2014

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Ecological Modelling 277 (2014) 1–12

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

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ARTICLE INFO

Article history:
Received 17 June 2013
Received in revised form 10 January 2014
Accepted 14 January 2014
Available online 6 February 2014

Keywords:
Net primary production
Biogeochemical model
MODIS
Crop inventory
USDA Cropland Data Layer
Mid-Continent Intensive Campaign

ABSTRACT

Accurately quantifying the spatial and temporal variability of net primary production (NPP) for croplands is essential to understand 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.

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 $g\,C\,m^{-2}\,yr^{-1}$ using different methods (Ciais et al., 2010). Such differences in NPP estimates are likely

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[1] Work performed under USGS contract G13PC00028.
[2] Work performed under USGS contract G10PC00044.

0304-3800/$ – see front matter
http://dx.doi.org/10.1016/j.ecolmodel.2014.01.012

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 ($-94.6\,\mathrm{Tg\,C\,yr^{-1}}$) than with inventory-based estimates ($-264.3\,\mathrm{Tg\,C\,yr^{-1}}$) and atmospheric inversion models ($-136.8\,\mathrm{Tg\,C\,yr^{-1}}$) (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 to over $850\,\mathrm{g\,C\,m^{-2}\,yr^{-1}}$ 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 $350\,\mathrm{g\,C\,m^{-2}\,yr^{-1}}$ in 1972 to $490\,\mathrm{g\,C\,m^{-2}\,yr^{-1}}$ 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):

$$\mathrm{GPP} = \varepsilon \times \mathrm{FPAR} \times \mathrm{PAR} \approx \varepsilon \times \mathrm{NDVI} \times \mathrm{PAR}, \tag{1}$$

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 (Lobell et al., 2002; Potter et al., 1993).

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. Materials and methods

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 (Fig. 1). The MCI region covers multiple major land resource areas (MLRA) and has large variation in climate, soil, and cropping systems. An MLRA is a region that has similar climate, soil, and land use systems 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 varies 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 a mean annual precipitation from 660 to 865 mm and a mean annual air temperature from 4 to 7 °C. The dominant soil type is Histosols and other major soil types include Alfisols, Spodosols, Entisols, and Mollisols. This region has large forest areas and the major cropping systems are corn and wheat.

Most of the central part and large fraction of the southwestern part of the MCI region is in the Central Feed Grains and Livestock Region. This region includes southern Minnesota, Iowa, Illinois, and northern Missouri (USDA, 2006). This region 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 a corn–soybean rotation. Most of the corn and soybeans in the United States are produced in this region.

The western part of the MCI region including part of South Dakota and Nebraska is in the Western Great Plains Range and Irrigated Region (USDA, 2006). This region has a mean annual precipitation from 330 to 560 mm and a mean annual air temperature

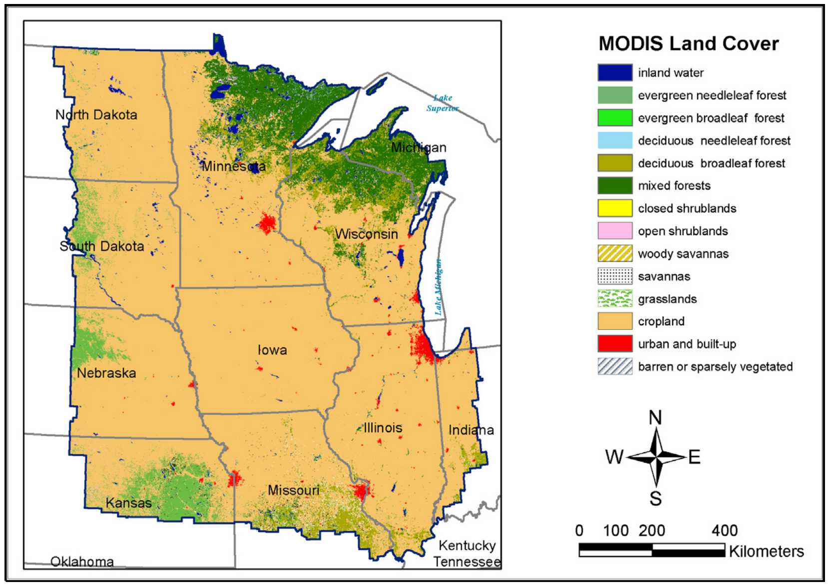

Fig. 1. The Mid-Continent Intensive Campaign (MCI) region boundary and land cover classes from the University of Maryland global land cover product.

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 are located mainly along streams, and a large amount of the water withdrawn is used for irrigation. The southwestern part of the MCI region including part of Nebraska and northern Kansas is in the Central Great Plains Winter Wheat and Range Region (USDA, 2006). This region has a mean annual precipitation from 815 to 990 mm and a 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 corn and soybean, and dry-farmed winter wheat.

Overall, the MCI region has a land area of about 124 million hectares (Mha), and over 40% of the land area is used for agriculture. Between 1990 and 2000, over 30 Mha of cropland were planted with corn and soybean, and about 10 Mha were planted with small grains and other crops (West et al., 2008). Corn, soybean, spring

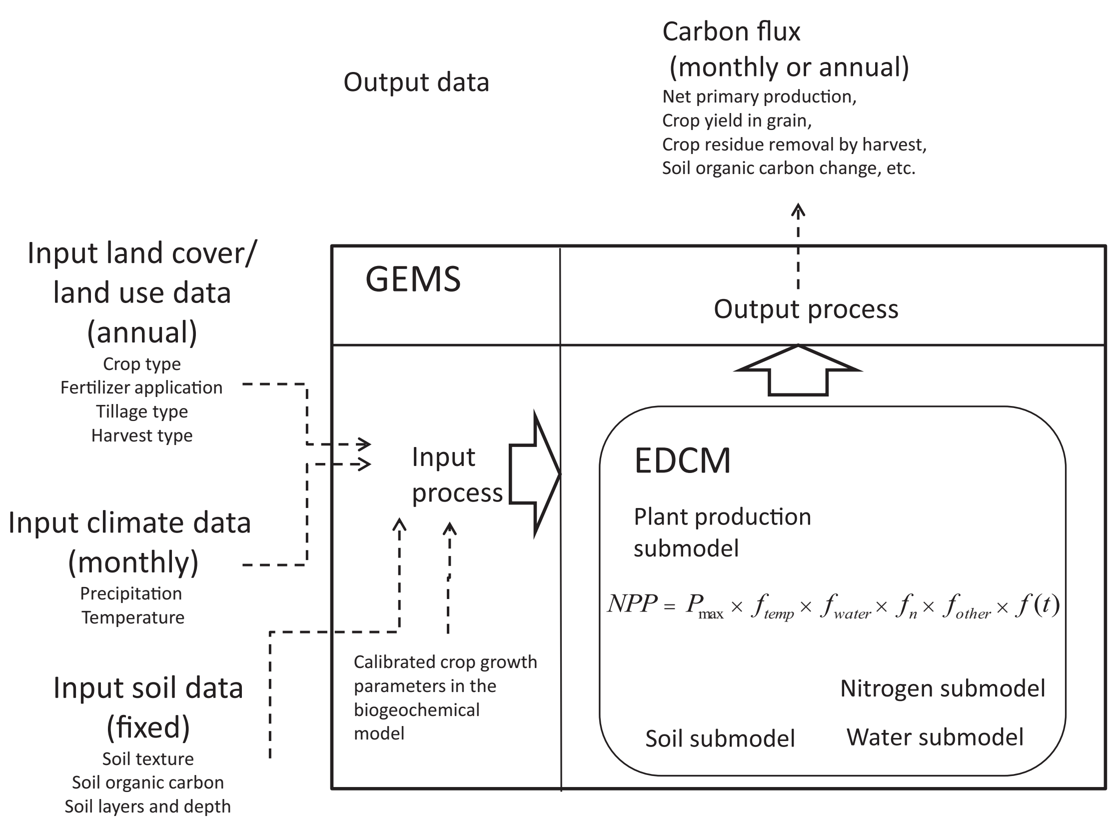

Fig. 2. A simplified schematic diagram of the General Ensemble biogeochemical Modeling System (GEMS) and major component to calculate the Net Primary Production (NPP) in the Erosion-Deposition-Carbon-Model (EDCM).

wheat, and winter wheat are the four major crops planted in the MCI region and together occupy more than 90% of the cropland area. 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. Methods for estimating NPP

2.2.1. Crop inventory

The USDA crop inventory contains crop yield data derived from the farm census records (USDA, 2009). USDA state and county-scale crop yield data are available since the 1970s and can be downloaded 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 yield data were converted to NPP using the method published by Prince et al. (2001). The crop NPP ($\mathrm{g\,C\,m^{-2}\,yr^{-1}}$) is calculated from the crop yield data by first converting the yield to the harvested carbon and then to the crop NPP as follows:

$$C_{\text{harvest}} = \text{Yield} \times f_{\text{mass}} \times f_{\text{dry}} \times f_{\text{carbon}}, \tag{2}$$

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

where C_{harvest} is the harvested carbon of the crop ($\mathrm{g\,C\,m^{-2}\,yr^{-1}}$), 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 g C 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 1.

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:

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

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 Figs. 5 and 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:

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

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

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:

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

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

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. 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 $\mathrm{km^2}$ 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.

Table 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

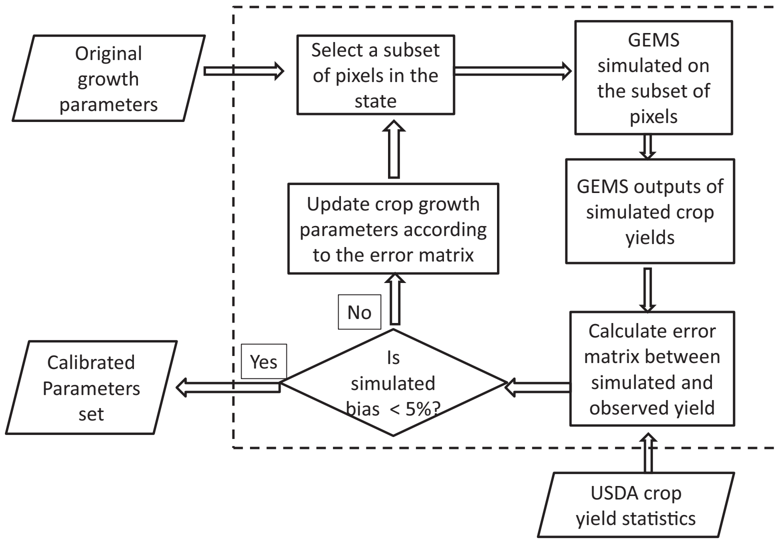

Fig. 3. Flowchart of the General Ensemble biogeochemical Modeling System (GEMS) calibration process.

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}.

2.2.3. 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 (Fig. 2).

2.2.3.1. 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., 2003, 2011). 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:

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

where P_{max} is the potential production of the crop (g C 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).

2.2.3.2. Input data. 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 February, 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). 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.

2.2.3.3. 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

Table 2
USDA Cropland Data Layer (CDL) temporal coverage between 2000 and 2008 in the states of the Mid-Continent Intensive Campaign (MCI) region.

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

carbon using the method in Section 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 (Fig. 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 (Fig. 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.

2.2.3.4. 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 (g C 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).

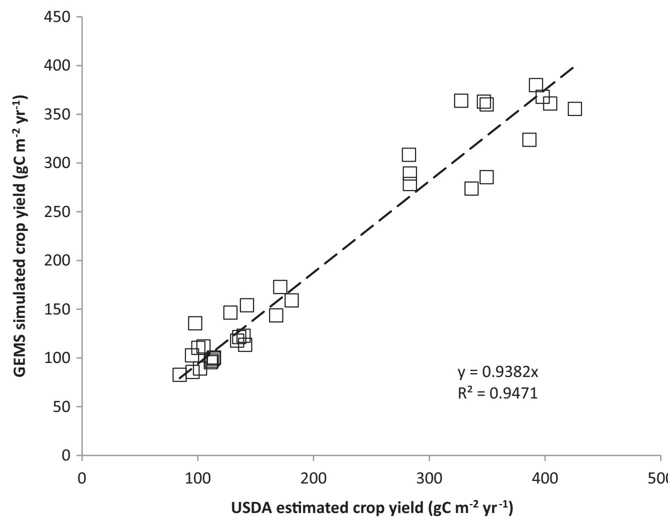

Fig. 4. Comparison between the General Ensemble biogeochemical Modeling System (GEMS) simulated crop yields and the USDA estimated crop yields for corn, soybean, spring wheat, and winter wheat in 11 states.

3. Results

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 (Fig. 4). As presented in Fig. 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 (Fig. 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.

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 3. The crop-specific NPP estimates for the four major crops from USDA yield data and GEMS are both presented in Table 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 Fig. 6.

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 Tg C yr^{-1} in 2007 to 318 Tg C yr^{-1} in 2008. In 2007, the total harvested cropland area

Table 3
Cropland Net Primary Production (NPP) estimates in the Mid-Continent Intensive Campaign (MCI) region from different methods.

Method	2007			2008		
	Mean NPP[a] ($g\,C\,m^{-2}\,yr^{-1}$)	Cropland area (Mha)	Total NPP ($Tg\,C\,yr^{-1}$)	Mean NPP[a] ($g\,C\,m^{-2}\,yr^{-1}$)	Cropland area (Mha)	Total NPP ($Tg\,C\,yr^{-1}$)
USDA	660 ± 320	49.8 (50.6[b])	329	656 ± 330	48.5 (49.5)[b]	318
MODIS	469 ± 79	100	469	490 ± 96	100	490
GEMS	683 ± 302	51.5	351	687 ± 349	52.5	359

[a] The values are the mean ± standard deviation of the estimated NPP values for the cropland. The calculation methods are listed in Sections 2.2.1–2.2.3.
[b] The number in the parentheses is the planted cropland area, outside is the harvested cropland area in the USDA inventory.

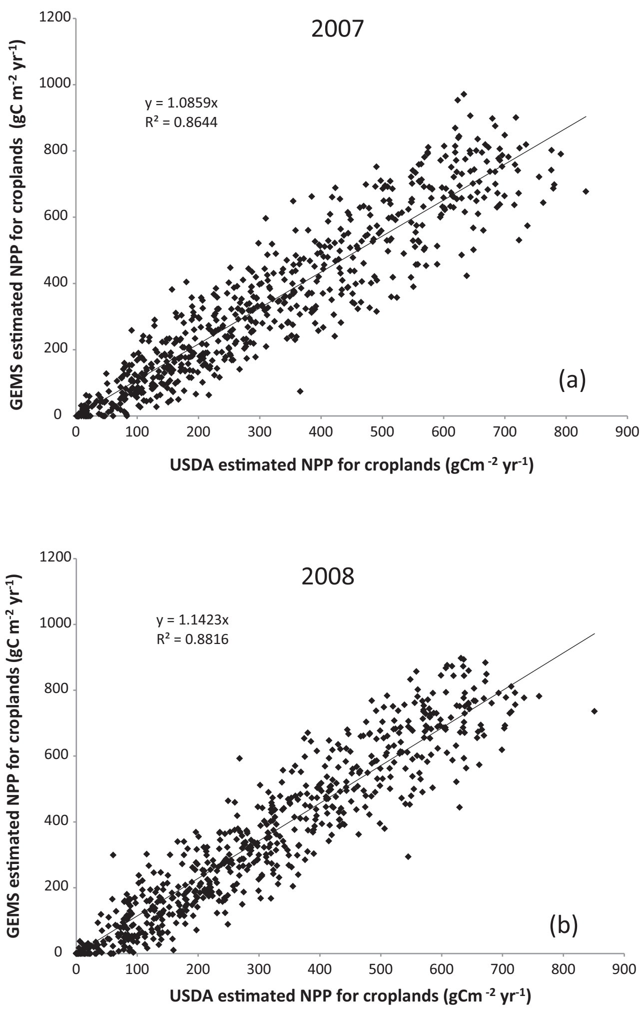

Fig. 5. Comparison between the General Ensemble biogeochemical Modeling System (GEMS) estimated cropland Net Primary Production (NPP) and USDA estimated cropland NPP at county-level in 2007 (a) and 2008 (b).

(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 Tg C in 2008. The net effect was that the total NPP for croplands was lower in 2008 than in 2007.

3.2.2. *Satellite-based model*

The mean NPP_{MODIS} was about 30% lower than the mean NPP_{USDA}, $469 \pm 79\,g\,C\,m^{-2}\,yr^{-1}$ in 2007 and $490 \pm 96\,g\,C\,m^{-2}\,yr^{-1}$ 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 $600\,g\,C\,m^{-2}\,yr^{-1}$, and only 3% of the values were higher than $600\,g\,C\,m^{-2}\,yr^{-1}$. In 2008, 83% of the NPP values were between 400 and $600\,g\,C\,m^{-2}\,yr^{-1}$ and 15% of the values were higher than $600\,g\,C\,m^{-2}\,yr^{-1}$. 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}.

3.2.3. *Process-based model*

The mean NPP_{GEMS} showed similar values to the mean NPP_{USDA}, $683 \pm 302\,g\,C\,m^{-2}\,yr^{-1}$ in 2007 and $687 \pm 349\,g\,C\,m^{-2}\,yr^{-1}$ 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 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 $351\,Tg\,C\,yr^{-1}$ in 2007 and $359\,Tg\,C\,yr^{-1}$ 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.

Table 4
The corn, soybean, spring wheat and winter wheat Net Primary Production (NPP) estimates in the Mid-Continent Intensive Campaign (MCI) region.

Method	Crop type	2007			2008		
		Mean NPP [a] ($g\,C\,m^{-2}\,yr^{-1}$)	Cropland area (Mha)	Total NPP ($Tg\,C\,yr^{-1}$)	Mean NPP[a] ($g\,C\,m^{-2}\,yr^{-1}$)	Cropland area (Mha)	Total NPP ($Tg\,C\,yr^{-1}$)
USDA	Corn	952 ± 163	23.8	226.4	990 ± 141	21.5	213.1
	Soybean	375 ± 74	16.8	63.2	352 ± 72	18.9	66.7
	Spring Wheat	391 ± 59	2.6	10.2	457 ± 109	2.4	11.1
	Winter Wheat	370 ± 141	2.9	11.0	480 ± 135	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 ± standard deviation of the estimated NPP values for each crop. The calculation methods are listed in Sections 2.2.1 and 2.2.3.

The corn–soybean rotation is a prevalent cropping system in the MCI region and the CDL data provided spatial explicitly information of the rotation (Fig. 6A and B). Given the large difference between the soybean NPP and the corn NPP (Table 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 (Fig. 6G and H).

3.3. Crop species impacts in cropland NPP

The CDL data showed that the crop species were not evenly distributed throughout the MCI region (Fig. 6A and B). Spring wheat

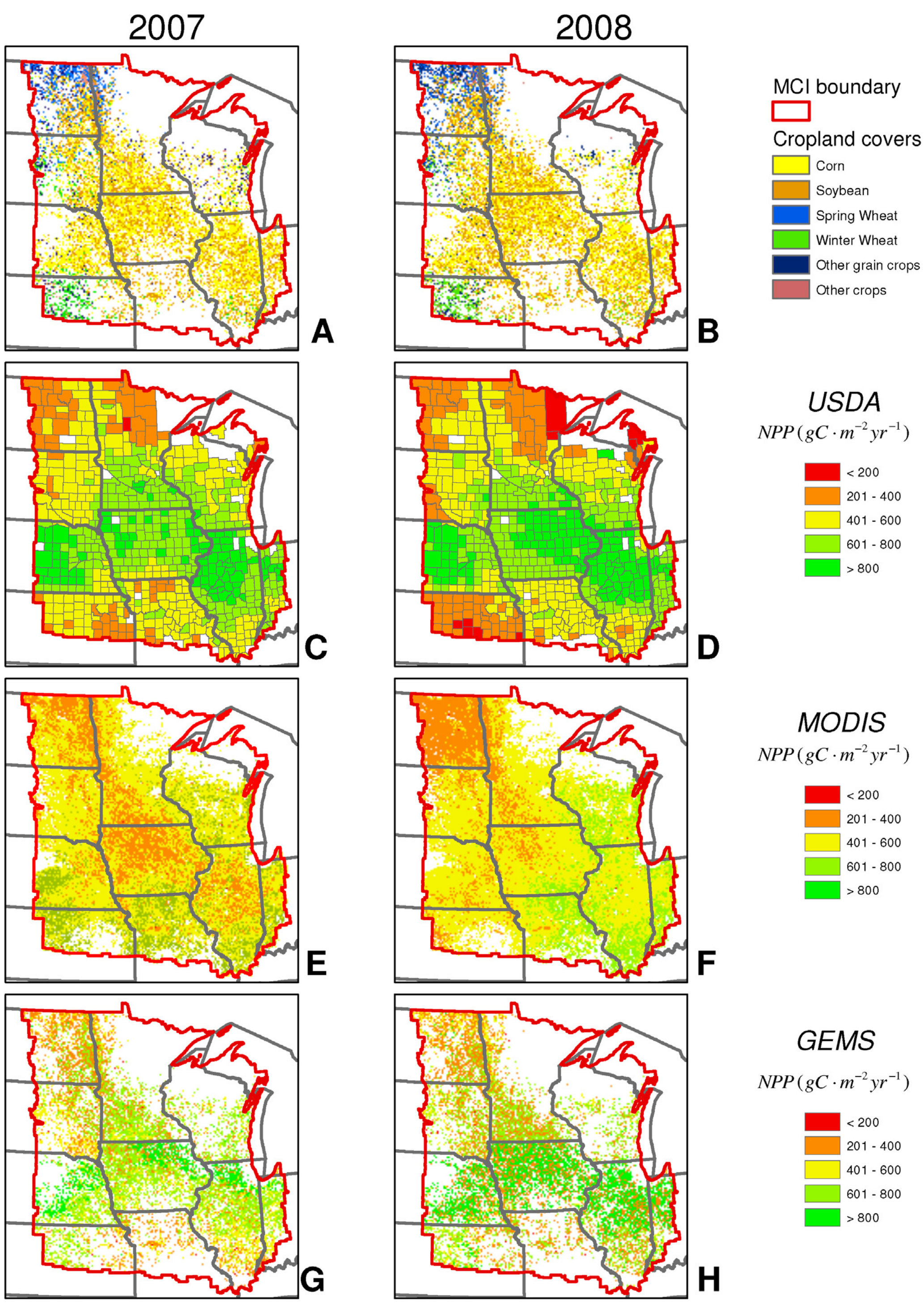

Fig. 6. USDA Cropland Data Layer (CDL) land covers in 2007 (A) and 2008 (B); cropland Net Primary Production (NPP) estimated from USDA yield data in 2007 (C) and 2008 (D); cropland NPP estimated from MODIS NPP product in 2007 (E) and 2008 (F); cropland NPP estimated from the General Ensemble biogeochemical Modeling System (GEMS) in 2007 (G) and 2008 (H) in the Mid-Continent Intensive Campaign (MCI) region.

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 (Fig. 6C–H).

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

4. Discussion

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 85–95% 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 km × 1 km). The assumption that the one MODIS pixel (1 km × 1 km) only contains one single land cover class usually fails to reflect the spatial heterogeneity in cropland cover. Crops generally are not planted in 1 km × 1 km 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.

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 g C m^{-2} yr^{-1}) than process-based models (585 g C m^{-2} yr^{-1}) and yield statistics (646 g C 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 g C 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 g C 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., 2005; Kalfas et al., 2011; Ruimy et al., 1994). 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., 2008, 2010). 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 and 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.

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 loss of NPP during the growing season such as the NPP loss through diseases and the NPP of 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.

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 $g\,C\,m^{-2}\,yr^{-1}$ and the total NPP for croplands was between 318 and 490 $Tg\,C\,yr^{-1}$. 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.

Acknowledgments

The funding for this research was provided by the USGS Land Change Science Program. Part of the work was under USGS contract G13PC00028. Contributions from Drs. Stephen Ogle and Tristram West were funded by a grant from the National Aeronautics and Space Administration (NASA), Terrestrial Ecology Program (NNX08AK08G). Any use of trade, product, or firm names is for descriptive purpose only and does not imply endorsement by the U.S. government. We also acknowledge the efforts of the two anonymous reviewers for greatly improving the quality of this manuscript through their constructive criticism.

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