Earth Syst. Dynam., 8, 875–887, 2017
https://doi.org/10.5194/esd-8-875-2017

Earth System Dynamics
Open Access

Estimating global cropland production from 1961 to 2010

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Received: 27 May 2017 – Discussion started: 26 June 2017
Accepted: 1 September 2017 – Published: 27 September 2017

Abstract. Global cropland net primary production (NPP) has tripled over the last 50 years, contributing 17–45 % to the increase in global atmospheric CO_2 seasonal amplitude. Although many regional-scale comparisons have been made between statistical data and modeling results, long-term national comparisons across global croplands are scarce due to the lack of detailed spatiotemporal management data. Here, we conducted a simulation study of global cropland NPP from 1961 to 2010 using a process-based model called Vegetation–Global Atmosphere–Soil (VEGAS) and compared the results with Food and Agriculture Organization of the United Nations (FAO) statistical data on both continental and country scales. According to the FAO data, the global cropland NPP was 1.3, 1.8, 2.2, 2.6, 3.0, and 3.6 $PgC\,yr^{-1}$ in the 1960s, 1970s, 1980s, 1990s, 2000s, and 2010s, respectively. The VEGAS model captured these major trends on global and continental scales. The NPP increased most notably in the US Midwest, western Europe, and the North China Plain and increased modestly in Africa and Oceania. However, significant biases remained in some regions such as Africa and Oceania, especially in temporal evolution. This finding is not surprising as VEGAS is the first global carbon cycle model with full parameterization representing the Green Revolution. To improve model performance for different major regions, we modified the default values of management intensity associated with the agricultural Green Revolution differences across various regions to better match the FAO statistical data at the continental level and for selected countries. Across all the selected countries, the updated results reduced the RMSE from 19.0 to 10.5 $TgC\,yr^{-1}$ ($\sim$45 % decrease). The results suggest that these regional differences in model parameterization are due to differences in socioeconomic development. To better explain the past changes and predict the future trends, it is important to calibrate key parameters on regional scales and develop data sets for land management history.

1 Introduction

Cropland net primary production (NPP) plays a crucial role in both food security and atmospheric CO_2 variations. Crop yield is part of crop NPP; thus, food security relies greatly on crop NPP. It has been reported that the increase in cropland NPP driven by the agricultural Green Revolution contributed 17–45 % of the increase in atmospheric CO_2 seasonal amplitude (Gray et al., 2014; Zeng et al., 2014). Furthermore, vegetation is the most active C reservoir in the terrestrial ecosystem and is easily affected by climate change (e.g., drought) and management practices, thus potentially affecting global climate change (Le Quéré et al., 2016; Zeng et al., 2005b; Zhao and Running, 2010).

Globally, agricultural areas cover $\sim$1370 million hectares, distributed across diverse climatic and edaphic conditions, with a variety of complex cropping systems and management practices (Foley et al., 2011; Gray et al., 2014; Lal,

Table 1. Features of the agricultural Green Revolution across regions.

Region/country	Starting period	Features	Ref.
Africa	1980s	Sustainable agriculture, plant breeding, and biotechnology	Evenson and Gollin (2003); Ejeta (2010); Pingali (2012)
Asia	1960s	Variety breeding, use of chemical fertilizers and pesticides, and irrigation	Hazell (2009)
Europe and North America	1960s	Large public investment in crop genetic improvement built on the scientific advances for the major staple crops – wheat, rice, and maize	Pingali (2012)
South America	1960s	Variety breeding, use of chemical fertilizers and pesticides, and irrigation	Evenson and Gollin (2003); Hazell (2009)
Mexico	1950s	New wheat and maize varieties developed by the International Maize and Wheat Improvement Center. Improve agricultural productivity with irrigated cultivation in northwest	Cotter (2005); Khush (2001); Pingali (2012)
Philippines	1966	A new dwarfed high-yield rice cultivar, IR8 was bred by IRRI	Fischer and Cordova (1998); Peng et al. (1999)
India	1960s	Plant breeding, irrigation development, and financing of agrochemicals	Hazell (2009);
China	1970s	Hybrid rice bred by Longping Yuan; fertilizer increased dramatically	Yuan (1966); Lin and Yuan (1980)
Brazil	1970s	High-yielding wheat varieties with aluminum toxicity resistance were developed	Davies (2003); Khush (2001); Marris (2005)

2004; Monfreda et al., 2008). Features of the agricultural Green Revolution include (1) adoption of improved varieties, (2) expansion of irrigation, and (3) increased use of chemical fertilizer and pesticide. These three factors have contributed approximately equally to increased crop NPP (Sinclair, 1998). Although the agricultural Green Revolution has been identified as a key driver of increased crop yield, its impact on crop NPP differs across time and space. Management intensity (here, mainly referring to the third feature of the Green Revolution) varies largely and has not always changed synchronously in different parts of the world (Table 1) (Ejeta, 2010; Evenson, 2005; Glaeser, 2010; Hazell, 2009). Thus, cropland NPP is highly variable, complicating the assessment of global cropland NPP (Bondeau et al., 2007; Ciais et al., 2007; Gray et al., 2014). For example, in the USA, the timing and magnitude of the agricultural Green Revolution occurred almost evenly from 1961 to 2010, while in Brazil, the most dramatic increase occurred after 2000 (Glaeser, 2010; Hazell, 2009). However, accounting for such effects of heterogeneity in management practices over time and space on crop NPP on a global scale has been rare to date.

Three methods are available for estimating vegetation NPP: statistical data, process-based models, and remote sensing. Statistical data and process-based models are the prevalent methods for estimating global NPP, but, except for a few recent studies, are generally limited to natural vegetation based on climate and edaphic variables, (Gray et al., 2014; Zeng et al., 2014). Therefore, global- and regional-scale estimates of cropland NPP must rely on census and survey data. However, these data report agricultural production, not NPP, and thus need crop-specific factors (dry matter fraction, harvest index (HI), root-to-shoot ratio, etc.) to calculate the NPP (Gray et al., 2014; Huang et al., 2007; Monfreda et al., 2008; Prince et al., 2001), which neglected the temporal evolution for crop-specific factors such as HI and root-to-shoot ratio (Lorenz et al., 2010; Sinclair, 1998). Remote sensing using satellites is a powerful tool for estimating global terrestrial NPP (Cleveland et al., 2015; Field et al., 1995; Nemani et al., 2003; Parazoo et al., 2014; Zhao and Running, 2010), yet croplands are coincident with natural vegetation, making it difficult to differentiate the two using remote sensing (Defries et al., 2000; Monfreda et al., 2008).

The current state of the global carbon models is as follows: (1) some models, such as Lund–Potsdam–Jena (LPJ) or ORCHIDEE, do not have an agricultural module; (2) models with an agricultural module, such as LPJ managed Land (LPJmL), do not fully represent the features of the Green Revolution; (3) the Vegetation–Global Atmosphere–Soil (VEGAS) model, by Zeng et al. (2014), was the first attempt to model the agricultural Green Revolution. The importance of parameter calibration has been recognized and addressed by numerous modeling studies (Bondeau et al., 2007; Chen et al., 2011; Crowther et al., 2016; Luo et al., 2016; Ogle et al., 2010; Peng et al., 2013). In addition, regional calibrated parameters are critical for global-scale modeling (Le Quéré et al., 2016). However, because the management data needed for most terrestrial models are spatially and temporally scarce, a precise regional simulation and calibration seems impossible (Bondeau et al., 2007).

Here, we conducted a study concentrated on calibrations on both the regional and the country scales. Instead of using an extensive set of actual management data that are unavailable or incomplete, we modeled the first-order effects on crop NPP using parameterizations. Our objectives were to (1) describe the method for simulating the three Green Revolution features, (2) quantify the cropland NPP over the last 50 years on both the continental and country scales, and (3) improve the model's performance by key parameterization.

2 Materials and methods

2.1 Simulating the Green Revolution with a dynamic vegetation model

We simulated agriculture using a generic crop functional type that represents an average of three dominant crops: maize, wheat, and rice. These crops are similar to warm C3 grass, one of the natural plant functional types in VEGAS (Zeng et al., 2005a, 2014). A major difference is the narrower temperature growth function, to represent a warmer temperature requirement than natural vegetation. Cropland management is modeled as an enhanced photosynthetic rate by the cultivar selection, irrigation, and application of fertilizers and pesticides. We modeled the first-order effects on the carbon cycle using regional-scale parameterizations with the following rules.

2.1.1 Variety

The selection of high-yield dwarf crop varieties has been a key feature of the agricultural Green Revolution since the 1960s, generally accompanied by an increase in the HI (the ratio of grain to aboveground biomass) (Sinclair, 1998). The HI varies for different crops, with a lower value for wheat (0.37–0.43) (Huang et al., 2007; Prince et al., 2001; Soltani et al., 2004) and higher values for rice (0.42–0.47) (Prasad et al., 2006; Witt et al., 1999) and maize (0.44–0.53) (Huang et al., 2007; Prince et al., 2001). We used a value of 0.45 for the year 2000, a typical value of the three major crops: maize, rice, and wheat (Haberl et al., 2007; Sinclair, 1998). The temporal change in HI is modeled as

$$\mathrm{HI_{crop}} = 0.45\left(1+0.6\tanh\left(\frac{y-2000}{70}\right)\right), \tag{1}$$

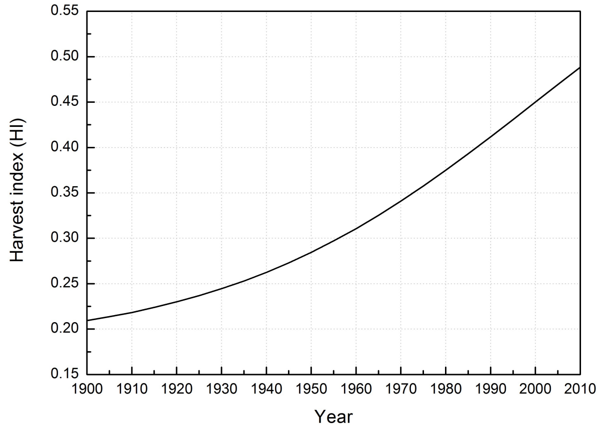

Figure 1. Harvest index change over time as used in the model and a harvest index of 0.31 in 1961 and 0.49 in 2010, based on literature review.

so that $\mathrm{HI_{crop}}$ was 0.31 at the beginning of the Green Revolution in 1961 and 0.45 for 2000 (Fig. 1), based on values found in the literature (Prince et al., 2001; Sinclair, 1998).

2.1.2 Irrigation

To represent the effect of irrigation, the soil moisture function ($\beta = w_1$ for unmanaged grass, where w_1 is surface soil wetness) is modified as

$$W_{\mathrm{irrg}} = 1 + 0.5\left(\frac{1}{1+\mathrm{Exp}\left(2\frac{\mathrm{MAT}-15}{5}\right)}\right) \tag{2}$$

$$\beta = 1 - \frac{(1-w_1)}{W_{\mathrm{irrg}}}. \tag{3}$$

The irrigation intensity W_{irrg} varies spatially from 1 (no irrigation) to 1.5 (high irrigation) using mean annual temperature (MAT) as a surrogate (Fig. 2a), with β ranging from 0 (no irrigation) to 0.33 (high irrigation) under extreme dry natural conditions (Fig. 2b). This function also modifies β when w_1 is not zero, but the effect of irrigation decreases when w_1 increases and levels off when w_1 equals 1 (soil is saturated). Thus, β (and thus the photosynthesis rate) is determined by both naturally available water (w_1) and irrigation. The spatial variation in W_{irrg} reflects a regional difference between tropical and temperate climates.

2.1.3 Fertilizer and pesticide

To represent the enhanced productivity from cultivar and fertilization, the gross carbon assimilation rate is modified by a management intensity (MI) factor that varies spatially and changes over time:

$$\mathrm{MI(region,\ year)} = M_0 M_1(\mathrm{regionMAT(latlon)}) M_2(\mathrm{year}) \tag{4}$$

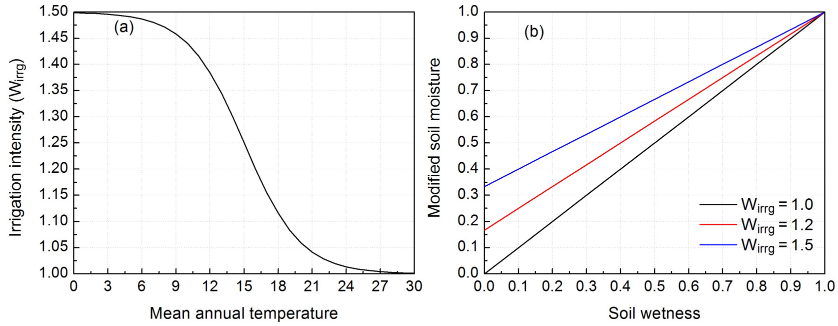

Figure 2. Irrigation intensity (W_{irrig}) changes with mean annual temperature (°C) (MAT) and β (beta) changes with soil wetness (Zucco et al., 2014) for typical W_{irrig} as used in the model.

Table 2. Default and calibrated regional management intensity parameter of M_{1r}. The default values were obtained from Zeng et al. (2014) and were parameterized mainly for global trend simulation. See Sect. 2.1.4 for the calibration. Updated M_{1r} values are represented by ↑ and ↓ symbols, indicating an increase or a decrease compared to the default ones, respectively.

Continent	Default	Calibrated
Africa	0.5	0.8↑
North America	1.3	1.1↓
South America	0.7	0.9↑
East Asia	1.5	1.5
Southeast Asia	1.0	0.7↓
South Asia	0.7	0.6↓
Central-west Asia	0.7	1.0↑
Former USSR	1.0	1.2↑
Rest of Europe	1.3	1.1↓
Oceania	1.0	0.6↓

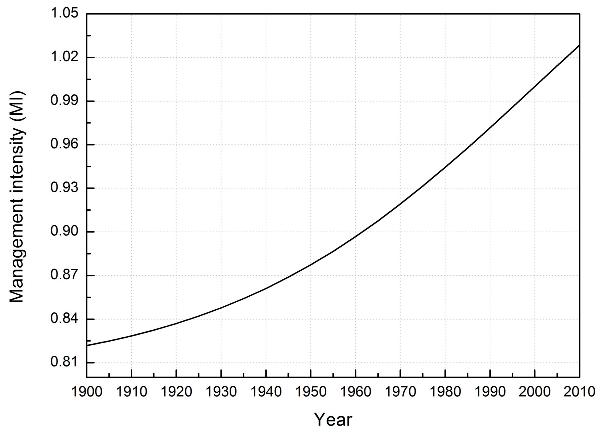

Figure 3. Management intensity (relative to year 2000) changes over time as used in the model. The analytical functions are hyperbolic tangent (see text). The parameter values correspond to a management intensity in 1961 that is 10 % smaller than in 2010.

$$M_1\,(\text{region},\ \text{MAT}) = M_{1r}(\text{region}) \cdot \text{Max}(1 - \tanh(\text{MAT(latlon)} - 15/25), 1.0) \quad (5)$$

$$M_2\,(\text{year}) = 1 + 0.2\tanh\left(\frac{\text{year} - 2000}{70}\right), \quad (6)$$

where M_0 is a scaling factor, the default value taken as 1.7 compared with natural vegetation 1.0, while M_1 is the spatially varying parameter, using major global regions as listed in Table 2 and MAT to differentiate (Eq. 4). M_{1r} is a region-dependent relative MI factor and M_1 is stronger in temperate and cold regions and weaker in tropical countries, for which we used the MAT as a surrogate (Eq. 4). M_2 is a temporal evolutionary factor (Eq. 3), and the term in parentheses represents the temporal evolution, modeled by a hyperbolic tangent function, with the MI values in 1961 approximately 10 % lower than in 2000 and 20 % lower asymptotically farther back in time (Fig. 3).

2.1.4 Motivation of the M_{1r} parameter calibration

M_{1r} is a region-dependent relative MI factor that varied largely across regions, and the default parameters were derived from a previous version used in Zeng et al. (2014), mainly to capture the global trends, which neglected the regional trends to some degree. A main focus of this study is to improve the M_{1r} parameter based on the FAO regional data to capture the regional trends. For each individual region, we used a series of parameters to drive the model and chose the best fit for the FAO statistical data (by naked eye observation) as follows:

1. Parameter M_{1r} was calibrated on a continental scale to match the FAO statistical data. During this period, countries within the same continent were assigned the same M_{1r}.

2. The M_{1r} for selected major countries was calibrated independently from the continental calibration, while the other countries that were not selected within the same

continent were tuned oppositely from the selected countries to keep the total simulated continental production close to the FAO data.

After the two steps, total production was summed as all countries with updated parameters.

2.1.5 Planting, harvesting, and lateral transport

Crop phenology was not decided beforehand but was determined by the climate condition. For example, when it is sufficiently warm in temperate and cool regions, crops begin to grow. This assumption captures most of the spring planting and simulates multiple cropping in low latitudes. However, one limitation of such a simple assumption is that it misses some other crop types such as winter wheat, which has an earlier growth and harvest.

When the leaf area index growth rate slows to a threshold value, a crop is assumed to be mature and is harvested. The automatic planting and harvest criteria allow multiple cropping in some warm regions and match areas with intense agriculture such as East Asia and Southeast Asia, but the criteria may overestimate regions with single cropping. Consequently, the simulated results tend to be the potential productivity due to the climate characteristics and our generic crop.

After harvest, grain and straw are assumed to be appropriated by farmers and then incorporated into the soil metabolic carbon pool. The harvested crop is redistributed according to population density, resulting in the horizontal transport of carbon. As a consequence, cropland areas act as net carbon sinks, and urban areas release large amounts of CO_2 through heterotrophic respiration. Lateral transport is applied within each continent to simulate the first-order approximation. Additional information on cross-regional trade was also taken into account for eight major world economic regions.

2.2 Data sets

2.2.1 Climate data

Gridded monthly climate data sets (i.e., maximum and minimum temperature, precipitation, and radiation) covering the period 1901–2013 with a spatial resolution of $0.5° \times 0.5°$ were obtained from the Climatic Research Unit, University of East Anglia (http://www.cru.uea.ac.uk/cru/data/hrg/). The time series CRU TS3.22 (Harris et al., 2013) are calculated on high-resolution grids, which are based on an archive of monthly mean temperatures provided by more than 4000 weather stations distributed around the world. The data set has been widely used for global change studies (Mitchell et al., 2004; Mitchell and Jones, 2005).

2.2.2 Land cover data

The land cover data set (crop and pasture versus natural vegetation) was derived from the History Database of the Global Environment (HYDE) data set (http://themasites.pbl.nl/tridion/en/themasites/hyde/download/index-2.html) (Goldewijk et al., 2010, 2011). It is an update of HYDE, with estimates of some of the underlying demographic and agricultural driving factors using historical population, cropland, and pasture statistics combined with satellite information and specific allocation algorithms. The 3.1 version has a $5'$ longitude and latitude grid resolution and covers the period 10 000 BC to AD 2000. This data set was also used in TRENDY and other model comparison projects (Chang et al., 2017; Sitch et al., 2015). The VEGAS model does not use high spatial resolution land use and management data such as crop type and harvest practices; thus, small-scale regional patterns may not be well simulated, and the results are more reliable on aggregated continental to global scales.

2.2.3 Crop production data

Crop production and cropland area are aggregated from FAO statistics for the major crops (FAOSTAT, http://www.fao.org/faostat/en/#data/QC, accessed June 2016). Specifically, they are the sum of the cereals (wheat, maize, rice, and barley, etc.) and five other major crops (cassava, oil palm, potatoes, soybean, and sugarcane), which comprise 90 % of the global amount of carbon harvested. Following Ciais et al. (2007), conversion factors are used to convert first wet to dry biomass, then to carbon content. The final conversion factors from wet biomass to carbon are 0.41 for cereals, 0.57 for oil palm, 0.11 for potatoes, 0.08 for sugarcane, and 0.41 for soybean and cassava.

2.3 Initialization and simulation

The VEGAS model used in TRENDY (Sitch et al., 2015; Zeng et al., 2005a) was run from 1700 to 2010 and forced by climate, annual mean CO_2, and land use and management history. Due to unavailable observed climate data before 1900, the average climate data over the period from 1900 to 1909 was used to drive the spin-up. The VEGAS model has a speed-up procedure for soil carbon to make it achieve equilibrium state (Zeng et al., 2005a).

3 Results

3.1 A brief revisit of the agricultural Green Revolution

The agricultural Green Revolution was mostly started in the 1960s to cope with the food–population balance, particularly in developing countries (Borlaug, 2002) (Table 1). Its features include the development of high-yield varieties of cereal grains, the expansion of irrigation, and applications of synthetic fertilizers and pesticides (Borlaug, 2007). The intensity of such management varies widely and has not always occurred synchronously in different parts of the world. Specifically, in the 1950s, new wheat and maize varieties were developed by the International Maize and Wheat Improvement Center (CIMMYT) in Mexico, and their agricultural productivity increased with irrigated cultivation in the northwest (Byerlee and Moya, 1993; Gollin, 2006; Pingali, 2012). Later in 1966, a new dwarf high-yield rice cultivar, IR8, was bred by the International Rice Research Institute (IRRI) in the Philippines, and it was spread and grown in most of the rice-growing countries of Asia, Africa, and Latin America (Fischer and Cordova, 1998; Khush, 2001; Peng et al., 1999). Also in the 1960s, India imported new wheat seed from CIMMYT to Punjab and later adopted the IR8 rice variety from Philippines that could produce more grains (Parayil, 1992). China began participating in the Green Revolution in the 1970s, with hybrid rice bred by Longping Yuan (Yuan, 1966), and the fertilizer application rate increased dramatically from 43 kg ha^{-1} in 1970 to 346 kg ha^{-1} in 1995 (Hazell, 2009). Meanwhile, Brazil began participating in the Green Revolution in the 1970s, and in collaboration with CIMMYT, high-yielding wheat varieties with aluminum toxicity resistance, which were efficient in dealing with the aluminum toxicity in the Cerrado soils of Brazil were developed (Davies, 2003; Khush, 2001). In contrast, African countries began their participation in the Green Revolution much later in the 1980s, with many obstacles from both climatic, edaphic, and socioeconomic factors (Ejeta, 2010; Sánchez, 2010) and it featured sustainable agriculture, plant breeding, and biotechnology.

3.2 Global and continental comparison between model simulation and FAO statistical data

Worldwide, the FAO data showed that cropland production increased from 439 TgC in 1961 to 1519 TgC in 2010 (246 % increase) (Fig. 4), and the VEGAS model captured most of this trend in both the default and the calibrated results. East Asia and North America contributed the most to this trend (Fig. 5). For East Asia, crop production increased from 65 TgC in 1961 to 342 TgC (426 % increase) in 2010. For North America, it increased from 90 TgC in 1961 to 235 TgC (161 % increase) in 2010. Other regions followed the increasing trend except for the former USSR region. The lowest crop production existed in central-west Asia and Oceania, with less than 50 TgC over the study period.

As described in Sect. 2.1.4, we calibrated the $M_{1\mathrm{r}}$ parameter for each region. The default and updated regional management intensity parameter (Table 2) produced dramatically different estimations for some continents, for example in North America, Southeast Asia, and Africa (Fig. 5a, b, e). However, for other continents, such as South Asia, the improvement was not so pronounced. For East Asia, the default parameter was sufficient to capture most of the crop production variations. Moreover, the timing and magnitude of the agricultural Green Revolution was quite different over different regions. For example, it occurred more recently in Africa and South America (Fig. 5a, c) and much earlier in

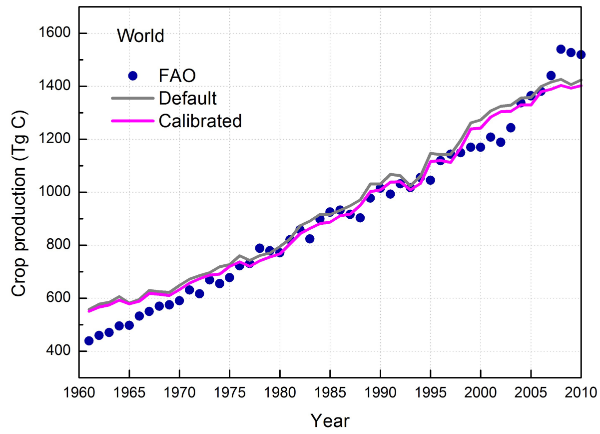

Figure 4. Annual global crop production from 1961 to 2010. Default parameters were derived from a previous version that was used in Zeng et al. (2014) to capture the global trends, and calibrated parameters were set in this study (see text) to capture the regional trends.

East Asia and Europe (Fig. 5d, i). In the region of the former USSR, crop production even decreased after 1990 (Fig. 5h) due to the large areas of abandoned croplands, thus making the regional-scale simulation more complicated.

Furthermore, the updated parameters in different regions did not substantially change the total production estimations (Fig. 4), indicating that a good agreement in global total production may be overestimated in some regions while underestimated in others, which does not reflect the true nature of the production distributions and variations.

3.3 Country-scale comparison between model simulation and FAO statistical data

At the country level, the FAO data showed that China, the USA, and India were the top three countries contributing to global crop production (Fig. 6). For China, crop production increased from 50 TgC in 1961 to 230 TgC in 2010 (360 % increase). For the USA, it increased from 76 TgC in 1961 to 204 TgC in 2010 (168 % increase). Other countries followed the same increasing trend with different rates. The lowest crop production in the top nine countries existed in Canada and Argentina, with less than 50 TgC over the study period.

As for the VEGAS simulations, the default parameters (Table 3) might overestimate results in some countries while underestimating others. The calibrated parameter could capture variations in most of the countries (Fig. 6). For Chinese crop production, a decreasing trend after 1999 was captured, but the magnitude was weaker (Fig. 6a) because the drop in cropland area was not represented in HYDE 3.0 for China. The calibrated parameter also performed well in other countries. For Brazil and Argentina, the dramatic increase after 2000 was not well captured due to the simple assumption

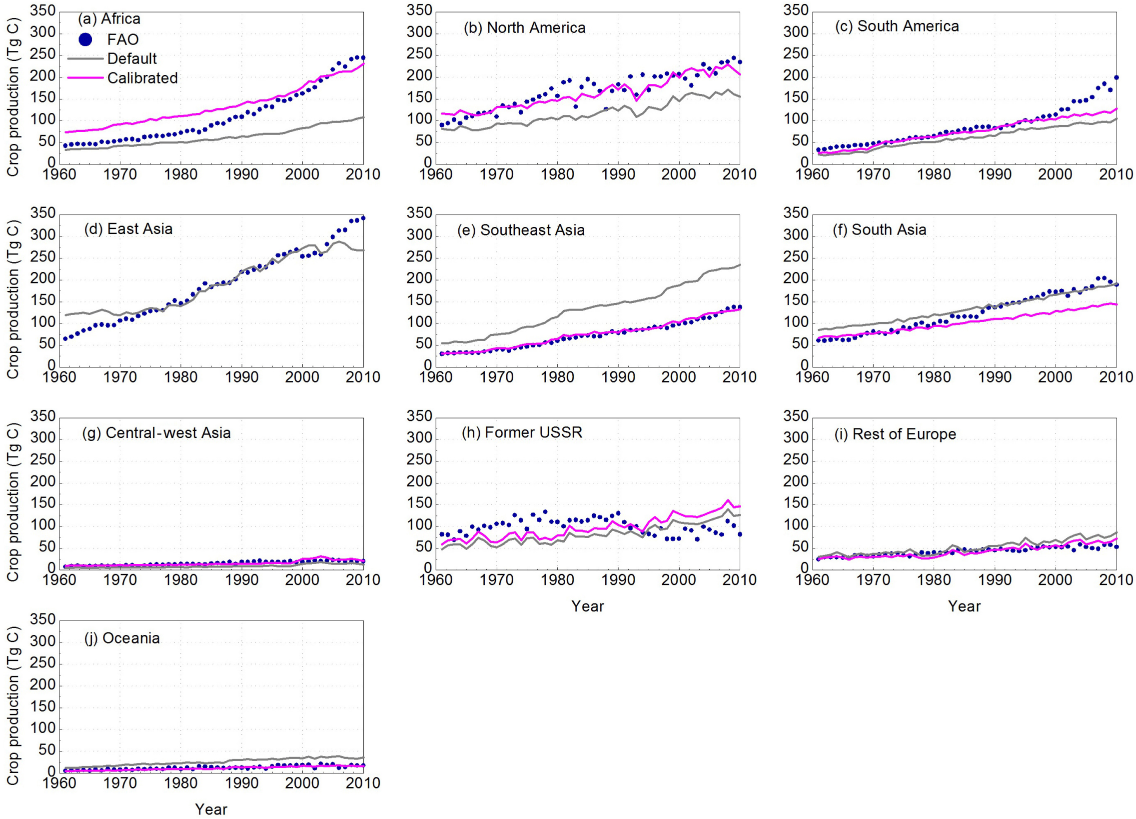

Figure 5. Annual crop production from 1961 to 2010 on a continental scale. The **(d)** subplot has no purple line since the default parameter produced the best fit for all the tuned simulations.

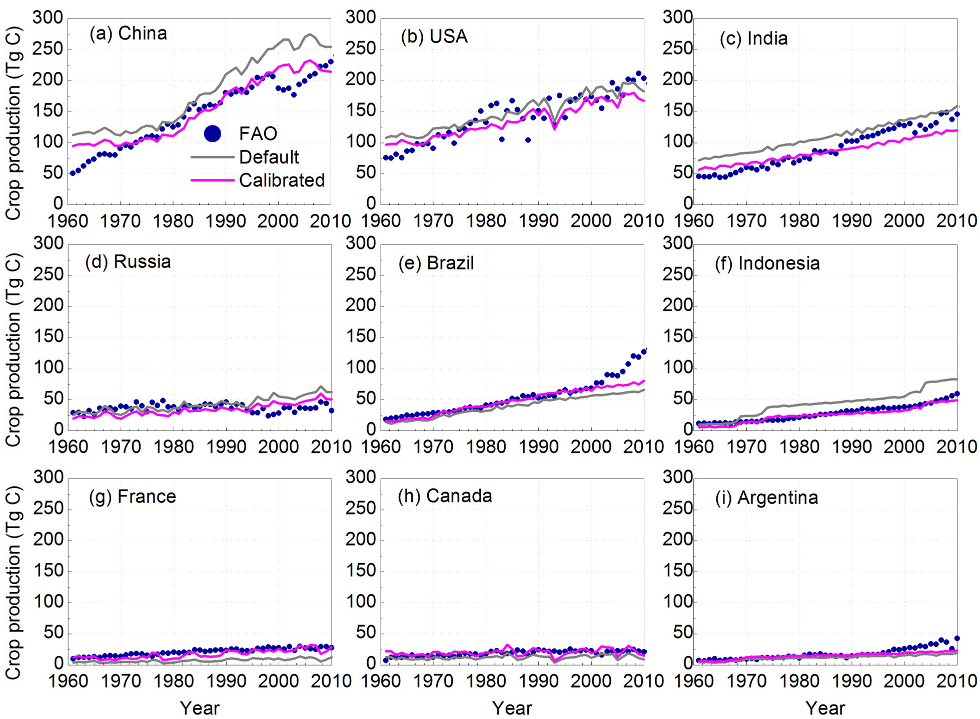

Figure 6. Annual crop production from 1961 to 2010 on a country scale.

Table 3. Default and calibrated national management intensity parameter of M_{1r}.

Country	Default	Calibrated
China	1.5	1.3↓
USA	1.3	1.0↓
India	0.7	0.6↓
Russia	1.0	0.9↓
Brazil	0.7	0.8↑
Indonesia	1.0	0.7↓
France	1.3	3.0↑
Canada	1.3	2.1↑
Argentina	0.7	0.8↑

that the strongest management occurred in 2000 and became weaker afterwards.

Based on the country-scale comparisons between the updated VEGAS simulations and the FAO statistical data of the decadal means, the linear regression slope was 1.00, with a higher R^2 of 0.97 ($p<0.01$), a smaller RMSE of 10.5 TgC ($\sim$ 45 % decrease), and a smaller mean deviation of 3.5 TgC ($\sim$ 31 % decrease) compared with the default results (Fig. 7).

3.4 Spatial comparison between the model simulation and the documented data

The two independent data sets produced similar spatial distributions of crop NPP (Fig. 8). The highest crop NPP regions were the Great Plains of North America and temperate western Europe and East Asia (> 1.0 Tg per 2500 km^2, Fig. 8), where the agricultural Green Revolution was the strongest, but high yields were also present locally within tropical regions (e.g., Southeast Asia), while the lowest production in Africa, eastern Europe, and Russia (< 0.4 Tg per 2500 km^2, Fig. 8) was due largely to the low input in agricultural research and development and the rigid climate and edaphic conditions. The model result overestimated Russian cropland NPP because of the simplified model representation of temporal changes, and the abandoned cropland after the collapse of the former USSR was not represented in the HYDE data set. Meanwhile, the high South American NPP was underestimated.

The average cereal NPP increased from 1.0 to 1.5 Mg ha^{-1} for African croplands (Fig. 9a), and it increased from 1.5 to 2.1 Mg ha^{-1} for Oceania croplands from 1961 to 2014. Europe, Asia, and South America showed similar increasing trends from 1.5 to 4.0 Mg ha^{-1}. North America showed the highest cereal NPP, with an increase of 2.5 to 8.0 Mg ha^{-1} over the 50 years. For soybean NPP, North America topped the six continents with 3.0 Mg ha^{-1} in 2010, while Africa showed the lowest NPP with 1.2 Mg ha^{-1} in 2010, one-third that of North America. Europe and Oceania had a middle level of $\sim$ 2.0 Mg ha^{-1} in 2010. This NPP trend was consistent with the progress of the Green Revolution on each continent.

4 Discussion

In the estimation of crop NPP, one of the sources of uncertainty is crop parameters, such as variations in HI. When accounting for this variation of 0.45 (0.37–0.53, or 18 % of the mean), the uncertainty resulted from the HI for the FAO production-derived NPP would be 1.3 ± 0.2 and 3.6 ± 0.6 PgC yr^{-1} in the 1960s and 2010s, respectively. Furthermore, the HI represented in Eq. (1) did not change with time in different regions. This was mainly restricted by the limited large-scale observed values over time. We mainly modeled the long-term decreased HI trend over time. In the future, a large-scale observed HI data set that changes with time should be collected and included in carbon modeling studies. Furthermore, the planting and harvest criteria allow multiple cropping in some warm regions, which captures trends in areas with multiple cropping practices such as East Asia and Southeast Asia, but the criteria may overestimate regions with single cropping in North America and Europe. Consequently, the simulated results tend to be the potential productivity due to the climate characteristics and the generic crop. Additionally, one of the main driving factors for the agricultural Green Revolution was the economic input. Gross domestic expenditures on food and agricultural research and development worldwide have increased from 27.4 to 65.5 billion of 2009 purchasing power parity (PPP) dollars from 1980 to 2010 (Pardey et al., 2016). The middle-income countries' research and development investment share increased from 29 % in 1980 to 43 % in 2011. This investment difference has dramatically influenced the crop NPP (Figs. 4, 5, 6, 8) due to improvements in crop varieties, fertilizer and pesticide application, and expansion of irrigation areas (Ejeta, 2010; Evenson, 2005; Evenson and Gollin, 2003; Gollin et al., 2005; Gray et al., 2014; Hazell, 2009). Despite a drought-induced reduction in the global terrestrial NPP of 0.55 PgC from 2000 to 2009 based on MODIS satellite data analysis (Zhao and Running, 2010), cropland NPP increased by 0.3–0.6 PgC for the same period in this study because of the agricultural Green Revolution (Fig. 4).

Gray et al. (2014) used production statistics and a carbon accounting model to show that increases in agricultural productivity explained $\sim$ 25 % changes in atmospheric CO_2 seasonality. Northern Hemisphere extratropical maize, wheat, rice, and soybean production increased by 0.33 PgC (240 %) between 1961 and 2008. This study showed a consistent estimation: the total cropland production increased by 1.0 PgC (300 %) and took up 0.5 Pg more carbon in July. Furthermore, Monfreda et al. (2008) estimated the global cropland NPP for the year 2000 on a sub-country scale using the FAO statistical yield data and cropland area distributions. Consistently, the global cropland mean NPP was estimated

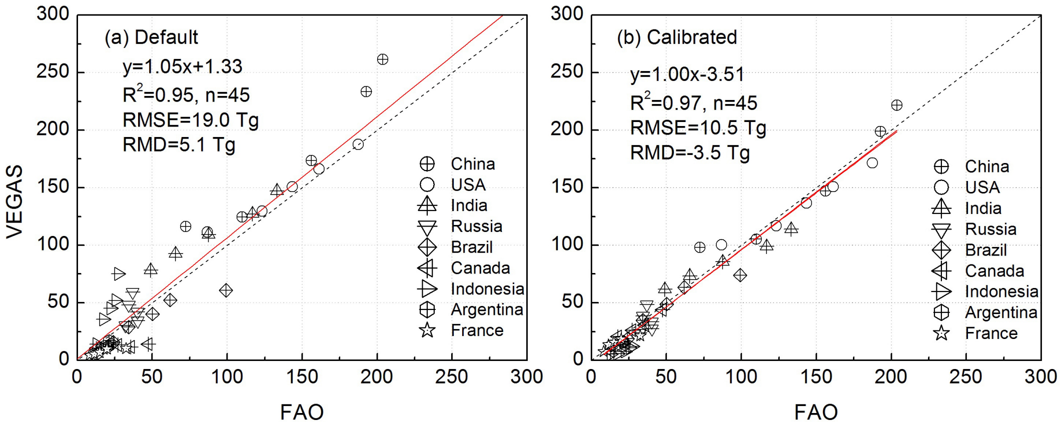

Figure 7. Country-based comparison of simulated and observed cropland productions (Tg) before **(a)** and after **(b)** calibration. Each country has five symbols representing the five decadal mean values.

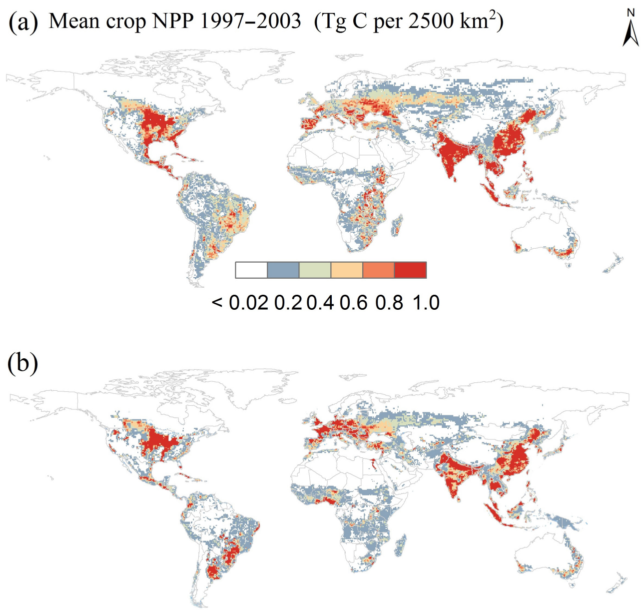

Figure 8. Mean cropland NPP from 1997 to 2003. VEGAS modeled patterns (Tg C per 2500 km^2, panel **a**) show major productions in the agricultural areas of North America, Europe, and Asia (panel **b** shows the mean crop NPP based on the FAO statistical data from Navin Ramankutty (http://www.earthstat.org/).

as 4.2 MgC ha^{-1}, with the highest NPP of 5.5 MgC ha^{-1} in Asian croplands and the lowest NPP of 2.5 MgC ha^{-1} in African croplands. Specifically, both studies agreed well in several regions that had the highest cultivated NPP due to intensive agriculture and/or multiple cropping: western Europe; East Asia; the central USA; and southern Brazil, with an NPP larger than 10 MgC ha^{-1} in most of these regions. Meanwhile, Bondeau et al. (2007) modeled the difference of agricultural NPP between LPJmL and LPJ, showing that agriculture increased NPP in intensively managed or irrigated areas (Europe, China, the southern USA, Argentina). However, their study could not capture the increasing trends in the US Central Plains and in the Australian wheat belt because of the unavailability of management data on those regional scales, showing the limitations of modeling using detailed regional management data. Moreover, using country-based agricultural statistics and activity maps of human and housed animal population densities, Ciais et al. (2007) estimated that the global carbon harvested in croplands was 1.3 PgC yr^{-1}, of which ∼13 % enters into horizontal displacement through international trade circuits, contributing ∼0.2–0.5 ppm mean latitudinal CO_2 gradients.

European cropland NPP increased 127 % over the last half century, as estimated by VEGAS (Fig. 5i), and the yield increased at a rate of 1.8 % per annum. Moreover, without the management intensity parameter updated, the crop yields for the 2000s would be 10.4 % lower. Similarly, a study showed that across all major crops cultivated in the EU, plant breeding has contributed approximately 74 % of total productivity growth since 2000, equivalent to a yield increase of 1.2 % per annum. European crop yields today would be more than 16 % lower without access to improved varieties (the British Society of Plant Breeders, BSPB). The 2003 drought and heat in Europe reduced the terrestrial gross primary productivity (GPP) by 30 % (Ciais et al., 2005), while it was decreased by 15 % for cropland NPP in this study (Fig. 5i). This decrease was smaller than the natural ecosystem response due largely to the counteractive effects of management inputs (irrigation, fertilization, etc.).

In the central USA, VEGAS modeled the cropland NPP as > 6 MgC ha^{-1} in the Great Plains and < 3 MgC ha^{-1} in the northwestern and northern USA for the 2000s. Prince et al. (2001) estimated crop NPP by applying crop-specific factors to statistical agricultural production. The NPP at the county level in 1992 ranged from 2 MgC ha^{-1} in North Dakota, Wisconsin, and Minnesota to > 8 MgC ha^{-1} in central Iowa, Illinois, and Ohio. Areas of the highest NPP were

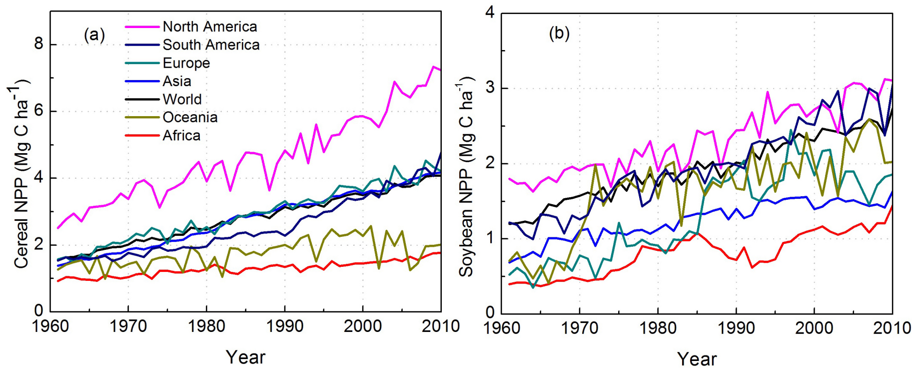

Figure 9. Cereal and soybean NPP on a continental scale over the last 60 years derived from FAO yield data. Note that the scales are different.

dominated by corn and soybean cultivation. Using a similar method, Hicke et al. (2004) estimated that crop NPP increased in counties throughout the USA, with the largest increases occurring in the Midwest, Great Plains, and Mississippi River valley regions. It was estimated that total coterminous cropland production increased from 0.37 to 0.53 (a 40 % increase) $\mathrm{Pg\,C\,yr^{-1}}$ during 1972–2001.

In Asian croplands, the percentage of harvested area for rice, wheat, and maize under modern varieties was lower than 10 % in the 1960s, and it increased to over 80 % in the 2000s (Evenson, 2005). Moreover, nitrogen (N) fertilizer increased from 23.9 $\mathrm{kg\,ha^{-1}}$ in 1970 to 168.6 $\mathrm{kg\,ha^{-1}}$ in 2012, while the irrigated area increased from 25.2 % in 1970 to 33.2 % in 1995 (Rosegrant and Hazell, 2000). Correspondingly, the crop NPP increased from 1.4 $\mathrm{MgC\,ha^{-1}}$ in 1961 to 4.5 $\mathrm{MgC\,ha^{-1}}$ in 2014 (Fig. 9). Cropland NPP in China was estimated to increase from 159 $\mathrm{TgC\,yr^{-1}}$ in the 1960s to 513 $\mathrm{TgC\,yr^{-1}}$ in the 1990s based on the National Agriculture Database (Statistics Bureau of China 2000) (Huang et al., 2007), and this study estimated the range as 286 $\mathrm{TgC\,yr^{-1}}$ in the 1960s to 559 $\mathrm{TgC\,yr^{-1}}$ in the 1990s. In tropical Asia, the new croplands were mainly derived from forests, which caused large amounts of carbon loss from both vegetation and soil (Gibbs et al., 2010; Tao et al., 2013; West et al., 2010).

The African croplands currently nourish over 1.0 billion people. The need for sustainable agriculture combined with stable grain yield production is particularly urgent in Africa. However, the continent is now trading carbon for food. Newly cleared land in the tropics releases nearly 3 tons of carbon for every 1 ton of annual crop yield compared with a similar area cleared in the temperate zone (West et al., 2010). This continent can triple its crop yields, provided the depletion of soil nutrients is addressed (Sánchez, 2010). Using chemical fertilizer as an example, the average N application rate from 2002 to 2012 was only $\sim 14\,\mathrm{kg\,ha^{-1}\,yr^{-1}}$ in Africa, which severely hampered crop production (Han et al., 2016). In addition, complete crop residue removal for fodder and fuel is a norm in Africa, causing soils in these areas to lack organic matter input and to become carbon sources (Lal, 2004). Since the mid-1970s, ~ 50 million hectares of Ethiopian land had no or low fertilizer application, resulting in low crop NPP ($< 2\,\mathrm{MgC\,ha^{-1}}$; Figs. 7, 8) (West et al., 2010) and soil degradation (Shiferaw et al., 2013). African agricultural development has to overcome a series of constraints such as drought, poor soil fertility, diverse agroecologies, unique pests and diseases, and persistent institutional and programmatic challenges (Ejeta, 2010).

In terms of the data gap in MI, very few data sets provide long-term time series data with high spatial resolution. HYDE is a land use data set that does not provide MI information (Goldewijk et al., 2011). Monfreda et al. (2008) developed a data set consisting of 175 crops consistent to the FAO statistical data for the period around year 2000. Moreover, Fritz et al. (2015) developed a cropland percentage map for the baseline year 2005. For the fertilizer data set, Potter et al. (2010) provided the global manure N and P application rate for a mean state around year 2000. Furthermore, Lu and Tian (2017) developed a global time series gridded data set for the synthetic N and phosphorous (P) fertilizer application rate in agricultural lands. For the irrigation data set, global monthly irrigated crop areas around the year 2000 were developed by Portmann et al. (2010). These data sets are mostly for a specific year or a period mean, and they are unsuitable for long-term simulations. Therefore, we still lack a comprehensive data set that reflects MI.

A more challenging task would be to calibrate regional parameters and explain spatial patterns better because models may significantly underestimate the high-latitude trend (Graven et al., 2013) and overestimate elsewhere even if the global total is simulated correctly (Zeng et al., 2014). More work should be directed to reduce uncertainties in regional model parameterizations (Le Quéré et al., 2015; Luo et al., 2016). This paper focuses on both the continental and country scales to calibrate key parameters to better constrain the future projections of global cropland NPP.

5 Conclusion

We used a process-based terrestrial model VEGAS to simulate global cropland production from 1960 to 2010 and adapted the management intensity parameter on both continental and country scales. The updated parameter could capture the temporal dynamics of crop NPP much better than the default ones. The results showed that cropland NPP tripled from $1.3 \pm 0.1\,\mathrm{Pg\,C\,yr^{-1}}$ in the 1960s to $3.6 \pm 0.2\,\mathrm{Pg\,C\,yr^{-1}}$ in the 2000s. The NPP increased most notably in the US Midwest, western Europe, and the North China Plain. In contrast, it increased slowly in Africa and Oceania. We highlight the large difference in model parameterization among regions when simulating the crop NPP due to the differences in timing and magnitude of the Green Revolution. To better explain the history and predict the future crop NPP trends, it is important to calibrate key parameters on regional scales and develop time series data sets for land management history.

Data availability. Several publicly available data sets were used in this study. The specific references and internet links to the data sources are given in the text. Model outputs are available upon request.

Author contributions. NZ conceived and designed the study; PFH and FZ performed the simulations and analyzed the results. NZ and PFH prepared the paper with contributions from all co-authors.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This research was supported by the National Key R&D Program of China (no. 2017YFB0504000), the Thousand Talents Program Foundation of China (no. Y763012601), and the Postdoctoral Science Foundation of LASG Dean (grant no. 7-091162).

Edited by: Govindasamy Bala
Reviewed by: two anonymous referees

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