(i,j)}{\sum_{j=1}^{n} \sum_{i=1}^{m} Area(i,j)}}, (6)$$

where n is the number of counties in the MCI region, m is the number of crop species in

the county, NPP (i, j) is the crop NPP calculated from crop yield data of crop (i) in county

(j), and Area (i, j) is the harvested area of crop (i) in county (j). The total cropland NPP in

the MCI region is calculated by adding the crop NPP for all the crop species in every

county. This NPP estimate excluded the NPP of grass crops such as hay, alfalfa, and

forage. The NPP estimated using this method is referred to as NPP_{USDA}.

For the four major crops (corn, soybean, spring wheat, and winter wheat), the mean and

the SD of crop NPP are calculated for the MCI region with the following equations:

$$\overline{NPP_{crop}} = \frac{\sum_{j=1}^{n} NPP(j) \times Area(j)}{\sum_{j=1}^{n} Area(j)} , (7)$$

$$SD = \sqrt{\frac{\sum_{j=1}^{n}(\text{NPP (j)} - \overline{NPP_{crop}})^2 \times \text{Area(j)}}{\sum_{j=1}^{n}\text{Area(j)}}}, \quad (8)$$

where n is the number of counties in the MCI region, NPP (j) is the crop NPP in county

(j), and Area (j) is the harvested area of the crop in county (j). These crop NPP estimates

are compared with crop NPP estimates from the process-based model. The cropland area

is the sum of all the harvested area.

2.2.2.2 Satellite based model

We used the global MODIS NPP (MOD17A3) product published by Numerical

Terradynamic Simulation Group (NTSG) for this study. The MODIS NPP product was

generated at 1 km^2 spatial resolution from 2000 to 2010 with the most recent algorithm

(Zhao and Running, 2012; Zhao et al., 2005). The MODIS NPP algorithm provides an

operational and near-real-time calculation of global GPP and NPP products from the

MODIS sensor (Heinsch et al., 2003; Zhao et al., 2005). It uses three input sources:

MODIS land cover product, daily meteorological data, and the Fraction of

Photosynthetically Active Radiation (FPAR) and Leaf Area Index (LAI) data from

MODIS FPAR/LAI product. The uncertainties in these input data will influence the NPP

estimates.

The global MODIS NPP data and the global MODIS land cover data were downloaded

from the NTSG ftp site (NTSG, 2012) for 2007 and 2008. Both the NPP and the land

cover data were extracted to the MCI region using ArcGIS software. The MODIS land

cover data are generated with the University of Maryland (UMD) classification scheme

and contain 14 land cover classes, with one land cover class for cropland. The cropland

class was used to mask out the NPP for croplands in 2007 and 2008 in the MCI region.

The mean and the SD of MODIS cropland NPP are calculated from all the NPP values for cropland pixels in each year. The total cropland area is calculated by multiplying the total number of cropland pixels and the area represented by each pixel (1 km^2). The total NPP is calculated by adding all the NPP at cropland pixels together. The NPP estimated using this method is referred to as NPP$_{MODIS}$.

2.2.2.3 Process based model

We used the General Ensemble biogeochemical Modeling System (GEMS) (Liu, 2009; Liu et al., 2003) to estimate the cropland NPP in the MCI region. GEMS is a modeling system developed to integrate well-established biogeochemical models with various spatial databases for simulating biogeochemical cycles over large areas (Figure 2.2).
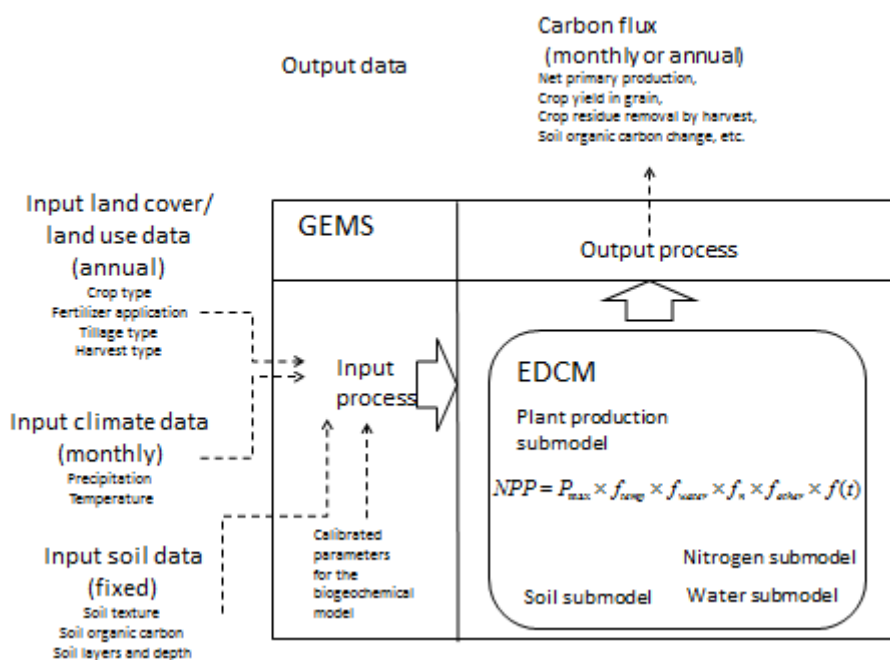
Figure 2.2. A simplified schematic diagram of the General Ensemble biogeochemical

Modeling System (GEMS) and major component to calculate the Net Primary Production

(NPP) in the Erosion-Deposition-Carbon-Model (EDCM).

（1）Biogeochemical model

We used the biogeochemical model Erosion-Deposition-Carbon-Model (EDCM) to

simulate the cropland NPP in GEMS. EDCM is a process-based model that was

developed to characterize the ecosystem carbon dynamics and to be capable of evaluating

the impacts of soil erosion and deposition (Liu et al., 2011, 2003). It simulates the NPP

based on the crop potential production, temperature, water balance, soil carbon, and

nitrogen dynamics at monthly time steps (Liu et al., 2003; Parton et al., 1993). The NPP

calculation in EDCM can be expressed in the following equation:

$$NPP = P_{max} \times f_{temp} \times f_{water} \times f_{nutrient} \times f_{other} \times f(t), (9)$$

where P_{max} is the potential production of the crop (gC m^{-2} yr^{-1}), f_{temp} is a temperature

factor to estimate the effect of temperature on NPP, f_{water} is a water factor to estimate the

effect of soil water content on NPP, $f_{nutrient}$ is a nutrient factor to estimate the effect of soil

nutrient on NPP, f_{other} is the other impact factor impacting NPP including factors for

enriched CO_2 effect, shading effect, etc., and f(t) is an empirical factor representing the

historical change in NPP through time (Liu et al., 2003).

(2) Input data sets

The soil organic carbon content and soil texture information were extracted from the

State Soil Geographic Data Base (STATSGO). STATSGO contains 132 survey units in

the MCI region. Each survey unit contains multiple soil components. GEMS uses a

Monte-Carlo method with multiple model runs to quantify the uncertainty caused by different soil components. In each model run, GEMS randomly chooses the soil component and uses the soil data (soil texture, soil organic carbon content, soil layer depth, soil field capacity, and soil wilting point) in this component for the simulation. The soil component that has more area fraction in the survey unit will be used for more model runs during the simulation.

For this study, we used nine years (2000 – 2008) of climate data produced by the Parameter-elevation Regressions on Independent Slopes Model (PRISM) from Oregon State University (PRISM Climate Group, http://www.prismclimate.org, accessed Feb 2010). The climate variables used in the model are monthly minimum temperature, maximum temperature, and precipitation.

We generated cropland cover data from 2000 to 2008 using the Cropland Data Layer (CDL) product downloaded from the Natural Resources Conservation Service (NRCS) geospatial data gateway (USDA, 2011). The CDL product is a raster land cover map with geo-referenced and crop-specific information produced by NASS (Boryan et al., 2011). In this study, the original 22 crop species in the CDL were combined into 6 representative crop groups (corn, soybean, spring wheat, winter wheat, other grains crops, and other crops). The CDL data do not have full-time coverage from 2000 to 2008 in all states (Table 2.2). In the states that do not have the data, missing data were filled in with the closest year.

We used the tillage data processed by West et al. (2008) in this study. It was generated from the tillage census data from the Conservation Technology Information Center

(CTIC) between 1989 and 2004. Irrigation, manure addition, and soil erosion dynamics were excluded due to data limitations.

STATE	2000	2001	2002	2003	2004	2005	2006	2007	2008
Illinois	×	×	×	×	×	×	×	×	×
Indiana	×	×	×	×	×	×	×	×	×
Iowa	×	×	×	×	×	×	×	×	×
Kansas							×	×	×
Michigan								×	×
Minnesota								×	×
Missouri		×	×	×	×	×	×	×	×
Nebraska		×	×	×	×	×	×	×	×
North Dakota	×	×	×	×	×	×	×	×	×
South Dakota							×	×	×
Wisconsin				×	×	×	×	×	×

Table 2.2. USDA Cropland Data Layer (CDL) temporal coverage between 2000 and 2008 in the states of the Mid-Continent Intensive Campaign (MCI) region.

(3) Model calibration

We downloaded the state level crop yield data from 2000 to 2008 for the four major crops (corn, soybean, spring wheat, and winter wheat) from the USDA NASS website (NASS, 2011). The crop yield was converted to harvested carbon using the method in 2.2.1 to compare with model simulated crop yield at the state level. We used the averaged crop yield in three years (2000, 2001, and 2003) for the calibration of the parameters. We excluded the crop yield data in 2002 because we found the reported crop yield data in 2002 were much lower than other years in some states due to a major drought in the Midwest.

The maximum growth rate of the vegetation, also referred to as the potential production, represents optimal plant growth when there are no environmental stresses. The potential production parameters of corn, soybean, spring wheat, and winter wheat

were calibrated at state level with crop yield data (Figure 2.3). The calibration procedure

included multiple calibration runs. All the calibration runs used the same input data and

assumptions as the simulation run. In each calibration run, GEMS randomly selected a

subset of cropland points inside each state to run the simulation and output the harvested

carbon for all the crops. The harvested carbon was calculated for each crop and compared

with harvested carbon estimated from the reported crop yield data in the state. For each

crop, if the simulated crop yield was larger than 105% or smaller than 95% of the

reported crop yield, then the model parameter representing the crop potential production

was adjusted (Figure 2.3). The new crop parameter was saved for this crop and used in

the next calibration run. GEMS repeated the calibration process until all the simulated

crop yields were within ±5% of the reported crop yields in each state. The calibrated

parameters were then saved for the simulation run.
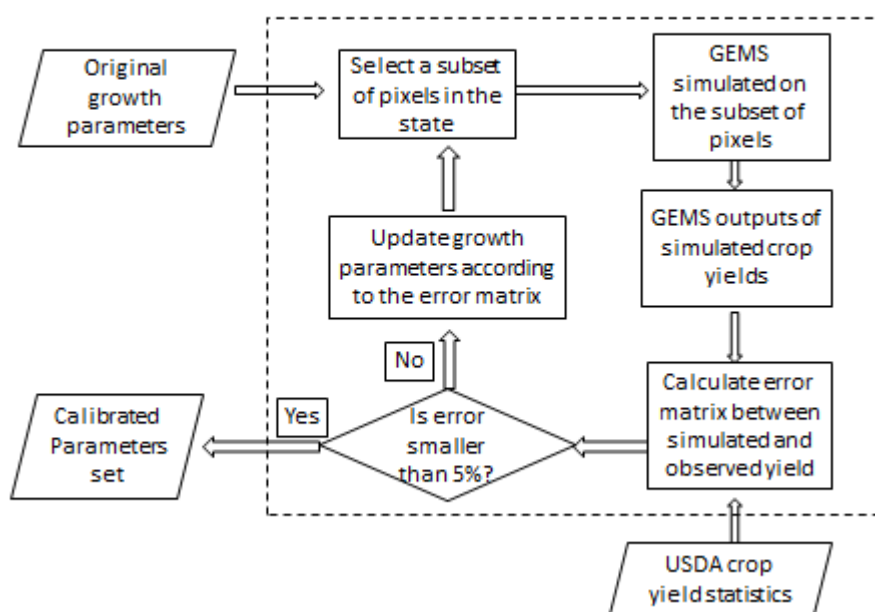
Figure 2.3. Flowchart of the General Ensemble biogeochemical Modeling System (GEMS) calibration process.

(4) Model simulation and comparison

The regional simulation was performed with an equal distance (5 km) sampling approach to reduce the model run time. The model ran from 2000 to 2008 with a pre-run time of 30 years to stabilize the soil pools. We assumed that the cropland in the region has enough nitrogen input from fertilization and all the planted crops are harvested. Effects of carbon dioxide (CO_2) fertilization were not included in the simulation because of the short simulation time period.

The model output NPP in 2007 and 2008 was used for comparison and analysis in this paper. The NPP at each pixel is treated as the mean NPP on the 25 km^2 pixel area. The county-level cropland NPP is calculated by averaging all the cropland NPP inside each county to compare with the county-level NPP_{USDA}. The mean and the SD of the cropland NPP are calculated from all the cropland NPP regardless of crop type. The total cropland NPP is the sum of all the cropland NPP ($gC\ m^{-2}\ yr^{-1}$) multiplied by the pixel area (25 km^2). The NPP estimated using this method is referred to as NPP_{GEMS}.

For the four major crops (corn, soybean, spring, and winter wheat), the mean and the SD of the NPP are calculated from all the NPP values for each crop in the MCI region. The results are compared with the crop NPP_{USDA}. The cropland area for each crop is calculated by multiplying the number of crop pixels in the CDL data by the pixel area (25 km^2).

2.3 RESULTS

2.3.1 Evaluation of GEMS simulated results

We first compared the model simulated crop yields in 2007 and 2008 against the reported USDA crop yields for the four major crops (corn, soybean, spring, and winter wheat) at the state level (Figure 2.4). As presented in Figure 2.4, the simulated crop yields by GEMS agreed well with the USDA crop yield data ($R^2 = 0.95$). We also compared the model-simulated NPP with the NPP estimates from USDA crop inventory at the county-level in 2007 and 2008 (Figure 2.5). The county-level comparisons between the NPP_{GEMS} and NPP_{USDA} also showed high correlation coefficients ($R^2 > 0.86$) in both years. The calibration procedure used is responsible for this good agreement.
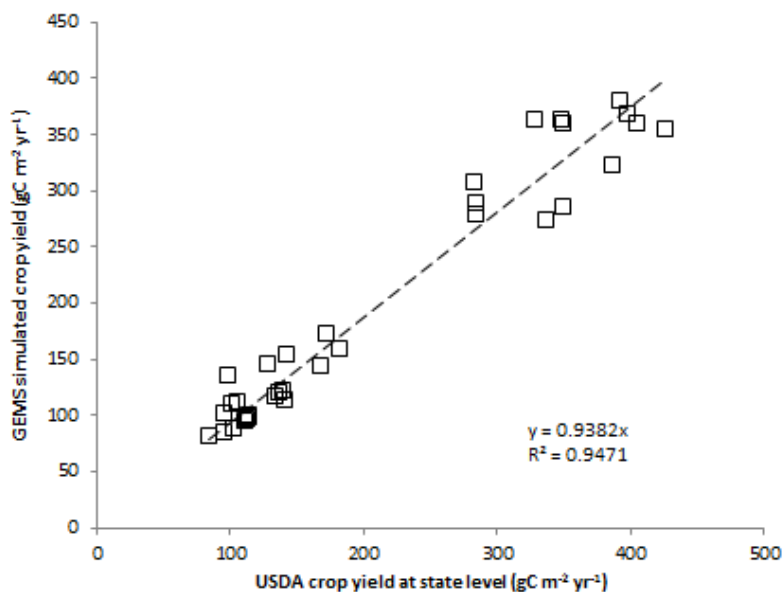
Figure 2.4. Validation of the General Ensemble biogeochemical Modeling System

(GEMS) simulated crop yields compare with crop yields estimated from USDA yield

data for the major crops in the 11 states: corn, soybean, spring wheat and winter wheat.
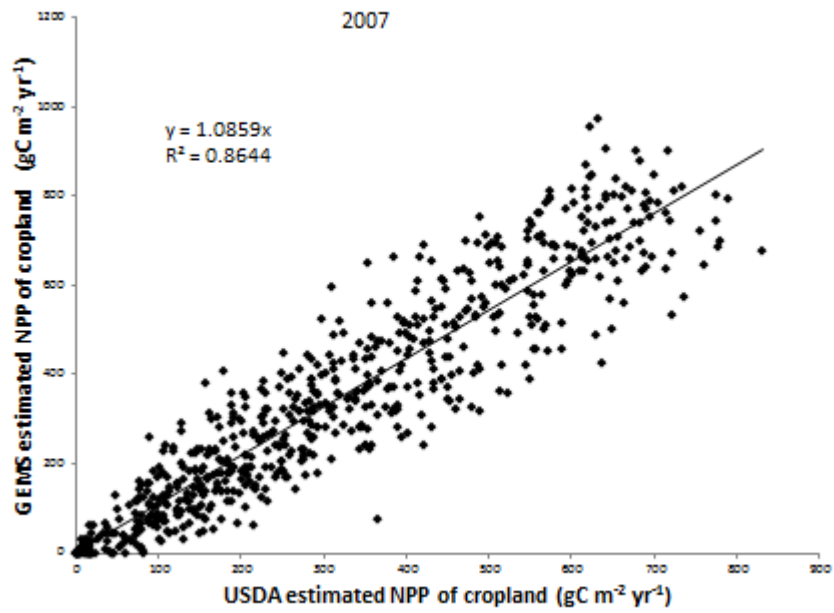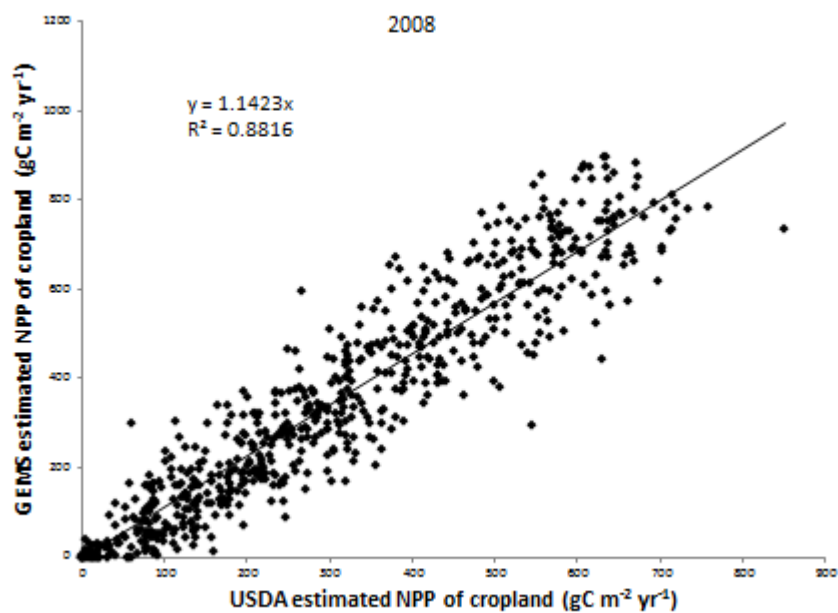
Figure 2.5. Validation of GEMS simulated cropland NPP with cropland NPP estimated from USDA yield data at county level in 2007(a) and 2008 (b).

2007   2008

MCI boundary

Cropland covers
- Corn
- Soybean
- Spring Wheat
- Winter Wheat
- Other grain crops
- Other crops

$NPP(gC \cdot m^{-2} yr^{-1})$
- < 200
- 201 - 400
- 401 - 600
- 601 - 800
- > 800

$NPP(gC \cdot m^{-2} yr^{-1})$
- < 200
- 201 - 400
- 401 - 600
- 601 - 800
- > 800

$NPP(gC \cdot m^{-2} yr^{-1})$
- < 200
- 201 - 400
- 401 - 600
- 601 - 800
- > 800
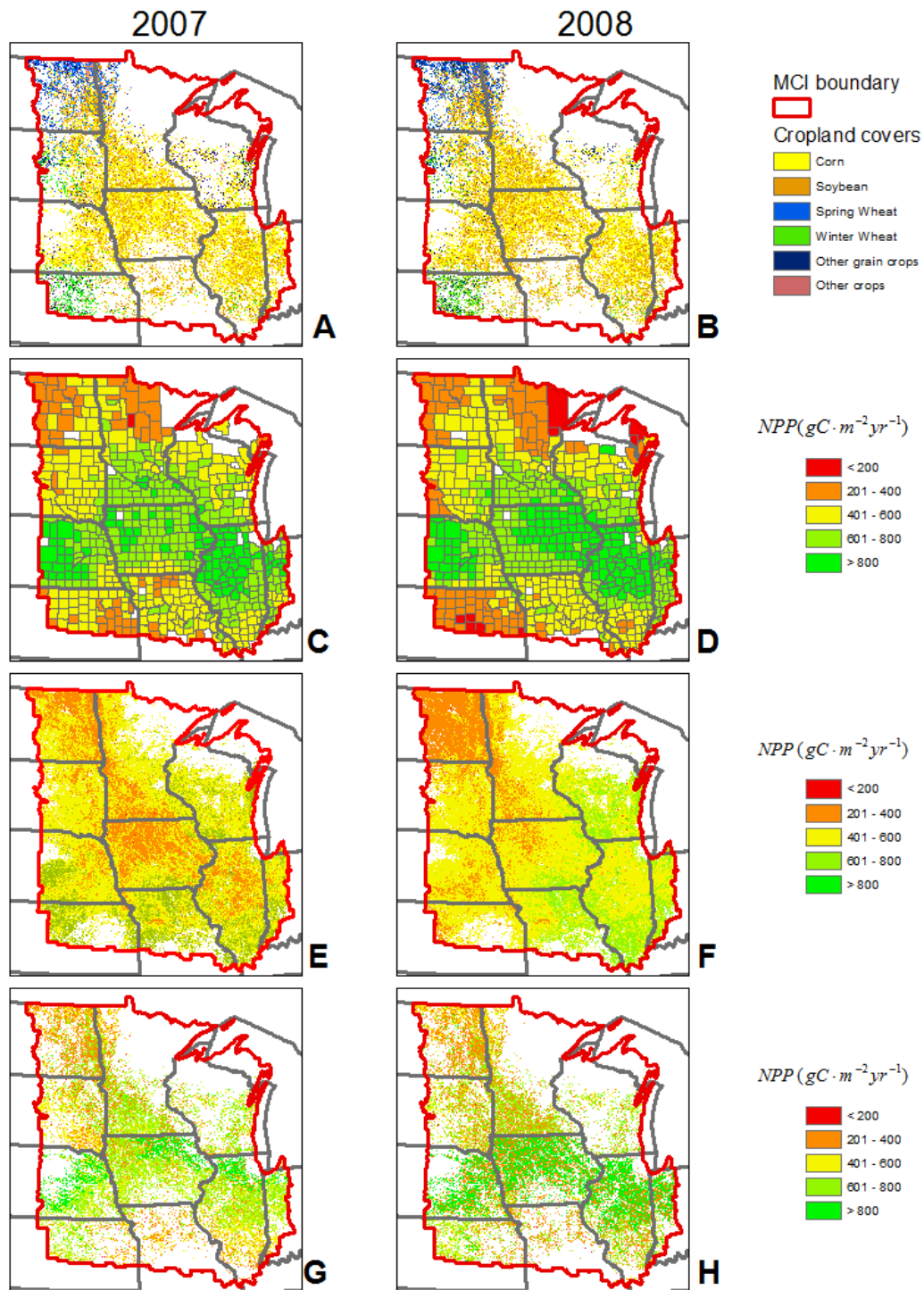
Figure 2.6. Spatial distribution of cropland covers in 2007 (A) and 2008 (B); cropland

mean NPP estimated from USDA yield data in 2007 (C) and 2008 (D); cropland mean

NPP estimated from MODIS NPP product in 2007 (E) and 2008 (F); cropland mean NPP

estimated from GEMS model in 2007 (G) and 2008 (H) in the Mid-Continent Intensive

Campaign (MCI) region.

2.3.2 NPP estimates for croplands

The mean and the SD of cropland NPP, the cropland area, and the total cropland NPP

estimates from different methods are presented in Table 2.3. The crop-specific NPP

estimates for the four major crops from USDA yield data and GEMS are both presented

in Table 2.4. The CDL land cover information and the detail on the three estimates that

produce the patterns of NPP in the cropland are illustrated in Figure 2.6.

Table 2.3. Net Primary Production (NPP) estimates of cropland in the Mid-Continent

Intensive Campaign (MCI) region from different methods.

	2007			2008		
Cropland NPP	Mean NPP $(gC\ m^{-2}\ yr^{-1})$	Cropland area (Mha)	Total NPP $(Tg\ C\ yr^{-1})$	Mean NPP $(gC\ m^{-2}\ yr^{-1})$	Cropland area (Mha)	Total NPP $(Tg\ C\ yr^{-1})$
USDA	672 ± 238	49.6 (50.6*)	333	668 ± 256	48.2 (49.5*)	322
MODIS	469 ± 79	100	469	490 ± 96	100	490
GEMS	683 ± 302	51.5	351	687 ± 349	52.5	359

*Note: the number in the parenthesis is the plant area, outside is the harvest area

a. The values are the mean ± the standard deviation of the estimated NPP values for the
cropland. The calculation methods are listed in section 2.2.2.1, 2.2.2.2 and 2.2.2.3.

b. The number in the parenthesis is the planted cropland area, outside is the harvested cropland area in the USDA yield data.

Table 2.4. Mean and standard deviation of Net Primary Production (NPP) of corn, soybean, spring wheat and winter wheat in the Mid-Continent Intensive Campaign (MCI) region.

		2007			2008		
Estimate method	Crop type	Mean NPP ($gC\ m^{-2}\ yr^{-1}$)	Harvested cropland area (Mha)	Total NPP ($Tg\ C\ yr^{-1}$)	Mean NPP ($gC\ m^{-2}\ yr^{-1}$)	Harvested cropland area (Mha)	Total NPP ($Tg\ C\ yr^{-1}$)
USDA	Corn	876 ± 191	24.3	226.4	928 ± 162	21.3	213.1
	Soybean	364 ± 80	16.6	63.2	346 ±71	18.7	66.7
	Spring Wheat	399 ± 127	2.6	10.2	464 ± 81	2.4	11.1
	Winter Wheat	456 ± 123	2.9	11.0	486 ± 123	2.6	12.2
GEMS	Corn	954 ± 153	25.8	247.0	1047 ± 137	24.0	247.7
	Soybean	367 ± 50	16.1	58.9	334 ± 45	19.1	64.0
	Spring Wheat	366 ± 55	3.0	10.8	398 ± 65	3.1	12.5
	Winter Wheat	571 ± 107	2.7	13.9	579 ± 89	2.8	16.6

a. The values are the mean $\pm$ the standard deviation of the estimated NPP values for each crop. The calculation methods are listed in section 2.2.2.1 and 2.2.2.3.

2.3.2.1 Crop inventory

The mean NPP_{USDA} was 660 ± 320 g C m^{-2} yr^{-1} in 2007 and 656 ± 330 g C m^{-2} yr^{-1} in 2008. The large variability of NPP is driven by large differences between crop-specific NPP. Corn NPP is the highest of the four major crops and its value is 30% higher than the mean cropland NPP, while soybean NPP is only about 50% of the mean cropland NPP (Table 4). In 2008, the NPP of corn and wheat were increased but the NPP of soybean was decreased compared to 2007 (Table 4). The increase of NPP in 2008 was possibly driven by the weather condition. Substantial rainfall events during the 2008 growing season in the Midwest caused flooding (Holmes et al., 2010). But the flood-related loss of cropland was offset by a large increase in crop yield due to the nearly ideal growing conditions from late June in this region (Schnepf, 2008). Thus, the cropland NPP increased in many counties in the center of the MCI region regardless of the flooding in 2008.

The total NPP_{USDA} decreased from 329 TgC yr^{-1} in 2007 to 318 TgC yr^{-1} in 2008. In 2007, the total harvested cropland area (49.6 Mha) was about 98% of the planted area (50.6 Mha). In 2008, both the planted cropland area (49.5 Mha) and the harvested cropland area (48.2 Mha) decreased about 3%. In 2008, the harvested corn area decreased 2.2 Mha from the harvested corn area in 2007, causing a subsequent decrease of 13.3 Tg C in total corn NPP. On the other hand, the corn/soybean rotation increased the

harvested soybean area by 2.1 Mha and the total soybean NPP by 3.5 TgC in 2008. The net effect was that the total NPP for croplands was lower in 2008 than in 2007.

2.3.2.2 Satellite based model

The mean NPP_{MODIS} was about 30% lower than the mean NPP_{USDA}, 469 $\pm$79 gC m^{-2} yr^{-1} in 2007 and 490 $\pm$96 gC m^{-2} yr^{-1} in 2008. Without incorporating crop-specific information in the calculation, NPP_{MODIS} showed less spatial variability than NPP_{USDA}. In 2007, 95% of the NPP values were between 400 and 600 gC m^{-2} yr^{-1}, and only 3% of the values were higher than 600 gC m^{-2} yr^{-1}. In 2008, 83% of the NPP values were between 400 and 600 gC m^{-2} yr^{-1} and 15% of the values were higher than 600 gC m^{-2} yr^{-1}. The MODIS cropland area (100 Mha) remained the same for 2007 and 2008, and it was 100% higher than the USDA harvested area. This overestimate of cropland area caused the total NPP_{MODIS} to be over 40% higher than the total NPP_{USDA}.

2.3.2.3 Process based model

The mean NPP_{GEMS} showed similar values to the mean NPP_{USDA}, 683 $\pm$302 gC m^{-2} yr^{-1} in 2007 and 687 $\pm$349 gC m^{-2} yr^{-1} in 2008, within 5% of the NPP_{USDA}. NPP_{GEMS} also showed a large difference between the crop-specific NPP. The corn NPP is about two times higher than the NPP of soybean and spring wheat (Table 2.4).

The cropland area from CDL data was 51.5 Mha in 2007 and 52.5 Mha in 2008. Both areas were higher than the NASS harvested cropland area by 4% in 2007 and by 9% in 2008. The total NPP_{GEMS} was 351 TgC yr^{-1} in 2007 and 359 TgC yr^{-1} in 2008, about 5–10% higher than the total NPP_{USDA}. Though the corn area was less than 50% of the total cropland area, the corn NPP accounted for over 66% of the total cropland NPP. Meanwhile, the soybean area was over 30% of the total cropland area but the soybean

NPP was less than 20% of the total cropland NPP. The sum of corn and soybean NPP was more than 87% of the total cropland NPP in the MCI region.

The corn-soybean rotation is a prevalent cropping system in the MCI region and the CDL data provided spatial explicitly information of the rotation (Figure 2.6A, 6B). Given the large difference between the soybean NPP and the corn NPP (Table 2.4), we can expect that NPP varies between the years under corn/soybean rotation. This temporal variability of NPP has been observed and shows a large impact on carbon flux at the site level (Baker and Griffis, 2005; Verma et al., 2005). The crop inventory data do not have enough spatial detail to recognize this type of temporal variability. The MODIS NPP product does not have crop-specific information to estimate this variability either. Using the CDL data, GEMS was able to identify the temporal variability of NPP for croplands driven by crop rotation in the Midwest (Figure 2.6G, 6H).

2.3.3 Crop species impacts in cropland NPP

The CDL data showed that the crop species were not evenly distributed throughout the MCI region (Figure 2.6A, 6B). Spring wheat was mainly planted in the northwestern part of the MCI region, whereas winter wheat was mainly planted in the southwestern part. Both corn and soybean were dominant in the central states of the MCI region, such as Iowa, Illinois, and Nebraska. The crop plant patterns, which represent the location of crop species, are important to estimate the spatial variability of NPP for croplands. This can be seen from the NPP estimates from the three methods (Figures 2.6C–6H).

All three NPP estimates for croplands showed the NPP increased from north to south (Figures 2.6C–6H). Both the NPP_{USDA} (Figure 2.6C, 6D) and NPP_{GEMS} (Figure 2.6G, 6H)

showed higher values (> 600 g C m^{-2} yr^{-1}) in Iowa, northern Illinois, and eastern

Nebraska. The location of high cropland NPP in these two methods agreed with an earlier

study using crop yield data (Prince et al., 2001). The states that had much larger corn

planted area had the highest cropland NPP. But NPP$_{MODIS}$ had different spatial patterns

than the other two NPP estimates. NPP$_{MODIS}$ showed higher values (> 600 g C m^{-2} yr^{-1}) in

Kansas and Missouri, where corn planted area is much smaller than Iowa (Figure 2.6E,

6F). Additionally, NPP$_{MODIS}$ was larger in southern Illinois and Iowa than the northern

parts of those states, while the opposite is found in the NPP$_{USDA}$ estimates. A similar

reverse pattern in NPP estimates was documented by Bandaru et al. (2013).

2.4 DISCUSSIONS

2.4.1 Differences in cropland area

The cropland in this study only includes the cropland planted for harvesting. This is

different than the total cropland defined by NRCS. According to the definition by NRCS,

the total cropland is "a category that includes cropland harvested, cropland used only for

pasture or grazing, cropland on which all crops failed or were abandoned, cropland in

cultivated summer fallow, and cropland idle or used for cover crops or soil improvement

but not harvested and not pastured or grazed" (USDA, 2009). We found that different

methods may only include part of the total cropland in their data sources.

USDA crop yield data only include harvested biomass so they only represent the NPP

on the cropland harvested. The cropland planted for harvesting usually is larger than the

cropland harvested. USDA inventory data include both the planted cropland area and the

harvested cropland area in the survey. The harvested cropland area is smaller than the

planted cropland area in two aspects. First, farmers may not harvest the cropland when the land cannot make enough economic returns. This includes the croplands with low crop yields or damaged crops due to unfavorable weather conditions or extreme events such as flooding or drought. The overall fraction of harvest/plant cropland area was 98% in 2007 and 97% in 2008 in this study. But this fraction can be much lower for some crops at the county-level in certain years. For example, the census data of Saunders County, Nebraska, showed only 92% of the cropland area planted with corn was harvested in 2008. A more extreme event is in Kewaunee County, Wisconsin, where USDA reported only 46% of the planted corn area was harvested in 2008 (USDA, 2011). Second, there are croplands that are planted with cover crops not intended for harvest. These croplands include winter cover and summer cover crops such as sorghum-sudan-grass, rye, and wheat (Snapp et al., 2005). USDA inventory data include these croplands in the cropland planted for harvest but do not have crop yield reported for them.

The GEMS model used the land cover inputs from the CDL image products. The CDL program used remote sensing data from multiple satellite sensors and ancillary data to classify the crop types in these image products (Boryan et al., 2011). The major two satellite sensors are the Advanced Wide Field Sensor (AWiFS) and Landsat Thematic Mapper (TM)have higher spatial resolution (56 m for AWiFS and 30 m for TM) compared with MODIS (250 m). According to Boryan et al. (2011), the accuracy of the CDL products on major crop types is generally 85% to 95% at state level. The crop area derived from the CDL product is closer to the planted area but larger than the harvested area from NASS statistics. Thus, the cropland NPP estimated from a process-based model should cover more cropland area than the crop inventory. In this study, the non-harvested

cropland caused a 5–10% difference for croplands between the total NPP estimates from crop inventory and the process-based model in the MCI region.

Neither crop inventory nor the process-based model estimates the NPP of the cropland types that are not planted for harvesting. These cropland types include pasture or forage, fallow, and the cropland in the Conservation Reserve Program (CRP) land. The total area of these croplands is 13 Mha in 2000, with 5 Mha in pasture or forage, 0.8 Mha in summer fallow, and 4.2 Mha in CRP land (West et al., 2008). These lands occupied about 19% of the total cropland area in 2000 but the NPP information for these lands was limited. The satellite-based model may include these cropland types in the NPP estimate.

The cropland cover data used by MODIS include about 100 Mha cropland in the MCI region. This is over 100% higher than the USDA inventory data (48–50 Mha) and the CDL data (51–52 Mha). This overestimation caused the total NPP_{MODIS} to be 40% higher than the other two methods. In the algorithm, the MODIS NPP product used the global UMD land cover dataset as an input to calculate the cropland NPP (Zhao and Running, 2012). The UMD land cover dataset was generated using a regression tree algorithm and only contained one land cover class for all the crops (Hansen et al., 2000). The classification approach used with the regression tree algorithm may have limited ability to depict grassland/pasture within areas of intensive cropping. It is possible that the cropland cover data in the dataset include not only cropland planted with cereal crops but also cropland planted with grass (forage or pasture) or even natural grassland. Another major issue is that the MODIS NPP product has coarse spatial resolution (1×1 km^2). The assumption that the one MODIS pixel (1×1 km^2) only contains one single land cover class usually fails to reflect the spatial heterogeneity in cropland cover. Crops generally

are not planted in 1×1 km^2 plots and may consist of crops and bare ground (Reeves et al., 2005). Including non-cropped area in the cropland pixel artificially increases the cropland area and brings more uncertainty in the NPP estimates.

2.4.2 Differences in crop species

We found the detailed mapping of crop species change in time and space is critical for estimating the spatial and temporal variability of the NPP for croplands. In this study, the mean NPP$_{MODIS}$ was about 30% lower than the mean NPP$_{USDA}$ and the mean NPP$_{GEMS}$ in the MCI region. The lower NPP estimates from MODIS were also found in other studies (Bandaru et al. 2013; Turner et al., 2005; West et al., 2010). The European carbon assessment found that satellite-based models estimated lower cropland NPP (419–494 gC m^{-2} yr^{-1}) than process-based models (585 gC m^{-2} yr^{-1}) and yield statistics (646 gC m^{-2} yr^{-1}) (Ciais et al., 2010). The bias of the NPP estimates may come from the bias in the LUE parameters in these models. The algorithm of the MODIS NPP product only used a single LUE parameter to calculate the photosynthesis for croplands (Heinsch et al., 2003; Zhao et al., 2011). Reeves et al. (2005) compared the MODIS NPP product with wheat yield in the United States and found the LUE value used in the MODIS algorithm is less than the LUE value used in wheat yield models developed at field level. Our study found the mean NPP$_{MODIS}$ is about 50% lower than the mean NPP of corn, but 30% higher than the mean NPP of soybean. These differences suggested that there may be large differences in the LUE between crops. Turner et al. (2002) studied the LUE in a corn soybean mixed land cover and found that the LUE for corn was 47% higher than the LUE for soybean in a central Illinois crop field. His study also shows that using an LUE model with high resolution land cover data can reduce the uncertainty in NPP estimates by considering the

difference in LUE parameter. Lobell et al. (2002) used USDA yield data to estimate the cropland LUE parameter in the CASA model and found the LUE parameter varied from 0.41 to 0.94 gC MJ PAR^{-1} for corn in the United States. Bandaru et al. (2013) similarly estimated LUE per crop and per county using USDA yield data, ranging from 0.77 to 1.73 gC MJ PAR^{-1} for soybean and corn, in order to capture the spatial patterns of MODIS while also maintaining inventory-based county-level NPP estimates. Other studies also found that LUE has more variance across crop species at a finer scale (Ahl et al., 2005a; Kalfas et al., 2011). Lobell (2013) reviewed different satellite remote sensing methods to measure crop yield and concluded that the misclassification of crop type is the most problematic issue to estimate crop yield in croplands growing with multiple crops. Thus, satellite-based models using a single LUE to estimate the cropland NPP may not correctly reflect the spatial and temporal variability of cropland NPP, especially when multiple crop species are present in the same region and crop rotation is applied between the years.

Regional or global land cover datasets developed earlier, such as the National Land Cover Dataset (NLCD), the International Geosphere-Biosphere Programme (IGBP) global land cover dataset, and MODIS land cover product, only provide a single cropland classification without crop-specific information. Using moderate to high resolution satellite-based land cover data can improve the estimates of cropland carbon dynamics (West et al., 2010, 2008). But the uncertainties in these satellite-based land cover datasets can also influence the NPP estimates. Land cover datasets that contain multiple crop species have been developed and have become available in recent years, such as the CDL product (Boryan et al., 2011). At global scale, Ramankutty et al. (2008) developed a

global cropland dataset with 175 crops by combining agricultural inventory data from FAO and satellite-derived land cover data. This dataset was used later with crop census data in the development of the Monthly Irrigated and Rainfed Crop Areas (MIRCA) dataset, which contains crop-specific information on irrigation (Portmann et al., 2010). Pittman et al. (2010) used multiple years of MODIS data to map the global croplands and validated them at the country level with four dominant crop types (corn, soybean, rice, and wheat). These regional and global datasets have provided more details for croplands and are available for the biosphere models to use.

However, many regional and global biosphere models still treat cropland as one single vegetation class. In the 17 biosphere models used in the North American Carbon Program Regional Synthesis, only two models used land cover data containing crop-specific information (Hayes et al., 2012). The use of cropland as a single vegetation class in the model generally assumes that the model parameter's variability is greater between different vegetation classes than within the single vegetation class. While this assumption is generally true for natural vegetation, it can be violated for crops. Studies have shown that crops have very different LUE values. Our study also showed that using the same model parameter for all crops in a remote sensing model brought large bias in the NPP estimates. We suggested that future model applications should consider using multiple crop information and model parameters to improve the studies on the carbon dynamics in croplands.

2.4.3 Comparing three NPP estimate methods

Crop inventory is originally used for monitoring the crop yields and understanding the agricultural product supply. It focuses on the carbon accumulated during the growing

season but does not account carbon loss during the growing season. The cropland NPP estimated from crop inventory data is more likely as part of NPP that can be consumed by people. Some studies were conducted to calculate the human appropriation of NPP in cropland using this method (e.g., Imhoff et al., 2004; Haberl et al., 2007). However, the carbon loss during the growing season, such as the tissue turnover and production of root executes, should be also included in the ecosystem NPP (Chapin et al., 2006). But the measurement of carbon loss during the growing season is still a challenge (Johnson et al., 2006). Haberl et al. (2007) generated a set of empirical factors to estimate the cropland NPP by considering the losses of biomass carbon during the growing season such as the biomass loss through diseases and the biomass produced by weeds. Using this set of factors could lead to a 30% discrepancy in mean NPP estimates compared with the other set of factors, which gives the largest bias in cropland NPP estimates using crop inventory data (Ciais et al., 2010). More field studies may be needed to better quantify the part of NPP lost during the growing season in the inventory approach. Another issue is the uncertainties in the conversion factors such as the root/shoot ratio and harvest index. These factors showed variations in different field studies and changed over time (Egli, 2008; Johnson et al., 2006; Prince et al., 2001). Field measurements in different regions of the world are still needed to develop region specific conversion factors for more accurate estimates of NPP for croplands.

   The MODIS NPP product is a continuous satellite-derived dataset for studying the global vegetation productivity (Running et al., 2004). This approach uses remote sensing information of the vegetation to directly estimate the carbon fixation through photosynthesis from the solar radiation. It measures the ecosystem level GPP through the

year and estimates the annual NPP by subtracting the ecosystem AR from the GPP. The MODIS NPP product provides spatially continuous and temporally consistent estimates across large regions. However, there are still many uncertainties in the MODIS NPP product. These uncertainties come from both the input datasets and the algorithm. Zhao et al. (2006) compared the MODIS NPP estimates by using three different meteorological datasets and found the global NPP varies from 47 to 74 PgC yr^{-1} between 2000 and 2003. Land cover accuracy is another input source that brought in uncertainties (Reeves et al., 2005; Zhao et al., 2011). Based on our study, the misclassification of cropland and lack of crop-specific information in the land cover data are the two major causes of bias in NPP estimates in the MCI region. Both could be corrected with more accurate and detailed cropland cover data. Further developments in satellite-based models, especially in land cover inputs and parameterization, can be valuable in ecosystem carbon studies.

The process-based model was originally developed at site scale to study carbon dynamics of the ecosystem. It uses the soil, climate, and other information to estimate the NPP from vegetation potential production. The model parameters usually need to be calibrated with observations to reduce uncertainties in large region applications. Current studies still show large uncertainties in ecosystem carbon dynamics. A model-data intercomparison of the Net Ecosystem Exchange indicated poor model performance with a large difference between observations and model results (Schwalm et al., 2010). In a recent study of the North American carbon balance, estimates from the terrestrial biosphere models suggested a much smaller sink over croplands, less than half of the sink strength compared to inventory-based estimates (Hayes et al., 2012). Since NPP is the major component in the carbon cycle, it is important to quantify NPP accurately to lower

the uncertainty of carbon-related estimates. In this study, the NPP estimates from the process-based model agreed well with NPP estimates from the inventory method. With the high resolution cropland cover generated from satellite data, it is possible to apply the process-based model at fine spatial scales and generate the carbon accounting at farm and project level. Such information is needed for developing effective management plans for croplands to fulfill human needs and mitigate the effects of future climate change (Michalak et al., 2011; Smith et al., 2012).

Each method has its own strength and weakness in estimating regional NPP. The inventory method is based on the statistical aggregation of limited observation data and represents the average NPP over a large region without spatial details of the NPP. The satellite-based model uses satellite remote sensing observations on vegetation and provides spatially consistent NPP estimates across large regions. However, this method may result in large uncertainties due to misclassified land cover pixels and inaccuracy in the model parameterization. The process-based model can be used with high resolution land cover data to provide detailed NPP estimates, even though the model parameters need to be calibrated with available observations to reduce uncertainty. Further research based on this method will be conducted to estimate the carbon dynamics in croplands in the Midwest.

2.5 SUMMARY AND CONCLUSIONS

We compared the NPP estimates for croplands with three different methods: crop inventory, a satellite-based model, and a process-based model in the Midwestern United States. Mean NPP for croplands was in the range of 469–687 gC m^{-2} yr^{-1} and the total

NPP for croplands was between 318 and 490 TgC yr^{-1}. We found the differences in the cropland area and the changes of the crop species planted in the cropland are the two major causes of variation in the cropland NPP estimates. We concluded that in this study, the satellite-based model produced the most biased NPP estimate due to deficiencies in the land cover input, but that bias could be potentially corrected with crop-specific land cover data. Our study suggested that the change of crops in time and space is critical for estimating the spatial and temporal variability of the NPP when multiple crops are growing in the croplands. We suggest that future models should consider using high resolution and crop-specific land cover data to improve NPP estimates and carbon dynamic studies for croplands.

2.6 REFERENCES

Ahl, D.E., Gower, S.T., Mackay, D.S., Burrows, S.N., Norman, J.M., Diak, G.R., 2005. The effects of aggregated land cover data on estimating NPP in northern Wisconsin. Remote Sens. Environ. 97, 1–14.

Baker, J.M., Griffis, T.J., 2005. Examining strategies to improve the carbon balance of corn/soybean agriculture using eddy covariance and mass balance techniques. Agric. For. Meteorol. 128, 163–177.

Bandaru, V., West, T.O., Ricciuto, D.M., César Izaurralde, R., 2013. Estimating crop net primary production using national inventory data and MODIS-derived parameters. ISPRS J. Photogramm. Remote Sens. 80, 61–71.

Boryan, C., Yang, Z., Mueller, R., Craig, M., 2011. Monitoring US agriculture: the US department of agriculture, national agricultural statistics service, cropland data layer program. Geocarto Int. 26, 341–358.

Chapin, I., Woodwell, G.., Randerson, J.T., Rastetter, E.B., Lovett, G.M., Baldocchi, D.D., et al., 2006. Reconciling carbon-cycle concepts, terminology, and methodology. Ecosystems 9, 10.

Ciais, P., Paris, J.D., Marland, G., Peylin, P., Piao, S.L., et al., 2010. The European carbon balance. Part 1: fossil fuel emissions. Glob. Change Biol. 16, 1395–1408.

Cramer, W., Kicklighter, D.W., Bondeau, A., Iii, B.M., Churkina, G., Nemry, B., et al., The participants of the Potsdam NPP model intercomparison, 1999. Comparing global models of terrestrial net primary productivity (NPP): overview and key results. Glob. Change Biol. 5, 1–15.

Egli, D.B., 2008. Comparison of corn and soybean yields in the United States: historical trends and future prospects. Agron. J. 100, S–79–S–88.

Goetz, S.J., Prince, S.D., Goward, S.N., Thawley, M.M., Small, J., 1999. Satellite remote sensing of primary production: an improved production efficiency modeling approach. Ecol. Model. 122, 239–255.

Haberl, H., Erb, K.H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., et al., 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. Proc. Natl. Acad. Sci. 104, 12942–12947.

Hansen, M.C., Defries, R.S., Townshend, J.R.G., Sohlberg, R., 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. Int. J. Remote Sens. 21, 1331–1364.

Hayes, D.J., Turner, D.P., Stinson, G., McGuire, A.D., Wei, Y., West, T.O., et al., 2012. Reconciling estimates of the contemporary North American carbon balance among terrestrial biosphere models, atmospheric inversions, and a new approach for estimating net ecosystem exchange from inventory-based data. Glob. Change Biol. 18, 1282–1299.

Heinsch, F.A., Reeves, M., Votava, P., Kang, S., Milesi, C., Zhao, M., et al., 2003. User's Guide GPP and NPP (MOD17A2/A3) Products NASA MODIS Land Algorithm (No. Version 2.0).

Hicke, J.A., Lobell, D.B., Asner, G.P., 2004. Cropland area and net primary production computed from 30 years of USDA agricultural harvest data. Earth Interact 8, 1–20.

Holmes, R.R., Koenig, T.A., Karstensen, K.A., 2010. Flooding in the United States Midwest, 2008 (U.S. Geological Survey Professional Paper 1775, 64 p). USGS.

Imhoff, M.L., Bounoua, L., Ricketts, T., Loucks, C., Harriss, R., Lawrence, W.T., 2004. Global patterns in human consumption of net primary production. Nature 429, 870–873.

Ito, A., 2011. A historical meta-analysis of global terrestrial net primary productivity: are estimates converging? Glob. Change Biol. 17, 3161–3175.

Izaurralde, R.C., Williams, J.R., McGill, W.B., Rosenberg, N.J., Jakas, M.C.Q., 2006. Simulating soil C dynamics with EPIC: Model description and testing against long-term data. Ecol. Model. 192, 362–384.

Jenkins, J.C., Birdsey, R.A., Pan, Y., 2001. Biomass and NPP estimation for the mid-atlantic region (USA) using plot-level forest inventory data. Ecol. Appl. 11, 1174–1193.

Johnson, J.M.-F., Allmaras, R.R., Reicosky, D.C., 2006. Estimating source carbon from crop residues, roots and rhizodeposits using the national grain-yield database. Agron. J. 98, 622–636.

Kalfas, J.L., Xiao, X., Vanegas, D.X., Verma, S.B., Suyker, A.E., 2011. Modeling gross primary production of irrigated and rain-fed maize using MODIS imagery and CO2 flux tower data. Agric. For. Meteorol. 151, 1514–1528.

Li, C., Frolking, S., Crocker, G.J., Grace, P.R., Klfr, J., KiSrchens, M., Poulton, P.R., 1997. Simulating trends in soil organic carbon in long-term experiments using the DNDC model. Geoderma 81, 45–60.

Liu, S., 2009. Quantifying the spatial details of carbon sequestration potential and performance, in: McPherson, B., Sundquist, E. (Eds.), Carbon Sequestration and Its Role in the Global Carbon Cycle. American Geophysical Union, Washington, DC, pp. pp. 117–128.

Liu, S., Bliss, N., Sundquist, E., Huntington, T.G., 2003. Modeling carbon dynamics in vegetation and soil under the impact of soil erosion and deposition. Glob. Biogeochem. Cycles 17, 1074.

Liu, S., Tan, Z., Li, Z., Zhao, S., Yuan, W., 2011. Are soils of Iowa USA currently a carbon sink or source? Simulated changes in SOC stock from 1972 to 2007. Agric. Ecosyst. Environ. 140, 106–112.

Lobell, D.B., Hicke, J.A., Asner, G.P., Field, C.B., Tucker, C.J., Los, S.O., 2002. Satellite estimates of productivity and light use efficiency in United States agriculture. Glob. Change Biol. 8, 722–735.

Lobell, D. (2013). The use of satellite data for crop yield gap analysis. Field Crops Research, 143: 56-64.

Michalak, A.M., Jackson, R.B., Marland, G., Sabine, C.L., the Carbon Cycle Science Working Group, 2011. A U.S. carbon cycle science plan.

Monteith, J.L., 1972. Solar radiation and productivity in tropical ecosystems. J. Appl. Ecol. 9, 747–766.

Monteith, J.L., Moss, C.J., 1977. Climate and the efficiency of crop production in Britain [and discussion]. Philos. Trans. R. Soc. Lond. B. Biol. Sci. 281, 277–294.

NASS, 2011. Quick Stats:database avaiable online (www.nass.usda.gov/QuickStats).

Numerical Terradynamic Simulation Group (NTSG), University of Montana, ftp://ftp.ntsg.umt.edu/pub/MODIS/NTSG_Products/, accessed Nov 2012.

Ogle, S., Davis, K., Andrews, A., Gurney, K., West, T.O., Cooke, R.B., et al., 2006. Science plan: Mid-Continent Intensive Campaign of the North American Carbon Program. Greenbelt, MD.

Parton, W.J., Scurlock, .M.O., Ojima, D.S., 1993. Observations and modeling of biomass and soil organic matter dynamics for the grassland biome worldwide. Glob. Biogeochem. Cycles 7, 785–809.

Pittman, K., Hansen, M.C., Becker-Reshef, I., Potapov, P.V., Justice, C.O., 2010. Estimating global cropland extent with multi-year MODIS data. Remote Sens. 2, 1844–1863.

Portmann, F.T., Siebert, S., Döll, P., 2010. MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Glob. Biogeochem Cycles 24, GB1011.

Potter, C.S., Randerson, J.T., Field, C.B., Matson, P.A., Vitousek, P.M., Mooney, H.A., Klooster, S.A., 1993. Terrestrial ecosystem production: A process model based on global satellite and surface data. Glob. Biogeochem. Cycles 7, 811–841.

Prince, S.D., 1991. A model of regional primary production for use with coarse resolution satellite data. Int. J. Remote Sens. 12, 1313–1330.

Prince, S.D., Goward, S.N., 1995. Global primary production: a remote sensing approach. J. Biogeogr. 22, 815–835.

Prince, S.D., Haskett, J., Steininger, M., Strand, H., Wright, R., 2001. Net primary production of U.S. Midwest croplands from agricultural harvest yield data. Ecol. Appl. 11, 1194–1205.

Ramankutty, N., Evan, A.T., Monfreda, C., Foley, J.A., 2008. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. Glob. Biogeochem Cycles 22, GB1003.

Reeves, M.C., Zhao, M., Running, S.W., 2005. Usefulness and limits of MODIS GPP for estimating wheat yield. Int. J. Remote Sens. 26, 1403–1421.

Ruimy, A., Saugier, B., Dedieu, G., 1994. Methodology for the estimation of terrestrial net primary production from remotely sensed data. J Geophys Res 99, 5263–5283.

Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M., Reeves, M., Hashimoto, H., 2004. A continuous satellite-derived measure of global terrestrial primary production. Bioscience 54, 547–560.

Schnepf, R., 2008. Midwest Floods of 2008: Potential Impact on Agriculture. Congressional Research Service report for Congress, http://www.nationalaglawcenter.org/assets/crs/RL34583.pdf.

Schwalm, C.R., Williams, C.A., Schaefer, K., Anderson, R., Arain, M.A., Baker, I., et al., 2010. A model-data intercomparison of CO_2 exchange across North America: Results from the North American Carbon Program site synthesis. J. Geophys. Res. Biogeosciences 115, G00H05.

Scurlock, J.M.O., Johnson, K., Olson, R.J., 2002. Estimating net primary productivity from grassland biomass dynamics measurements. Glob. Change Biol. 8, 736–753.

Smith, P., Davies, C.A., Ogle, S., Zanchi, G., Bellarby, J., Bird, N., et al., 2012. Towards an integrated global framework to assess the impacts of land use and management change on soil carbon: current capability and future vision. Glob. Change Biol. 18, 2089–2101.

Snapp, S.S., Swinton, S.M., Labarta, R., Mutch, D., Black, J.R., Leep, R., et al., 2005. Evaluating cover crops for benefits, costs and performance within cropping system niches. Agron. J. 97, 322–332.

Tian, H., Chen, G., Liu, M., Zhang, C., Sun, G., Lu, C., et al., 2010. Model estimates of net primary productivity, evapotranspiration, and water use efficiency in the terrestrial ecosystems of the southern United States during 1895-2007. For. Ecol. Manag. 259, 1311–1327.

Turner, D.P., Gower, S.T., Cohen, W.B., Gregory, M., Maiersperger, T.K., 2002. Effects of spatial variability in light use efficiency on satellite-based NPP monitoring. Remote Sens. Environ. 80, 397–405.

Turner, D.P., Ritts, W.D., Cohen, W.B., Maeirsperger, T.K., Gower, S.T., Kirschbaum, A.A., et al., 2005. Site-level evaluation of satellite-based global terrestrial gross primary production and net primary production monitoring. Glob. Change Biol. 11, 666–684.

United States Department of Agriculture (USDA), 2006. Major land resource regions custom report (USDA Agriculture handbook 296). USDA. http://soils.usda.gov/MLRAExplorer, accessed Oct 22nd 2012.

United States Department of Agriculture (USDA), 2009. 2007 census of agriculture, United States Summary and State Data, http://www.agcensus.usda.gov/Publications/2007/Full_Report/, (accessed 09.22.2012).

United States Department of Agriculture (USDA), 2011, Cropland Data Layer (CDL), created by the USDA, National Agricultural Statistics Service, Research and Development Division, Geospatial Information Branch, Spatial Analysis Research Section, Available from: http://www.nass.usda.gov/research/Cropland/SARS1a.htm, (accessed 12.06.11).

United States Environmental Protection Agency (US-EPA), 2012, Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2010.

Verma, S.B., Dobermann, A., Cassman, K.G., Walters, D.T., Knops, J.M., Arkebauer, T.J., et al., 2005. Annual carbon dioxide exchange in irrigated and rainfed maize-based agroecosystems. Agric. For. Meteorol. 131, 77–96.

West, T.O., Brandt, C.C., Baskaran, L.M., Hellwinckel, C.M., Mueller, R., Bernacchi, C.J., et al., 2010. Cropland carbon fluxes in the United States: increasing geospatial resolution of inventory-based carbon accounting. Ecol. Appl. 20, 1074–1086.

West, T.O., Brandt, C.C., Marland, G., De La Torre Ugarte, D.G., Larson, J., Hellwinckel, C.M., et al., 2008. Estimating regional changes in soil carbon with high spatial resolution. Soil Sci. Soc. Am. J. 72, 285–294.

White, M.A., Thornton, P.E., Running, S.W., Nemani, R.R., 2000. Parameterization and sensitivity analysis of the biome-bgc terrestrial ecosystem model: net primary production controls. Earth Interact. 4, 1–85.

Zhao, M., Heinsch, F.A., Nemani, R.R., Running, S.W., 2005. Improvements of the MODIS terrestrial gross and net primary production global data set. Remote Sens. Environ. 95, 164–176.

Zhao, M., Running, S.W., 2012. Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. Science 329, 940–943.

Zhao, M., Running, S.W., Nemani, R.R., 2006. Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. J. Geophys. Res. Biogeosciences 111, G01002.

Zhao, M., Running, S.W., Heinsch, F.A., Nemani, R.R. MODIS-derived terrestrial primary production. In: Ramachandran B. et al. editors. Land Remote Sensing and Global Environmental Change, Remote Sensing and Digital Image Processing 11, DOI 10.1007/978-1-4419-6749-7_28, Springer Science+Business Media, LLC 2011. p. 635-660.

CHAPTER 3. EVALUTING LAND COVER INFLUENCES ON MODEL

UNCERTAINTIES – A CASE STUDY OF CROPLAND CARBON DYNAMICS IN

THE MID-CONTINENT INTENSIVE CAMPAIGN REGION

Li, Z., Liu, S., Zhang, X., West, T.O., Ogle, S.M., Zhou, N. 2016. Evaluating land cover

influences on model uncertainties – A case study of cropland carbon dynamics in the

Mid-Continent Intensive Campaign region. Submitted to Ecological Modelling, reference

number ECOMOD-16-173.

3.0 ABSTRACT

Quantifying spatial and temporal patterns of carbon sources and sinks and their uncertainties across agriculture-dominated areas remains challenging for understanding regional carbon cycles. Land-use land-cover (LULC) change could impact the estimates of regional carbon fluxes but the effect has not been fully evaluated in the past. Within the North American Carbon Program Mid-Continent Intensive (MCI) Campaign, three models were developed to estimate carbon fluxes on croplands: an inventory-based model, the Environmental Policy Integrated Climate (EPIC) model, and the General Ensemble biogeochemical Modeling System (GEMS) model. They all provided estimates of three major carbon fluxes: cropland net primary production (NPP), net ecosystem production (NEP), and soil organic carbon (SOC) change. Using data mining and spatial statistics, we studied the relationships between the uncertainties of these carbon fluxes estimates and the input land cover characteristics. Results indicated that uncertainties for all three carbon fluxes were not randomly distributed, but instead formed multiple clusters within the MCI region. We investigated the impacts of cropland percentage, cropland richness and cropland diversity on these uncertainties. The results indicated that cropland percentage significantly influenced the uncertainties of NPP and NEP, but not on the uncertainties of SOC changes. Greater uncertainties of NPP and NEP were found in the counties with small cropland percentage than the counties with large cropland percentage. Cropland species richness and diversity also showed negative correlations with the model uncertainties. Our study demonstrated that the LULC can contribute to regional carbon fluxes uncertainties. The approaches we used in this study can be applied

to other ecosystem models to identify the areas with high uncertainties and where models can be improved to reduce overall uncertainties for regional carbon flux estimates.

3.1 INTRODUCTION

Understanding carbon sources and sinks is important for carbon management (USCCS, 2012). However, estimates of carbon dynamics in large regions still have large uncertainties among different methods (Ciais et al., 2010; Huntzinger et al., 2012; Ito, 2011). Intercomparisons between model estimates can help to identify the limitations of the models and suggest future research priorities. The North American Carbon Program (NACP) conducted a series of comparisons between model estimates and observations from local to continental scales (Huntzinger et al., 2012). For example, a comparison of 21 terrestrial biosphere models at multiple NACP tower sites showed that net ecosystem exchange (NEE) simulation results were better in forest sites than in non-forest sites (Schwalm et al., 2010). Another study compared gross primary production (GPP) between 26 terrestrial biosphere models and observations at flux tower sites (Schaefer et al., 2012). The study found that overall the model performance was poor in GPP estimates and was possibly caused by inadequate representation of observed light use efficiency. It also suggested that model improvement should focus on improving leaf-to-canopy scaling and obtaining better estimates of the model parameters that control light use efficiency.   At the continental scale, a comparison of 19 terrestrial biosphere models found that ecosystem net ecosystem productivity (NEP) for North America varied from -0.7 to +2.2 PgC yr^{-1}, which was much narrower than estimates of GPP and respiration

(Huntzinger et al., 2012). Another study on the North America carbon balance compared the NEE estimates between inventory-based estimates, atmospheric inversion models and terrestrial biosphere models (Hayes et al., 2012). The inventory based estimate (-327 TgC yr^{-1}) was significantly different from the mean values of the atmospheric inversion models (-931 TgC yr^{-1}) and the terrestrial biosphere models (-511 TgC yr^{-1}). For the terrestrial biosphere models, the estimated NEE values ranged from +29 to -3210 TgC yr^{-1}. Such large uncertainties in the model estimates could be driven by poorly simulated processes and input data (Hayes et al., 2012).

For regional simulations, land cover information usually is required as an important input to the process-based models (Ahl et al., 2005b). Different land cover types could bring different physical parameters to the biosphere model and create large differences in simulated outputs, such as carbon fluxes (Sellers et al., 1996). The comparison between multiple terrestrial biosphere models at flux tower sites found the biome classification was the most important factor controlling the model-data mismatch (Schwalm et al., 2010). Another comparison of global NPP estimates from multiple biosphere models also found that differences in the vegetation maps and associated parameters were as important as the differences in model assumptions in influencing seasonal NPP (Cramer et al., 1999). However, the assessment of how land cover impacts the model uncertainties was informal, and there is still a need for more research to better quality the effects of land cover inputs on model uncertainty.

The Mid-Continent Intensive Campaign (MCI) was a project that focused on reducing the uncertainties in estimating carbon fluxes between the terrestrial surface and atmosphere (Ogle, 2006). Multiple methods have been applied in the MCI region to

quantify ecosystem carbon fluxes (Li et al., 2014; Ogle et al., 2003; Schuh et al., 2013; West et al., 2010; Zhang et al., 2015). For croplands in the MCI region, multiple crop species are planted in different areas inside the region and annual changes in planted crops (crop rotations) are common. Variations in the spatial and temporal patterns of cropland area and crop species are major components of land use and land cover (LULC) change in the region. These LULC changes were found to impact the carbon fluxes, such as NPP and soil organic carbon changes (Li et al., 2014; Zhang et al., 2015).

In this study, we investigated whether the observed pattern of the uncertainties was related to the distribution of land cover. Our null hypothesis was that the spatial distribution of model uncertainties is random in the MCI region. This null hypothesis was tested on the uncertainties of three major carbon fluxes: net primary production (NPP), net ecosystem production (NEP) and change in soil organic carbon (SOC). The uncertainties of these carbon fluxes were calculated based on the estimates from three models: a crop inventory model; the Environmental Policy Integrated Climate (EPIC) model through the geospatial agricultural modeling system (GCAM) framework; and the General Ensemble biogeochemical Modeling System (GEMS). In situations where the null hypothesis was proved to be false, we further investigated the influences of three land cover characteristics with the uncertainties: cropland percentage, cropland richness and diversity.

3.2 MATERIALS AND METHODS

3.2.1 Study area

The research area is the Mid-Continent Intensive Campaign (MCI) region (Ogle, 2006). It encompasses 678 counties from 11 states in the northern Great Plains and Western Corn Belt (Figure 3.1). The land area in the MCI is about 124 million hectare (Mha) and over 40% of the land area is used for agriculture. Corn, soybean, spring wheat, and winter wheat are the four major planted crops in the MCI region and occupy more than 90% of the planted area. The crop inventory data showed over 30 Mha of cropland area was used to plant corn and soybean, and about 10 Mha was planted with small grains and other crops in this region (West et al., 2008). The mean annual precipitation varies from 355 to 535 mm and the mean annual air temperature varies from 5 to 7 °C.
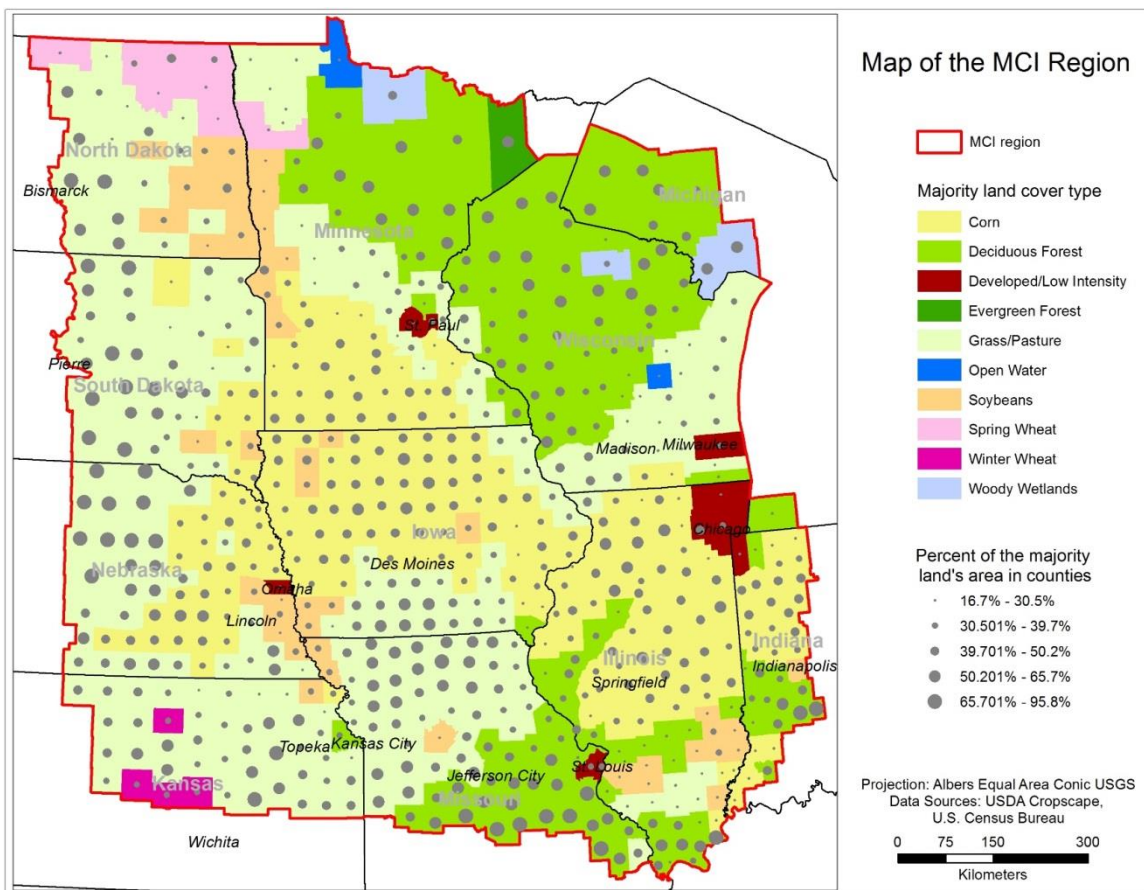
Figure 3.1 The Mid-Continent Intensive Campaign region boundary and land cover classes from the Cropland Data Layer in 2008.

The spatial details of crop species in the MCI region are provided by the USDA crop land data layer (CDL) product (Boryan et al., 2011). The CDL program used remote sensing data from multiple satellite sensors and ancillary data to classify the crop types since 1990s (Boryan et al., 2011). The major two satellite sensors are the Advanced Wide Field Sensor (AWiFS) and Landsat Thematic Mapper (TM) that have high spatial resolution (56 m for AWiFS and 30 m for TM). The CDL map provided a wall-to-wall mapping across the states with the spatial resolution at 30 m before 2005, and at 56 m between 2006 and 2010. The accuracies of the CDL products for major crop types are generally from 85% to 95% at state level (Boryan et al., 2011). These high resolution

crop maps have been widely used in biogeochemical models and with inventory data to estimate the carbon dynamics at region and national scale (Li et al., 2014; West et al., 2010; West et al., 2008; Zhang et al., 2015). In the MCI region, CDL maps are available for all the states in 2007 and 2008.

3.2.2   Inventory

The inventory method estimates the carbon fluxes of crops based on county-scale crop yield data (NASS, 2013). The county-scale crop yield data include the reported crop planted and harvested area, crop production and crop yield estimates on an annual basis from 2001 to 2008. Yield data are reported for harvested crop commodities, therefore cover crops are not included. Generally the crop harvested area is about 1-3% smaller than crop planted area at the state level, due to crop failures.

The inventory method calculated NPP for each crop from crop yield data with crop specific parameters such as harvest indices, root:shoot ratio and estimated dry weight values (West et al., 2011; West et al., 2010). The SOC change is estimated by using empirical relationships between land management and soil carbon change based on crop species, land management, soil attributes and regional mean climate regimes (West et al., 2008). The annual estimates of NEE include the sum of net soil carbon change, uptake of crop carbon, and decomposition of above- and below-crop carbon. The spatial distribution of the NEE was calculated using weighted distribution and remote sensing land cover data(West et al., 2010). For this comparison, the NEP is estimated as the negative of NEE and the estimates are aggregated to county level.

3.2.3 EPIC

The Environmental Policy Integrated Climate (EPIC) model was originally developed based on site-level observations and has been extensively tested for many agricultural cropping systems landscapes (Causarano et al., 2008; Zhang et al., 2015; Zhang et al., 2014). Recent development of the EPIC model used a geospatial agricultural modeling system (GAMS) to integrate the EPIC model with the spatially-explicit climate, land use, soil and management data for assessing regional carbon fluxes (Zhang et al., 2015; Zhang et al., 2014).

Multi-year CDL maps (2007-2011) were processed by GAMS to provide crop rotation information for the regional simulation (Zhang, 2015). For each state, major crop rotations were extracted from CDL maps and used to simulate land cover change in cropland areas. The SSURGO soil data was used for initializing soil carbon contents, and the climate inputs to the model were from the North- American Land Data Assimilation System 2 (NASA, 2014). Crop management information such as tillage, conservation type, and fertilizer application rate were also used as inputs to the model. GAMS processed all the information into homogeneous spatial modeling units (HSMUs) and performed EPIC simulations from 1991 to 2008 (Zhang et al., 2015).

In the EPIC model, NPP is computed a part of the plant canopy's interception of daily photosynthetically-active solar radiation. The NPP is affected by vapor pressure deficits, atmospheric CO_2 concentrations, nutrient availability, and other environmental controls and stresses. SOC dynamics is computed by considering many factors and processes, such as soil texture, crop yields, atmospheric nitrogen input, fertilizer and manure, and tillage for the decomposition and transformation of soil carbon and nitrogen from the

model inputs. NEE was calculated as heterotrophic soil respiration minus the net carbon sequestration from the atmosphere into plant biomass (i.e. NPP) and is opposite in sign to NEP (Zhang et al., 2015). NEP is computed as the negative of NEE for the comparison.

3.2.4   GEMS

GEMS is a modeling framework developed to quantify the regional ecosystem carbon sequestration and its uncertainties (Liu, 2009; Liu et al., 2004). GEMS used an ensemble approach to apply land-cover/use data, along with information on soils, terrain, and management factors, to provide geospatially explicit inputs data to the ecosystem level biogeochemical model. The uncertainty of model simulations can be quantified by a Monte-Carlo based ensemble approach and multiple modeling runs in the region.

Spatial information about crop types was obtained from the CDL. The original crop types were regrouped into 6 representative crops (corn, soybean, spring wheat, winter wheat, other grains crops, other crops) for this study. The GEMS model was run for the MCI region using an equal distance (5km) sampling approach and results were aggregated to the county level for comparison.

Meteorological inputs to the model were monthly minimum temperature, maximum temperature and precipitation from Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM, 2004). The soil data were extracted from State Soil Geographic Data Base (STATSGO) (NRCS, 1994). The major crop growth parameters were calibrated using state level crop yield data by GEMS internal subroutines (Li et al., 2014).

The biogeochemical model EDCM was used in GEMS to simulate carbon dynamics on agricultural land (Liu et al., 2003). EDCM is an ecosystem level model that simulates soil carbon and nitrogen dynamics, vegetation primary productivity and water balance at monthly time steps. EDCM computes NPP based on vegetation potential production and environmental factors such as temperature, water and nitrogen. SOC dynamics are modeled as a combination of soil movement (including the addition of manure) and decomposition. Decomposition of carbon is a function of soil carbon pool size and soil carbon decomposition rates, which are calculated based on the availability of temperature, water and nitrogen in each soil pool. The NEP on the cropland is calculated as the change of total ecosystem carbon plus the harvested carbon (grain and residue removal).

3.2.5   Data mining and spatial analysis

To analyze the spatial distribution of the model uncertainties, we combined both spatial and non-spatial methods. First, we processed three major carbon fluxes (NPP, NEP and SOC change) into the county level. For each method, the mean value of each flux in the county was calculated by adding all the estimated fluxes for the crops and dividing by the total cropland area in the county. We then applied data mining method (k-means clustering) to identify similar patterns of model estimates. For each county, all the estimates from the three models are treated as one vector, then all the counties are clustered into groups of the vectors. The cluster size of each group is determined with the elbow method (Thorndike, 1953) and the mean vector of each group is computed. We found the distribution of the clusters show strong spatial pattern that lead to the following research.

Based on the spatial distribution of the clusters produced from the above step, the hypothesis is tested: the spatial distribution of the uncertainty is random. We evaluated model uncertainties by using the Coefficient of Variation (CV) which is computed as:

$$CV = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}}{\frac{1}{N}\sum_{i=1}^{N}x_i} \tag{1}$$

where N is the total number of estimated variables in each county and N = 3 in this study (inventory, EPIC and GEMS). For SOC changes, which have a large portion of negative values, we used standard deviation (STDEV) instead of CV.

We computed the spatial autocorrelation index, Moran's I, measures the degree of association of uncertainty (e.g., the CVs of the three method results) between neighboring observations (Getis and Ord, 1992; Getis and Ord, 2010). Therefore, Moran's I can detect whether there exists one or more spatial clusters of similar CV values in the whole study area. With a range of values between -1 and 1, Moran's I is positive when neighboring counties have more similar CVs, and Moran's I is 0 if the spatial distribution of CVs is random.

$$I = \frac{n \times \sum_{i=1}^{n}\sum_{j=1}^{n}[w_{i,j} \times (z_i - \bar{Z}) \times (z_j - \bar{Z})]}{(\sum_{i=1}^{n}\sum_{j=1}^{n}w_{i,j}) \times (\sum_{i=1}^{n}(z_i - \bar{Z})^2} \tag{2}$$

where, *n* is the number of counties, z_i is the CV value in county *i*, z_j is the CV value in county *j*. $\overline{Z}$ is the mean CV of all the counties, and $w_{i,j}$ is the spatial weight. The spatial weight $w_{i,j}$ is computed as the inverse distance between county *i* and *j*.

We also used the hot spot and cold spot statistics (Getis-Ord Gi* statistic) to analysis the spatial patterns of the uncertainties. For each feature *i* (county in this study), G_i^* will calculate the weighted sum of the variable (e.g., CV or cropland percentage) for the feature's local neighbors then compare the local sum with the global sum for the variable (Getis and Ord, 1992).

$$G_i^* = \frac{\sum\limits_{j=1}^{n} w_{i,j} z_j - \overline{Z} \sum\limits_{j=1}^{n} w_{i,j}}{S \sqrt{\dfrac{n \sum\limits_{j=1}^{n} w_{i,j}^2 - (\sum\limits_{j=1}^{n} w_{i,j})^2}{n-1}}} \qquad (3)$$

$$S = \sqrt{\frac{\sum\limits_{j=1}^{n} x_j^2}{n} - (\overline{Z})^2} \qquad (4)$$

where, *n* is the number of counties, z_j is the CV value of county *j*. $\overline{Z}$ is the mean of the CV values of all counties, and $w_{i,j}$ is the spatial weight calculated as the inverse distance between county i and j without row standardization. We used this analysis to investigate if the CVs of the estimates are impacted by the cropland percentage. For cropland percentage (with each county the total area of cropland divided by the total area), if a county is spatially surrounded by counties with high cropland percentage, the county is a

hot spot of cropland percentage. Similarly, for the CVs of the three models, if a county is surrounded by counties with low CV values, the county is a cold spot of CVs. By comparing the hot and cold spots of the cropland percentage and the CVs, the spatial correlation between cropland percentage and the model CVs can be visually discovered.

We also investigated whether the spatial configuration of different land cover type is related to the uncertainties. The spatial configuration is measured with two indices: land cover richness and Shannon equitability index. The land cover richness is defined as the number of unique land cover types inside each county. The Shannon equitability index is an index that is widely used in ecology, landscape ecology to describe the biodiversity. It is the Shannon diversity index divided by the maximum diversity and calculated as:

$$SI = \frac{-\sum_{i=1}^{M} p(i) \ln p(i)}{\ln(M)} \tag{5}$$

Where, i is the land cover type in a county, $p(i)$ is the proportion of the value i to the total of the values, and M is the total number of values. For a well-sampled region, we can estimate this proportion as $p(i) = area(i)/total\_area$, where area(i) is the area for each land cover within a county and total area is the area of all the land covers in the county. The Shannon equitability index takes values between 0 and 1, which lower values indicate more diversity while higher values indicate less diversity.

Both 2007 and 2008 data were used in the uncertainty analysis. The statistics and data mining method were implemented with R software and the spatial patterns were displayed using ArcGIS software.

3.3 RESULTS

3.3.1 Influence of model estimates on carbon dynamics

Figure 3.2 show the estimates of cropland area, NPP, NEP and SOC change in 2007 and 2008 at the county level. The total cropland area estimated from the three methods was 53.0 ± 3.0 Mha in 2007 and 54.3 ± 3.1 Mha in 2008. The cropland area showed very similar spatial distributions in both years (Figure 3.2A, 2B). About 15% of the counties have cropland area smaller than 25,000 ha and about 30% of the counties have cropland area larger than 100,000 ha in the MCI region. Large cropland areas mainly exist in Illinois, Iowa, Nebraska, North Dakota, and South Dakota. Northern Minnesota, Missouri and Wisconsin have less cropland area.

The total NPP estimated from the three methods was 344.5 ± 5.8 in 2007 and 366.4 ± 38.4 TgC yr^{-1} in 2008. About 90% of the counties had NPP values between 250 and 850 gC m^{-2} yr^{-1} and 7% had NPP values above 850 gC m^{-2} yr^{-1} in 2007. In 2008, cropland NPP increased in most counties and about 19% of the counties have NPP values higher than 850 gC m^{-2} yr^{-2}. These highest NPP values were mainly in Iowa and Illinois. Lower NPPs were in northern Minnesota, northern Wisconsin, and central Missouri (Figure 3.2C, 2D).
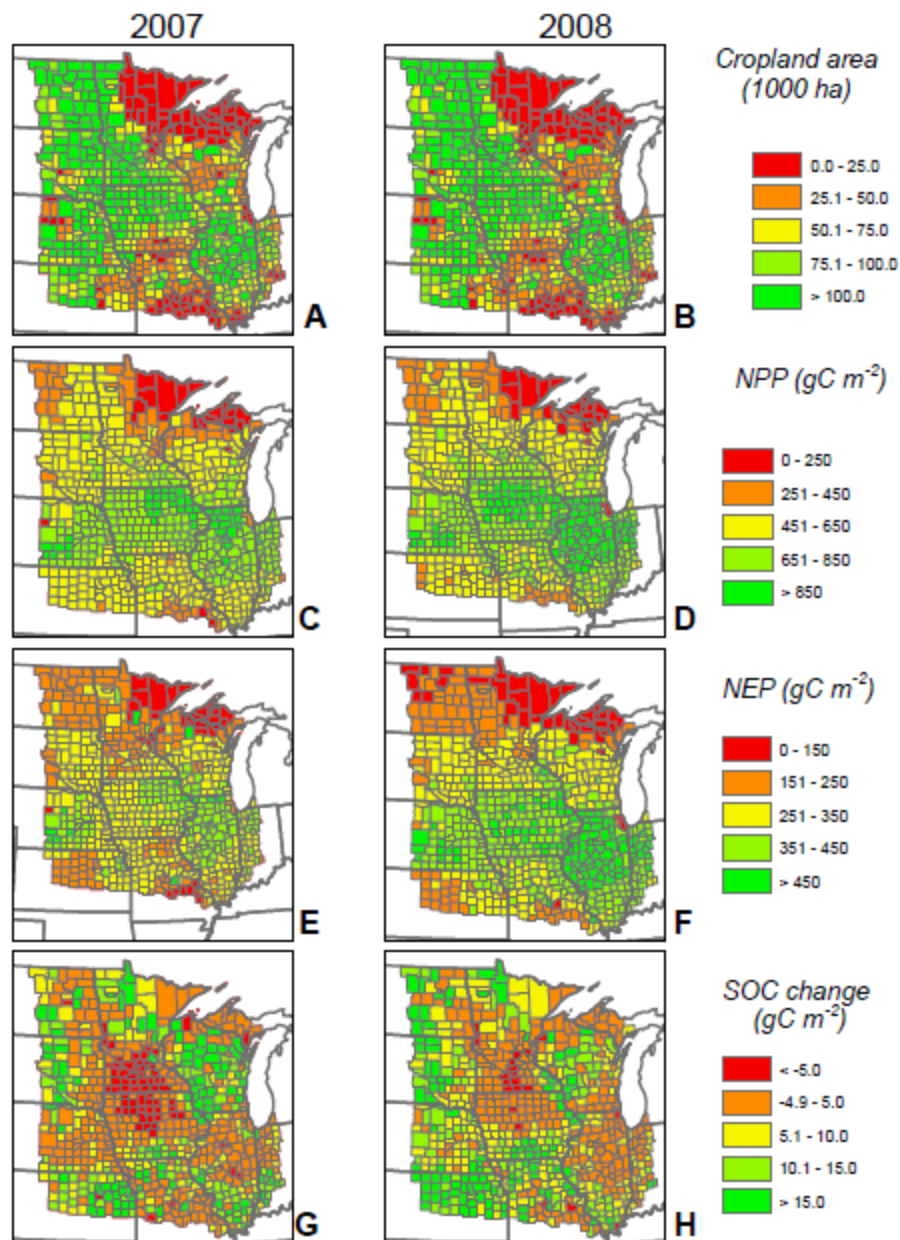
Figure 3.2. Cropland area in 2007 (A) and 2008 (B); cropland mean Net Primary Production (NPP) in 2007 (C) and 2008 (D); cropland mean Net Ecosystem Production NEP in 2007 (E) and 2008 (F); cropland mean soil organic carbon (SOC) change in 2007 (G) and 2008 (H) in the Mid-Continent Intensive Campaign (MCI) region.

The total NEP on croplands was 159.7 $\pm$ 7.7 in 2007 and 183.3 $\pm$ 47.8 TgC yr^{-1} in 2008 based on the three methods. The county level NEP had a smaller range than NPP. About 92% of the counties had NEP values between 250 and 450 gC m^{-2} yr^{-1} and 2% had NEP values above 450 gC m^{-2} yr^{-1} in 2007. In 2008, 78% of the counties had NEP between 250 and 450 gC m^{-2} yr^{-1}, and about 16% of the counties have NEP values higher than 450 gC m^{-2} yr^{-2}. The spatial distributions of NEP showed similar patterns as NPP, with high values in Iowa and Illinois, and low values in northern Minnesota, northern Wisconsin, and central Missouri (Figure 3.2E, 2F).

The total SOC change was 4.0 $\pm$ 4.9 TgC yr^{-1} in 2007 and 8.0 $\pm$ 10.5 TgC yr^{-1} in 2008. About 43% of the counties showed relatively small SOC changes (-4.9 – 5.0 gC m^{-2} yr^{-1}) in 2007. About 10% of the counties showed SOC change less than -5.0 gC m^{-2} yr^{-1} and these counties locate mainly in south Minnesota and north Iowa. In 2008, only 4% of the counties showed SOC change less than -5.0 gC m^{-2} yr^{-1} and about 60% of the counties showed SOC change higher than 5.0 gC m^{-2} yr^{-1}. The spatial distribution of SOC changes was quite different from the spatial distribution of NPP and NEP (Figure 3.2G, 2H).

3.3.2 Model uncertainties in the MCI region

Figure 3.3 show the uncertainty of the estimates in cropland area, NPP, NEP and SOC change in 2007 and 2008. For cropland area, most counties had small CVs but some high CVs were found in northern Minnesota, northern Wisconsin, and central Missouri (Figure 3.3A, 3B). The CVs of cropland area showed similar results in 2007 and 2008.
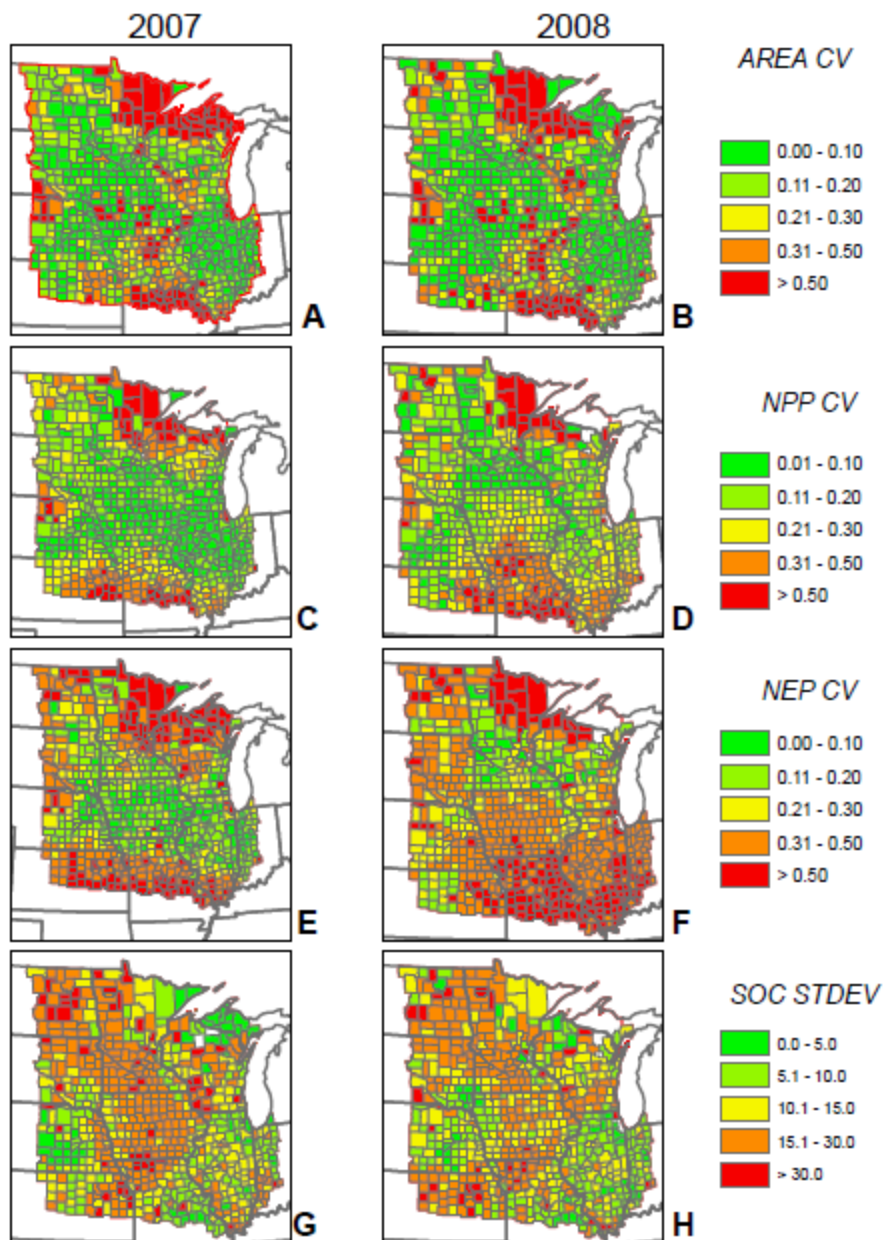
Figure 3.3. Cropland area CVs in 2007 (A) and 2008 (B); cropland NPP CVs in 2007 (C) and 2008 (D); cropland NEP CVs in 2007 (E) and 2008 (F); cropland SOC change standard deviation in 2007 (G) and 2008 (H) in the Mid-Continent Intensive Campaign (MCI) region.

The three models agreed well on the NPP estimates in the MCI region. The CVs of NPP estimates showed that more counties had smaller CVs in 2007 than in 2008 (Figure 3.3C, 3D). About 64% of the counties had CVs less than 0.2 in 2007 and only about 45% of the counties had CVs less than 0.2 in 2008. Higher CVs in 2008 were mainly located in Iowa and Illinois. It also seems that NPP CVs showed similar spatial patterns as the cropland area CVs. The highest NPP CVs tended to occur at counties with high cropland area CVs such as the Northern Minnesota, Northern Wisconsin and Central Missouri. The CVs of NEP showed similar spatial patterns as those for NPP but with higher values (Figure 3.3E, 3F). Only 45% of the counties had NEP CVs less than 0.2 in 2007 and 15% of the counties had CVs less than 0.2 in 2008. This result indicates that NEP estimates from the three models had higher uncertainties than NPP. One noticeable difference between 2007 and 2008 was that NEP CVs were higher in Iowa and Illinois in 2008, similar as the CV changes in NPP.

The STDEVs of SOC changes showed quite different spatial pattern from the CV maps of NEP and NPP. The largest uncertainties were in Iowa, Minnesota, and North Dakota. Low uncertainties were in Nebraska and Illinois (Figure 3.3G, 3H). Based on these uncertainties, we are more confident that the cropland was a weak soil carbon sink in Nebraska and Illinois but less confident about the soil carbon loss in Iowa and south Minnesota where larger STDEVs were found.

We computed the correlation coefficients and p-values between the model uncertainties and the input land cover characteristics for all the counties (Table 3.1). For

both 2007 and 2008, the CVs of cropland area showed significant positive correlations with the CVs of NPP and NEP. Meanwhile, there were significant negative correlations between the cropland percentage and the CVs of NPP and NEP. This indicated that in the counties with large cropland percentage, the cropland area CVs were small, as well as the CVs of the NPP and NEP. But in the counties with small cropland percentage, the CVs of cropland area, as well as the CVs of NPP and NEP, were large. In contrast, the STDEVs of SOC change did not show significant correlation with the CVs of cropland area, and less significant correlations with the cropland percentages than the CVs of NPP and NEP (Table 3.1).

Table 3.1. Correlation coefficient and p-value between the cropland area CVs, cropland percentage, richness and Shannon equitability index and model uncertainties in 2007 (A) and 2008 (B).

A.

2007	NPP CV		NEP CV		SOC STDEV	
	Correlation coefficient	p-value	Correlation coefficient	p-value	Correlation coefficient	p-value
Cropland area CVs	0.780	< 2.2 e-16	0.700	< 2.2 e-16	-0.087	0.0258
Cropland percentage	-0.589	< 2.2 e-16	-0.607	< 2.2 e-16	-0.098	0.0107

Cropland richness	-0.122	0.00145	-0.022	0.562	0.132	0.00059
Shannon equitability	-0.241	2.14 e-10	-0.182	1.88 e-6	-0.029	0.445

B.

2008	NPP CV		NEP CV		SOC STDEV	
	Correlation coefficient	p-value	Correlation coefficient	p-value	Correlation coefficient	p-value
Cropland area CVs	0.812	< 2.2 e-16	0.668	< 2.2 e-16	-0.038	0.324
Cropland percentage	-0.534	< 2.2 e-16	-0.404	< 2.2 e-16	-0.175	2.55 e-10
Cropland richness	-0.255	1.86 e-15	-0.312	< 2.2 e-16	0.146	0.00134
Shannon equitability	-0.216	5.87 e-13	-0.171	1.03 e-5	-0.069	0.105

Both cropland richness and Shannon equitability index showed negative correlations

with the CVs of NPP and NEP (Table 3.1). That is, the uncertainties of the NPP and NEP

were smaller in the county with higher richness or lower diversity. However, the p-values showed their correlations were less significant than cropland percentage. The STDEVs of the SOC changes did not showed significant correlations with cropland richness and the Shannon equitability. These results indicated that the distribution of crop types had less impact on the uncertainties of SOC changes than the uncertainties of NPP and NEP.

3.3.3 Spatial patterns of clustered model uncertainties

The data mining method, k-means cluster analysis, identified multiple clusters for the model uncertainties in both 2007 and 2008 (Figure 3.4), and Table 3.2 also gave the number of clusters for each method. The clusters were not the same but showed some similarities between the two years. For example, a cluster with small NPP CVs was in Nebraska, Iowa and Illinois in 2007 and this cluster extended its range with larger CV value in 2008. This agrees with the NPP CV map that in 2008, larger CVs were shown in Iowa and Illinois. The cluster of NEP CVs also showed the counties in Iowa were in one cluster in both 2007 and 2008. Generally for NPP and NEP, the clusters with small uncertainties are in cropland dominated areas, such as Iowa and Illinois, and clusters with large uncertainties are in the counties with small cropland areas, such as northern Minnesota and northern Wisconsin. The clusters of SOC changes showed different spatial patterns than NPP and NEP. Cluster with high STDEV value were in Iowa, Minnesota, and North Dakota. Low uncertainties were in Nebraska and Illinois (Figure 3.4E, 4F).
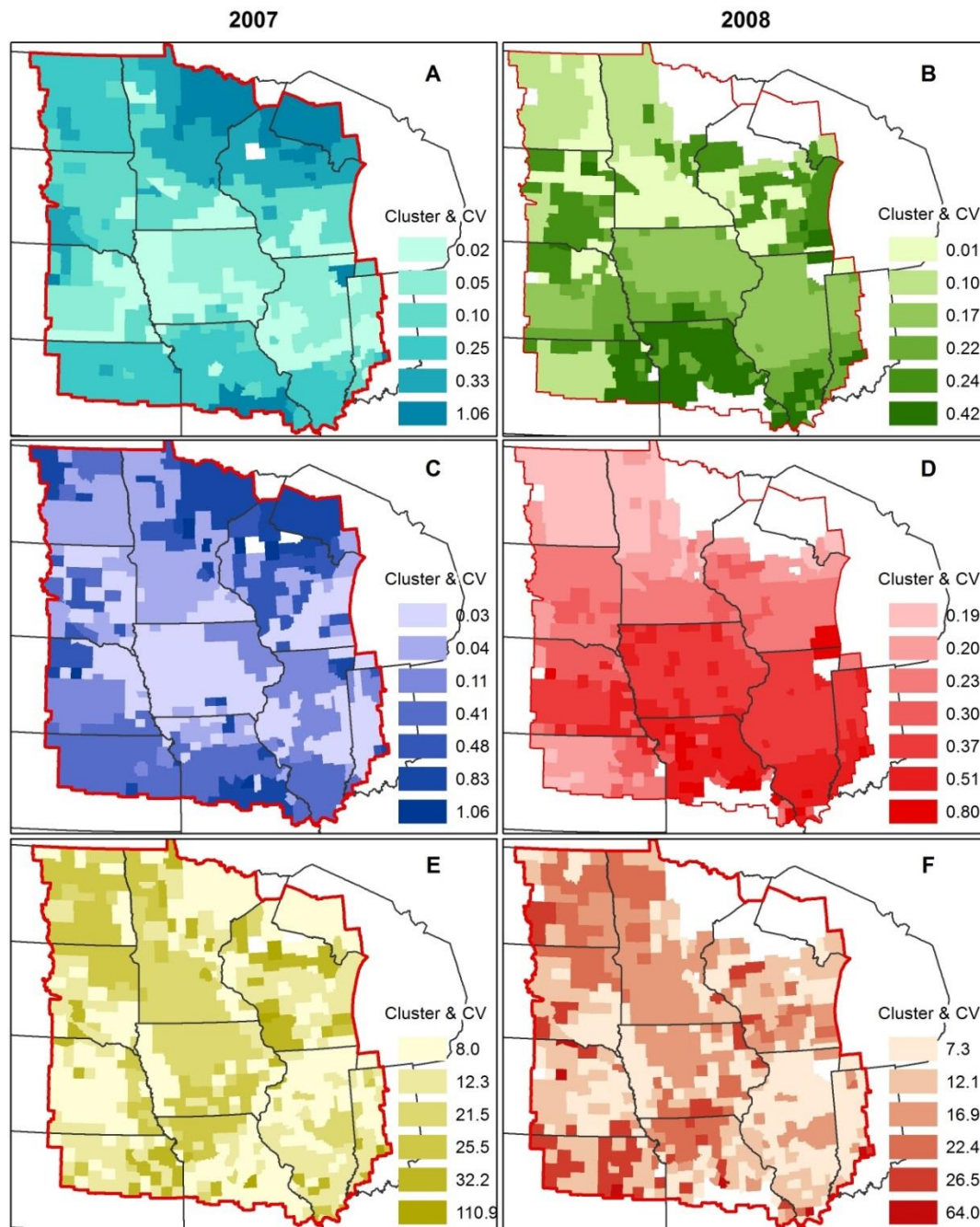
Figure 3.4. k-means clustering analysis for NPP in 2007 (A) and 2008(B); NEP in 2007 (C) and 2008 (D); SOC change in 2007 (E) and 2008 (F).

Table 3.2. Moran I's analysis on the uncertainties.

Variable CVs	Moran's I index	z-score	p-value	Number of clusters
NPP in 2007	0.457	26.420	0.000	6
NPP in 2008	0.475	30.142	0.000	6
NEP in 2007	0.374	26.118	0.000	7
NEP in 2008	0.373	24.887	0.000	7
SOC change in 2007*	0.193	13.224	0.000	6
SOC change in 2008*	0.198	12.914	0.000	6

*The uncertainty of SOC change is calculated as standard deviation (STDEV) instead of CV.

We performed the Moran's *I* analysis on the uncertainties and the results are listed in Table 3.2. Distributions of the model uncertainties exhibited statistically significant spatial patterns instead of being randomly distributed. With high Z-scores and low p-values all the results indicate that the model uncertainties (CVs and STDEVs) are positively spatially autocorrelated (i.e., similar CVs are clustered near one another). The uncertainties of NPP and NEP showed stronger spatial autocorrelation than the uncertainties of SOC in both years. Interestingly, the Moran's *I* values are very similar

for each type of uncertainty (NPP, NEP, SOC) between 2007 and 2008, indicating the spatial patterns of the model uncertainties are temporally stable.

3.3.4 Hot spots and cold spots analysis

A hot/ cold spots analysis for cropland percentage, cropland cover richness and cropland Shannon equitability index (equitability) within counties was conducted (Figure 3.5). The hot spots of cropland percentage were located in corn and soybean dominated area, such as central Iowa, southern Minnesota, eastern South Dakota, eastern Nebraska, and Illinois (Figure 3.5A, 5B). The cold spots were mainly located in the northwestern MCI region (northern Minnesota, Wisconsin and Michigan) and northern Missouri, where cropland is not the major land cover type. The hot and cold spots of cropland richness showed different spatial pattern from the cropland percentage (Figure 3.5C, 5D). The hot spots with a high number of crops planted in the county were in North Dakota, Minnesota and Wisconsin. The cold spots with low number of crop types were mainly located in Iowa, eastern Nebraska and northern Missouri. The cropland richness hot/cold spots showed slightly different spatial patterns in 2007 and 2008 (Figure 3.5C, 5D). Cold spots showed less coverage in 2008 than in 2007, while hot spots showed more coverage. The hot/cold spots of Shannon equitability index showed more scattered results than cropland percentage and cropland richness (Figure 3.5E, 5F). The hot spots were in North Dakota, central Minnesota, Wisconsin and southern Illinois in both 2007 and 2008. More hot spots were shown in southeast Iowa and fewer hot spots were in North Dakota and Minnesota in 2008. The cold spots were in central Nebraska, northwestern Iowa, central Missouri and parts of Kansas.

The hot/cold spots of NPP CVs, NEP CVs and SOC change STDEVs are shown in Figure 3.6. The NPP CVs showed similar patterns in both 2007 and 2008 (Figure 3.6A, 6B). The hot spots were in northern Wisconsin, northern Minnesota and Missouri. The cold spots were in Iowa, parts of Nebraska and northern Illinois. The NEP CVs had similar hot/cold spots pattern as the NPP CVs, except there were fewer cold spots in Nebraska and Kansas (Figure 3.6C, 6D). The SOC change STDEVs showed more scattered results than NPP and NEP (Figure 3.6E, 6F). The hot spots were in North Dakota, Kansas and along the border between Iowa and Missouri. The cold spots were in parts of Nebraska and Illinois.
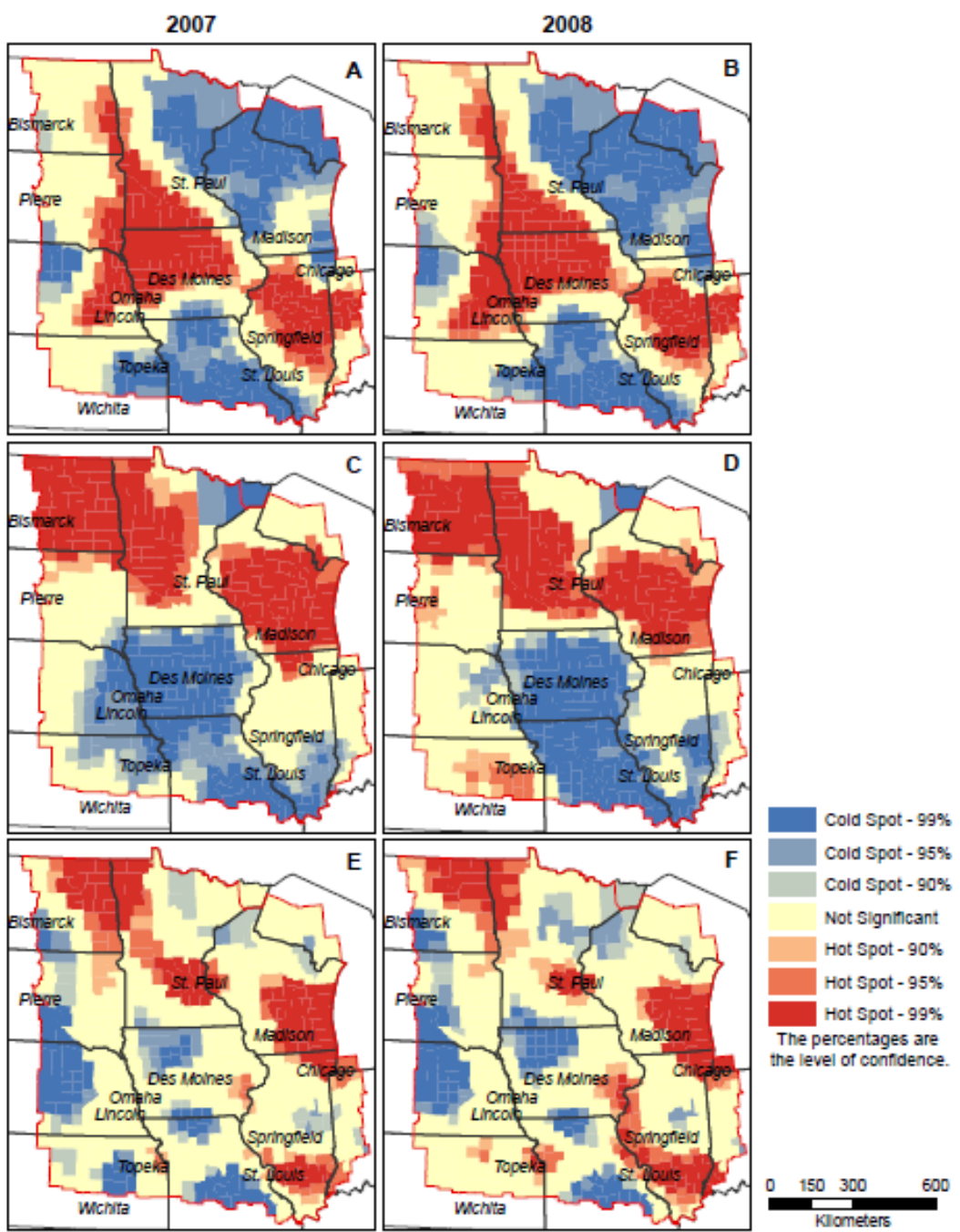
Figure 3.5. Hot and cold spots analysis on cropland percentage in 2007 (A) and 2008(B); cropland cover richness in 2007 (C) and 2008 (D); and Shannon diversity in 2007 (E) and in 2008 (F). Note: the percentages (99%, 95%, 90%) represent the areas with statistically significant clusters at alpha-levels of 0.01, 0.05, and 0.1.
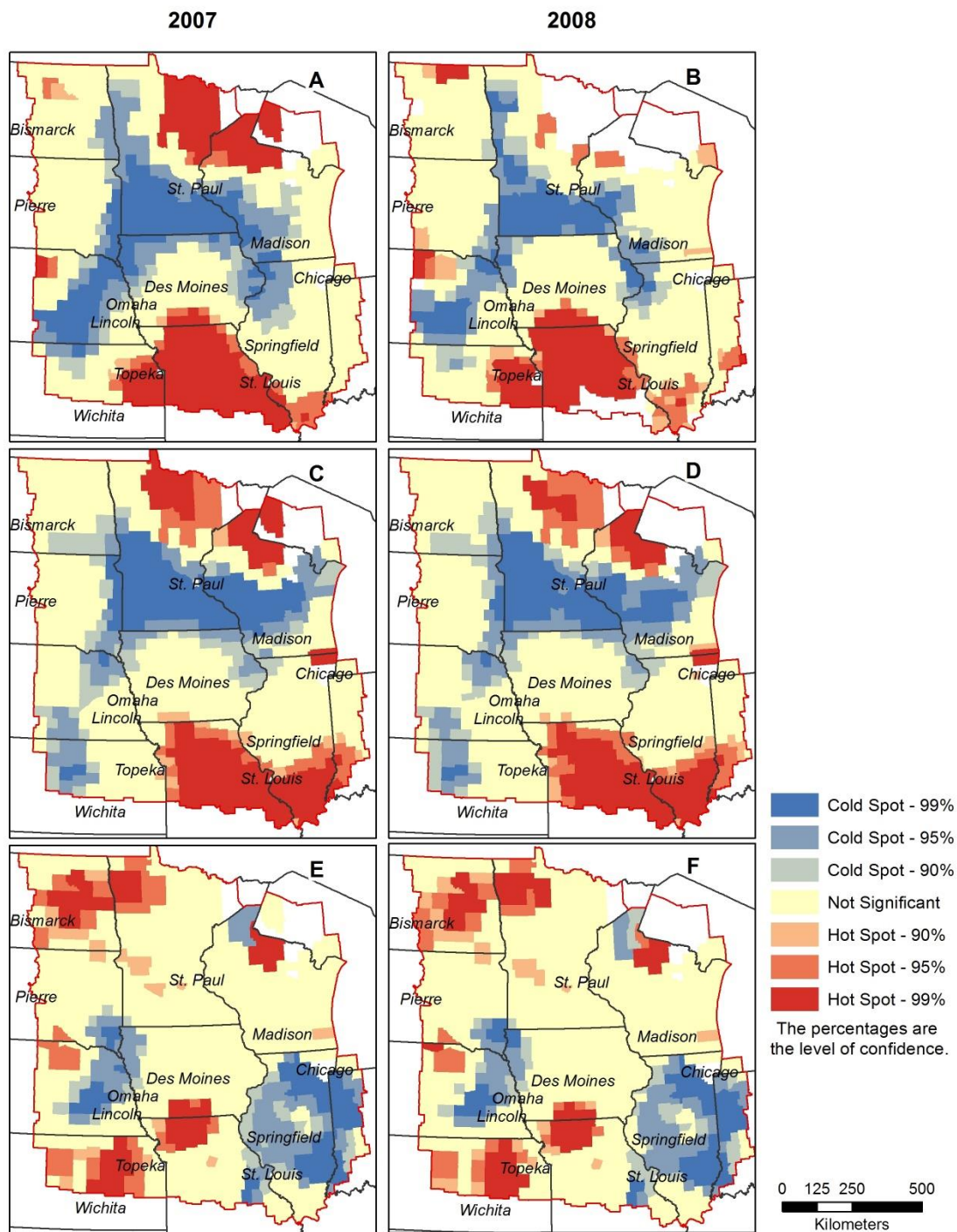
Figure 3.6. Hot and cold spots analysis on model uncertainty using NPP CVs in 2007 (A) and 2008(B); NEP CVs in 2007 (C) and 2008 (D); SOC change STDEVs in 2007 (E) and in 2008 (F).

The comparison between the cropland percentage hot/cold spots and the uncertainties hot/cold spots showed that in northern Wisconsin, western Michigan and Missouri, the cold spots of cropland percentages corresponded to the hot spots of NPP and NEP CVs, while the hot spots of cropland percentages corresponded to cold spots of CVs in Nebraska and south Minnesota (Figure 3.5A, 5B; Figure 3.6A, 6B, 6C, 6D). Such correlations between cold and hot spots indicated that higher cropland percentages may lead to smaller difference in uncertainties for NPP and NEP. One interesting observations was that the counties in Iowa and Illinois had large cropland percentages but not low CVs.

The cropland richness and Shannon equitability index hot/cold spots showed quite different patterns from the hot/cold spots of the three carbon fluxes uncertainties. These differences may explain the weak relationships between both characteristics and the uncertainties in the correlation analysis (Table 3.1).

3.4 DISCUSSIONS

The evaluation of process-based models at the regional scale is necessary to assess the credibility of these models for large-scale carbon budget estimates (Zhang et al., 2015). In our study, we focused on analyzing the influence of land cover inputs on the uncertainties of estimated cropland carbon fluxes.

The land cover inputs are different in the three methods and resulting uncertainty can be propagated into the model results. The inventory method used the reported harvested cropland area to estimate the carbon fluxes but the harvest area usually smaller than the planted cropland area as represented by the CDL data. The EPIC model used the representative crop rotations instead of the observed CDL data (Sahajpal et al., 2014;

Zhang et al., 2015). This approach reduced the redundancy and computation time but may introduce some inaccuracies from year to year. For example, corn area in EPIC increased from 26.3 Mha in 2007 to 31.1 Mha in 2008, while in NASS reported corn area decreased from 30.1 Mha in 2007 to 26.9 Mha in 2008. GEMS used a sampling method based on CDL data to simulate the annual crop rotations. This approach could result in large inaccuracies if the input data are not consistent between years at the pixel level. Though this paper was not trying to evaluate the accuracy of CDL map, we did find some disagreement between years of CDL products, which may be caused by inconsistent classification algorithms applied among years. For example, the annual CDL map showed large amount of grassland in 2006 transferred to forest land in 2007, and a large amount of forest land transferred back to grassland in 2008. In reality, this magnitude of change is unlikely within a single year. We did not find any support for this kind of transition in the literature so it is likely that the change is caused by classification error. Similar conditions may occur in crop rotations. The approaches based on CDL data may have large annual differences when the cropland area is small due to misclassification and representation of cropland. When cropland area is large, such differences will have smaller impacts on the model uncertainties.

The three methods have different classification schemes for the crop types. The inventory method listed 19 crop types in the factor table to compute the NPP (West, 2011). EPIC used over 10 crop types and calibrated the model parameters for each crop using fluxnet data (Zhang, 2015). GEMS use a more simplified approach and only classified the crops into 6 categories (Li, 2014). These differences in representing the crop types may lead to greater uncertainties when there are more crop types in a single

county. Both cropland richness and Shannon equitability index showed less significant

correlations with the uncertainties of NPP and NEP in this study. Such differences may

be caused by other cropland management practices in addition to crop types, such as

cropland irrigation. Irrigation generally changes the water availability and plant growth in

the cropland as well as the cropland carbon fluxes. Zhang et al. (2015) found that lack of

spatial representation of irrigated cropland in CDL data could explain the discrepancies

between the EPIC simulation and inventory estimates. Adding such information into the

model inputs may reduce the uncertainties between the models.

   Another possible source of uncertainty related to crop types is from the model

parameters. In the site level intercomparison of the NACP models, Schwalm (2010)

pointed out that model parameter sets showed clear impact on model skills. The EPIC

model used flux tower based measurements to calibrate the model parameters and then

applied the same parameters in the MCI region. The GEMS model used the state level

crop inventory data to calibrate the crop growth parameters and used a different set of

parameters in each state. When there are more cropland types in a county, the differences

in the model parameters may propagate higher uncertainties to the model results.

   The NACP multi-scale synthesis and terrestrial model intercomparison project pointed

to the need for evaluating model performances and better addressing the model

differences (Huntzinger et al., 2013). Though our study only compared three model

estimates, the data mining and spatial analysis techniques we used in this study could be

easily applied to other model ensemble and their driving variables for different regions.

Both Moran's *I* analysis and hot/cold spot statistics can help to find the areas with high

uncertainties, which leads to identify the sources of the uncertainties in both model inputs

and structures. More research can be done to reduce the uncertainties and improve the model performance. Based on our study, we suggested using high quality land cover inputs with crop species information is critical to reduce the uncertainties between the models. Integrating other cropland management information such as irrigation may also bring more accurate estimates for cropland fluxes estimates.

3.5 CONCLUSIONS

We used data mining and spatial statistical methods to study the relationships between land cover inputs and the uncertainty of carbon flux estimates in the MCI region. Our null hypothesis is proved to be false since the k-mean clustering analysis showed that the uncertainties in flux estimates are not distributed randomly but are instead spatially correlated. The Moran's I's analysis also showed the uncertainties have significant positive autocorrelation in neighboring counties in the MCI region. For both NPP and NEP, the uncertainty of the estimates showed significant negative correlations with the cropland percentage in the county. But the uncertainty of the SOC change estimates showed no significant correlation with the cropland percentage. The cropland richness and Shannon equitability indices showed significant negative relationship with the uncertainties of NPP and NEP but not the uncertainties of SOC changes. Our results demonstrated that land cover inputs clearly affected the spatial patterns of the uncertainties of NPP and NEP estimates, but not that of the SOC changes. Spatial analysis techniques are powerful tools for revealing the patterns and drivers of uncertainties in regional scale carbon estimates.

3.6 REFERENCE

Ahl, D.E., Gower, S.T., Mackay, D.S., Burrows, S.N., Norman, J.M., Diak, G.R., 2005. The effects of aggregated land cover data on estimating NPP in northern Wisconsin. Remote Sensing of Environment 97, 1-14.

Bondeau, A., Smith, P.C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze-Campen, H., MÜLler, C., Reichstein, M., Smith, B., 2007. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Global Change Biology 13, 679-706.

Boryan, C., Yang, Z., Mueller, R., Craig, M., 2011. Monitoring US agriculture: the US department of agriculture, national agricultural statistics service, cropland data layer program. Geocarto International 26, 341-358.

Boyer, J.S., Byrne, P., Cassman, K.G., Cooper, M., Delmer, D., Greene, T., Gruis, F., Habben, J., Hausmann, N., Kenny, N., Lafitte, R., Paszkiewicz, S., Porter, D., Schlegel, A., Schussler, J., Setter, T., Shanahan, J., Sharp, R.E., Vyn, T.J., Warner, D., Gaffney, J., 2013. The U.S. drought of 2012 in perspective: A call to action. Global Food Security 2, 139-143.

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., 2003. An overview of the crop model STICS. European Journal of agronomy 18, 309-332.

Causarano, H.J., Doraiswamy, P.C., McCarty, G.W., Hatfield, J.L., Milak, S., Stern, A.J., 2008. EPIC modeling of soil organic carbon sequestration in croplands of Iowa. J. Environ. Qual. 37, 8.

Ciais, P., Wattenbach, M., Vuichard, N., Smith, P., Piao, S.L., Don, A., Luyssaert, S., Janssens, I.A., Bondeau, A., Dechow, R., Leip, A., Smith, P.C., Beer, C., Van Der Werf, G.R., Gervois, S., Van Oost, K., Tomelleri, E., Freibauer, A., Schulze, E.D., Carboeurope Synthesis, T., 2010. The European carbon balance. part 2: croplands. Global Change Biology 16, 1409-1428.

Cramer, W., Kicklighter, D.W., Bondeau, A., Iii, B.M., Churkina, G., Nemry, B., et al., The participants of the Potsdam NPP model intercomparison, 1999. Comparing global models of terrestrial net primary productivity (NPP): overview and key results. Glob. Change Biol. 5, 1–15.

CTIC, 2008. National crop residue management survey data. Conservation Technology Information Center.

Eve, M.D., Sperow, M., Paustian, K., Follett, R.F., 2002. National-scale estimation of changes in soil carbon stocks on agricultural lands. Environmental Pollution 116, 431-438.

Follett, R.F., 2001. Soil management concepts and carbon sequestration in cropland soils. XVth ISTRO Conference on Tillage at the Threshold of the 21st Century: Looking Ahead 61, 77-92.

Friedl, M.A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., Huang, X., 2010. MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote Sensing of Environment 114, 168-182.

Gervois, S., Ciais, P., de Noblet-Ducoudré, N., Brisson, N., Vuichard, N., Viovy, N., 2008. Carbon and water balance of European croplands throughout the 20th century. Global Biogeochem. Cycles 22, GB2022.

Getis, A., Ord, J.K., 1992. The analysis of spatial association by use of distance statistics. Geographical analysis 24, 189-206.

Getis, A., Ord, J.K., 2010. The Analysis of Spatial Association by Use of Distance Statistics, in: Anselin, L., Rey, S.J. (eds.), Perspectives on Spatial Data Analysis. Springer Berlin Heidelberg, pp. 127-145.

Goward, S.N., Masek, J.G., Cohen, W., Moisen, G., Collatz, G.J., Healey, S., Houghton, R.A., Huang, C., Kennedy, R., Law, B., Powell, S., Turner, D., Wulder, M.A., 2008. Forest Disturbance and North American Carbon Flux. Eos Trans. AGU 89.

Hansen, M.C., Defries, R.S., Townshend, J.R.G., Sohlberg, R., 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. International Journal of Remote Sensing 21, 1331-1364.

Hartman, M.D., Merchant, E.R., Parton, W.J., Gutmann, M.P., Lutz, S.M., Williams, S.A., 2011. Impact of historical land-use changes on greenhouse gas exchange in the U.S. Great Plains, 1883–2003. Ecological Applications 21, 1105-1119.

Hayes, D.J., Turner, D.P., Stinson, G., McGuire, A.D., Wei, Y., West, T.O., Heath, L.S., de Jong, B., McConkey, B.G., Birdsey, R.A., Kurz, W.A., Jacobson, A.R., Huntzinger, D.N., Pan, Y., Post, W.M., Cook, R.B., 2012. Reconciling estimates of the contemporary North American carbon balance among terrestrial biosphere models, atmospheric inversions, and a new approach for estimating net ecosystem exchange from inventory-based data. Global Change Biology 18, 1282-1299.

Hicke, J.A., Lobell, D.B., Asner, G.P., 2004. Cropland area and net primary production computed from 30 years of USDA agricultural harvest data. Earth Interact. 8, 1-20.

Huntzinger, D.N., Post, W.M., Wei, Y., Michalak, A.M., West, T.O., Jacobson, A.R., Baker, I.T., Chen, J.M., Davis, K.J., Hayes, D.J., Hoffman, F.M., Jain, A.K., Liu, S., McGuire, A.D., Neilson, R.P., Potter, C., Poulter, B., Price, D., Raczka, B.M., Tian, H.Q., Thornton, P., Tomelleri, E., Viovy, N., Xiao, J., Yuan, W., Zeng, N., Zhao, M., Cook, R., 2012. North American Carbon Program (NACP) regional interim synthesis: Terrestrial biospheric model intercomparison. Ecological Modelling 232, 144-157.

Huntzinger, D.N., Schwalm, C., Michalak, A.M., Schaefer, K., King, A.W., Wei, Y., Jacobson, A., Liu, S., Cook, R.B., Post, W.M., Berthier, G., Hayes, D., Huang, M., Ito, A., Lei, H., Lu, C., Mao, J., Peng, C.H., Peng, S., Poulter, B., Riccuito, D., Shi, X., Tian, H., Wang, W., Zeng, N., Zhao, F., Zhu, Q., 2013. The North American Carbon Program Multi-Scale Synthesis and Terrestrial Model Intercomparison Project – Part 1: Overview and experimental design. Geosci. Model Dev. 6, 2121-2133.

Ito, A., 2011. A historical meta-analysis of global terrestrial net primary productivity: are estimates converging? Global Change Biology 17, 3161-3175.

Johnson, J.M.-F., Allmaras, R.R., Reicosky, D.C., 2006. Estimating source carbon from crop residues, roots and rhizodeposits using the national grain-yield database. Agronomy Journal 98, 622-636.

Kalfas, J.L., Xiao, X., Vanegas, D.X., Verma, S.B., Suyker, A.E., 2011. Modeling gross primary production of irrigated and rain-fed maize using MODIS imagery and CO2 flux tower data. Agricultural and Forest Meteorology 151, 1514-1528.

Lal, R., Follett, R.F., Stewart, B.A., Kimble, J.M., 2007a. Soil Carbon Sequestration to Mitigate Climate Change and Advance Food Security. Soil Science 172.

Lal, R., Reicosky, D.C., Hanson, J.D., 2007b. Evolution of the plow over 10,000 years and the rationale for no-till farming. Soil and Tillage Research 93, 1-12.

Li, Z., Liu, S., Tan, Z., Bliss, N.B., Young, C.J., West, T.O., Ogle, S.M., 2014. Comparing cropland net primary production estimates from inventory, a satellite-based model, and a process-based model in the Midwest of the United States. Ecological Modelling 277, 1-12.

Liu, S., 2009. Quantifying the spatial details of carbon sequestration potential and performance, in: McPherson, B., Sundquist, E. (eds.), Carbon Sequestration and its Role in the Global Carbon Cycle. American Geophysical Union, Washington, DC, pp. pp. 117-128.

Liu, S., 2012. Quantifying the spatial details of carbon sequestration potential and performance, in: McPherson, B., Sundquist, E. (eds.), Carbon Sequestration and its Role in the Global Carbon Cycle. American Geophysical Union, Washington, DC, pp. 117-128.

Liu, S., Bliss, N., Sundquist, E., Huntington, T.G., 2003. Modeling carbon dynamics in vegetation and soil under the impact of soil erosion and deposition. Global Biogeochemical Cycles 17, 1074, doi:1010.1029/2002GB002010.

Liu, S., Loveland, T.R., Kurtz, R., 2004. Contemporary carbon dynamics in terrestrial ecosystems in the southeastern plains of the United States. Environmental Management 33, S442-S456.

Liu, S., Tan, Z., Li, Z., Zhao, S., Yuan, W., 2011. Are soils of Iowa USA currently a carbon sink or source? Simulated changes in SOC stock from 1972 to 2007. Agriculture, Ecosystems & Environment 140, 106-112.

Lobell, D.B., Hicke, J.A., Asner, G.P., Field, C.B., Tucker, C.J., Los, S.O., 2002. Satellite estimates of productivity and light use efficiency in United States agriculture. Global Change Biology 8, 722-735.

Lokupitiya, E., Paustian, K., Easter, M., Williams, S., Andrén, O., Kätterer, T., 2012. Carbon balances in US croplands during the last two decades of the twentieth century. Biogeochemistry 107, 207-225.

Loveland, T.R., Belward, A.S., 1997. The IGBP-DIS global 1km land cover data set, DISCover: First results. International Journal of Remote Sensing 18, 3289-3295.

Loveland, T.R., Reed, B.C., Brown, J.F., Ohlen, D.O., Zhu, Z., Yang, L., Merchant, J.W., 2000. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. International Journal of Remote Sensing 21, 1303-1330.

Michalak, Anna M., Robert B. Jackson, Gregg Marland, Christopher L. Sabine, and the Carbon Cycle Science Working Group. 2011. A U.S. Carbon Cycle Science Plan.

NASA, 2014. North American Land Data Assimilation System project phase 2 NASA GSFC Hydrological Sciences Laboratory (HSL) and Goddard Earth Sciences Data and Information Services Center (GES DISC) ldas.gsfc.nasa.gov/nldas.

NASS, 2013. Agricultural statistics data base. National Agriculture Statistics Service, U.S. Department of Agriculture, Washington, D.C., USA., http://www.nass.usda.gov.

NRCS, 1994. U.S. general soil map (STATSGO). Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Web Soil Survey, Available online at http://websoilsurvey.nrcs.usda.gov/.

Ogle, S.M., Davis, K., Andrews, A., Gurney, K., West, T.O., Cooke, R.B., et al., 2006. Science plan: Mid-Continent Intensive Campaign of the North American Carbon Program. Greenbelt, MD.

Ogle, S.M., Breidt, F.J., Easter, M., Williams, S., Killian, K., Paustian, K., 2009. Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. Global Change Biology 16, 810-822.

Ogle, S.M., Jay Breidt, F., Eve, M.D., Paustian, K., 2003. Uncertainty in estimating land use and management impacts on soil organic carbon storage for US agricultural lands between 1982 and 1997.

Ogle, S.M., Swan, A., Paustian, K., 2012. No-till management impacts on crop productivity, carbon input and soil carbon sequestration. Agriculture, Ecosystems & Environment 149, 37-49.

Parton, W.J., Gutmann, M.P., Ojima, D., 2007. Long-term Trends in Population, Farm Income, and Crop Production in the Great Plains. BioScience 57, 737-747.

Parton, W.J., Schimel, D.S., Cole, C.V., Ojima, D.S., 1987. Analysis of factors controlling soil organic matter levels in great plains grasslands1. Soil Sci. Soc. Am. J. 51, 1173-1179.

Potter, C., Klooster, S., Myneni, R., Genovese, V., Tan, P.-N., Kumar, V., 2003. Continental-scale comparisons of terrestrial carbon sinks estimated from satellite data and ecosystem modeling 1982-1998. Global and Planetary Change 39, 201-213.

Prince, S.D., Haskett, J., Steininger, M., Strand, H., Wright, R., 2001. Net primary production of U.S. Midwest croplands from agricultural harvest yield data. Ecological Applications 11, 1194-1205.

PRISM, 2004. PRISM Climate Group, Oregon State University,, http://prism.oregonstate.edu, accessed Feb 2014.

Sahajpal, R., Zhang, X., Izaurralde, R.C., Gelfand, I., Hurtt, G.C., 2014. Identifying representative crop rotation patterns and grassland loss in the US Western Corn Belt. Computers and Electronics in Agriculture 108, 173-182.

Schaefer, K., Schwalm, C.R., Williams, C., Arain, M.A., Barr, A., Chen, J.M., Davis, K.J., Dimitrov, D., Hilton, T.W., Hollinger, D.Y., Humphreys, E., Poulter, B., Raczka, B.M., Richardson, A.D., Sahoo, A., Thornton, P., Vargas, R., Verbeeck, H., Anderson, R., Baker, I., Black, T.A., Bolstad, P., Chen, J., Curtis, P.S., Desai, A.R., Dietze, M., Dragoni, D., Gough, C., Grant, R.F., Gu, L., Jain, A., Kucharik, C., Law, B., Liu, S., Lokipitiya, E., Margolis, H.A., Matamala, R., McCaughey, J.H., Monson, R., Munger, J.W., Oechel, W., Peng, C., Price, D.T., Ricciuto, D., Riley, W.J., Roulet, N., Tian, H., Tonitto, C., Torn, M., Weng, E., Zhou, X., 2012. A model-data comparison of gross primary productivity: Results from the North American Carbon Program site synthesis. Journal of Geophysical Research: Biogeosciences 117, n/a-n/a.

Schmidt, Gail, Liu, Shuguang, and Oeding, Jennifer, 2011, Derived crop management data for the LandCarbon Project: U.S. Geological Survey Open-File Report, 2011–1303, 15 p.

Schuh, A.E., Lauvaux, T., West, T.O., Denning, A.S., Davis, K.J., Miles, N., Richardson, S., Uliasz, M., Lokupitiya, E., Cooley, D., Andrews, A., Ogle, S., 2013. Evaluating atmospheric CO2 inversions at multiple scales over a highly inventoried agricultural landscape. Global Change Biology 19, 1424-1439.

Schwalm, C.R., Williams, C.A., Schaefer, K., Anderson, R., Arain, M.A., Baker, I., Barr, A., Black, T.A., Chen, G., Chen, J.M., Ciais, P., Davis, K.J., Desai, A., Dietze, M., Dragoni, D., Fischer, M.L., Flanagan, L.B., Grant, R., Gu, L., Hollinger, D., Izaurralde, R.C., Kucharik, C., Lafleur, P., Law, B.E., Li, L., Li, Z., Liu, S., Lokupitiya, E., Luo, Y., Ma, S., Margolis, H., Matamala, R., McCaughey, H., Monson, R.K., Oechel, W.C., Peng, C., Poulter, B., Price, D.T., Riciutto, D.M., Riley, W., Sahoo, A.K., Sprintsin, M., Sun, J., Tian, H., Tonitto, C., Verbeeck, H., Verma, S.B., 2010. A model-data intercomparison of CO2 exchange across North America: Results from the North American Carbon Program site synthesis. Journal of Geophysical Research: Biogeosciences 115, G00H05.

Sellers, P.J., Tucker, C.J., Collatz, G.J., Los, S.O., Justice, C.O., Dazlich, D.A., Randall, D.A., 1996. A Revised Land Surface Parameterization (SiB2) for Atmospheric GCMS. Part II: The Generation of Global Fields of Terrestrial Biophysical Parameters from Satellite Data. Journal of Climate 9, 706-737.

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

Smith, P., Davies, C.A., Ogle, S., Zanchi, G., Bellarby, J., Bird, N., Boddey, R.M., McNamara, N.P., Powlson, D., Cowie, A., van Noordwijk, M., Davis, S.C., Richter, D.D.B., Kryzanowski, L., van Wijk, M.T., Stuart, J., Kirton, A., Eggar, D., Newton-Cross, G., Adhya, T.K., Braimoh, A.K., 2012. Towards an integrated global framework to assess the impacts of land use and management change on soil carbon: current capability and future vision. Global Change Biology 18, 2089-2101.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., Scholes, B., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., Towprayoon, S., Wattenbach, M., Smith, J., 2008. Greenhouse gas mitigation in agriculture. Philosophical Transactions of the Royal Society B: Biological Sciences 363, 789-813.

Sohl, T., Loveland, T., Sleeter, B., Sayler, K., Barnes, C., 2010. Addressing foundational elements of regional land-use change forecasting. Landscape Ecology 25, 233-247.

Sohl, T.L., Sayler, K.L., Drummond, M.A., Loveland, T.R., 2007. The FORE-SCE model: a practical approach for projecting land cover change using scenario-based modeling. Journal of Land Use Science 2, 103-126.

Tan, Z., Liu, S., 2013. Baseline-Dependent Responses of Soil Organic Carbon Dynamics to Climate and Land Disturbances. Applied and Environmental Soil Science 2013, 7.

Tan, Z., Liu, S., Johnston, C.A., Liu, J., Tieszen, L.L., 2006. Analysis of ecosystem controls on soil carbon source-sink relationships in the northwest Great Plains. Global Biogeochemical Cycles 20.

Tan, Z., Liu, S., Johnston, C.A., Loveland, T.R., Tieszen, L.L., Liu, J., Kurtz, R., 2005. Soil organic carbon dynamics as related to land use history in the northwestern Great Plains. Global Biogeochemical Cycles 19, GB3011.

Thorndike, R.L., 1953. Who Belongs in the Family? Psychometrika 18, 10.

Townshend, J., Justice, C., Li, W., Gurney, C., McManus, J., 1991. Global land cover classification by remote sensing: present capabilities and future possibilities. Remote Sensing of Environment 35, 243-255.

United States Department of Agriculture (USDA), 2006. Major land resource regions custom report (USDA Agriculture handbook 296). USDA. http://soils.usda.gov/MLRAExplorer, accessed Oct 22nd 2012.

USDA, N., 2012. NRCS Geospatial Data Gateway.

Vogelmann, J.E., S.M. Howard, L. Yang, C. R. Larson, B. K. Wylie, and J. N. Van Driel,, 2001. Completion of the 1990's National Land Cover Data Set for the conterminous United States. Photogrammetric Engineering and Remote Sensing 67, 650-662.

West, T.O., Bandaru, V., Brandt, C.C., Schuh, A.E., Ogle, S.M., 2011. Regional uptake and release of crop carbon in the United States. Biogeosciences 8, 2037-2046.

West, T.O., Brandt, C.C., Baskaran, L.M., Hellwinckel, C.M., Mueller, R., Bernacchi, C.J., Bandaru, V., Yang, B., Wilson, B.S., Marland, G., Nelson, R.G., Ugarte, D.G.D.L.T., Post, W.M., 2010. Cropland carbon fluxes in the United States: increasing geospatial resolution of inventory-based carbon accounting. Ecological Applications 20, 1074-1086.

West, T.O., Brandt, C.C., Marland, G., De La Torre Ugarte, D.G., Larson, J., Hellwinckel, C.M., Wilson, B., Tyler, D.G., Nelson, R.G., 2008. Estimating regional changes in soil carbon with high spatial resolution. Soil Science Society of America Journal 72, 285-294.

West, T.O., Post, W.M., 2002. Soil organic carbon sequestration rates by tillage and crop rotation. Soil Sci. Soc. Am. J. 66, 1930-1946.

Wiken, E., Jiménez Nava, F., Griffith, G., 2011. North American Terrestrial Ecoregions

Level III, in: Cooperation, C.f.E. (Ed.), Montreal, Canada, p. 149.

Williams, J.R., 1990. The Erosion-Productivity Impact Calculator (EPIC) Model: A Case History. Philosophical Transactions of the Royal Society of London B: Biological Sciences 329, 421-428.

Wilts, A.R., Reicosky, D.C., Allmaras, R.R., Clapp, C.E., 2004. Long-term corn residue effects. Soil Science Society of America Journal 68, 1342-1351.

Wu, Y., Liu, S., Li, Z., Dahal, D., Young, C.J., Schmidt, G.L., Liu, J., Davis, B., Sohl, T.L., Werner, J.M., Oeding, J., 2014. Development of a generic auto-calibration package for regional ecological modeling and application in the Central Plains of the United States. Ecological Informatics 19, 35-46.

Zhang, X., Izaurralde, R.C., Manowitz, D.H., Sahajpal, R., West, T.O., Thomson, A.M., Xu, M., Zhao, K., LeDuc, S.D., Williams, J.R., 2015. Regional scale cropland carbon budgets: Evaluating a geospatial agricultural modeling system using inventory data. Environmental Modelling & Software 63, 199-216.

Zhang, X., Sahajpal, R., Manowitz, D.H., Zhao, K., LeDuc, S.D., Xu, M., Xiong, W., Zhang, A., Izaurralde, R.C., Thomson, A.M., West, T.O., Post, W.M., 2014. Multi-scale geospatial agroecosystem modeling: A case study on the influence of soil data resolution on carbon budget estimates. Science of The Total Environment 479–480, 138-150.

Zhao, M., Running, S.W., Nemani, R.R., 2006. Sensitivity of Moderate Resolution Imaging Spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. Journal of Geophysical Research: Biogeosciences 111, G01002.

Zhao, S., Liu, S., 2014. Scale criticality in estimating ecosystem carbon dynamics. Global change biology 20, 2240-2251.

Zhao, S., Liu, S., Li, Z., Sohl, T.L., 2009. Ignoring detailed fast-changing dynamics of land use overestimates regional terrestrial carbon sequestration. Biogeosciences 6, 1647-1654.

Zhao, S., Liu, S., Li, Z., Sohl, T.L., 2010. A spatial resolution threshold of land cover in estimating terrestrial carbon sequestration in four counties in Georgia and Alabama, USA. Biogeosciences 7, 71-80.

CHAPTER 4. SIMULATING CROPLAND SOIL ORGANIC CARBON CHANGES IN THE MIDWEST TEMPERATE PRAIRIES FROM 1980 TO 2012

Li, Z., Liu, S., Tan, Z., Sohl, T.L. 2016. Simulating cropland soil organic carbon changes in the Midwest temperate prairies from 1980 to 2012. To be submitted to Ecological Modelling.

4.0 ABSTRACT

Understanding the effects of management practices on soil organic carbon (SOC) is important for designing effective policies to mitigate greenhouse gas emissions in agriculture. In the Midwest United States, management practices in the croplands have been improved to increase crop production and reduce SOC loss since the 1980s. Many studies of SOC dynamics in croplands have been performed to understand the effects of management, but the results are still not conclusive. This study quantified SOC dynamics in the Midwest croplands from 1980 to 2012 with the General Ensemble Biogeochemical Modeling System (GEMS) and available management data. Our results showed that the total SOC in the croplands decreased from 1190 Tg C in 1980 to 1107 TgC in 1995, and then increased to 1176 TgC in 2012. The continuous cropping and intensive tillage may drive the SOC loss in the early period. The increase of crop production and adoption of conservation tillage increased the total SOC so there was only 1% decrease in the total SOC stock after 32 years. The SOC changes also have large spatial variations. Major SOC losses occurred in the north and south of the region, where SOC baseline values were high and cropland production were low. The SOC gains took place in the central of the region where SOC baseline values were moderate and cropland production were higher than the other areas. We simulated multiple land-use land-cover (LULC) change scenarios and analyzed the results. The analysis showed that among all the LULC changes, agricultural technology that increased cropland production had the greatest impact on the SOC changes, followed by the tillage practices, changes in crop species, and the conversions of cropland to other land use. The information of management practice-induced spatial variation in SOC can be useful for policy makers and farm

managers to develop long-term management strategies for increasing SOC sequestration in different areas.

4.1 INTRODUCTION

Identifying the key processes and drivers controlling carbon fluxes is critical to make carbon management decisions (Michalak et al., 2011). Soil organic carbon (SOC) is an important storage component of ecosystem carbon that is influenced largely by human activities. Many early studies showed that SOC declined after land use change from natural grassland to cropland (Follett R.F., 2001; Guo and Gifford, 2002; Rattan Lal et al., 1998). But studies have also showed that improved agricultural management practices have increased SOC in cropland (Ogle et al., 2003; US-EPA, 2012). There are also studies suggesting that cropland has a large potential to sequestrate carbon and mitigate greenhouse gas (GHG) emissions (Lal, 2004; Pacala et al., 2001). However, there are still substantial discrepancies among studies of carbon sequestration in croplands. For example, a study in Iowa found that the carbon sequestrated in cropland soils by reduction in tillage intensity was about 1.9 TgC based on 1998 data (Brenner et al., 2001). A later study showed that the increase in SOC may be much lower (0.6 TgC) by accounting for SOC loss due to the periodic alternating of low- and high-intensity tillage practices (West et al., 2008). But a study using process model indicate that SOC in Iowa is a carbon source if the whole soil profile was considered instead of only the top 20cm soil (Causarano et al., 2008). Another study using a process model also found that SOC in

the whole soil profile decreased in Iowa due to the improvement of cropland soil drainage conditions (Liu et al., 2010).

In the Midwest temperate prairies, most of the native grasslands were converted to cropland after the European settlement beginning in the 1860s (Parton et al., 2007). The grassland SOC declines by up to 50% after cultivation, but such losses could be overcome by improved cropland management. Past research suggested that increases in conservation tillage in cropland have sequestrated more SOC in the cropland than other practices (Eve et al., 2002; Lal et al., 2007; West et al., 2008). Several studies have showed that SOC increased on cropland in the USA due to conservation tillage and cropland restoration programs (Eve et al., 2002; Ogle et al., 2009; Ogle et al., 2003; West et al., 2008). However, about 37% of the cropland in the USA is still using intensive tillage (CTIC, 2008). These croplands may not sequester much SOC, or may even lose SOC since they have higher SOC decomposition rates and surface erosion. A study in the Midwest cropland found the change to less intensive tillage increased SOC of 45 TgC from 1990 to 2000 but the tillage intensification caused a SOC loss of 11.2 TgC during the same time period (West et al., 2008). Thus, when considering the effects of tillage management on cropland SOC dynamics, it's necessary to include all the changes in tillage practices.

Research has also showed that increasing carbon input through cropping practices is as important as reducing tillage intensity (Ogle et al., 2005). Increases in crop NPP not only produced more crop residues but also increased root biomass amount, both of which increased carbon inputs into the SOC (Follett, 2001; Lal et al., 2007). Given the large increase in crop production from 1980 to 2000, increased carbon inputs may become an

important factor in the SOC dynamics in the Midwest region. A study on European cropland carbon dynamics using model simulation found that increasing crop residue return to the soil can build up the SOC, but this effect is compensated by other management practices, such as intensification of tillage and replacement of manure by mineral fertilizers (Gervois et al., 2008). A later study using multiple models and inventory data concluded that the agricultural management practices impacting litter inputs were as important as the decomposition of soil organic matter in European croplands (Ciais et al., 2010).

The goal of this research is to study the SOC dynamics for croplands in the Midwest temperate prairies from 1980 to 2012 and understand the mechanisms of the SOC changes under the land use and land cover change (LULC) and management practices. We used spatially explicit LULC data and available cropland management statistics to investigate two key science questions: Is the cropland in the region a carbon sink or source, and what is the major driver of the carbon dynamics in cropland? It will be necessary to find out the major driving factors of SOC dynamics in this region and the mechanisms behind them. These findings will help to develop more effective carbon management plans for vulnerable carbon pools in this region.

4.2 METHODS

4.2.1 Study area

The research area is the Temperate Prairies of the Northern Great Plains (Figure 4.1). The U.S. Environmental Protection Agency (EPA) defines this area as level III Ecoregion 9.2 and stretches across eastern North Dakota, Minnesota, eastern South Dakota, most of

Iowa, Nebraska, Missouri, Kansas and northern Oklahoma (US EPA, 1999). This ecoregion covers multiple major land resource areas (MLRA) and has large variation in climate, soil, and cropping systems (USDA, 2006). Eastern North Dakota and eastern South Dakota are in the Northern Great Plains Spring Wheat Region (USDA, 2006). The dominant soil type is Mollisols and the major cropping system is dry-farmed spring wheat. Iowa and western part of South Dakota, Nebraska and Kansas falls in the Central Feed Grains and Livestock Region (USDA, 2006). This region has the most favorable climate and soil for agriculture. The major cropping systems are continuous corn and a corn-soybean rotation. Southern Nebraska and Kansas belong to the Central Great Plains Winter Wheat and Range Region (USDA, 2006). The dominant soil type is Mollisols with large acreages of Alfisols, Entisols, and Inceptisols. Grazing and dry-farmed winter wheat are the major land uses in this region.
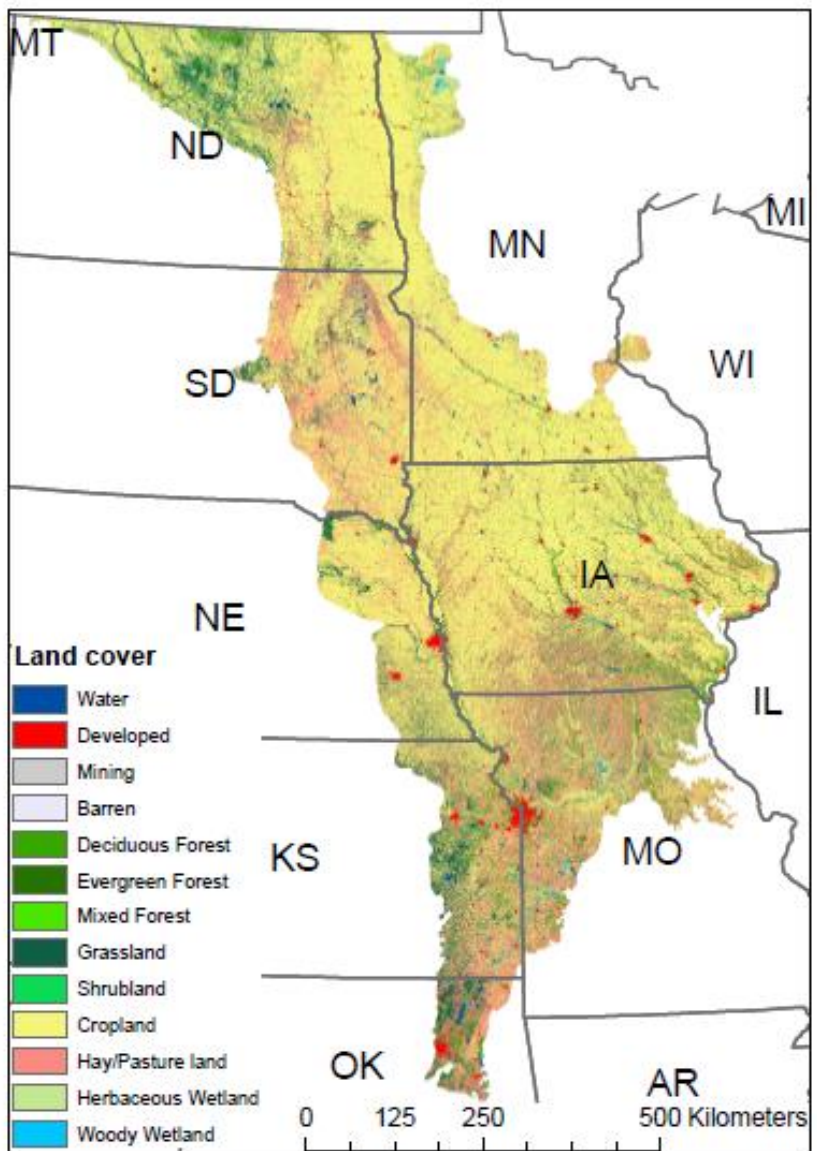
Figure 4.1 Land use and land cover types in the Temperate Prairies.

4.2.2 GEMS modeling framework

The General Ensemble Biogeochemical Modeling System (GEMS) is a regional

modeling framework that uses spatially explicit LULC data and biogeochemical models

to study the carbon dynamics in large regions (Liu, 2009; Liu et al., 2004). GEMS applies

LULC data from remotely sensed products along with information on soils, terrain, and

other environmental factors, to provide spatially explicit inputs of vegetation biomass, soil nutrient status, and management impacts to the biogeochemical models. GEMS model has been extensively tested for crop management to enable automated processes for calibrating the biogeochemical model parameters with crop inventory data and the explicit inclusion of the major types of management and disturbances on ecosystems (Li et al., 2014; Liu, 2012; Wu et al., 2014).

This study used the biogeochemical model Erosion-Deposition-Carbon-Model (EDCM) in GEMS to simulate the LULC and management impacts on soil organic carbon. EDCM is an ecosystem model that simulates the dynamics of carbon and nitrogen in vegetation biomass and soil (Liu et al., 2003). It simulates crop land soil carbon dynamics based on multiple processes such as crop production, residue inputs and soil decomposition at monthly time steps.

4.2.3 Input datasets

4.2.3.1 Land-use and land-cover (LULC) data

Two LULC spatial data sets published by USGS were used to construct the LULC impact on the SOC dynamics from 1980 to 2012 in this study. Both datasets were simulation results of the FORE-SCE framework developed by the USGS (Sohl et al., 2010; Sohl et al., 2007). The first LULC data were developed to study the ecological processes driving landscape changes in the Great Plains and contains 250 meter resolution LULC data from 1938 to 1992. The second dataset was generated for USGS land carbon project and used for assessing LULC impacts on ecosystem carbon dynamics and carbon sequestration potential (Zhu et al., 2010). This LULC dataset was also

simulated using FORE-SCE and provided historical data from 1992 to 2005 and future scenario data from 2005 to 2050 (Zhu et al., 2011).

Both datasets have the same spatial resolution and land cover classifications. To save computation time and match with climate data, we used the 4km instead of 250m as the spatial resolution. We downloaded the original datasets from USGS land cover modeling website (http://landcover-modeling.cr.usgs.gov). The two datasets were combined with python programs using nearest neighbor method to generate a land cover time series from 1980 to 2012 in the study area with 4km spatial resolution. For the years from 2006 to 2012, we used the A2 scenario outputs from the FORE-SCE model. A2 scenario showed dramatic increases in anthropogenic land covers and corresponding declines in natural land covers (Sohl et al., 2012). In A2 scenario outputs, the cropland area increase from 2006 to 2012, which matched the observations from USDA surveys in this region.

4.2.3.2 Climate data

For this study, we used climate data produced by the Parameter-elevation Regressions on Independent Slopes Model (PRISM) from the Oregon State University (PRISM Climate Group, http://www.prismclimate.org, accessed Feb 2014). The PRISM data were downloaded from Oregon State University ftp site and processed for the study area. The meteorological inputs to the GEMS model were monthly minimum temperature, maximum temperature and precipitation from 1980 to 2012 with 4 km spatial resolution.

4.2.3.3 Soil data

We used the spatial soil dataset generated for Land Carbon project as the initial soil input for this study. The soil attributes were generated with data from the SSURGO database (USDA Natural Resources Conservation Service, 2009) and processed to

generate multiple maps at a 250 meter resolution. The soil attributes included soil organic carbon content, bulk density, available water content and soil texture (sand, silt and clay).

4.2.3.4 Crop management data

We used county level USDA census data and the spatial LULC change dataset to create the crop rotations in the cropland. The census data included the county FIPS, year, total acres planted for major crops, total acres harvested and yields for major crops within each county from 1980 to 2012. We grouped all the harvested crops into five major categories: corn, soybean, spring wheat, winter wheat and other crops. The planted area for each crop was converted to percentage of the total cropland area in the county. For each simulated cropland pixel, a Monte-Carlo method was used to decide the crop type for each year (Schmidt et al., 2011). The reported yields for the major crops were converted to carbon using the conversion factors from earlier studies and compared with GEMS simulated yields (Li et al., 2014; West et al., 2010).

The tillage practice data was obtained from the National Crop Residue Management Survey collected by the Conservation Technology Information Center (CTIC) (CTIC, 2008). CTIC collected the area information for intensive tillage, reduced tillage, and conservational tillage from 1989 to 2004 for corn, soybean and small grains for all the counties. We converted the tillage area to the probability of the tillage using the crop planted area in the county. A Monte-Carlo method was then used to decide the tillage type for each crop pixel in a given year. Any years before 1989 used the tillage probability in 1989 and the years after 2004 used the information in 2004.

4.2.4 Model calibration and verification

The major crop growth parameters were calibrated using state-level crop yield data (Li et al., 2014). A subset of points within the state were randomly selected and simulated to predict crop yields between 1980 and 2012. The simulated crop yields were compared with USDA reported yield data in the state. GEMS then adjusted the parameters by the difference and repeated this procedure until the overall prediction error was less than 5% (Li et al., 2014; Wu et al., 2014). The parameters for the major crops (corn, soybean, spring wheat and winter wheat) were adjusted using this method for all the states in the study area and the calibrated parameter values were stored in an external file to be used in the simulation.

The simulated crop yields of the four major crops were compared with the USDA reported yield data (Figure 4.2). Generally, the simulated grain yields achieved a good match with the observed crop yields for the four major crops. GEMS simulated corn yields better than other crops with R-square value at 0.70. Compared with corn and soybeans, the simulated wheat yields showed poor performance for capturing annual variations. We encountered some difficulties in matching the planting date with winter wheat in the spring. For winter wheat, the typical planting date is usually in the fall and harvest date is in the late spring. GEMS simulates crop growth at monthly time step and this simplification may bring more bias in the spring than in the summer when temperatures are high. We also noticed some over estimation of crop yields for all the crops in certain years. GEMS simulations may overestimate the crop yields under extreme climate conditions, such as drought and flooding. For example, in 2012, severe

drought happened in the Midwest and lowered the yields of major crops (Boyer et al., 2013) but all the simulated crop yields were 5-20% higher than reported yields in 2012.
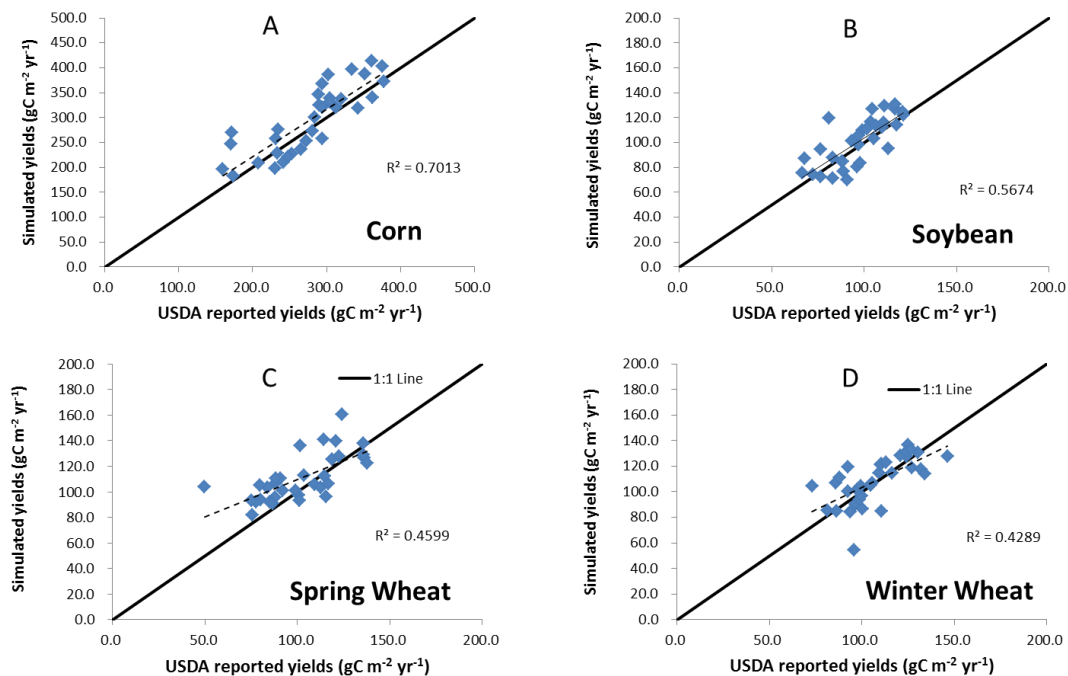
Figure 4.2. Simulated annual crop yields comparing with USDA reported yields for corn (A), soybean (B), spring wheat(C), winter wheat(D).

4.2.5   Model simulation scenarios

To assess the LULC and management practice impacts on SOC dynamics, we built five model scenarios based on the data availability:

1. Historical scenario (HIST): This scenario used historical LULC, crop growth information and CTIC data sources. The simulation was done by combining all the historical management data from 1980 to 2012. This scenario also considered cropland production increases under improved technology.

2. Tillage scenario (TILL1980): This scenario assumed that all the tillage practices remained the same since 1980. Other modeling data were the same as HIST.

3. Land cover scenario (LC1980): This scenario assumed that cropland area remained the same since 1980, with cropland change to other land covers between 1980 and 2012. Other modeling data were the same as HIST.

4. Crop composition scenario (COMP1980): This scenario assumes that the distribution of crop species planted in the cropland remained the same since 1980. Other modeling data were the same as HIST.

5. Technology scenario (TECH1980): This scenario assumes that technological improvements that increased the cropland production did not occur after 1980. All other modeling data were the same as HIST.

For each simulation, GEMS first run for 10 years to stabilize the carbon pools and other state variables. The preliminary run used the PRISM climate data in 1980 and applied the same land cover and management practices in 1980. After the preliminary run, GEMS was run with the climate and LULC data from 1980 to 2012 to simulate the SOC dynamics under each scenario. The simulation results from these scenarios were compared to estimate the effects of management practices on SOC dynamics.

The spatial distribution of SOC changes was analyzed at the pixel level in the HIST scenario. The change of SOC in the HIST scenario was calculated for each pixel as:

$$\Delta SOC = (\ SOC[2012] - SOC[1980])$$

In order to demonstrate the consequences of the different land management practices on ecosystem SOC, we examined the simulated impact of these practices on SOC for all

the counties. To make the results comparable, we used the relative change instead of actual change values. For the HIST scenario, we calculated the SOC ratio in each county between1980 and 2012 by:

$$\text{Ratio}_{\text{HIST}} = \text{SOC}[2012] / \text{SOC}[1980]$$

For all the other scenarios, we computed the ratio of the 2012 SOC values between each scenario and the HIST scenario in each county.

$$\text{Ratio} = \text{SOC}_{\text{sce}}[2012]/ \text{SOC}_{\text{HIST}}[2012]$$

The ratio value is lower than 1.0 when less SOC was accumulated than the HIST scenario, or more SOC was lost than in the HIST scenario. This indicated that the changes of the management practice after 1980 had positive impacts on the SOC in the county. If the value was higher than 1.0, it meant that keeping the management practice as in 1980 would had higher SOC values instead of changing. This indicated the mananegative impacts on the SOC in this county.

4.3 RESULTS

4.3.1 Changes in LULC and management practices

Cropland occupied about 60% of the total land area and 74% of the agricultural area in Ecoregion 9.2. The cropland area showed small changes in FORE-SCE model results and the amount of change varied in different time periods. The total cropland area decreased about 1.8% between 1980 and 2001, from 32.03 Mha in 1980 to 31.46 Mha in 2001. After 2001, the total cropland area increased slightly to 31.52 Mha in 2012. In all the modeled cropland pixels, 77% of them had no land use change for the 33 year period.

About 23% of the cropland pixels experienced some type of land use change between 1980 and 2012, with most of the changes happening between 1989 and 2000. Of the cropland pixels that changed to other land cover types, about 84% of the pixels changed to grassland/pasture, 10% changed to wetlands, 5% changed to developed land, and only 1% changed to forest land.
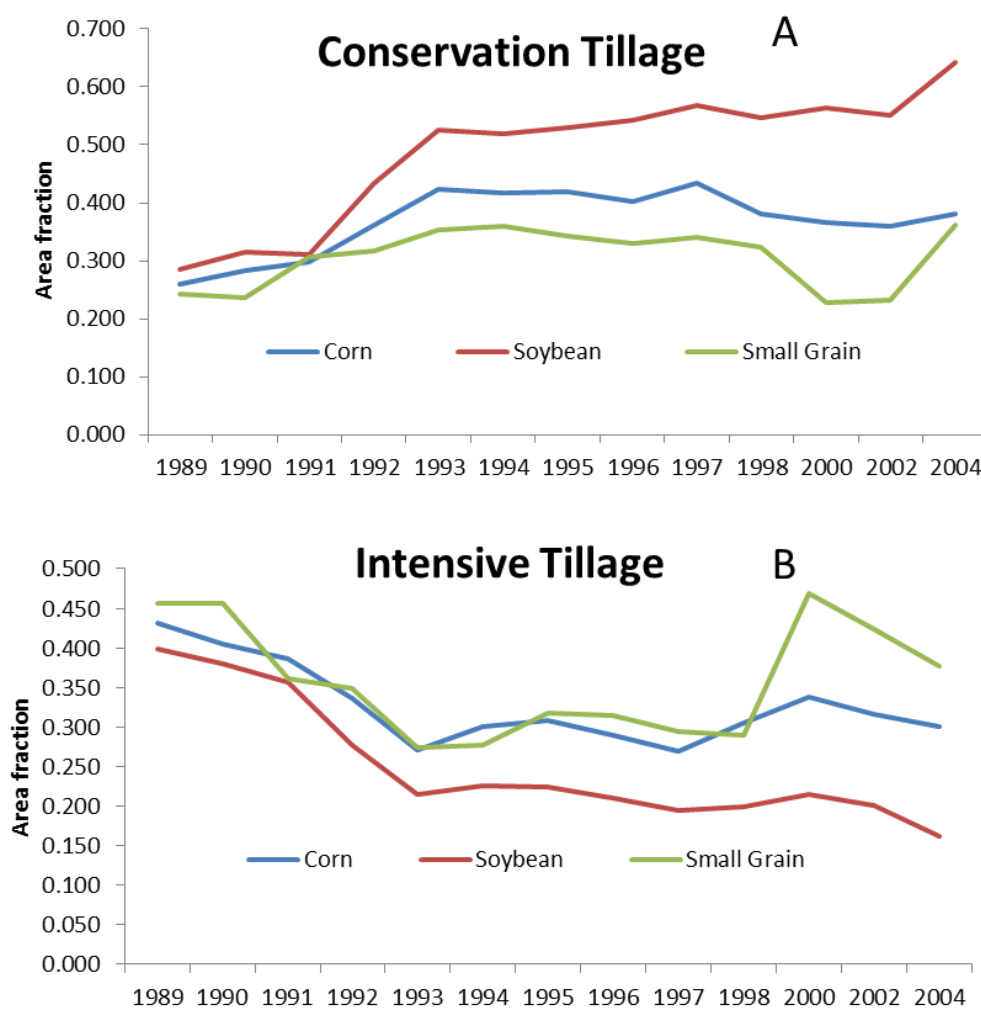

Figure 4.3. The change of conservation tillage area fraction (A) and intensive tillage area fraction (B) for the three crop categories between 1989 and 2004 in the study region.

Fractions of conservation tillage and intensive tillage were shown in Figure 4.3. All three crop categories showed clear increases in conservation tillage fractions from 1989 to 1994. For corn, the fraction of conservation tillage increased from 28% in 1989 to 42% in 1993. After 1993, the fraction of conservation tillage remained stable at around 40% for about 5 years and dropped to 38% in early 2000s. The tillage practices on soybean fields showed highest growth in conservation tillage. The fraction of conservation tillage increased from 28% in 1989 to 52% in 1993. Between 1993 and 2002, the fraction of conservation tillage changed varied 52% and 56%. For small grains, the fraction of conservation tillage practices increased from 24% in 1989 to 35% in 1993 and remained around that level until 1998. The fraction of conservation tillage decreased to 23% in 2000 and 2002 but retuned to 36% in 2004. The changes in intensive tillage showed decreasing trends for the three crop categories. For corn, the fraction of intensive tillage decreased from 43% in 1989 to about 30% between 1993 and 2004. The intensive tillage on soybean fields decreased from 39% in 1989 to 21 - 23% between 1993 and 2004. For small grains, intensive tillage decreased from 45% in 1989 to 27% in 1993, but increased thereafter to 47% in 2002 and 37% in 2004.

In addition to changes in the tillage practices, the planted area for the major crops also changed from 1980 to 2012 in the region. The USDA data showed that the planted area of the two major crops: corn and soybean, steadily increased from 1980 to 2012 (Figure 4.4). The fraction of corn planted area increased from 30% in 1980s to 34% in 2000s. The fraction of soybean planted area also increased from 24% in 1980s to 35% in 2000s. Meanwhile, the total fraction of planted wheat (spring and winter) and other crops decreased from 45% in 1980s to 30% in 2000s.
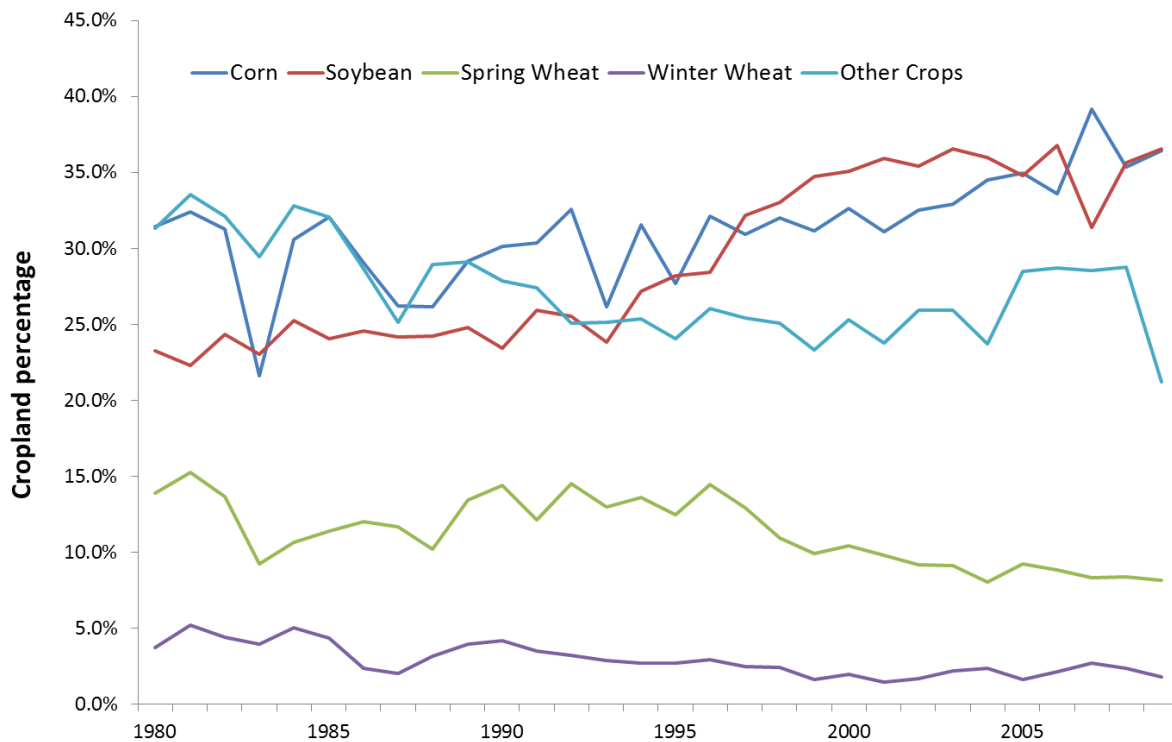
Figure 4.4. USDA reported major crop harvested areas between 1980 and 2015.

The USDA yield data for the four major crops are shown in Figure 4.5. The four major crops showed slightly different trends. Corn yields had the highest values and also showed the largest increase between 1980 and 2012. The yields of corn increased about 48%, from 223 gC m^{-2} yr^{-1} in the 1980s to 331 gC m^{-2} yr^{-1} after 2000. For the same time, the yields of soybean increased 30%, from 83 gC m^{-2} yr^{-1} in the 1980s to 107 gC m^{-2} yr^{-1} after 2000. The spring wheat increased 41% from 87 gC m^{-2} yr^{-1} (1980-1990) to 123 gC m^{-2} yr^{-1} (2000-2012). The winter wheat yields increased 32%, from 95 gC m^{-2} yr^{-1} (1980-1990) to 125 gC m^{-2} yr^{-1} (2000-2012).

Figure 4.5. USDA reported yields for corn, soybean, spring wheat, winter wheat from 1980 to 2012.

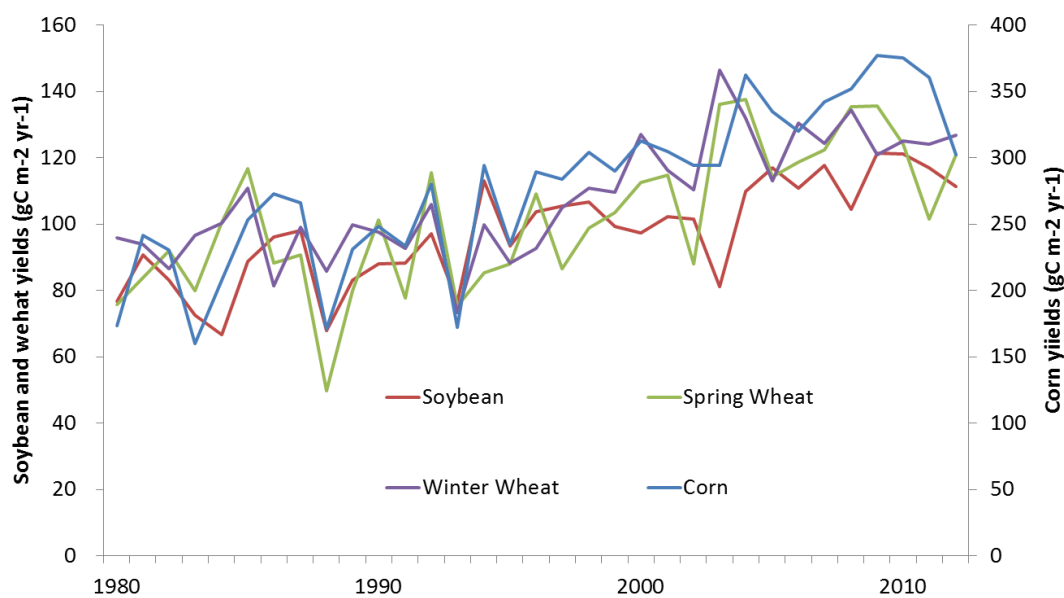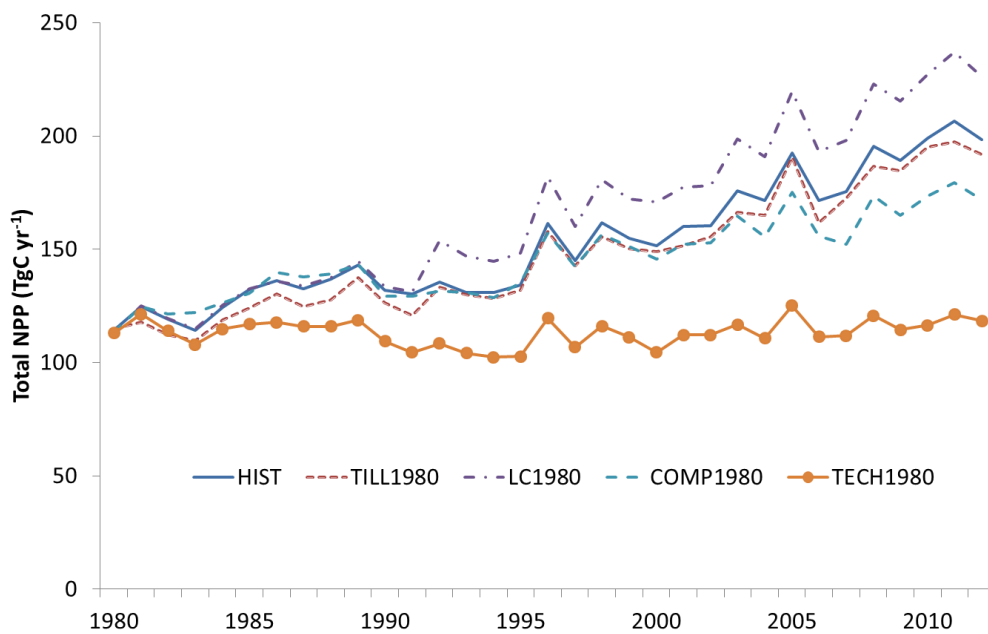Figure 4.6. Simulated cropland total NPP change from 1980 to 2012 in the 5 scenarios.

4.3.2   Simulated cropland carbon dynamics under the scenarios

The simulated cropland NPP of all the five scenarios is shown in Figure 4.6. The

simulated cropland total NPP increased from 1980 to 2012 for all the scenarios except

TECH1980. The total NPP for cropland increased about 43% over time in the HIST

scenario, from 128.1 $\pm$ 9.5 TgC yr^{-1} (1980 – 1990) to 183.3 $\pm$ 15.8 TgC yr^{-1} (2000 –

2012). This increase agreed with previous studies that the cropland production in the

Midwest has increased since 1980 (Hicke et al., 2004; Parton et al., 2007; Prince et al.,

2001). The simulated NPP showed slightly lower NPP between the TILL1980 and HIST

scenarios. The higher NPP in the HIST scenario was mainly caused by better SOC levels.

Out of all the scenarios, the highest NPP was in the LC1980 scenario, mainly caused by

the largest cropland area it had. Other studies also in the Great Plains have also showed

that restoring grassland/pasture on previous cropland caused a large decrease in plant

production (Hartman et al., 2011). The COMP1980 scenario showed lower total NPP

than HIST scenario after 1995. This is because in COMP1980 scenario, less corn was

planted than in the HIST scenario. Since corn has much higher production than all the

other field crops, less corn planted area produced lower values of total NPP than the

HIST scenario. The TECH1980 scenario has the lowest NPP since it excluded the

technology improvement effects on crop production.

The simulated total cropland SOC changes in the five scenarios are shown in Figure

4.7. The SOC changes generally followed the same trend, with an exception of the

TECH1980 scenario. The total SOC under the HIST scenario decreased about 6%

between 1980 and 1996, from 1190 TgC to 1107 TgC, and then increased about 5% to

1176 TgC in 2012 (Figure 4.7). The change of the total SOC is -1.2% after 32 years. This

indicated the whole region is a weak carbon source. The annual decrease rate of SOC under the HIST scenario was 5.1 TgC yr^{-1} from 1980 to 1996 and the mean rate of increase was 4.3 TgC yr^{-1} from 1996 to 2012. The other three scenarios: TILL1980, LC1980 and COMP1980 all showed similar trends but with different turning points and SOC levels in 2012. In the TILL1980 scenario, the total SOC kept decreasing until 2000 and increased to 1133 TgC in 2012. The total SOC under the LC1980 scenario decreased from 1980 to 1992 and increased to 1212 TgC in 2012. The total SOC under the COMP1980 scenario decreased from 1980 to 1996 and increased to 1144 TgC in 2012. Among all the scenarios, the LC1980 scenario led to the highest SOC after 32 years, about 2% higher than the SOC in 1980. The HIST scenario showed about 1% loss in SOC, followed by the COMP1980 (4%) and TILL1980 (5%). The largest SOC loss (14%) between 1980 and 2012 came under the TECH1980 scenario. These results indicated that technology improvements and the effects of increased cropland production were the largest factors on the total SOC changes in the region.
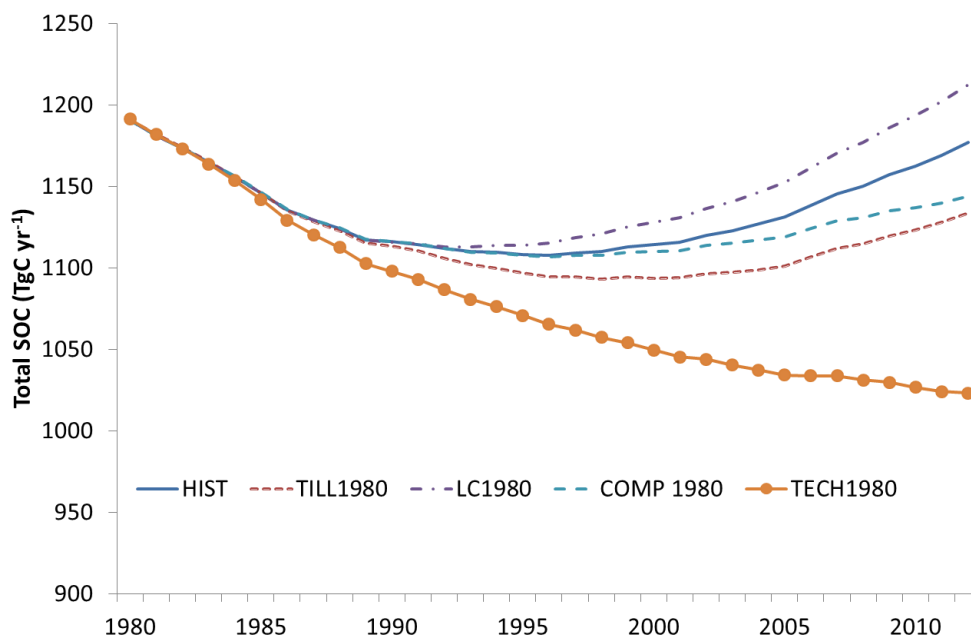
Figure 4.7. Simulated cropland total soil organic carbon change from 1980 to 2012 in the 5 scenarios.

4.3.3   Spatial distributions of soil organic carbon changes

The initial SOC level in 1980 and the simulated annual SOC change in the HIST scenario are shown in Figure 4.8. The SOC gains occurred in North Dakota, Minnesota and Iowa (Figure 4.8A). The SOC losses were mainly in the north part of the region and the SOC gains were in the central of the region (Figure 4.8B). In all the cropland pixels simulated, 47.8% showed SOC loss higher than 5% after 32 years, 37.5% showed SOC gain by more than 5% and 14.7% had smaller change in SOC after 32 years (< 5%). SOC gains were mainly in the regions with low initial SOC and SOC losses occurred in the region with high initial SOC. Generally, carbon sources were in the north and south, while carbon sinks presented in the center of the region.
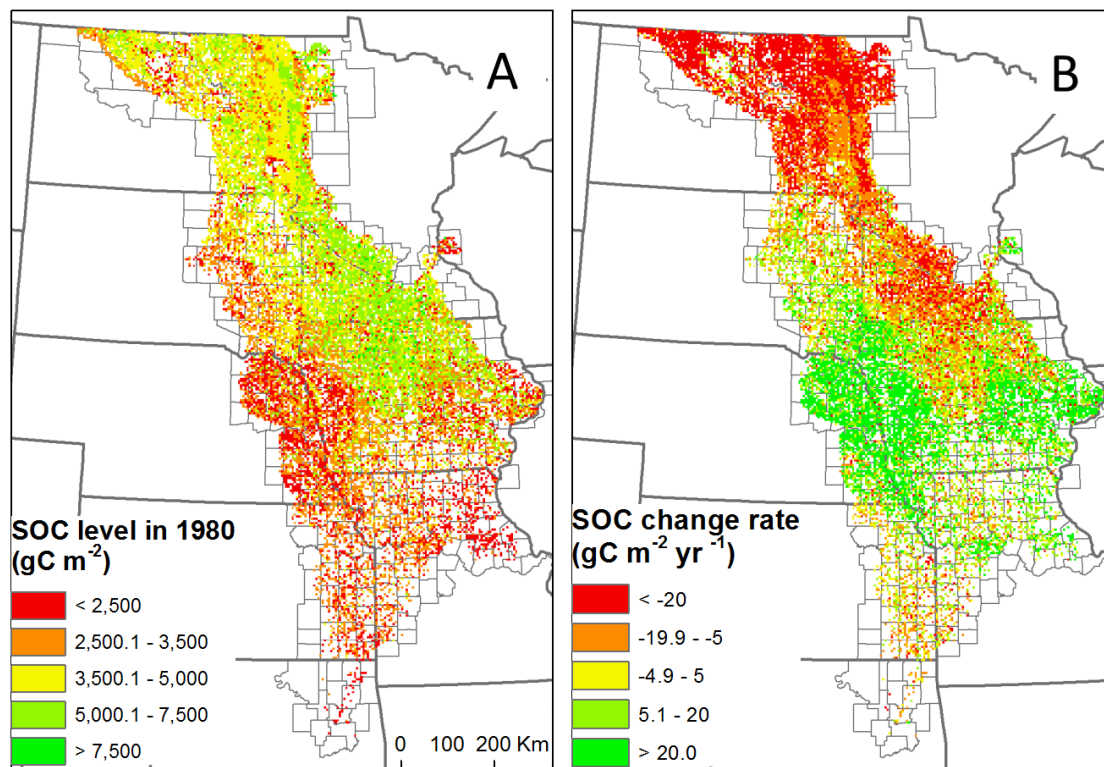
Figure 4.8. Top 20 cm soil organic carbon in the croplands in 1980 (A) and the SOC change rate in the HIST scenario (B).

The SOC changes at county levels are shown in Figure 4.9. At the county level, 31% of all the counties showed SOC loss by more than 5% after 32 years and 45% of the counties showed SOC gain by more than 5%. SOC losses tended to occur in the north and south parts of the region, included North Dakota, Minnesota, and Oklahoma. SOC gains were in Nebraska, Iowa, and north Missouri (Figure 4.9A).

As illustrated in Figure 4.9B, SOC showed large spatial variations between HIST scenario and the TILL1980 scenario. In all the counties, 43% showed lower SOC stocks in 2012 under the TILL1980 scenario than under the HIST scenario, and 13% showed higher SOC stocks than. Such difference may be driven by the different change trends of

tillage practices in the county. Though the CTIC data showed that the total conservation tillage area increased in the region (Figure 4.3), the conservation tillage area decreased in some counties. For example, in McHenry county, North Dakota. The conservation tillage area for small grains decreased about 25% between 1989 and 2004, from 28800 ha to 21596 ha in this county. The simulation result in this county showed keeping the conservation tillage the same as 1989 caused 9% higher SOC than decreased the conservation tillage to 2004 level. Thus, the counties showed higher SOC stocks under TILL1980 scenario than under HIST scenario mainly because the conservation tillage area were higher in these counties.
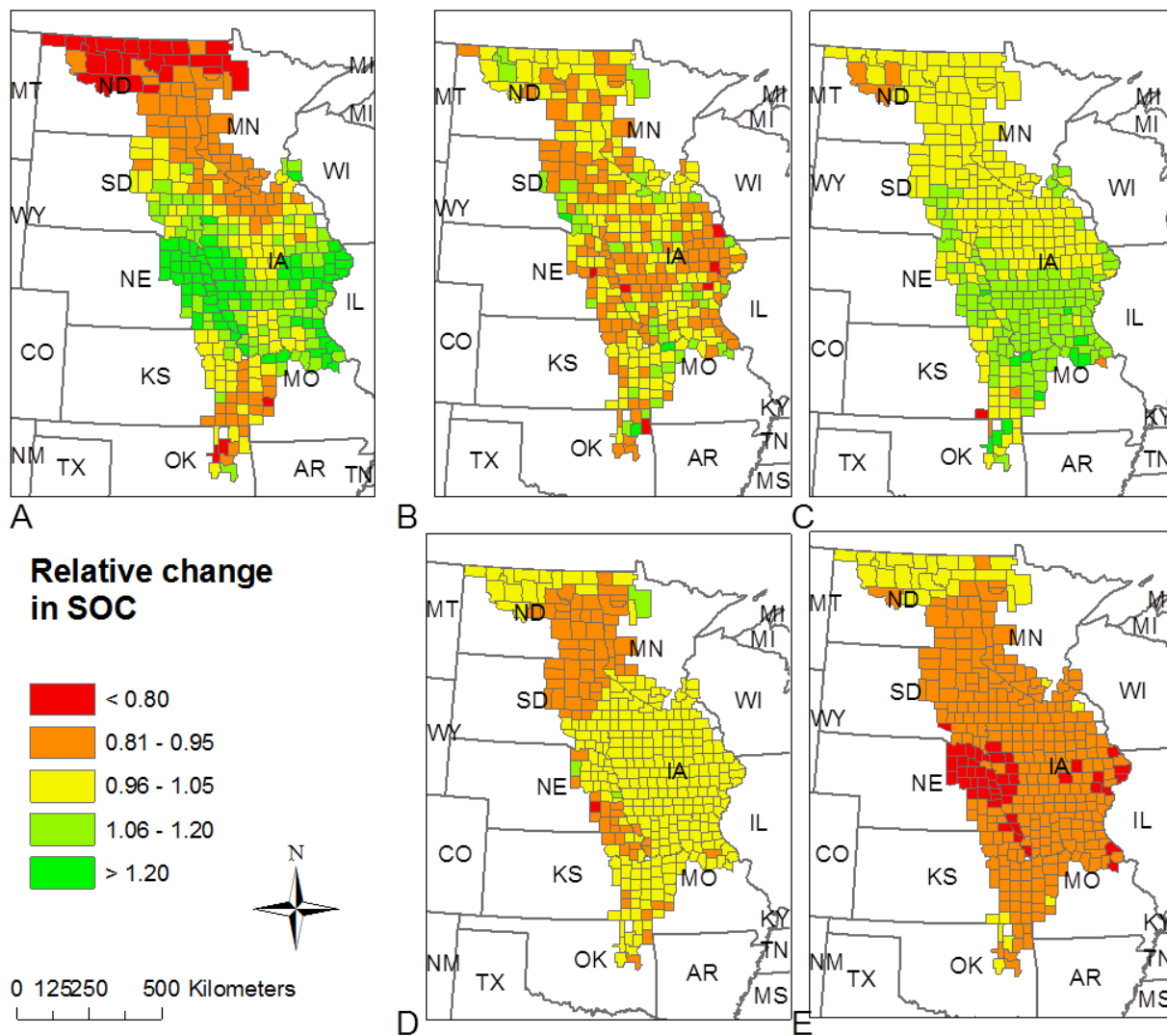
Figure 4.9. Relative change of soil organic carbon between1980 and 2012 in the HIST scenario (A); Relative change of the soil organic carbon in 2012 between HIST and TILL1980 scenario (B); between HIST and LC1980 scenario (C); between HIST and COMP1980 scenario (D); between HIST and TECH1980 scenario (E).

Figure 4.9C indicated that the conversion to other land cover types, such as grassland, did not necessarily increase the SOC as much as the improved management practices could do on the croplands, especially in the counties located in Iowa, Nebraska and Missouri, where croplands were mainly managed with conservation tillage and had

higher crop production and. In the LC1980 scenario, less than 2% of the counties showed lower SOC than the HIST scenario and 42% of the counties showed higher SOC in the cropland in 2012. About 56% of the counties only showed small changes (<5%) comparing with the HIST scenario after 32 years. Generally, both the increase in cropland production and the increase in conservation tillage could bring more carbon inputs, such as surface residue and root biomass into the soil than the natural grassland/shrubland. The simulation results also showed the conversion from cropland to other LULC had more effect in the counties with lower cropland production and higher percentage of intensive tillage, such as in North Dakota. In these counties, converting cropland to other LULC sequestered more SOC than keeping the cropland as cropland.

In the COMP1980 scenario, about 76% of the counties showed small SOC changes (<5%) comparing with the HIST scenario. 23% of the counties showed lower SOC than the HIST scenario and only 3 counties showed higher SOC after 32 years. The results indicated the changes in crop composition did not have large impacts on the SOC changes compared with other management practices. Figure 4.9D showed the counties with lower SOC were located in north part of the region, includes South Dakota, North Dakota and Minnesota. In these counties, the corn planted area increased more than other counties. In Nebraska and Iowa, the counties with soybean planted area increased after 1980 did not show as much increase in SOC as the counties with corn planted area increased. For example, in Antelope county, Nebraska, the soybean planted area increased more than 300%, from 14000 ha in the 1980s to over 48000 ha after 2000. During the same time, the corn planted area decreased about 15%, from over 80000 ha in the 1980s to 70000 ha after 2000. The simulated result in this county showed the

cropland could have 8% higher SOC stocks if the planted area for crops kept the same as in 1980. Thus, switching to high production crops instead of low production crops would more likely to increase the SOC carbon stocks.

Figure 4.9E indicated the TECH1980 scenario showed largest SOC changes. Comparing with other scenarios, 91% of the counties under TECH1980 scenario showed more SOC loss than the HIST scenario and the rest of the counties showed small differences (<5%). The counties showed the large SOC losses were mainly in Nebraska and Iowa. In these counties, the corn planted area was usually large and the production increase also large, with both showing higher impacts on the SOC than other counties in the region. The counties with smaller changes in SOC were mainly planted with low yield crops, such as Spring Wheat and Winter Wheat. The production increase in these crops also increased the carbon input into the cropland but the impacts are less than the crops with high yields, such as corn.

4.4 DISCUSSIONS

To our knowledge, our study is the first that comprehensively incorporated various land management practices into regional carbon cycle simulations. As can be seen from our study that the land use change activities can be major factors affecting the carbon cycle, and the characterization of these land use activities in space and time are usually not available. Therefore developing relevant geospatial data layers characterizing LULC changes is a major challenge in advancing carbon cycle research at regional and global scales, corroborating with the findings by the NACP interim synthesis (Liu et al., 2011).

Our study indicated a large increase in cropland production in this region, which agrees well with previous observations (e.g., Parton et al., 2007), and the increased productivity had the largest impact on SOC among all factors we have investigated. Enhancement of long-term crop production in the Great Plains can be attributed to increased irrigation, pest management, fertilizer applications, improved tillage practices, and improved plant varieties (Parton et al., 2007). The increase of crop NPP can in turn produce more aboveground residue and root biomass inputs into the soil, resulting in higher levels of SOC (Johnson et al., 2006; Lokupitiya et al., 2012; Wilts et al., 2004). An assessment of European SOC also found that enhanced NPP slowed the loss of SOC and may further increase SOC (Smith et al., 2005). However, some field studies showed NPP increase only had limited impacts on SOC as other factors (e.g., crop rotation) might be changing as well. For example, after reviewing the effects of enhancing crop rotations on the SOC dynamics, West and Post (2008) found changing wheat-fallow rotation to continuous wheat did not increase SOC even though the cropland production increased. In addition, SOC dynamics is confounded by other important factors such as initial SOC level. NPP increase might lead to SOC increase in less fertile regions, as shown in this study and others (Tan and Liu, 2013).

We found the change of tillage practices had the second largest impact on the cropland SOC in this region. Past studies have found that increased use of conservation tillage in cropland has sequestrated more SOC in the cropland than other management practices (Lal et al., 2007; Smith et al., 2008; West and Post, 2002). Several studies also found that SOC has increased on cropland in the USA due to conservation tillage (Ogle et al., 2003; West et al., 2008; Ogle et al., 2009). In this study, we found that while overall

conservation tillage increased in the region, intensive tillage increased in some areas as well. These local increases in intensive tillage may reduce the impact of conservation tillage effect at the regional level, as suggested by earlier study (West et al., 2008). The usage of conservation tillage may also cause lower crop productivity under certain conditions. A review of no-till management impacts on crop productivity found that corn yield could be reduced considerably with no-till under low nitrogen fertilization rates (Ogle et al., 2012).

The pathways of SOC under various scenarios showed two general temporal patterns of SOC change in our study (Figure 4.7). The first was the continuous decrease of SOC under TECH1980, which might be caused by the instability in the simulated soil carbon pools. In our study, we used 10 years as the initialization time, which is a common pre-run time in the regional studies (Potter et al., 2009 ; Zhang et al., 2015). Some studies used long initial time from 2000 to 7000 years when long-term land use data are available (Ogle et al., 2007; Ogle et al., 2009; Hartman et al., 2011). The second was the decrease-increase pattern under the other scenarios. The decrease of SOC before 1995 were shown in some studies might be possible but with high uncertainty. For example, a study of carbon balances in US croplands found the total carbon stock was slightly decreasing prior to 1990 (Lokupitiya et al., 2012). But another study with process-based model reported the SOC increased in US croplands from 1990 to 2000 (Ogle et al., 2009). US-EPA also reported that the cropland remaining cropland sequestrated 14.2 TgC in 1990 (US-EPA, 2012). The differences of the results may be driven by the differences in initial conditions, model inputs, and spatial coverage. Studies with long-term land use data showed that the increase of SOC started could be earlier in

the dryland, roughly in the 1950s. A simulation of 120 years dryland cropping in Great

Plains suggested that the cropland SOC declined since 1890 but increased after 1950

(Hartman et al., 2011). One major discrepancy is that our study showed large SOC loss in

poorly drained soils in the northern part of the region. These poorly drain soils contained

much higher SOC than dryland, which might result in large SOC decrease when drained

for cropping. Combining the decreased SOC in these poorly drained soils with the SOC

gains in dryland might have resulted in loss of SOC in this region before 1995. This

finding agreed with an earlier study which found the land use and management practice

changes on the cropland increased SOC in mineral soils by about 6.5 – 15.3 TgC yr^{-1} but

decreased SOC in organic or poorly-drained soils by 6.4 - 13.3 TgC yr^{-1} from 1982 to

1997 (Ogle et al., 2003).

In our simulations, we found that different management practices showed

geographically variable effects across the region. For example, SOC loss was obvious in

the northern part of the study area and SOC gain can be seen in most of the south-central

region (Figure 4.8). This spatial pattern of SOC change agrees well with previous studies

(Liu et al., 2011; Zhu et al., 2011). The reasons that define the spatial pattern are multi-

folds including initial SOC storage, change of site drainage conditions, and crop species

distributions that are dictated more by climate regimes. The north part of the study area

was dotted by numerous prairie potholes with poorly-drained conditions that promoted

high SOC storage (Figure 4.8A). The installation of tile drainage in the region for

agricultural purposes along with relatively low ecosystem productivity due to climate

conditions has led the loss of SOC (Liu et al., 2011). Therefore the loss of SOC in the

north was resulted from land use legacy, and it is unlikely that current agricultural land

use change activities can reverse this trend. In contrast, the high productivity of crops in the south-central, particularly in Iowa, can maintain or increase of SOC.

The area of crop land conversion to other land covers in the region was small during the study period. Consequently, its impact on SOC dynamics was minimal. Our study highlights the importance of considering land use change activities in carbon cycle research in agricultural regions. It is apparent that one cannot assume carbon sinks or sources are neutral in areas experiencing little change in land covers. The carbon conditions (i.e., stocks and fluxes) of the ecosystems under the same or similar land covers might be altered by a suite of other agents.

We noticed there are some limitations of this study. One major limitation is this study did not include the estimates of all GHG emissions from croplands. Past studies showed that when cropland production increased, the net GHG emissions also increased (Hartman et al., 2011). Such increase will reduce the effect of increase in SOC stock to mitigate the GHG emissions. Another limitation is the changes of soil drainage conditions in the region. Earlier studies showed installation of drainage system could lead to large carbon loss in deep soils (Liu et al., 2011). These limitations could be addressed in future studies by integrating more data sets, such as the historical change in nitrogen fertilizer, cropland drainage map.

Using spatial explicit LULC data inputs and county level survey data, we were able to simulate the SOC changes at a relatively high spatial resolution. Land managers can use such information, as well as other observations, such as the long-term field studies

and carbon fluxes measurements from flux towers, to choose the best management

practices in the region for cropland SOC sequestration.

4.5 CONCLUSIONS

The GEMS modeling framework with a coupled biogeochemical EDCM was utilized

to investigate management impacts on cropland SOC in Midwest temperate prairies from

1980 to 2012. Our simulation results showed the total SOC declined in the temperate

grassland region from 1980 to 1995 and then rose again to 2012. Overall the cropland in

the region is a weak carbon source over the 32 years and the results also showed clear

spatial differences in the SOC changes. Large SOC losses occurred in northern North

Dakota and Minnesota and large SOC gains were in Iowa, Nebraska and Northern

Missouri. The simulation of multiple management scenarios showed that technology that

increased the cropland production had the largest impacts on the cropland SOC changes,

followed by the tillage practices, changes in planted species and cropland change to other

land cover. The impacts of these practices also showed large differences spatially.

Understanding the spatial patterns of management impacts is important to study SOC

dynamics and provide useful information for better SOC management.

4.6 REFERENCES

Boyer, J.S., Byrne, P., Cassman, K.G., Cooper, M., Delmer, D., Greene, T., Gruis, F., Habben, J., Hausmann, N., Kenny, N., Lafitte, R., Paszkiewicz, S., Porter, D., Schlegel, A., Schussler, J., Setter, T., Shanahan, J., Sharp, R.E., Vyn, T.J., Warner, D., Gaffney, J., 2013. The U.S. drought of 2012 in perspective: A call to action. Global Food Security 2, 139-143.

Ciais, P., Wattenbach, M., Vuichard, N., Smith, P., Piao, S.L., Don, A., Luyssaert, S., Janssens, I.A., Bondeau, A., Dechow, R., Leip, A., Smith, P.C., Beer, C., Van Der Werf, G.R., Gervois, S., Van Oost, K., Tomelleri, E., Freibauer, A., Schulze, E.D., Carboeurope

Synthesis, T., 2010. The European carbon balance. part 2: croplands. Global Change Biology 16, 1409-1428.

CTIC, 2008. National crop residue management survey data. Conservation Technology Information Center.

Eve, M.D., Sperow, M., Paustian, K., Follett, R.F., 2002. National-scale estimation of changes in soil carbon stocks on agricultural lands. Environmental Pollution 116, 431-438.

Follett, R.F., 2001. Soil management concepts and carbon sequestration in cropland soils. XVth ISTRO Conference on Tillage at the Threshold of the 21st Century: Looking Ahead 61, 77-92.

Gervois, S., Ciais, P., de Noblet-Ducoudré, N., Brisson, N., Vuichard, N., Viovy, N., 2008. Carbon and water balance of European croplands throughout the 20th century. Global Biogeochem. Cycles 22, GB2022.

Hartman, M.D., Merchant, E.R., Parton, W.J., Gutmann, M.P., Lutz, S.M., Williams, S.A., 2011. Impact of historical land-use changes on greenhouse gas exchange in the U.S. Great Plains, 1883–2003. Ecological Applications 21, 1105-1119.

Hicke, J.A., Lobell, D.B., Asner, G.P., 2004. Cropland area and net primary production computed from 30 years of USDA agricultural harvest data. Earth Interact. 8, 1-20.

Johnson, J.M.-F., Allmaras, R.R., Reicosky, D.C., 2006. Estimating source carbon from crop residues, roots and rhizodeposits using the national grain-yield database. Agronomy Journal 98, 622-636.

Lal, R., Follett, R.F., Stewart, B.A., Kimble, J.M., 2007a. Soil Carbon Sequestration to Mitigate Climate Change and Advance Food Security. Soil Science 172.

Lal, R., Reicosky, D.C., Hanson, J.D., 2007b. Evolution of the plow over 10,000 years and the rationale for no-till farming. Soil and Tillage Research 93, 1-12.

Li, Z., Liu, S., Tan, Z., Bliss, N.B., Young, C.J., West, T.O., Ogle, S.M., 2014. Comparing cropland net primary production estimates from inventory, a satellite-based model, and a process-based model in the Midwest of the United States. Ecological Modelling 277, 1-12.

Liu, S., 2009. Quantifying the spatial details of carbon sequestration potential and performance, in: McPherson, B., Sundquist, E. (eds.), Carbon Sequestration and its Role in the Global Carbon Cycle. American Geophysical Union, Washington, DC, pp. pp. 117-128.

Liu, S., 2012. Quantifying the spatial details of carbon sequestration potential and performance, in: McPherson, B., Sundquist, E. (eds.), Carbon Sequestration and its Role in the Global Carbon Cycle. American Geophysical Union, Washington, DC, pp. 117-128.

Liu, S., Bliss, N., Sundquist, E., Huntington, T.G., 2003. Modeling carbon dynamics in vegetation and soil under the impact of soil erosion and deposition. Global Biogeochemical Cycles 17, 1074, doi:1010.1029/2002GB002010.

Liu, S., Loveland, T.R., Kurtz, R., 2004. Contemporary carbon dynamics in terrestrial ecosystems in the southeastern plains of the United States. Environmental Management 33, S442-S456.

Liu, S., Tan, Z., Li, Z., Zhao, S., Yuan, W., 2011. Are soils of Iowa USA currently a carbon sink or source? Simulated changes in SOC stock from 1972 to 2007. Agriculture, Ecosystems & Environment 140, 106-112.

Lokupitiya, E., Paustian, K., Easter, M., Williams, S., Andrén, O., Kätterer, T., 2012. Carbon balances in US croplands during the last two decades of the twentieth century. Biogeochemistry 107, 207-225.

Michalak, Anna M., Robert B. Jackson, Gregg Marland, Christopher L. Sabine, and the Carbon Cycle Science Working Group. 2011. A U.S. Carbon Cycle Science Plan.

Ogle, S.M., Breidt, F.J., Easter, M., Williams, S., Killian, K., Paustian, K., 2009. Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. Global Change Biology 16, 810-822.

Ogle, S.M., Jay Breidt, F., Eve, M.D., Paustian, K., 2003. Uncertainty in estimating land use and management impacts on soil organic carbon storage for US agricultural lands between 1982 and 1997.

Ogle, S.M., Swan, A., Paustian, K., 2012. No-till management impacts on crop productivity, carbon input and soil carbon sequestration. Agriculture, Ecosystems & Environment 149, 37-49.

Parton, W.J., Gutmann, M.P., Ojima, D., 2007. Long-term Trends in Population, Farm Income, and Crop Production in the Great Plains. BioScience 57, 737-747.

Potter, S. R., Atwood, J. D., Lemunyon, J., & Kellogg, R. L. (2009). A national assessment of soil carbon sequestration on cropland: a microsimulation modeling approach. Soil carbon sequestration and the greenhouse effect, (soilcarbonseque), 1-11.

Prince, S.D., Haskett, J., Steininger, M., Strand, H., Wright, R., 2001. Net primary production of U.S. Midwest croplands from agricultural harvest yield data. Ecological Applications 11, 1194-1205.

Schmidt, Gail, Liu, Shuguang, and Oeding, Jennifer, 2011, Derived crop management data for the LandCarbon Project: U.S. Geological Survey Open-File Report, 2011–1303, 15 p.

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

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., Scholes, B., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., Towprayoon, S., Wattenbach, M., Smith, J., 2008. Greenhouse gas mitigation in agriculture. Philosophical Transactions of the Royal Society B: Biological Sciences 363, 789-813.

Sohl, T., Loveland, T., Sleeter, B., Sayler, K., Barnes, C., 2010. Addressing foundational elements of regional land-use change forecasting. Landscape Ecology 25, 233-247.

Sohl, T.L., Sayler, K.L., Drummond, M.A., Loveland, T.R., 2007. The FORE-SCE model: a practical approach for projecting land cover change using scenario-based modeling. Journal of Land Use Science 2, 103-126.

Sohl, T.L., Sleeter, B.M., Sayler, K.L., Bouchard, M.A., Reker, R.R., Bennett, S.L., Sleeter, R.R., Kanengieter, R.L., Zhu, Z., 2012. Spatially explicit land-use and land-cover scenarios for the Great Plains of the United States. Agriculture, Ecosystems & Environment 153, 1-15.

Tan, Z., Liu, S., 2013. Baseline-Dependent Responses of Soil Organic Carbon Dynamics to Climate and Land Disturbances. Applied and Environmental Soil Science 2013, 7.

United States Department of Agriculture (USDA), 2006. Major land resource regions custom report (USDA Agriculture handbook 296). USDA.

US Environmental Protection Agency (EPA), 1999. Level III Ecoregions of the Continental United States. In: Karl, T.R., Melillo, J.M., Peterson, T.C. (Eds.), National Health and Environmental Effects Research Laboratory, Scale 1:7,500,000. U.S. Environmental Protection Agency, Corvallis, Oregon.

United States Environmental Protection Agency (US-EPA), 2012, Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2010.

West, T.O., Brandt, C.C., Baskaran, L.M., Hellwinckel, C.M., Mueller, R., Bernacchi, C.J., Bandaru, V., Yang, B., Wilson, B.S., Marland, G., Nelson, R.G., Ugarte, D.G.D.L.T., Post, W.M., 2010. Cropland carbon fluxes in the United States: increasing

geospatial resolution of inventory-based carbon accounting. Ecological Applications 20, 1074-1086.

West, T.O., Brandt, C.C., Marland, G., De La Torre Ugarte, D.G., Larson, J., Hellwinckel, C.M., Wilson, B., Tyler, D.G., Nelson, R.G., 2008. Estimating regional changes in soil carbon with high spatial resolution. Soil Science Society of America Journal 72, 285-294.

West, T.O., Post, W.M., 2002. Soil organic carbon sequestration rates by tillage and crop rotation. Soil Sci. Soc. Am. J. 66, 1930-1946.

Wilts, A.R., Reicosky, D.C., Allmaras, R.R., Clapp, C.E., 2004. Long-term corn residue effects. Soil Science Society of America Journal 68, 1342-1351.

Wu, Y., Liu, S., Li, Z., Dahal, D., Young, C.J., Schmidt, G.L., Liu, J., Davis, B., Sohl, T.L., Werner, J.M., Oeding, J., 2014. Development of a generic auto-calibration package for regional ecological modeling and application in the Central Plains of the United States. Ecological Informatics 19, 35-46.

Zhu, Zhiliang, ed., Bergamaschi, Brian, Bernknopf, Richard, Clow, David, Dye, Dennis, Faulkner, Stephen, Forney, William, Gleason, Robert, Hawbaker, Todd, Liu, Jinxun, Liu, Shuguang, Prisley, Stephen, Reed, Bradley, Reeves, Matthew, Rollins, Matthew, Sleeter, Benjamin, Sohl, Terry, Stackpoole, Sarah, Stehman, Stephen, Striegl, Robert, Wein, Anne, and Zhu, Zhiliang, 2010, A method for assessing carbon stocks, carbon sequestration, and greenhouse-gas fluxes in ecosystems of the United States under present conditions and future scenarios: U.S. Geological Survey Scientific Investigations Report 2010–5233, 188 p. (Also available at http://pubs.usgs.gov/sir/2010/5233/.)

Zhu, Zhiliang, ed., Bouchard, Michelle, Butman, David, Hawbaker, Todd, Li, Zhengpeng, Liu, Jinxun, Liu, Shuguang, McDonald, Cory, Reker, Ryan, Sayler, Kristi, Sleeter, Benjamin, Sohl, Terry, Stackpoole, Sarah, Wein, Anne, and Zhu, Zhiliang, 2011, Baseline and projected future carbon storage and greenhouse-gas fluxes in the Great Plains region of the United States: U.S. Geological Survey Professional Paper 1787, 28 p. (Also available at http://pubs.usgs.gov/pp/1787/.)

CHAPTER 5. SUMMARIES AND CONCLUSIONS

Cropland plays an important role in global carbon cycle and quantifying cropland carbon dynamics is important to ensuring food security and mitigating greenhouse gas emissions. Cropland carbon dynamic estimates remain highly uncertain over large regions. In recent years, high resolution cropland cover data sets were generated from remotely sensed satellite images. It is possible to use these spatially explicit data to advance the carbon cycle studies.

In this study, we developed the General Ensemble biogeochemical Modeling System (GEMS) that integrated spatially explicit land cover products with biogeochemical models for simulating regional carbon dynamics. I have simulated multiple carbon fluxes on cropland in the Midwest and tested the four research hypothesis in Chapter 1. The efforts are presented in three chapters (chapter 2 to 4) in journal article formats. The major findings are summarized as follows.

Hypothesis 1: Changes in the spatial patterns of planted crop types will not change the spatial patterns of cropland carbon fluxes.

This hypothesis was proved to be false. I used the Cropland Data Layer (CDL) from the U.S. Department of Agriculture (USDA) as the land cover input in GEMS to simulate multiple carbon fluxes in the Mid-Continent Intensive Campaign (MCI) region. The carbon fluxes simulated included net primary production (NPP), net ecosystem production (NEP), and soil organic carbon (SOC) change of the cropland. I compared the simulated results with the NPP estimates from USDA crop yield data and MODerate resolution Imaging Spectroradiometer (MODIS) NPP product. I found the three methods

showed large difference in cropland NPP estimates because they have different cropland areas and crop species inputs. I found the change in crop species could change the spatial patterns of the cropland NPP. Thus, the detailed mapping of crop species change in time and space is critical for estimating the spatial and temporal variability of cropland NPP.

Hypothesis 2: The uncertainties of the carbon fluxes estimated from multiple models are randomly distributed across croplands.

This hypothesis was proved to be false. I computed the model uncertainties of three cropland carbon fluxes from three methods (GEMS, crop inventory and the Environmental Policy Integrated Climate (EPIC) model). Using data mining and spatial statistics, I studied the spatial distributions of the uncertainties in relation to the land cover inputs. Results indicated that uncertainties for all three carbon fluxes were not randomly distributed, but instead formed multiple clusters within the MCI region. I further investigated the impacts of cropland percentage, cropland richness, and cropland diversity on these uncertainties at the county level. The results indicated that cropland percentage significantly influenced the uncertainties of NPP and NEP, but not on the uncertainties of SOC change. Greater uncertainties of NPP and NEP were found in counties with small cropland percentage. Cropland richness and diversity showed weaker impacts on the model uncertainties than cropland percentage. Our study demonstrated that the model uncertainties are not distributed randomly and land cover characteristics can contribute to form the spatial patterns of regional carbon fluxes uncertainties.

Hypothesis 3: cropland is a major carbon sink from 1980 to 2012.

This hypothesis was proved to be false. We used spatially explicit land cover datasets and management practice data as inputs to GEMS and simulated the cropland SOC dynamics from 1980 to 2012. According to the simulation results, the total cropland SOC decreased about 1% after 32 years. This indicated that the cropland was not a major carbon sink from 1980 to 2012. The spatial pattern of the cropland SOC changes also showed that cropland in the northern and southern part of the region lost carbon, while the cropland in the central of the region gained carbon.

Hypothesis 4: The increase of conservation tillage is the most important driving factor of the SOC changes from 1980 to 2012.

This hypothesis was proved to be false. We simulated multiple scenarios in the Midwest temperate prairie using GEMS and available land use and management data. The analysis of the results showed that technology that increased the cropland production had the largest impact on the cropland SOC change, followed by the tillage practices, planted species changes, and cropland change to other land cover.

In summary, our studies have the following findings:

1. The crop species information in the land cover inputs was important to provide accurate estimates on cropland NPP.
2. The cropland characteristics, such as cropland percentage, richness, and diversity can contribute uncertainties in cropland fluxes estimates of NPP and NEP, but not SOC changes.

3. Although the total SOC changes suggested the cropland was a weak carbon source in the Midwest, carbon sinks and sources showed large spatial differences across the region.

4. In all the management practices that impact the cropland SOC changes, technologies that increased cropland production had the largest impact, followed by tillage practices in the Midwest cropland.

Our study demonstrated the usage of spatially explicit land-use land-cover (LULC) in the carbon model is critical to estimate cropland carbon fluxes at the regional scale. Satellite remote sensing data can provide timely information on LULC across large region. Many earlier modeling works either use the prescribed LULC information generated from dynamic vegetation model or static land cover. These approaches ignored the spatial heterogeneity and temporal change of LULC and underestimated the spatial and temporal variations of carbon fluxes, particularly in agriculture-dominated regions. Future model development should consider using the LULC data sets derived from satellite remote sensing data instead of prescribed or static LULC data, along with other ancillary information on land use which can rarely be observed using remote sensing technology. Only through integrating the details of land cover change with ancillary land use change information, the complete picture of LULC can be characterized.

Our studies showed whether the cropland in the Midwest USA was a carbon sink or source depending on the management practices applied on the cropland. Such changes were impacted by the changes in management practices as well as other factors, such as climate and soil baselines. It is reasonable to expect the same management practices may

have different effects on SOC changes across the region. The GEMS modeling framework used in this study is capable of producing the distribution of carbon sources and sinks under certain management scenarios. It can be a powerful tool to investigate the outcomes and risks of the future potential carbon management plans on cropland.

The modeling framework could be further developed to evaluate more LULC impacts on carbon cycles. For example, if annual maps of irrigation are available for the region, we can effectively estimate the changes of carbon uptakes and SOC stocks under different irrigation scenarios in response to future climate change. If a drought severity map is available, we can use GEMS to give an estimate on the drought impacts on the carbon fluxes. These estimates can be compared with other observations, such as flux tower measurements for better understanding of the consequences of extreme events.

This study advanced the scientific knowledge of the cropland carbon cycle by using the LULC changes data produced from satellite observations. Using the geospatial information of LULC changes could produce more detailed carbon fluxes estimates and identified the mechanisms driving the spatial and temporal variations of the carbon fluxes in croplands. Our findings could help future studies to provide more accurate estimates on carbon fluxes and reduce the uncertainties from land cover inputs. The outcome of the study also provided the scientific basis for understanding of the carbon cycle in croplands.