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Global cropland monthly gross primary production in the year 2000

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Abstract. Croplands cover about 12 % of the ice-free terrestrial land surface. Compared with natural ecosystems, croplands have distinct characteristics due to anthropogenic influences. Their global gross primary production (GPP) is not well constrained and estimates vary between 8.2 and 14.2 Pg C yr^{-1}. We quantified global cropland GPP using a light use efficiency (LUE) model, employing satellite observations and survey data of crop types and distribution. A novel step in our analysis was to assign a maximum light use efficiency estimate (ε^*_{GPP}) to each of the 26 different crop types, instead of taking a uniform value as done in the past. These ε^*_{GPP} values were calculated based on flux tower CO_2 exchange measurements and a literature survey of field studies, and ranged from 1.20 to 2.96 g C MJ^{-1}. Global cropland GPP was estimated to be 11.05 Pg C yr^{-1} in the year 2000. Maize contributed most to this (1.55 Pg C yr^{-1}), and the continent of Asia contributed most with 38.9 % of global cropland GPP. In the continental United States, annual cropland GPP (1.28 Pg C yr^{-1}) was close to values reported previously (1.24 Pg C yr^{-1}) constrained by harvest records, but our estimates of ε^*_{GPP} values were considerably higher. Our results are sensitive to satellite information and survey data on crop type and extent, but provide a consistent and data-driven approach to generate a look-up table of ε^*_{GPP} for the 26 crop types for potential use in other vegetation models.

1 Introduction

The terrestrial biosphere assimilates an estimated 120–150 Pg C yr^{-1} (Beer et al., 2010; Welp et al., 2011) as gross primary production (GPP). Roughly, half of the GPP is used for plant maintenance processes and is generally referred to as autotrophic respiration (R_a). The remainder is available for plant growth as net primary production (NPP), which is subsequently consumed mostly by heterotrophs (R_h) and fire.

Biochemical processes of photosynthesis at cell or leaf level are relatively well known, but accurate estimates of GPP at larger scales (regional or global) are still uncertain. Direct measurements of net ecosystem exchange (NEE: GPP $- R_h - R_a$), such as eddy covariance measurements, suffer from the large spatial heterogeneity in the CO_2 exchange between plants and the atmosphere which makes upscaling difficult. Therefore, current global GPP estimates still mainly rely on model results. However, considerable differences exist between various studies (Zhao et al., 2005; Ryu et al., 2011; Koffi et al., 2012; Beer et al., 2010), in particular for croplands. For example, Beer et al. (2010) reported global cropland GPP of 14.8 Pg C yr^{-1}using flux tower measurements based on eddy covariance methods and several diagnostic models. In contrast, Saugier et al. (2001) estimated this number to be 8.2 Pg C yr^{-1}.

Croplands cover about 12 % of the ice-free land surface globally (Ramankutty et al., 2008), contributing considerably to the global carbon cycle (Hicke et al., 2004). Additionally, the area occupied by croplands changes over time with consequences for global carbon stocks. For example, a large carbon sink was found in the abandoned croplands of the Soviet Union (Vuichard et al., 2008). Vice versa, deforestation is often related to the expansion of cropland (Morton et al., 2006) which leads to a decrease in aboveground biomass. However, croplands may also have a large capacity for carbon sequestration (Parr and Sullivan, 2011).

The light use efficiency (LUE) approach has been widely used to estimate GPP. Monteith (1972) developed this approach assuming that the growth in plant biomass is directly proportional to absorbed solar radiation. Since the 1970s, this LUE approach was mostly evaluated using field measurements of plant dry matter and solar radiation. The LUE approach was also applied to estimate net primary production (NPP) in large-scale models (Field et al., 1995; Knorr and Heimann, 1995; Potter et al., 1993; Ruimy et al., 1994, 1999). The LUE application was later extended to estimate GPP mostly because LUE is more likely to be fundamentally related to GPP, the direct outcome of photosynthesis (Prince and Goward, 1995; Ruimy et al., 1996; Running et al., 2000; Landsberg et al., 1997).

In the LUE approach, NPP or GPP is assumed proportional to the absorbed photosynthetically active radiation (PAR) at an efficiency rate, ε. Because ε is affected by environmental factors, the maximum light use efficiency (ε^*) (Haxeltine and Prentice, 1996; Potter et al., 1993), defined as an environmentally optimized ε, is widely used in models. Numerous studies have estimated ε or ε^* at site level (Supplement Table S1). In the parameterizations of models, ε^* is more often used than ε because ε^* tends to be more stable between various plant types. Besides, subsequent environmental restrictions can be calculated using local environmental inputs. The LUE approach is thus widely used to estimate GPP or NPP from site level to large scales by combining satellite-based vegetation index measurements (Goerner et al., 2011; Potter et al., 1993; Xiao et al., 2005; Yuan et al., 2010; Zhao and Running, 2010; Field et al., 1995; Knorr and Heimann, 1995; Ruimy et al., 1994, 1996, 1999; Prince and Goward, 1995). Although all these models use the LUE concept, they often use different vegetation indices, ε^* values, and may calculate environmental stresses in a different way.

Observational studies have illustrated that ε varies widely between crops even when corrected for environmental stresses and nutrient limitation (Supplement Table S1). The LUE method is an empirical approach, requiring high quantity look-up tables of the key parameters to quantify the diversified ecosystems. However, in practice, the ε^* in LUE models is assumed to be identical for all plant types or for major vegetation classes, such as croplands or grasslands (Goerner et al., 2011; Potter et al., 1993; Xiao et al., 2005; Yuan et al., 2010; Zhao and Running, 2010). Usually croplands have only one ε^* value in models to represent the average condition, which introduces inevitable biases at local scales. This situation is largely due to two main constraints, suggesting also a strategy for improvement of the estimates. One is the paucity of land cover data, most of which does not offer sufficient detail to separate plant or crop types. The other is how to adequately use the large number of studies that have aimed to parameterize ε^* using site level measurements.

This study aims to estimate global cropland GPP, using recently developed global cropland distribution data for the year 2000 to partition global croplands into 26 crop types. To improve the parameterization of the $\varepsilon^*_{\mathrm{GPP}}$ model, both eddy covariance flux measurements and a survey of previous reported $\varepsilon^*_{\mathrm{GPP}}$ values are used to generate a look-up table of $\varepsilon^*_{\mathrm{GPP}}$ for these 26 crop types.

2 Methods and data sets

2.1 Introduction

We used a biogeochemical model based on the LUE approach, the Carnegie–Ames–Stanford Approach (CASA, Potter et al., 1993; van der Werf et al., 2010). Croplands were separated into 26 crop types based on a new data set described in Sect. 2.2. We estimated $\varepsilon^*_{\mathrm{GPP}}$ using 16 eddy covariance flux tower sites (FLUXNET) following Chen et al. (2011) and conducted a literature survey on previously reported ε^* values. A combination of these two ε^* resources yielded the look-up table of $\varepsilon^*_{\mathrm{GPP}}$ for the 26 crop types. These steps are explained in more detail below.

2.2 LUE model and croplands data

The CASA biogeochemical model with the version described in van der Werf et al. (2010) was used in this study. GPP was calculated by multiplying absorbed photosynthetically active radiation (PAR) and a light use efficiency coefficient, ε (Monteith, 1972; Monteith and Moss, 1977):

$$\mathrm{GPP} = \mathrm{PAR} \times \mathrm{fPAR} \times \varepsilon^*_{\mathrm{GPP}} \times T(\varepsilon) \times W(\varepsilon), \quad (1)$$

where fPAR (also known as fAPAR) is the fraction of PAR absorbed by vegetation. Environmental stresses related to temperature and water are indicated by $T(\varepsilon)$ and $W(\varepsilon)$ respectively. More details about the model structure can be found in Potter et al. (1993).

The monthly distribution of cropland-growth data of MIRCA2000 (monthly irrigated and rainfed crop areas; Portmann et al., 2010) was used as the map of global croplands at a 5 arcmin spatial resolution. The 26 crop types were separated in MIRCA2000. Correspondingly, 5 arcmin monthly fPAR data from the Joint Research Centre (JRC) were prepared based on original finer grid records (Gobron et al., 2010) which is further described in Sect. 2.3. $\varepsilon^*_{\mathrm{GPP}}$ was set crop specific, using the values estimated as described in Sect. 2.3. International Satellite Cloud Climatology Project (ISCCP) solar radiation data from the Goddard Institute for

Space Studies (GISS) (Zhang et al., 2004) were used to generate PAR. Precipitation of the Global Precipitation Climatology Project (GPCP) version 1.1 (Huffman et al., 2001) and temperature of the GISS surface temperature analysis (Hansen et al., 1999) were employed to force environmental stress functions as described in Potter et al. (1993).

2.3 The maximum light use efficiency, $\varepsilon^*_{\mathrm{GPP}}$

To fulfill the model requirements for the crop types, we needed to estimate and assign $\varepsilon^*_{\mathrm{GPP}}$ to these 26 crop types of the MIRCA2000 map. $\varepsilon^*_{\mathrm{GPP}}$ based on direct field measurements is ideal to ensure that the parameters in our model are consistent with regard to the vegetation index and environmental factors. Therefore, we applied a similar procedure as in our previous work (Chen et al., 2011) by constraining CASA modeled GPP with field GPP measurements from FLUXNET.

Eddy covariance instrumentation directly measures ecosystem net exchange (NEE), which can then be partitioned into GPP and respiration using various approaches (Reichstein et al., 2005; Lasslop et al., 2010). Combining satellite and eddy covariance tower measurements, $\varepsilon^*_{\mathrm{GPP}}$ can be directly estimated. FLUXNET offers a high level of global consistency between individual flux tower measurements (see http://www.fluxdata.org). The FLUXNET data set contains about 30 cropland sites. To accomplish our purpose of LUE evaluation, we included only those sites where PAR, temperature and precipitation records were available. Besides that, we also collected the rotation histories with details of growing periods and plant types from individual FLUXNET PI's. The information of the sites used in this study is listed in Supplement Table S2.

Satellite-based fPAR was used to indicate vegetation activity in our study, using JRC collocated fPAR products over the FLUXNET sites, available on http://fapar.jrc.ec.europa.eu/Home.php. JRC-fPAR data are generated based on the data collections of the SeaWiFS (Sea-viewing Wide Field-of-view Sensor) sensor on the SeaStar satellite and the MERIS (Medium Resolution Imaging Spectrometer) sensor on the Envisat (Environmental Satellite) platform of the European Space Agency. These collections have a 10-day temporal scale and cover 3 by 3 pixels, about 6 km × 6 km, around the central pixel where the FLUXNET sites are located. These data are specifically designed for validation of remote sensing products and models or for characterization of field sites. Because usually there are not sufficient fPAR observations on the ground, fPAR from the center pixel is assumed to represent the fPAR influencing the footprint of the tower.

To optimize $\varepsilon^*_{\mathrm{GPP}}$, we iteratively changed its value with steps of $0.05\,\mathrm{g\,C\,MJ^{-1}}$ and choose the $\varepsilon^*_{\mathrm{GPP}}$ with the lowest RMSE (root mean square error) between CASA and FLUXNET GPP:

$$\mathrm{RMSE} = \left[\frac{1}{N}\sum_{n=1}^{N}(\mathrm{NEE_{CASA}} - \mathrm{NEE_{ECFT}})^2\right]^{1/2}. \quad (2)$$

This approach yielded direct estimates of $\varepsilon^*_{\mathrm{GPP}}$ for 8 crop types out of 26 crops due to the distribution of the FLUXNET sites. To fill in the gaps we conducted a survey of previous studies that reported ε across a wide variety of crop types. However, these previous studies were quite different in their methodology. For example, solar radiation, intercepted PAR and absorbed PAR were interchangeably used to indicate radiation. Direct measurements of dry matter were often used to calculate production while we focused on GPP here. For consistency, we therefore used a conversion equation:

$$\varepsilon^*_{\mathrm{GPP}} = \varepsilon_{\mathrm{biomass}} \times R_{\mathrm{CB}} \times R^{-1}_{\mathrm{NG}} \times R_{\mathrm{ES}}, \quad (3)$$

where R_{CB} is the carbon content per unit of dry biomass, R_{NG} is the ratio between NPP and GPP and R_{ES} indicates environmental stresses. R_{CB} was found to be quite stable within a 45–50 % range (Schlesinger, 1991). Magnussen and Reed (2004) suggested a conversion rate of 0.475 which was used here ($R_{\mathrm{CB}} = 0.475$). GPP could be roughly estimated by doubling NPP because autotrophic respiration (R_{a}) usually takes about half of GPP (Waring et al., 1998), but with substantial variability across plant types and sites (DeLucia et al., 2007; Litton et al., 2007; Luyssaert et al., 2007). NPP is usually treated as half the value of GPP in most analyses (Beer et al., 2010). Therefore, we used $R_{\mathrm{NG}} = 0.5$ in this paper.

Most biomass measurements only consider aboveground dry matter (ADM). To calculate total dry matter (TDM) we used an ADM / TDM ratio of 0.8 (Gallagher and Biscoe, 1978; Steingrobe et al., 2001) when ε values reported were based on ADM measurements only. The maximum light use efficiency concept assumes no environmental stresses, therefore, only the well-watered sites and those without diseases or drought were included in this study ($R_{\mathrm{ES}} \approx 1$). As a result, 89 $\varepsilon^*_{\mathrm{GPP}}$ values using Eq. (3) were converted based on literature, covering 21 crop types (Supplement Table S1).

3 Results

3.1 Light use efficiency $\varepsilon^*_{\mathrm{GPP}}$

The direct estimates of $\varepsilon^*_{\mathrm{GPP}}$ using FLUXNET crop sites are listed in Table 1. At these sites, the ratios between modeled and observed GPP varied between 0.86 and 1.23 and were on average 1.04 ± 0.08 (standard deviation – SD). The corresponding correlation coefficients of monthly modeled and observed GPP over each site were on average 0.85 ± 0.14. We summarized these measured $\varepsilon^*_{\mathrm{GPP}}$ and the ones derived from the literature for the 26 crop types in MIRCA2000 in Table 2. Of the 26 crop types, 8 were directly calculated in this paper, covering 55 % of the global

Table 1. Statistics of GPP_{CASA} to $GPP_{FLUXNET}$ relation and ε^*_{GPP} estimates at FLUXNET sites.

Site code	Crop types	Correlation coefficient	Standard deviation[1]	Centered RMSE[1]	GPP_{CASA} / $GPP_{FLUXNET}$	ε^*_{GPP} ($g\,C\,MJ^{-1}$)
BE_Lon	Sugar beet	0.47	0.46	0.88	1.00	2.90
	Winter wheat	0.72	0.75	0.69	0.95	2.40
	Potato	0.98	0.39	0.61	1.12	1.50
CN_Du1	Wheat	0.83	0.56	0.62	1.10	1.65
DE_Geb	Rapeseed	0.94	0.89	0.36	1.04	2.30
	Winter barley	0.72	0.79	0.70	0.86	1.55
	Sugar beet	0.90	0.84	0.43	1.23	1.00
DE_Kli	Rapeseed	0.81	0.87	0.59	0.94	1.80
	Winter wheat	0.95	0.83	0.33	1.20	2.45
DK_Ris	Winter wheat	0.92	0.98	0.41	0.95	2.25
ES_ES2	Rice	0.94	0.94	0.33	1.01	2.90
FR_Gri	Winter wheat	0.92	0.93	0.40	0.96	2.80
IE_Ca1	Spring barley	0.83	0.66	0.58	1.09	1.90
JP_Mas	Rice	0.90	0.53	0.57	1.07	2.60
NL_Lan	Maize	0.47	0.52	0.88	1.00	2.35
US_ARM	Wheat	0.96	1.02	0.30	0.94	1.25
US_Bo1	Soybean	0.87	0.75	0.51	1.12	1.55
	Maize	0.96	0.85	0.31	1.06	2.00
US_Bo2	Maize	0.99	0.87	0.16	1.09	2.90
	Soybean	0.96	0.85	0.29	1.07	1.45
US_Ne1	Maize	0.90	0.61	0.53	1.11	2.95
US_Ne2	Maize	0.92	0.71	0.45	1.10	3.45
	Soybean	0.79	0.63	0.63	1.07	1.75
US_Ne3	Maize	0.84	0.65	0.58	1.10	3.40
	Soybean	0.74	0.64	0.68	1.03	1.80

[1] Both modeled standard deviation and centered RMSE were nondimensionalized by dividing by the standard deviation of the corresponding observation. More details are in Sect. 3.2 of Taylor (2001).

cropland areas (Portmann et al., 2010). FLUXNET-based ε^*_{GPP} varied between crop types with potatoes having the lowest value ($1.5\,g\,C\,MJ^{-1}$) and maize having the highest ($2.84\,g\,C\,MJ^{-1}$). Our estimates and those of previous studies (Lobell et al., 2002; Chen et al., 2011; Supplement Table S1) thus confirm a higher LUE value for maize than most of other crops. On average our ε^*_{GPP} values are higher than the one used in Zhao and Running (2010) (i.e., $1.044\,g\,C\,MJ^{-1}$) and the default values in the CASA model (i.e., $1\,g\,C\,MJ^{-1}$), but are still within the range of values reported based on previous site measurements (e.g., Lobell et al., 2002; Supplement Table S1).

As shown in Fig. 1a, our direct estimates are generally lower than the literature-based values. We prefer to use our direct estimates based on FLUXNET measurements, because this enables us to upscale site level results to large domains using identical JRC fPAR data. To harmonize our ε^*_{GPP} values, a linear regression was calculated when both FLUXNET- and literature-based ε^*_{GPP} were available (Fig. 1b). The linear relation was further applied to generate the ε^*_{GPP} for the crop types that were not available in

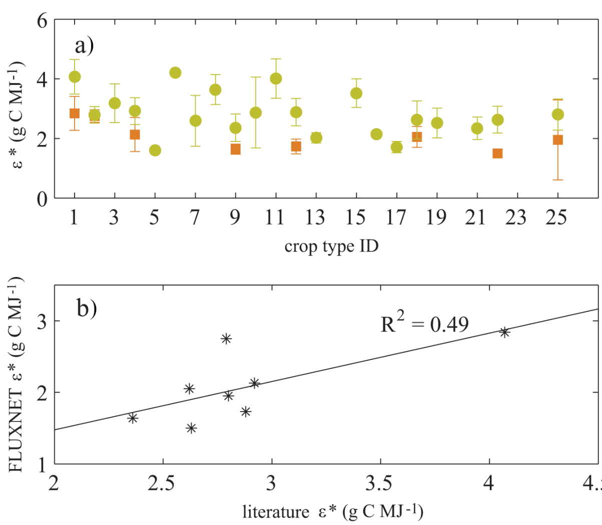

Figure 1. Maximum light use efficiency (ε^*_{GPP} in $g\,C\,MJ^{-1}$) for **(a)** different crop types based on FLUXNET sites (orange) and literature (green) with error bars representing two standard deviations of ε^*_{GPP}. The corresponding crop types are given in Table 2. **(b)** Linear relation between FLUXNET-based and literature-based ε^*_{GPP} estimations for the eight crop types listed in Table 2.

Table 2. $\varepsilon^*_{\mathrm{GPP}}$ used in our study and global cropland GPP estimates for various crop types.

ID	Crop types	$\varepsilon^*_{\mathrm{GPP_{FLUXNET}}}$ ± SD	$\varepsilon^*\mathrm{GPP_{literature}}$ ± SD	$\varepsilon^*_{\mathrm{GPP_{regress}}}$	$\varepsilon^*_{\mathrm{GPP_{model}}}$	GPP (Pg C yr^{-1})
1	Maize	2.84 ± 0.57	4.07 ± 0.58	2.87	2.84	1.545
2	Rice	2.75 ± 0.21	2.79 ± 0.28	2.01	2.75	1.514
3	Fodder grasses		3.18 ± 0.65	2.28	2.28	1.389
4	Wheat	2.13 ± 0.57	2.92 ± 0.45	2.10	2.13	1.384
5	Others perennial		1.60	1.21	1.21	0.795
6	Cassava		4.20	2.96	2.96	0.612
7	Others annual		2.59 ± 0.85	1.87	1.87	0.508
8	Sugar cane		3.64 ± 0.50	2.59	2.59	0.494
9	Soybeans	1.64 ± 0.17	2.36 ± 0.46	1.72	1.64	0.491
10	Pulses		2.87 ± 1.19	2.06	2.06	0.353
11	Sorghum		4.01 ± 0.66	2.83	2.83	0.272
12	Barley	1.73 ± 0.25	2.88 ± 0.46	2.07	1.73	0.260
13	Oil palm		2.02 ± 0.17	1.49	1.49	0.210
14	Coffee				1.20	0.158
15	Millet		3.52 ± 0.48	2.51	2.51	0.134
16	Cocoa		2.14	1.57	1.57	0.132
17	Cotton		1.71 ± 0.19	1.28	1.28	0.123
18	Rapeseed	2.05 ± 0.35	2.62 ± 0.64	1.89	2.05	0.115
19	Sunflower		2.52 ± 0.50	1.83	1.83	0.112
20	Rye				2.13	0.109
21	Groundnuts		2.34 ± 0.38	1.71	1.71	0.105
22	Potatoes	1.50	2.63 ± 0.45	1.91	1.50	0.091
23	Citrus				1.20	0.064
24	Grapes				1.20	0.041
25	Sugar beet	1.95 ± 1.34	2.80 ± 0.52	2.02	1.95	0.040
26	Date palm				1.20	0.001
	Global					11.05

FLUXNET-based $\varepsilon^*_{\mathrm{GPP}}$ as

$$\varepsilon^*_{\mathrm{GPP_{FLUXNET}}} = 0.6757 \times \varepsilon^*_{\mathrm{GPP_{literature}}} + 0.1252\,. \tag{4}$$

Because $\varepsilon^*_{\mathrm{GPP}}$ should always be larger than zero, we kept the physically unrealistic offset (i.e., 0.1252) to best preserve the relation within the range of estimates. For five crop types we had neither FLUXNET nor literature values available. For rye, the same $\varepsilon^*_{\mathrm{GPP}}$ of wheat was assigned because rye is a member of the wheat tribe. The other four types (citrus, date palm, grapes and coffee) were all assigned 1.2 g C MJ^{-1}, which is the lowest value of our estimates for other perennial crops (1.21 g C MJ^{-1}) rounded to one decimal.

3.2 Global cropland monthly GPP in the year 2000

We calculated monthly GPP for these 26 crop types at 5 arcmin resolution for the year 2000, the only year for which the cropland distribution was available (Portmann et al., 2010). Global annual GPP amounts for each crop type as well as for all cropland combined are listed in Table 2. The annual global cropland GPP was 11.05 Pg C yr^{-1} in the year 2000. This estimate was between the 8.2 and 14.8 Pg C yr^{-1} reported previously by Saugier et al. (2001) and Beer et al. (2010), respectively. Maize, rice and wheat had the three highest GPP values for grains, contributing 40 % of the global cropland GPP. Fodder grasses are the most important crop type that is not grain and ranked third in all crops. The eight crop types with $\varepsilon^*_{\mathrm{GPP}}$ based on FLUXNET sites contributed 49 % of the global cropland GPP.

Figure 2 illustrates the global spatial distribution of annual cropland GPP. High GPP regions extend mostly in the warm humid or semi-humid plains of the Northern Hemisphere, such as the central and eastern part of United States, Europe, the eastern plain of China and the Ganges plain of South Asia. Per unit area, tropical regions had the highest GPP, such as in the lower reaches of the Ganges River over the contiguous areas of India and Bangladesh, and the lower reaches of the Niger River in Nigeria.

Asia produced over one third of global cropland GPP, which is more than two times that of any other continent (Table 3). Within the 26 types, rice contributed the most (1336.3 Tg C yr^{-1}) to the annual GPP in Asia. GPP of rice in Asia contributed 88.3 % of global rice GPP. North America and Europe accounted for respectively 16.6 % and 16.2 % of the global cropland GPP. The United States is the main producer of maize and soybean in the world, and this is reflected

Table 3. Annual GPP (Tg C yr^{-1}) for different regions in the year 2000.

Crop types	North America[1]	South America	Europe[2]	Asia	Africa	Oceania
Maize	504.2	277.2	204.6	342.6	215.5	1.0
Rice	22.0	78.1	3.6	1336.3	73.2	0.9
Fodder grasses	494.5	135.6	504.2	205.3	26.0	24.2
Wheat	196.4	87.5	481.6	525.4	35.4	58.2
Others perennial	34.2	64.7	55.9	505.1	121.1	14.3
Cassava	9.9	103.9	0	143.6	354.4	0.8
Others annual	31.9	37.2	117.7	215.6	95.8	9.5
Sugar cane	85.2	180.8	0	186.8	30.4	11.0
Soybeans	215.1	198.2	5.5	65.8	5.9	0.2
Pulses	29.8	54.4	25.7	143.8	92.5	6.6
Sorghum	54.1	28.3	1.4	70.4	112.0	5.6
Barley	24.5	5.5	149.4	55.0	9.9	16.2
Oil palm	2.6	6.9	0	138.0	60.8	2.1
Coffee	33.2	56.2	0	36.0	30.7	1.6
Millet	0.9	0.3	3.6	62.7	65.9	0.2
Cocoa	6.2	28.7	0	14.2	80.3	2.9
Cotton	31.6	11.9	1.5	54.2	21.3	2.2
Rapeseed	16.2	0.4	36.6	56.4	0.1	5.4
Sunflower	9.3	24.4	53.7	19.2	4.5	0.5
Rye	1.7	0.7	98.4	7.2	0.4	0.2
Groundnuts	6.5	3.8	0.1	55.4	39.4	0.2
Potatoes	3.9	5.1	49.3	28.6	3.8	0.3
Citrus	12.3	18.8	3.3	18.9	10.2	0.3
Grapes	2.5	3.4	27.2	6.0	1.2	1.0
Sugar beet	3.0	0.3	32.0	3.8	0.4	0
Date palm	0	0	0	0.6	0.8	0
Total	1831.7	1412.1	1855.4	4297.0	1492.0	165.5
Percent (%)	16.6	12.8	16.8	38.9	13.5	1.5

[1] North America includes Central America.
[2] Europe does not contain Russia east of the Urals.

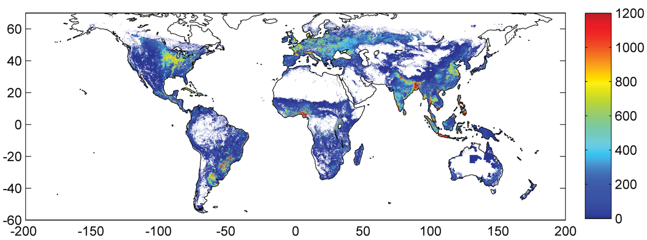

Figure 2. Spatial distribution of annual GPP flux (g C m^{-2} yr^{-1}) for each 5 arcmin grid cell in the year 2000 with values capped at 1200 g C m^{-2} yr^{-1}. Annual GPP flux values of some grid cells in the tropics are larger than 2000 g C m^{-2} yr^{-1}.

in the proportion of maize and soybean (Table 3). Africa was the fourth most important region (13.5 %) with the most cassava GPP (57.9 %) of the world. The annual cropland GPP in South America (12.8 %) was very close to that of Africa. Maize and soybean contributed most to the cropland GPP in South America (Table 3). The cropland GPP in Oceania was the lowest of the continents, due to the small areas of croplands.

4 Discussion

After the initial development of the LUE approach (Monteith, 1972; Monteith and Moss, 1977) to estimate ecosystem production (GPP or NPP), considerable efforts have been made to evaluate ε to meet the need of the model parameterizations. We chose to estimate $\varepsilon^*_{\mathrm{GPP}}$ directly by combining FLUXNET measurements and JRC fPAR, the same vegetation index as we used in our model. Our estimates of $\varepsilon^*_{\mathrm{GPP}}$ are within the range reported previously by field measurements (Table 1; Supplement Table S1). In our model we treated the directly estimated $\varepsilon^*_{\mathrm{GPP}}$ as superior to the literature-based values. On average, the $\varepsilon^*_{\mathrm{GPP}}$ values based on biomass (dry matter) measurements are higher than our estimates based on FLUXNET observations. Therefore, we adjusted the literature-based $\varepsilon^*_{\mathrm{GPP}}$ values using ratios between the FLUXNET- and literature-based estimates when available. Because both the $\varepsilon^*_{\mathrm{GPP}}$ values based on biomass as well as the FLUXNET-based values are relatively high, the values finally used in our model are therefore higher than those used in other models (Zhao and Running, 2010; Lobell et al., 2002; Field et al., 1995; Potter et al., 1993). A look-up table of $\varepsilon^*_{\mathrm{GPP}}$ for 26 crop types was created, offering much more sophisticated parameters of the LUE empirical models than previous studies.

Global cropland GPP was estimated to be 11.05 $\mathrm{Pg\,C\,yr^{-1}}$, which is within the range of previous studies (Beer et al., 2010; Saugier et al., 2001). Several model studies found that $\varepsilon^*_{\mathrm{GPP}}$ or $\varepsilon^*_{\mathrm{NPP}}$ values based on site measurements could not be used in models directly because this would lead to excessively high cropland GPP values (Lobell et al., 2002; Potter et al., 1993). For example, Potter et al. (1993) found that if $\varepsilon^*_{\mathrm{NPP}}$ would be set to 1.25 $\mathrm{g\,C\,MJ^{-1}}$ as in Heimann and Keeling (1989), annual NPP would be an unrealistic high 185 $\mathrm{Pg\,C\,yr^{-1}}$. Therefore, a value of 0.5 $\mathrm{g\,C\,MJ^{-1}}$ for $\varepsilon^*_{\mathrm{NPP}}$ was initially used in CASA (Potter et al., 1993). Even if we double the 0.5 $\mathrm{g\,C\,MJ^{-1}}$ number to account for the GPP / NPP ratio of about 2, the value is still much lower than the $\varepsilon^*_{\mathrm{GPP}}$ values we found here.

The difference between in situ measurements of $\varepsilon^*_{\mathrm{GPP}}$ and the values used in models may reflect model structural biases which have to be compensated for by adjusting parameters. Inventory-based estimates could be used to validate and improve crop models from local regions (Bandaru et al., 2013; Doraiswamy et al., 2007) to the continental scale (Lobell et al., 2002). Therefore, we echo the findings of Lobell et al. (2002) who used both CASA and harvest records. Cropland NPP for continental United States (excluding Alaska and Hawaii) was estimated to be 0.62 $\mathrm{Pg\,C\,yr^{-1}}$, or 1.24 $\mathrm{Pg\,C\,yr^{-1}}$ GPP by doubling NPP (Lobell et al., 2002). $\varepsilon^*_{\mathrm{NPP}}$ in Lobell et al. (2000) was estimated by constraining the model results with NPP based on harvest data across each county. In our estimations, GPP in the United States was 1.28 $\mathrm{Pg\,C\,yr^{-1}}$, which is very close to the value obtained in Lobell et al. (2002). However, the $\varepsilon^*_{\mathrm{GPP}}$ values in Lobell et al. (2002) by doubling $\varepsilon^*_{\mathrm{NPP}}$ are still much smaller than the values we used here. There is therefore no conflict between field-based $\varepsilon^*_{\mathrm{GPP}}$ and the direct parameterization application in our model. The main distinction between the current and previous studies are the two main innovations of our study: (1) we used cropland areas distribution data to define the cropland types by month in order to distinguish the growing and fallow periods; and (2) we assigned each of the 26 crops a different $\varepsilon^*_{\mathrm{GPP}}$ value.

Compared with natural ecosystems, usually croplands have three important distinct features which influence their carbon exchange. First, plant (crop) types are much more homogeneous than natural ecosystems due to management practice of farmers. Second, the plant types change much faster than natural ecosystems due to crop rotation schemes used, which means the land cover type does not uniquely determine plant types as in more natural ecosystems. Third, planting, ploughing and harvesting activities change the ecosystems in croplands abruptly and leave land fallow for long periods, sometimes even during the growing season. Therefore, cropland distributions from survey data are the only option to separate crop rotation and planting times fully at present. However, the spatial resolution of these data is still larger than a single field, implying that one cell still contains several crop yields and types. These crops have different light use efficiencies in reality but are treated in models with the same vegetation index and environmental factors.

Uncertainties in our estimates were due to several aspects. First, the ε^* varies between plant types and even changes within one crop type with changing environmental conditions. More evaluations of $\varepsilon^*_{\mathrm{GPP}}$ are required to constrain the parameters of different crop types. Second, the literature-based ε^* values depend on the choice of vegetation indices, such as fPAR, PRI (photochemical reflectance index), EVI (enhanced vegetation index), and different environment descriptions. Satellite fPAR is used in $\varepsilon^*_{\mathrm{GPP}}$ estimations due to the lack of ground fPAR observation, which brings uncertainties in consequence due to scale difference. In most cases, if a satellite's pixel contains roads or other human buildings, that may reduce the fPAR value and lead to an overestimated $\varepsilon^*_{\mathrm{GPP}}$ as well. Finally, we were unable to separate irrigated and rain-fed crops in our current approach. The exact magnitude of these uncertainties is impossible for us to quantify, but it should be possible when more ε^* observations become available and when a systematic estimate of the error due to different vegetation indices is known in the future.

5 Conclusions

In this paper, we estimated global cropland GPP using a LUE model with improved input data and parameterization of $\varepsilon^*_{\mathrm{GPP}}$. A total of 26 crop types were separated in our model with different $\varepsilon^*_{\mathrm{GPP}}$ values compared to the previously default parameterization with a constant $\varepsilon^*_{\mathrm{GPP}}$ for all crop types. To meet the parameterization requirements, we evaluated $\varepsilon^*_{\mathrm{GPP}}$ based on FLUXNET data for eight crop types. We also performed a literature survey and gathered 89 $\varepsilon^*_{\mathrm{GPP}}$ values that met our requirements necessary to harmonize these values. Our FLUXNET-based $\varepsilon^*_{\mathrm{GPP}}$ values are within the range of previous studies but are higher than those used in most LUE models. Finally, a look-up table of $\varepsilon^*_{\mathrm{GPP}}$ for the 26 crop types was created based on measurements.

$\varepsilon^*_{\mathrm{GPP}}$ (assumed equal to 2 times $\varepsilon^*_{\mathrm{NPP}}$) based on field measurements and the values used in vegetation models differ widely, as discussed by Potter et al. (1993), Ruimy et al. (1994) and Lobell et al. (2002). Our previous work (Chen et al., 2011) also highlighted the need to improve the LUE parameterization in vegetation models. In this study, we estimated global cropland annual GPP at 11.05 $\mathrm{Pg\,C\,yr^{-1}}$ using field-based $\varepsilon^*_{\mathrm{GPP}}$. This estimate is in the middle of previous studies indicating 14.2 $\mathrm{Pg\,C\,yr^{-1}}$ by Beer et al. (2010)

and 8.2 $Pg\,C\,yr^{-1}$ by Saugier et al. (2001). GPP in the United States was estimated to be 1.28 $Pg\,C\,yr^{-1}$, close to the 1.24 $Pg\,C\,yr^{-1}$ reported by Lobell et al. (2002). Our results demonstrate a successful usage of directly estimated ε^*_{GPP} in a LUE-approach-based vegetation model. We only focused on the year 2000 because the cropland distribution data was only available for this year. Our improvements, separating croplands which are generally treated as one biome in global models into different plant types with corresponding spatial distribution and using more specific ε^*_{GPP} values for each type, may lead to more realistic cropland GPP estimates.

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