1 **Estimating crop yield using a satellite-based light use efficiency model**

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11

12 **Abstract** Satellite-based techniques that provide temporally and spatially continuous

13 information over vegetated surfaces have become increasingly important in monitoring the global

14 agriculture yield. In this study, we examine the performance of a light use efficiency model

15 (EC-LUE) for simulating the Gross Primary Production (GPP) and yield of crops. The EC-LUE

16 model can explain on average approximately 90% of the variability in GPP for 36 FLUXNET sites

17 globally. The results indicate that a universal set of parameters, independent of crop species

18 (except for C4 crops), can be adopted in the EC-LUE model for simulating crops' GPP. At both

19 irrigated and rainfed sites, the EC-LUE model exhibits a similar level of performance. However,

20 large errors are found when simulating yield based on crop harvest index. This analysis highlights

21 the need to improve the representation of the harvest index and carbon allocation for improving

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22 crop yield estimations from satellite-based methods.

23 **Key words:** Light use efficiency; EC-LUE; Gross primary production; Crop yield

24 **1. Introduction**

25 Approximately 12% of the Earth's land surface is presently represented by cultivated
26 cropland, which supplies the great part of human food production. Sustained world population
27 growth, rising meat and dairy consumption and expanding biofuel use are exerting increasing
28 pressure on global agriculture (Ray et al., 2012). Global food production, however, is and will be
29 significantly affected by climate change (Parry et al., 2004; Schmidhuber and Tubiello, 2007). In
30 this perspective, crop production monitoring and forecasting is of fundamental importance for
31 agricultural management, food security threats, food trade policy and carbon cycle research
32 (Tilman et al., 2011).

33 Remotely sensed data provides temporally and spatially continuous information over
34 vegetated surfaces and is useful for accurately monitoring cropland yield and spatial patterns.
35 Generally, there are two approaches for yield estimation using remote sensing data. The first
36 method includes biophysical crop-simulation models that retrieve crop growth parameters from
37 remotely sensed data, which are used as inputs to calibrate and drive the models (Brisson et al.,
38 1998). The main drawback of such models is that they typically require numerous crop-specific
39 inputs such as soil characteristics, management practices, agro-meteorological data and planting
40 dates to simulate crop growth and development through the crop cycle (Moriondo et al., 2007).
41 Such crop-simulation models include CERES (Ritchie and Otter, 1985), WOFOST (van Diepen et
42 al., 1989) and CROPSYST (van Evert and Campbell, 1994). The second scheme includes

43 statistical regression-based methods, which are the most commonly used remote sensing-based
44 approaches (Wall et al., 2008). These are based on empirical relationships between historic yields
45 and reflectance-based vegetation indices. They are typically straightforward to implement and do
46 not require numerous inputs. A main drawback of empirically based approaches is that the
47 relationships between yield and reflectance are typically localized and are not easily extendable to
48 other areas (Doraiswamy et al., 2003; Moriondo et al., 2007).

49 Satellite-based light use efficiency (LUE) models are an alternative approach that makes
50 it possible to accurately estimate crop yield, because they can successfully estimate the
51 vegetation's gross primary production (GPP), which is at the basis of the ecosystem's carbon
52 biogeochemical cycle and the main variable determining crop yield. The LUE models build upon
53 the assumption that ecosystem GPP is directly related to the absorbed photosynthetically active
54 radiation (APAR) through LUE (Monteith 1972; Monteith 1977). Actual LUE may be reduced
55 below its theoretical potential value by environmental stresses such as low temperatures or water
56 shortages (Landsberg, 1986; Goerner et al., 2009,). Some studies have evaluated LUE models at
57 regional and global scales in major ecosystem types (Potter et al., 1993; Turner et al., 2006;
58 Huntzinger et al., 2012; Yuan et al., 2012; Raczka et al., 2013; Cai et al., 2014).

59 In recent years, several studies have used the LUE models to address the spatial and
60 temporal patterns of cropland vegetation production (Chen et al., 2014) and to simulate crop yield
61 over large areas (Xin et al., 2013). On the other hand, some authors examined the capability of
62 LUE models to estimate crop yield and demonstrated large uncertainties. For example, based on
63 the MODIS-GPP products (MOD17), Reeves et al. (2005) found a weak correlation between GPP
64 estimates and the national agricultural yield data at the county level for the states of Montana and

65 North Dakota in the United States, and highlighted the need to use crop-specific model parameters.
66 Moreover, the model performance for simulating crop yield has never been evaluated at the site
67 scale. Previous studies often examined model performance over large regions by comparing
68 outputs with regional crop inventory data (Xin et al., 2013; Li et al., 2014). The uncertainties from
69 model inputs, which are needed for regional estimates, will hinder the judgment of model
70 performance. Li et al. (2014) found the misclassification of cropland from a land cover product is
71 one of the major causes of bias in the NPP estimates of cropland in the midwestern United States.

72 This study aims to examine the performance of a LUE model (i.e., EC-LUE, Yuan et al.,
73 2007) for the prediction of crop biomass and yield production, over multiple crop species globally.
74 The overarching goals of this study are to (1) examine the model performance for vegetative
75 primary production across various crop types and management, (2) assess the possibility for
76 simulating crop yield from crop vegetation production estimates, and (3) investigate the most
77 relevant processes for crop yield simulations based on the LUE models.

78 **2. Model and Data**

79 **2.1 EC-LUE model**

80 Yuan et al. (2007, 2010) developed the Eddy Covariance-Light Use Efficiency (EC-LUE)
81 model to simulate daily vegetation GPP. The EC-LUE model is driven by only four variables: the
82 Normalized Difference Vegetation Index (*NDVI*), Photosynthetically Active Radiation (*PAR*), air
83 temperature (*T*), and the Bowen ratio of sensible to latent heat flux. The EC-LUE model has the
84 great advantage to map daily GPP over large areas because the potential LUE is invariant across
85 various land cover types (Yuan et al., 2014b). Previous study indicated that a universal set of

parameters, which is independent of vegetation cover type and characteristics can be adopted in EC-LUE model (Yuan et al., 2014b). Availability of this well tested and universal set of parameters would help to improve the accuracy and applicability of LUE models in various biomes and geographic regions.

The model equations are as follows:

$$GPP = PAR \times fPAR \times \varepsilon_{\max} \times \text{Min}(T_s, W_{SEF}) \quad (1)$$

$$fPAR = 1.24 \times NDVI - 0.168 \quad (2)$$

$$T_s = \frac{(T - T_{\min}) \times (T - T_{\max})}{((T - T_{\min}) \times (T - T_{\max}) - (T - T_{opt})^2)} \quad (3)$$

$$W_{SEF} = \frac{LE}{R_n} \quad (4)$$

where fPAR is the fraction of intercepted incident PAR. $\varepsilon_{\max}$ is the potential light use efficiency without environmental stress ($2.14 \text{ g C m}^{-2} \text{ MJ}^{-1} \text{ APAR}$). *Min* denotes the minimum values of T_s and W_{SEF} , (it is assumed that the impacts of temperature and moisture follow Liebig's Law, so that LUE is only affected by the most limiting factor at any given time). $T_{\min}$, $T_{\max}$ and T_{opt} are the minimum, maximum and optimum air temperatures ($^{\circ}\text{C}$) for photosynthetic activity, respectively. If the air temperature falls below $T_{\min}$ or increases beyond $T_{\max}$, T_s is set to zero. In this study, $T_{\min}$ and $T_{\max}$ were set to 0 and 40°C (Yuan et al., 2007), respectively, while T_{opt} was determined using nonlinear optimization to be 21°C (Yuan et al., 2007). LE is the daily latent heat flux (MJ m^{-2}), which is estimated using the revised RS-PM (Remote Sensing–Penman Monteith) model (Yuan et al., 2010). R_n is the daily net radiation (MJ m^{-2}).

105 2.2 Data

106 Data collected at 36 eddy covariance (EC) sites (78 site-year) were used in this study to
107 examine the performance of the EC-LUE model (Table 1). These sites covered several dominant
108 cropland ecosystem types (Table 1). EC data were obtained from the websites: FLUXNET
109 (<http://www.fluxdata.org>), HiWATER (<http://westdc.westgis.ac.cn/hiwater>) (Li et al., 2013), and
110 AsiaFlux (<http://www.asiaflux.net>). Supplementary information on the vegetation, climate and soil
111 at each site was also available at the above web sites. Half-hourly or hourly averaged PAR, T and
112 friction velocity (u^*) were used along with Net ecosystem CO₂ exchange (NEE) in this study.
113 FLUXNET datasets that were gap-filled by site investigators were used directly for this study (i.e.,
114 the LaThuile database) (Agarwal et al., 2010).

115 <<Table 1>>

116 For the sites that were not in the LaThuile FLUXNET database, the following established
117 procedures were used to fill data gaps (Yuan et al., 2014a): nonlinear regression relationships were
118 fitted between the measured fluxes and controlling environmental variables (air temperature, PAR)
119 and subsequently used to fill the missing values using a 15-day moving window. The van't Hoff
120 equation was used to estimate missing night time NEE ($F_{c, night}$) (Lloyd and Taylor, 1994):

$$121 \quad F_{c, night} = A \times e^{(B \times T)} \quad (5)$$

122 where A and B are estimated model coefficients and T is the air temperature. A Michaelis-Menten
123 light response equation was used for daytime NEE ($F_{c, day}$) (Falge et al., 2001):

$$124 \quad F_{c, day} = \frac{\alpha \times \text{PAR} \times F_{GPP, sat}}{F_{GPP, sat} + \alpha \times \text{PAR}} - F_{RE, day} \quad (6)$$

125 where $F_{GPP,sat}$ (the GPP at saturating light) and α (the initial slope of the light response function)
 126 are empirically estimated coefficients, and $F_{RE,day}$ (ecosystem respiration) was estimated by the
 127 extrapolation of Eq. (5) using the daytime air temperature. The daily NEE, ecosystem respiration
 128 (Re), and meteorological variables were averaged based on half-hourly or hourly values, and the
 129 daily values were flagged as missing when more than 20% of the data for a given day was lacking;
 130 otherwise, the daily values were calculated by multiplying the averaged half-hourly or hourly rate
 131 by 24 hours. The GPP was calculated as the sum of the NEE and Re . Based on the daily dataset,
 132 the 8-day GPP mean value could be calculated. If more than 2 days of daily data were missing
 133 within a given 8-day period, the 8-day value was indicated as missing.

134 We adapted the harvest index methods (Prince et al., 2001) to estimate crop yield using
 135 the following equations:

$$136 \quad Yield = GPP \times AR \times HI \times RS \quad (7)$$

137 where $Yield$ is the crop yield ($\text{g C m}^{-2} \text{ yr}^{-1}$). AR is the autotrophic respiration proportion accounting
 138 for GPP (0.53) (Waring et al., 1998), and $GPP \times AR$ indicates the net primary production (NPP) (g
 139 $\text{C m}^{-2} \text{ yr}^{-1}$). HI refers to the harvest index, a standard measure of the proportion of total crop
 140 aboveground biomass allocated to the economic yield of the plant (Donald and Hamblin, 1976;
 141 Hay, 1995). The carbon allocation coefficient, RS , indicates the ratio of aboveground NPP to the
 142 total NPP. This study uses the HI and RS values collected by Monfreda et al. (2008) for various
 143 crop types. A constant mean carbon content of $0.45 \text{ g C g dry matter}^{-1}$ was used to derive crop
 144 yield from economic yield (g dry matter). In this study, we used both of estimated GPP based on
 145 EC measurements and simulated GPP of EC-LUE to calculate crop yield, and compared them with
 146 yield observations. The former comparison is to evaluate the performance of Eq. (7) to estimate

147 yield, and the latter comparison can indicate the EC-LUE model performance for estimating crop
148 yield.

149 The 8-day NDVI data with a 1-km spatial resolution (MOD13) were retrieved at each of
150 the EC sites. MOD13 has a quality control (QC) layer to indicate the data reliability for each pixel
151 (good data, marginal data, snow/ice, cloudy and missing). In this study, we considered NDVI data
152 with a 'marginal' or 'cloudy' QC flag to be unreliable. We temporally filled the missing or
153 unreliable NDVI at each 1-km MODIS pixel based on its corresponding quality assessment data
154 field (Zhao et al., 2005).

155 Three metrics were used to evaluate the performance of the models, including the
156 correlation coefficient of determination (R^2), root mean square error (RMSE), and mean predictive
157 error (BIAS, difference between the mean observations and simulations).

158 **3. Results**

159 The EC-LUE model successfully predicted the magnitudes and seasonal variations of
160 the estimated GPP from the EC measurements at most of the cropland sites (Fig. 1). Individually,
161 the coefficients of determination (R^2) varied from 0.43 at the NL-Lan site to 0.92 at the US-Ne3
162 site, with all being statistically significant at $p < 0.05$ (Table 2). The predicted seasonal patterns, as
163 well as the beginning and end of the growing seasons, agreed well with the estimated values from
164 EC measurements at most sites (Fig. 1).

165 <<Figure 1>>

166 <<Table 2>>

167 Large differences between the predicted and estimated GPP could be evidenced at a few

168 sites. At almost all sites where maize was grown, the EC-LUE model strongly underestimated
169 GPP when the original ε_{max} model parameter value was used (Fig. 2). The original ε_{max} was
170 calibrated at twelve EC towers with dominated by C3 grasses and trees (Yuan et al., 2007). We
171 therefore calibrated the potential LUE over all of the EC sites where maize was planted, and the
172 derived parameter was equal to 2.84 g C MJ^{-1} . Substituting the calibrated parameter value in the
173 equation substantially improved the model performance for maize (Fig. 2), and the EC-LUE
174 model explained 90% of the GPP variations across all 36 sites (Fig. 2). The EC-LUE model
175 performed very well under both irrigated (16 sites) and rainfed (9 sites) conditions (see table 2),
176 since no significant differences in GPP simulations could be detected (Fig. 3).

177 <<Figure 2>>

178 <<Figure 3>>

179 Using the yield observations collected at 12 sites, we examined the model performance
180 for simulating crop yield. The model explained approximately 61% of the variation in crop yield
181 over a total of 26 site-years (Fig. 4a). However, large differences between the predicted yield and
182 observations still existed at a few sites. The model underestimated yield between 61% and 32% at
183 several sites (e.g., US-Ne3 (2001), DE-Geb, CH-Oe2 and US-Ne1) (data not shown). On the other
184 side, predictions were higher than those observed for the crop yield at US-Ne3 (2003), FR-Aur
185 and BE-Lon with RPE values that varied from 34% to 55%. Moreover, the results showed the
186 errors of simulated yield using estimated GPP based on EC measurements, which implied the
187 uncertainties of the harvest index method for estimating crop yield (Fig. 4b).

188 <<Figure 4>>

189 **4. Discussion**

190 **4.1 Model performance for simulating GPP**

191 The successful model validation at 36 EC crop sites globally suggested that the EC-LUE
192 model was robust and reliable for estimating GPP across cropland ecosystems. The results showed
193 that the EC-LUE model did not produce significant predictive errors of the GPP across the
194 majority of all investigated sites, only underestimating the GPP of the C4 crops. Specifically, the
195 EC-LUE model uses a universal set of parameters (i.e., potential light use efficiency, ϵ_{max}), which
196 are independent of the vegetation cover type, that makes it easy to map the GPP over large areas
197 (Yuan et al., 2014b). Conversely, other LUE models also require vegetation-specific model
198 parameters that might limit model applicability. For example, a recent study found that the
199 estimated potential LUE of the CASA model varied substantially over 12 agricultural eddy flux
200 measurement sites in North America and Europe (Chen et al., 2011).

201 Theoretically, the potential light use efficiency of C4 crops is larger compared with that
202 of C3 plants (DeLucia et al., 2014). The parameters of the EC-LUE model, however, were
203 originally calibrated for C3 plant dominant ecosystems, which was the major cause for the
204 underestimation of the GPP of the C4 crops. Monfreda et al. (2008) showed that although the C4
205 crops are few (maize, sorghum, millet, sugarcane, and some grasses), they comprise 3.2 million
206 km², which is a disproportionate 24% of the entire harvested area and 17% of all C4 vegetation.
207 Therefore, it is of great importance to improve the model performance for C4 crops. Our results
208 showed that a specific potential LUE could be derived for C4 crops, to improve the performance
209 of the EC-LUE model. This implies that it is necessary to use a spatial distribution map of C3 and

210 C4 crops to improve the accuracy in quantifying crop GPP at a global scale.

211 For cropland ecosystems, strong agricultural management, such as fertilization,
212 irrigation and crop protection, impacts photosynthetic capacity by affecting leaf CO₂ exchange
213 rate as well as green leaf area index. Validation showed the ability of the model to simulate GPP
214 across different crops, climatic conditions and field management. This results from the fact that
215 the remotely sensed vegetation index effectively integrates the photosynthetic capacity, also across
216 different soil moisture and nutrient limitation conditions (Yao et al., 2010). A previous study
217 compared the vegetation index over three adjacent sites at the University of Nebraska-Lincoln's
218 Agricultural Research and Development Center near Mead, Nebraska, USA. The results showed
219 that the vegetation index was lower at a rainfed site than at the irrigated site, and the measured
220 difference was a quantitative measure of the impact of irrigation on crop canopy development
221 (Kalfas et al., 2011).

222 **4.2 Challenges for simulating crop yield**

223 This study used the carbon allocation coefficient and harvest index to simulate crop
224 yield based on GPP estimations (see method). The former indicates the ratio of aboveground NPP
225 to total NPP and the latter the weight of the harvested product as a percentage of the total plant
226 weight. In this study, we used a constant carbon allocation coefficient and harvest index for each
227 species (Monfreda et al., 2008) and did not take into account temporal or spatial variations. In
228 general, resource limitations such as water and nutrient deficits can enhance translocation from
229 source to sink organs (Temperton et al., 2003), increasing resource use efficiency (Yuan et al.,
230 2006; Ikegami and Whigham, 2007; Matzek, 2011). Xu et al. (2007) showed that a marked

231 increase in the root-to-shoot ratio of biomass/carbon under drought conditions allowed for the
232 absorption of more soil water. Similar effects have been observed across conditions of varying
233 nutrient supply (Chirinda et al., 2012).

234 With global climatic change, water availability is expected to become increasingly
235 important as a key controlling factor for crop yield, especially considering that globally only 18%
236 of the cultivated area is irrigated (FAO, 2005) and the frequency and severity of summer droughts
237 are expected to increase (IPCC, 2013). In the United States, for example, the average crop yields
238 of irrigated farms exceeded, in 2003, the corresponding yields of dryland farms by 15% for
239 soybeans, 30% for maize, 99% for barley, and 118% for wheat (Veneman et al., 2004). In this
240 study, we found that the impact of water availability cannot be ignored for simulating crop yield,
241 as it strongly determined the carbon allocation to seeds. Figure 5 compares the ratios of the crop
242 yield and observed GPP between the irrigated and rainfed sites at the University of
243 Nebraska-Lincoln's Agricultural Research and Development Center near Mead, Nebraska, USA.
244 The results show the ratio of the observed GPP is approximately 1, but the ratios of the crop yield
245 are much lower than those of the GPP, which indicates the strong impact of soil moisture on
246 carbon allocation to the seeds.

247 <<Figure 5>>

248 In addition to the carbon allocation coefficient, the harvest index is another important
249 factor for determining the accuracy of yield simulations. As the Fig. 4b showed the uncertainties
250 in simulated crop yield using estimated GPP based on EC measurements. This study used the
251 harvest index values proposed by Monfreda et al. (2008). However, harvest index is known to
252 vary with cultivars and growing conditions (Hay and Gilbert, 2001). López-Castaneda and

253 Richards (1994) found a negative correlation between the harvest index and number of days to
254 anthesis in barley, wheat, triticale, and oats under Mediterranean conditions; earlier flowering in
255 that environment allows for grain filling to occur before both the temperature and vapor pressure
256 deficit increase. Much of the increase in wheat yield over the past century stems from the selection
257 for a higher harvest index (Sinclair, 1998). Another study found that the harvest indices were not
258 highly heritable and fluctuated with season, management, and environmental conditions, in a
259 survey of the tropical varieties of maize in Mexico and Malawi (Hay and Gilbert, 2001). The
260 harvest index is also decreased by other yield limiting factors, such as pests and diseases (Olesen
261 et al., 2000).

262 **5. Conclusions**

263 Model validation at 36 eddy covariance sites globally suggested that the EC-LUE model
264 was robust and reliable for simulating the vegetative primary production of cropland. The model
265 may be a good candidate for mapping the GPP of regional and global cropland because it is
266 independent of crop (except for C4 species) and all driving variables can be retrieved from
267 satellites or standard weather observation networks. Moreover, the EC-LUE model can be used to
268 simulate crop yield from GPP estimates based on the harvest index. However, large biases of yield
269 estimates still exist because of uncertainties for the harvest index and carbon allocation.

270

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287 **References**

- 288 Agarwal, D.A., Humphrey, M., Beekwilder, N.F., Jackson, K.R., Goode, M.M., & Lngen C.V.
 289 2010. A data-centered collaboration portal to support global carbon-flux analysis.
 290 *Concurrency and Computation: Practice and Experience*, 22, 2323-2334.
- 291 Anthoni, P.M., Freibauer, A., Kolle, O., & Schulze, E.D. 2004. Winter wheat carbon exchange in
 292 Thuringia, Germany. *Agricultural and Forest Meteorology*, 121, 55–67.
- 293 Aubinet, M., Moureaux, C., Bodson, B., Dufranne, D., Heinesch, B., Suleau, M., Vancutsem, F., &

294 Vilret, A. 2009. Carbon sequestration by a crop over a 4-year sugar beet/winter
 295 wheat/seed potato/winter wheat rotation cycle. *Agricultural and Forest Meteorology*,
 296 149, 407–418.

297 Béziat, P., Ceschia, E., & Dedieu, G. 2009. Carbon balance of a three crop succession over two
 298 cropland sites in South West France. *Agricultural and Forest Meteorology*, 149,
 299 1628–1645.

300 Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M.H., Ruget, F., Nicoullaud, B., Gate, P., et al. 1998.
 301 STICS: a generic model for the simulation of crops and their water and nitrogen
 302 balances. I. Theory and parameterization applied to wheat and corn. *Agronomie*, 18
 303 (5-6), 311-346.

304 Cai, W.W., Yuan, W.P., Liang, S.L., Zhang, X.T., Dong, W.J., Xia, J.Z., Fu, Y., Chen, Y., Liu, D., &
 305 Zhang, Q. 2014. Improved estimations of gross primary production using
 306 satellite-derived photosynthetically active radiation. *Journal of Geophysical Research:*
 307 *Biogeosciences*, 119 (1), 110-123.

308 Chen, T., van der Werf, G.R., Gobron, N., Moors, E.J. & Dolman, A.J. 2014. Global cropland
 309 monthly gross primary production in the year 2000. *Biogeosciences*, 11, 3871-3880.

310 Chen, T.X., van der Werf, G.R., Dolman, A.J. & Groenendijk, M. 2011. Evaluation of cropland
 311 maximum light use efficiency using eddy flux measurements in North America and
 312 Europe. *Geophysical Research Letters*, 38, L14707.

313 Chirinda, N., Olesen, J.E. & Porter, J.R. 2012. Root carbon input in organic and inorganic
 314 fertilizer-based systems. *Plant and Soil* 359, 321-333.

315 Dietiker, D., Buchmann, N., & Eugster, W. 2010. Testing the ability of the DNDC model to predict

316 CO₂ and water vapour fluxes of a Swiss cropland site. *Agriculture, Ecosystems and*
317 *Environment*, 139, 396–401.

318 Donald, C.M., & Hamblin, J. 1976. The biological yield and harvest index of cereals as agronomic
319 and plant breeding criteria. *Advances in Agronomy*, 28, 361-415.

320 Doraiswamy, P. C., Moulin, S., & Cook, P. W. 2003. Crop yield assessment from remote sensing.
321 *Photogrammetric Engineering and Remote Sensing*, 69, 665 – 674.

322 DeLucia, E.H., Gomez-Casanovas, N., Greenberg, J.A., Hudiburg, T.W., Kantola, I.B., Long, S.P.
323 et al. 2014. The theoretical limit to plant productivity. *Environmental Science and*
324 *Technology*, 48, 9471–9477.

325 Eugster, W., Moffat, A.M., Ceschia, E. 2010. Management effects on European cropland
326 respiration. *Agriculture Ecosystems and Environment*, 139, 346-362.

327 Falge, E., Baldocchi, D., Olson, R., Anthoni, P., Aubinet, M., Bernhofer, C., et al. 2001. Gap
328 filling strategies for defensible annual sums of net ecosystem exchange. *Agricultural*
329 *and Forest Meteorology*, 107, 43-69.

330 Food and Agriculture Organization of the United Nations (FAO) 2005. FAO Stat. FAO Statistical
331 Databases. Available online at. <http://faostat.fao.org/>

332 Hay, R.K. 1995. Harvest index: a review of its use in plant breeding and crop physiology. *Annals*
333 *of Applied Biology*, 126, 197-216.

334 Hay, R. K. M., & Gilbert, R.A. 2001. Variation in the harvest index of tropical maize: evaluation
335 of recent evidence from Mexico and Malawi. *Annals of Applied Biology*, 138(1),
336 103-109.

337 Huntzinger, D.N., Post, W.M., Wei, Y., Michalak, A.M., West, T.O., Jacobson, A.R., et al. 2012.

338 North American Carbon Program (NACP) regional interim synthesis: Terrestrial
 339 biospheric model intercomparison. *Ecological Modelling*, 232, 144-157.

340 Ikegami, M., Whigham, D.F., & Werger, M.J.A. 2007. Responses of rhizome length and ramet
 341 production to resource availability in the clonal sedge *Scirpus olneyi* A. Gray. *Plant*
 342 *Ecology*, 189, 247-259.

343 IPCC 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I
 344 to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In
 345 Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y.
 346 Xia, V. Bex and P.M. Midgley (Eds.). Cambridge & United Kingdom and New York:
 347 Cambridge University Press.

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

351 Landsberg, J. J. 1986. *Physiological Ecology of Forest Production*. London: Academic Press, 352.

352 Monteith, J.L. 1972. Solar radiation and productivity in tropical ecosystems. *J. Appl. Ecol.* 9,
 353 747-766.

354 Monteith, J.L. 1977. Climate and the efficiency of crop production in Britain. *Philos. Trans. R.*
 355 *Soc. Lond., Ser. B.* 281, 277-294.

356 Goerner, A., Reichstein, M., & Rambal, S. 2009. Tracking seasonal drought effects on ecosystem
 357 light use efficiency with satellite-based PRI in a Mediterranean forest. *Remote Sensing*
 358 *of Environment*, 113, 1101-1111.

359 Lehuger, S., Gabrielle, B., Cellier, P., Loubet, B., Roche, R., Béziat, P., Ceschia, E., & Wattenbach,

360 M. 2010. Predicting the net carbon exchanges of crop rotations in Europe with an
361 agro-ecosystem model. *Agriculture, Ecosystems and Environment*, 139, 384–395.

362 Li, X., Cheng, G.D., Liu, S.M., Xiao, Q., Ma, M.G., Jin, R., Che, T., Liu, Q.H., Wang, W.Z., et al.
363 2013. Heihe Watershed Allied Telemetry Experimental Research (HiWATER): scientific
364 objectives and experimental design. *Bulletin of the American Meteorological Society*, 94,
365 1145-1160.

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

370 Liu, S.M., Xu, Z.W., Zhu, Z.L., Jia, Z.Z., & Zhu, M.J. 2013. Measurements of evapotranspiration
371 from eddy-covariance systems and large aperture scintillometers in the Hai River Basin,
372 China. *Journal of Hydrology*, 487, 24-38.

373 Lloyd, L. & Taylor, J.A. 1994. On the temperature dependence of soil respiration. *Functional*
374 *Ecology*, 8, 315-323.

375 López-Castañeda, C., & Richards, R.A. 1994. Variation in temperate cereals in rainfed
376 environments I. Grain yield, biomass and agronomic characteristics. *Field Crops*
377 *Research*, 37, 51–62.

378 Matzek, V. 2011. Superior performance and nutrient-use efficiency of invasive plants over
379 non-invasive congeners in a resource-limited environment. *Biological Invasions*, 13,
380 3005–3014.

381 Meijide, A., Manca, G., Goded, I., Magliulo, V., di Tommasi, P., Seufert, G., & Cescatti, A. 2011.

382 Seasonal trends and environmental controls of methane emissions in a rice paddy field
383 in Northern Italy. *Biogeosciences*, 8, 3809–3821.

384 Meyers, T. P., & Hollinger, S. E. 2004. An assessment of storage terms in the surface energy
385 balance of maize and soybean. *Agricultural and Forest Meteorology*, 125, 105–115.

386 Monfreda, C., Ramankutty, N., & Foley, J.A. 2008. Farming the planet: 2. Geographic distribution
387 of crop areas, yields, physiological types, and net primary production in the year 2000.
388 *Global Biogeochemical Cycles*, 22, GB1022.

389 Moors, E.J., Jacobs, C., Jans, W., Supit, I., Kutsch, W. L., Bernhofer, C., et al. 2010. Variability in
390 carbon exchange of European croplands. *Agriculture, Ecosystems and Environment*, 139,
391 325-335.

392 Moriondo, M., Maselli, F., & Bindi, M. 2007. A simple model of regional wheat yield based on
393 NDVI data. *European Journal of Agronomy*, 26 (3), 266-274.

394 Olesen, J.E., Mortensen, J.V., Jørgensen, L.N. & Andersen, M.N. 2000. Irrigation strat-egy,
395 nitrogen application and fungicide control in winter wheat on a sandy soil. I. Yield, yield
396 components and nitrogen uptake. *Journal of Agricultural Science, Cambridge* 134, 1-11.

397 Parry, M.L., Rosenzweig, C., Iglesias, A., Livermore, M., & Fischer, G. 2004. Effects of climate
398 change on global food production under SRES emissions and socio-economic scenarios.
399 *Global Environmental Change*, 14, 53-67.

400 Potter, C.S., Randerson, J.T., Field, C.B., Matson, P. A., Vitousek, P.M., Mooney, H.A., & Klooster,
401 S.A. 1993. Terrestrial ecosystem production: A process model based on global satellite
402 and surface data. *Global Biogeochemical Cycles*, 7 (4), 811-841.

403 Prince, S., Haskett, J., Steininger, M., Strand, H., & Wright, R. 2001. Net primary production of

404 U.S. midwest croplands from agricultural harvest yield data. *Ecological Applications*,
 405 11(4), 1194–1205.

406 Raczka, B.M., Davis, K.J., Huntzinger, D.N., Neilson, R., Poulter, B., Richardson, A., et al. 2013.
 407 Evaluation of continental carbon cycle simulations with North American flux tower
 408 observations. *Ecological Monographs*, 83, 531-556.

409 Ray, D.K., Ramankutty, N., Mueller, N.D., West, P.C. & Foley, J.A. 2012. Recent patterns of crop
 410 yield growth and stagnation. *Nature Communications*, 3, 1293.

411 Reeves, M.C., Zhao, M. & Running, S.W. 2005. Usefulness and limits of MODIS GPP for
 412 estimating wheat yield. *International Journal of Remote Sensing*, 26, 1403–1421.

413 Ritchie, J.R. & Otter, S. 1985. Description and performance of CERES-Wheat: a user-oriented
 414 wheat yield model. *United States Department of Agriculture, Agricultural Research*
 415 *Service*, 38, 159-175.

416 Schmidhuber, J., & Tubiello, F.N. 2007. Global food security under climate change. *Proceedings*
 417 *of the National Academy of Sciences of the United States of America*, 104,
 418 19703-19708.

419 Sinclair, R.S. 1998. Historical changes in harvest index and crop nitrogen accumulation. *Crop*
 420 *Science*, 38, 638–643.

421 Temperton, V.M., Grayston, S.J., Jackson, G., Barton, C.V.M., Millard, P. & Jarvis, P.G.
 422 2003. Effects of elevated carbon dioxide concentration on growth and nitrogen fixation
 423 in *Alnus glutinosa* in a long-term field experiment. *Tree Physiology*, 23 (15), 1051-1059

424 Tilman, D, Balzer, C, Hill, J, Befort, BL. 2011. Global food demand and the sustainable
 425 intensification of agriculture. *Proceedings of the National Academy of Sciences of the*

426 *United States of America*, 108: 20260-20264.

427 Turner, D.P., Ritts, W.D., Styles, J.M., Yang, Z., Cohen, W.B., Law, B.E., & Thornton, P.E. 2006.

428 A diagnostic carbon flux model to monitor the effects of disturbance and interannual

429 variation in climate on regional NEP. *Tellus B*, 58(5), 476-490.

430 Van Den, C.A., Wolf, J., van Keulen, H., & Rappoldt, C. 1989. WOFOST: a simulation model

431 of crop production. *Soil Use and Management*, 5(1), 16-24.

432 Van Evert, F. K., & Campbell, G.S. 1994. CropSyst: A Collection of Object-Oriented Simulation

433 Models of Agricultural Systems. *Agronomy Journal*, 86 (2), 325-331.

434 Veneman, A.M., Jen, J.J., & Bosecker, R.R. 2004. 2002 Census of Agriculture – Farm and Ranch

435 Irrigation Survey (2003), United States Department of Agriculture (USDA), National

436 Agricultural Statistics Survey (NASS), <http://www.usda.gov/nass/>.

437 Verma, S. B., Dobermann, A., Cassman, K. G., Walters, D. T., Knops, J. M., Arkebauer, T. J., et al.

438 2005. Annual carbon dioxide exchange in irrigated and rainfed maize-based

439 agroecosystems. *Agricultural and Forest Meteorology*, 131, 77–96.

440 Waring, H., Landsberg, J. J., & Williams, M. 1998. Net primary production of forests: a constant

441 fraction of gross primary production? *Tree Physiol.*, 18, 129–134.

442 Wall, L., Larocque, D., & Léger, P.M. 2008. The early explanatory power of NDVI in crop yield

443 modelling. *International Journal of Remote Sensing*, 29(8), 2211-2225.

444 Xin, Q.C., Gong, P., Yu, C.Q., Yu, L., Broich, M., Suyker, A.E. & Myneni, R.B. 2013. A

445 Production Efficiency Model-Based Method for Satellite Estimates of Corn and

446 Soybean Yields in the Midwestern US. *Remote Sensing*, 5, 5926-5943.

447 Xu, X.Y., McGrath, S.P., & Zhao, F.J. 2007. Rapid reduction of arsenate in the medium mediated

448 by plant roots. *New Phytologist*, 176, 590–599.

449 Xu, Z.W., Liu, S.M., Li, X., Shi, S.J., Wang, J.M., Zhu, Z.L., Xu, T.R., Wang, W.Z., & Ma, M.G.

450 2013. Intercomparison of surface energy flux measurement systems used during the

451 HiWATER-MUSOEXE. *Journal of Geophysical Research*, 118, 13140-13157.

452 Yao, X., Zhu, Y., Tian, Y.C., Feng, W., & Cao, W.X. 2010. Exploring hyperspectral bands and

453 estimation indices for leaf nitrogen accumulation in wheat. *International Journal of*

454 *Applied Earth Observation and Geoinformation*, 12, 89–100.

455 Yuan, W.P., Liu, S.G., Dong, W.J., Liang, S.L., Zhao, S.Q., & Chen, J.Q., et al. 2014a.

456 Differentiating moss from higher plants is critical in studying the carbon cycle of the

457 boreal biome. *Nature Communications*, 5, 4270.

458 Yuan, W.P., Liu, S.G., Cai, W.W., Liu, S.G., Dong, W.J., Chen, J.Q., et al. 2014b. Are

459 vegetation-specific model parameters required for estimating gross primary production?

460 *Ecological Modelling*, 292, 1-10.

461 Yuan, W.P., Liang, S.L., Liu, S.G., Weng, E.S., Luo, Y.Q., Hollinger, D., & Zhang, H.C. 2012.

462 Improving model parameter estimation using coupling relationships between vegetation

463 production and ecosystem respiration. *Ecological Modelling*, 240, 29–40.

464 Yuan, W.P., Liu, S.G., Yu, G.R., Bonnefond, J. –M., Chen, J., Davis, K., et al. 2010. Global

465 estimates of evapotranspiration and gross primary production based on MODIS and

466 global meteorology data. *Remote Sensing of Environment*, 114, 1416-1431.

467 Yuan, W.P., Liu, S.G., Zhou, G.S., Zhou, G.Y., Tieszen, L.L., Baldocchi, D., Bernhofer, C., et al.

468 2007. Deriving a light use efficiency model from eddy covariance flux data for

469 predicting daily gross primary production across biomes. *Agricultural and Forest*

470 *Meteorology*, 143, 189-207.

471 Yuan, X.F., Wu, P.T., & Wang, Y.K. 2006. Study on the effect of irrigation under plastic

472 preservation of soil moisture on soil and crop. *Journal of Irrigation and Drainage*, 25,

473 21–25.

474 Zhang, W.L., Chen, S.P., Chen, J., Wei, L., Han, X.G., & Lin, G.H. 2007. Biophysical regulations

475 of carbon fluxes of a steppe and a cultivated cropland in semiarid Inner Mongolia.

476 *Agricultural and Forest Meteorology*, 146, 216-229.

477 Zhao, M. S., Heinsch, F. A., Nemani, R. R. & Running, S. W. 2005. Improvements of the MODIS

478 terrestrial gross and net primary production global data set. *Remote Sensing of*

479 *Environment*, 95, 164–176.

480

Table 1 Name, location, annual mean temperature (AMT), annual precipitation (AP), and other characteristics of the study sites used for model validation.

Site	Latitude, Longitude	Crop specie	AMT	AP	Irrigation	Study period	Reference
BE-Lon*	50.55°N, 4.74°E	Sugar Beet (2004), Winter Wheat (2005), Potato (2006)	9.44	843	No	2004-2006	Aubinet et al., 2009
CH-Oe2*	47.28°N, 7.73°E	Winter Barley	9.14	943	No	2005	Dietiker et al., 2010
CN-Du1	42.04°N, 116.67°E	Common Wheat	2.13	336	No	2005-2006	Zhang et al., 2007
CN-H03	38.89°N, 100.37°E	Maize	7.00	129	Yes	2012	Xu et al., 2013
CN-H05	38.87°N, 100.35°E	Maize	7.00	129	Yes	2012	Xu et al., 2013
CN-H06	38.87°N, 100.36°E	Maize	7.00	129	Yes	2012	Xu et al., 2013
CN-H07	38.88°N, 100.36°E	Maize	7.00	129	Yes	2012	Xu et al., 2013
CN-H08	38.87°N, 100.37°E	Maize	7.00	129	Yes	2012	Xu et al., 2013
CN-H09	38.87°N, 100.38°E	Maize	7.00	129	Yes	2012	Xu et al., 2013
CN-H10	38.87°N, 100.39°E	Maize	7.00	129	Yes	2012	Xu et al., 2013
CN-Myu	40.63°N, 117.32°E	Orchard/Maize	12.90	532	No	2008-2010	Liu et al., 2013

DE-Geb*	51.10°N, 10.91°E	Winter Wheat	8.74	443	No	2004-2006	Anthoni et al., 2004
DE-Kil*	50.89°N, 13.52°E	-	7.30	850	Yes	2004-2006	-
DK-Fou*	56.48°N, 9.58°E	Maize	7.59	742	No	2005	-
DK-Ris*	55.53°N, 12.09°E	-	8.23	581	Yes	2004-2005	-
ES-Es2	39.27°N, 0.31°W	-	17.77	465	Yes	2005-2006	-
FR-Aur*	43.54°N, 1.10°E	Rapeseed	12.16	673	No	2005	Béziat et al., 2009
FR-Gri	48.84°N, 1.95°E	Winter Wheat – White Barley	10.20	769	-	2005-2006	Lehuger et al., 2010
FR-Lam	43.49°N, 1.23°E	-	12.69	702	-	2005	-
IE-Ca1	52.85°N, 6.91°W	Winter Cereal/Sugar Beet/Potato	9.40	824	-	2004-2006	-
IT-Bci	40.52°N, 14.95°E	Maize	16.31	735	Yes	2004-2006	Eugster et al., 2010
IT-Cas*	45.06°N, 8.66°E	Rice Paddy	12.9	658	Yes	2006	Meijide et al., 2011
KR-Hnm	34.55°N, 126.57°E	Rice/Farm land	13.3	1306		2005-2006, 2008	
JP-Mas	36.05°N, 140.02°E	Rice Paddy	14.57	1388	Yes	2002-2003	

US-Nc2*	41.16°N, 96.47°W	Maize (2001, 2003, 2005), Soybean (2002, 2004)	10.08	788	Yes	2001-2005	Verma et al., 2005
US-Nc3*	41.17°N, 96.43°W	Maize (2001, 2003, 2005), Soybean (2002, 2004)	10.11	783	No	2001-2005	Verma et al., 2005

482 *Sites with star mark also featured observed yield data and could be used for model validation.

Table 2 Average estimated GPP from EC flux tower data ($\text{g C m}^{-2} \text{ day}^{-1}$), average model predicted GPP ($\text{g C m}^{-2} \text{ day}^{-1}$), and model statistics for all sites under investigation

Site	Estimated GPP	Predicted GPP	R ²	RMSE	BIAS
BE-Lon	3.77	4.91	0.85	2.20	1.14
CH-Oe2	6.10	7.31	0.49	3.72	1.21
CN-Du1	1.58	1.61	0.77	1.13	0.03
CN-H03	12.89	15.07	0.8	2.79	2.18
CN-H05	13.00	14.79	0.58	3.33	1.79
CN-H06	15.05	15.87	0.65	4.66	0.82
CN-H07	12.84	14.65	0.70	3.22	1.81
CN-H08	12.99	12.92	0.58	5.00	-0.07
CN-H09	12.60	11.64	0.72	4.51	-0.96
CN-H10	14.27	16.27	0.70	3.56	2.00
CN-Myu	1.49	1.89	0.67	0.97	0.40
DE-Geb	5.64	4.97	0.86	2.29	-0.67
DE-Kli	5.59	5.92	0.83	2.29	0.33
DK-Fou	5.27	6.19	0.61	2.43	0.92
DK-Ris	5.32	5.17	0.84	2.09	-0.15
ES-Es2	5.32	5.17	0.84	2.09	-0.15
FR-Aur	4.20	5.23	0.85	2.04	1.03
FR-Gri	4.38	4.45	0.87	2.08	0.07
FR-Lam	5.01	4.64	0.81	2.14	-0.37
IE-Ca1	3.77	2.72	0.59	3.08	-1.04
IT-Bci	12.54	13.74	0.80	3.40	1.20
IT-Cas	9.61	7.68	0.91	4.71	-1.93
JP-Hfk	2.52	2.43	0.69	1.36	-0.09
JP-Mas	2.14	4.03	0.47	3.37	1.89
KR-Hnm	2.98	3.31	0.62	1.75	0.33
NL-Lan	7.66	11.01	0.43	4.12	3.34
NL-Lut	7.22	7.12	0.83	2.91	-0.12

NL-Mol	7.47	8.43	0.59	2.92	0.96
UK-Esa	7.95	6.51	0.49	4.02	-1.44
UK-Her	7.62	7.71	0.86	2.73	0.09
US-Bo1 Maize	6.26	6.65	0.86	2.71	0.39
US-Bo1 Soybean	3.89	5.29	0.83	2.82	1.39
US-Bo2 Maize	8.68	8.98	0.80	4.72	0.29
US-Ib1 Maize	6.16	6.03	0.87	3.92	-0.13
US-Ne1 Maize	5.69	5.36	0.92	2.30	-0.33
US-Ne2 Maize	7.62	7.54	0.87	3.09	-0.08
US-Ne2 Soybean	2.69	4.54	0.91	2.93	1.84
US-Ne3 Maize	7.91	6.84	0.83	3.18	-1.05
US-Ne3 Soybean	3.14	5.05	0.92	2.83	1.91

483

484 **Figure captions**

485 Figure 1 Daily variation of EC-LUE model predicted (black solid lines) and estimated (open
486 circle dots) GPP at all study sites. The x-axis indicates the day of the year at CN-He3, CN-He5,
487 CN-He6, CN-He7, CN-He8, CN-He9 and CN-He10, since only one season data was available at
488 these sites.

489

490 Figure 2 Average predicted GPP from the EC-LUE and estimated GPP from the EC
491 measurements for various crop species. The dashed line is a 1:1 line. The solid red and black lines
492 are linear regression lines with a revised C4 crop parameter ($y = 0.98x + 0.55$, $R^2 = 0.90$) and
493 original model parameter ($y = 0.67x + 1.64$, $R^2 = 0.82$), respectively.

494

495 Figure 3 Predicted GPP from the EC-LUE and estimated GPP from the EC measurements for all
496 study sites in Table 1. The short dashed line is a 1:1 line and the solid line is a linear regression
497 line.

498

499 Figure 4 Predicted and observed crop yield at 12 sites (see Table 1). The short dashed line is a
500 1:1 line and the solid line is a linear regression line. (a) Estimated yield based on the simulated
501 GPP of EC-LUE model; (b) estimated yield based on the estimated GPP using EC measurements.

502

503 Figure 5 Ratio of observed GPP and yield between irrigated and rainfed maize (a) and soybean
504 (b) at the US-NE2 and US-NE3 FLUXNET sites

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Figure 1 Daily variation of EC-LUE model predicted (black solid lines) and estimated (open circle dots) GPP at all study sites.. The x-axis indicates the day of the year at CN-He3, CN-He5, CN-He6, CN-He7, CN-He8, CN-He9 and CN-He10, since only one season data was available at these sites.

510
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 512 measurements for various crop species. The dashed line is a 1:1 line. The solid red and black lines
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 514 original model parameter ($y = 0.67x + 1.64$, $R^2 = 0.82$), respectively.

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 517 study sites in Table 1. The short dashed line is a 1:1 line and the solid line is a linear regression
 518 line.

519

520 Figure 4 Predicted and observed crop yield at 12 sites (see Table 1). The short dashed line is a

521 1:1 line and the solid line is a linear regression line. (a) Estimated yield based on the simulated

522 GPP of EC-LUE model; (b) estimated yield based on the estimated GPP using EC measurements.

523

524 Figure 5 Ratio of observed GPP and yield between irrigated and rainfed maize (a) and soybean

525

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Figure 1

Figure 2

Figure 3

Figure 4

Figure 5