INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

IFPRI

IFPRI Discussion Paper 01584

December 2016

Harnessing Net Primary Productivity Data for Monitoring Sustainable Development of Agriculture

Nathaniel P. Robinson

Cindy M. Cox

Jawoo Koo

Environment and Production Technology Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), established in 1975, provides evidence-based policy solutions to sustainably end hunger and malnutrition, and reduce poverty. The institute conducts research, communicates results, optimizes partnerships, and builds capacity to ensure sustainable food production, promote healthy food systems, improve markets and trade, transform agriculture, build resilience, and strengthen institutions and governance. Gender is considered in all of the institute's work. IFPRI collaborates with partners around the world, including development implementers, public institutions, the private sector, and farmers' organizations, to ensure that local, national, regional, and global food policies are based on evidence.

AUTHORS

Nathaniel P. Robinson (nathaniel.robinson@umontana.edu) is a Ph.D. candidate in the College of Forestry and Conservation at the University of Montana, Missoula.

Cindy M. Cox (c.cox@cgiar.org) is a technical writer in the Environment and Production Technology Division of the International Food Policy Research Institute (IFPRI), Washington, DC.

Jawoo Koo (j.koo@cgiar.org) is a senior research fellow in the Environment and Production Technology Division of IFPRI, Washington, DC.
Corresponding author

Contents

Tables

Figures

Boxes

ABSTRACT

This study was undertaken to assess the utility of remotely sensed net primary productivity (NPP) data to measure agricultural sustainability by applying a new methodology that captures spatial variability and trends in total NPP and in NPP removed at harvest. The sustainable intensification of agriculture is widely promoted as a means for achieving the Sustainable Development Goals (SDGs) and transitioning toward a more productive, sustainable, and inclusive agriculture, particularity in fragile environments. Yet critics claim that the 17 SDGs and 169 targets are immeasurable and unmanageable. We propose adoption of satellite-estimated, time-series NPP data to monitor agricultural intensification and sustainability, as it is one indicator potentially valuable across several SDGs. To illustrate, we present a unique monitoring framework and a novel indicator, the agricultural appropriation of net primary productivity (AANPP) and analyze spatial trends in NPP and AANPP across the continent of Africa. AANPP focuses on the proportion of total crop NPP removed at harvest. We estimate AANPP by overlaying remotely sensed satellite imagery with rasterized crop production data at 10-by-10-kilometer spatial resolution; we explore variation in NPP and AANPP in terms of food and ecological security. The spatial distribution of NPP and AANPP illustrates the dominance of cropping systems as spatial drivers of NPP across many regions in West and East Africa, as well as in the fertile river valleys across North Africa and the Sahel, where access to irrigation and other technological inputs are inflating AANPP relative to NPP. A comparison of 2000 and 2005 datasets showed increasing AANPP in African countries south of the Sahara—particularly in Mozambique, Angola, and Zambia—whereas NPP either held stable or decreased considerably. This pattern was especially evident subnationally in Ethiopia. Such trends highlight increasing vulnerability of populations to food and ecological insecurity. When combined with other indicators and time-series data, the significance of NPP and the capacity of spatially explicit datasets have far-reaching implications for monitoring the progress of sustainable development in a post-2015 world.

Keywords: net primary productivity, agricultural appropriation of net primary productivity, Sustainable Development Goals, sustainable intensification of agriculture, spatial allocation production model

ACKNOWLEDGMENTS

This work was undertaken as part of, and partially funded by, the CGIAR Research Program on Policies, Institutions, and Markets (PIM), which is led by the International Food Policy Research Institute (IFPRI) and funded by CGIAR Fund Donors.We also acknowledge financial and technical support provided by the HarvestChoice project (www.harvestchoice.org). Finally, we thank Z. Guo from IFPRI and J. D. Glover from the Bureau of Food Security at the United States Agency for International Development for their thoughtful comments on methodology and earlier drafts of this manuscript, respectively. This paper has not gone through IFPRI's standard peer-review procedure. The opinions expressed here belong to the authors, and do not necessarily reflect those of PIM, IFPRI, or CGIAR.

1. INTRODUCTION

Intensive agriculture and inefficiencies in farming contribute to climate change and other global environmental challenges, increasingly undermining long-term food and ecological security (Foley et al. 2011). At the same time, as the world's growing population continues to demand more from the planet's resources, there is little area for agriculture expansion (Lambin and Meyfroidt, 2011). In light of these challenges, business-as-usual trajectories for marginal increases in crop yields are outdated. Rather, the sustainable intensification of agriculture—increased production per unit land while conserving natural resources and ecosystem services—may provide the solution to sustainably produce much more food on the same number of hectares; thus, it is key for the next green revolution in agriculture (Pretty, Toulmin, and Williams 2011; Glover, Reganold, and Cox 2012; Garnett et al. 2013; Campbell et al. 2014). Sustainable intensification requires a radical rethinking of our global food systems (Campbell et al. 2014) and, we argue, an equally radical approach to data.

The UN Sustainable Development Goals (SDGs) are poised to turn the tide in post-2015 development by targeting sustainable agriculture and food security, climate change, biodiversity and ecosystems services, and poverty and nutrition, to name a few. Achieving these goals will largely depend on progress in agriculture. The Food and Agriculture Organization of the United Nations (FAO) promotes the sustainable intensification of agriculture in globally relevant policy agendas as a means for achieving the SDGs and transitioning toward a more "productive, sustainable and inclusive agriculture" (FAO 2016). What remains challenging, however—and with no shortage of opinions on what defines sustainability (Binder, Feola, and Steinberger 2010)—is how to measure and manage the 17 SDGs and 169 targets (Davis et al. 2015). However, one variable potentially valuable across several SDGs, with crosscutting implications for decision support in terms of agricultural development and land use considerations, is net primary productivity (NPP).

Since the inauguration of the SDGs in 2015, the United Nations has proposed 230 global indicators to measure progress toward goals and targets,[1] though most reporting will undoubtedly be at the national level. Each country will need to customize its own suite of indicators that reflect the nation's national interests and data capacities. Moreover, the United Nations has been stressing the vital role of geospatial data in achieving the SDGs. Indeed, along with country statistics and nationally representative household data, alternative data sources, such as satellite earth observation, are expected to play a major role in the 2030 agenda by closing critical data gaps; this is particularity important for traditionally data-poor and hard-to-reach places (see, for example, Joppa et al. 2016). Here we propose the adoption of satellite-estimated, time-series NPP data to monitor agricultural intensification and sustainability—a global "earthworm indicator" of sorts for monitoring human activity on the planet. NPP has implications for the environment, including climate change mitigation, as well as for food security, human well-being, and livelihoods. As such, it is a touchstone for many SDGs. We do not suggest using NPP as a solo indicator for small-scale programs or snapshot assessments, but rather as part of a package of critical indicators with crosscutting implications for future global development. The challenge, however, is how stakeholders and researchers can manipulate NPP data to suit geographically dependent program needs and assessments, such as the SDGs and similar regionally tailored programs (such as the African Union's Malabo Declaration[2]).

NPP is central to terrestrial ecosystem processes, both biochemically (nitrogen and carbon cycling) and physically (soil formation and structure). It is also important in terms of biodiversity, food and soil webs, plant productivity and biomass, and climate change mitigation and resilience (Field 2001; Roy, Mooney, and Saugier 2001; Haberl et al. 2004, 2007; Lal 2004; Houghton et al., 2012; Campbell et al. 2014). Yet globally, Niedertscheider et al. (2016) found that two-thirds of NPP from croplands is well below native NPP potential, particularly in developing, (sub)tropical regions. On the other hand,

---

[1] See http://unstats.un.org/sdgs/.

[2] See http://pages.au.int/caadp/documents/malabo-declaration-accelerated-agricultural-growth-and-transformation-shared-prosper.

agricultural sustainability and productivity massively surpass natural NPP on irrigated drylands and in many industrialized temperate regions, creating an unsustainable cosmos of resource overconsumption. A bundle of indicators is needed to monitor the different domains of agricultural production and sustainability in the context of sustainable intensification and the SDGs. However, from economics and social welfare to productivity and environment, spatially explicit data are currently underused for monitoring and evaluating the sustainable intensification of agriculture and land-use efficiencies on the large scale (Azzarri et al. 2016). Global NPP reflects myriad farm-generated outcomes that underscore multiple dimensions of sustainability.

Among the variables proposed to measure the scale of human activity on the planet, the human appropriation of net primary productivity (HANPP) is arguably the most useful (Field 2001). HANPP aggregates additional indicators with NPP to help more fully understand the impact of human activity on the planet (Field 2001; Roy, Mooney, and Saugier 2001; Haberl et al. 2004, 2007). HANPP reflects the total amount of NPP removed or altered by humans, which is consequently unavailable to other organisms in an ecosystem, such as when humans convert land to agroecosystems and harvest plant material or otherwise divert natural capital to human consumption (Haberl et al. 2004, 2007). Not surprisingly, increasing HANPP is linked to decreasing biodiversity and ecosystem function (Haberl et al. 2004), both of which are widely considered underlying indictors of sustainability (Foley 2005). HANPP currently accounts for about a quarter of the world's potential NPP, with nearly half (12 percent) represented by crop harvests (Haberl et al. 2007). At current rates of human activity, HANPP is expected to reach well over 50 percent of global NPP by 2050 (Haberl et al. 2004). Improved efficiencies in crop production and technological changes can, however, result in considerable biomass (NPP) increases overtime (Foley et al. 2011)—and not necessarily at the expense of increased HANPP (Krausmann et al. 2013).

While earlier studies have estimated NPP and HANPP for terrestrial ecosystems (Field 2001; Roy, Mooney, and Saugier 2001; Haberl et al. 2004, 2007), the utility of satellite measurements for indicators of agricultural sustainability has not been widely implemented. This paper illustrates a unique monitoring framework using a novel indicator—the agricultural appropriation of net primary productivity (AANPP)—with potential value across disciplines. AANPP is a less formidable adaptation of HANPP that focuses on agricultural activity by capturing the proportion of total crop NPP removed at harvest. This paper further demonstrates the capacity of remotely sensed satellite imagery by overlaying it with rasterized crop production data at fine, 10-by-10-kilometer spatial resolution. Finally, we explore spatial variation in NPP and AANPP across the continent of Africa from 2000 to 2005 in the context of food and ecological security. Whereas previous estimates of HANPP were based on national-level crop production statistics and other land-use variables, such as timber harvest, our approach focuses on the appropriation of NPP to agriculture and integrates spatially disaggregated subnational crop production statistics data (You and Wood 2006; You, Wood, and Wood-Sichra 2009; Wood et al. 2014) into estimates of agriculturally appropriated NPP—thereby allowing for aggregation of data at the subnational level and across country borders. When combined with other indicators and time-series data, the significance of NPP and the capacity of spatial datasets have far-reaching implications for monitoring post-2015 sustainable development.

2. MATERIALS AND METHODS

Measuring Net Primary Productivity

Although direct measurements of NPP at the global scale are not possible, there are many excellent models based on physiological principles and global terrestrial dynamics (Cramer et al. 1999). Models range from simple regressions between climatic variables to complex mechanistic simulations of biophysical and ecophysical processes. These models capture one of three methodologies: (1) carbon fluxes based on a given vegetation structure, (2) both carbon fluxes and vegetation structure, and (3) remotely sensed satellite data. Each model produces global estimates of NPP ranging from 44.4 to 66.3 billion tons of carbon per year (Cramer et al. 1999). Satellite-derived datasets are particularly useful as they provide mechanisms for estimating, monitoring, and evaluating spatial and temporal variations within terrestrial ecosystem productivity (Crabtree et al. 2009).

For our estimates of NPP, we use MODIS (moderate-resolution image spectrometer) NPP product (MOD17A3), developed by Numerical Terradynamic Simulation Group at the University of Montana (Heinsch et al. 2003a). The MOD17A3 algorithm uses a combination of remotely sensed data from the MODIS sensor, climate models, and biome-specific parameters to calculate annual global NPP at 1-by-1-kilometer resolution. We processed this data to match the spatial and temporal extents of a spatially disaggregated crop production dataset (You and Wood 2006; You, Wood, and Wood-Sichra 2009; Wood et al. 2014) to calculate AANPP at 5 arc-minute spatial resolution.[3] A more detailed description of the MOD17A3 product and a conceptual model of the algorithm are available in the supporting information (Appendix Box A.1 and Figure A.1), based on Heinsch et al. (2003).

Measuring Crop Production

The grid-based crop production dataset used in our model was acquired from MapSPAM (You et al. 2014). The spatial production allocation model (SPAM) provides global, spatially disaggregated subnational crop production statistical datasets on production, area, value of production, and yield for a variety of crops and crop groups (You and Wood 2006; You, Wood, and Wood-Sichra 2009; Wood et al. 2014). Earlier versions of the database, such as SPAM2000 (circa 2000), included 20 crops, whereas the updated SPAM2005 database (circa 2005) includes 42 crops. For a comparison between 2000 and 2005, the SPAM2005 database was modified to match the SPAM2000 database by removing crops and crop types not present in SPAM2000, representing approximately 80 percent of the world's crop production (FAO 2015). Production data, available in metric tons, were converted to units of carbon to be used with the MODIS NPP data in calculations of AANPP. Parameters used to convert crop production in metric tons to carbon included moisture content, harvest index, and aboveground biomass for each crop and crop type with conversion factors, values of which were adapted from Prince et al. (2001) and Monfreda, Ramankutty, and Foley (2008). This conversion model calculated the mass of dry carbon removed from the landscape due to harvest of crop. A more detailed description of the SPAM processing workflow and a list of individual crop parameters are available in the supporting information (Appendix Box A.2 and Table A.2).

[3] The 5 arc-minute, often referred to as 10 kilometers, is one of the most commonly used, standard spatial resolutions in global- and regional-scale geospatial datasets and modeling analyses on grid-based platforms. For example, FAO's Global Agro-ecological Zone database (http://gaez.fao.org), University of Frankfurt's MIRCA database (https://www.uni-frankfurt.de/45218023/MIRCA), and University of Minnesota's EarthStat database (http://www.earthstat.org) use the same spatial resolution, facilitating harmonization and interoperability across datasets. There are 368,120 grid cells at this resolution in Africa's land area.

Calculating Agricultural Appropriation of Net Primary Productivity

MODIS and SPAM data were used to calculate AANPP. The theoretical calculation for HANPP is

$$NPP_0 = NPP_t + NPP_h + \Delta NPP_{lc},$$

where $NPP_{act} = NPP_t + NPP_h$ and $HANPP = NPP_h + \Delta NPP_{lc}$ (Haberl et al. 2004, 2007). In this formula, NPP_0 is the potential biomass in the absence of human influence. This is generally estimated using dynamic global vegetation models at large scales and is beyond the capacity of the present study. NPP_{act} is the actual biomass produced on the landscape and is represented by the MOD17A3 NPP product. NPP_h is the total biomass removed or destroyed due to crop harvests and was derived from SPAM data. NPP_t is the total biomass left after harvest and was deduced from NPP_{act} and NPP_h. ΔNPP_{lc} is the difference in NPP due to human-induced land-use change or land-cover alterations; it was inherent in the MODIS data as it was based on up-to-date land-use data (Appendix Table A.1). Thus, to calculate AANPP as a proportion of available NPP, the results from the SPAM processing were divided by the results from the MODIS processing. This created a 10-by-10-kilometer grid of AANPP values across Africa. A more detailed account of MODIS and SPAM data processing for AANPP estimations is available in the supporting information (Appendix Box A.2 and Figure A.2).

AANPP values were reaggregated to the country level for Africa and the level-2 administration level (zone) for Ethiopia. These values were plotted against the average NPP over the same spatial and temporal extents, creating a quadrant graph of high NPP / high AANPP, high NPP / low AANPP, low NPP / low AANPP, and low NPP / high AANPP scenarios, providing an indication of both the crop production potential (NPP) and crop production intensity (AANPP). For a subset of countries in Africa south of the Sahara and a subset of zones in Ethiopia, these plots were created for both the 2000 and 2005 datasets. By measuring the direction and magnitude of change for each area, we can see the trajectory of agricultural production during the period studied.

Data Assumptions and Limitations

This study relies on the integration of two large datasets and assumes that both are accurate and reliable. Both datasets are created through complex models with numerous parameters to estimate respective outputs. The SPAM crop production data rely heavily on agricultural production statistics collected from a variety of sources at a variety of scales. Data are disaggregated using specific crop parameters, such as crop-specific suitability, crop price, and cropland extent, to create spatially explicit coverage of crop production. SPAM includes approximately 80 (circa 2000) to 99 percent (circa 2005) of the earth's total crop production, as reported by FAO. In addition, SPAM excludes crucial components, such as livestock-related production statistics, required for a full calculation of AANPP.

There are also several simplifying assumptions required in the MODIS model for calculating the gross primary productivity (GPP) and NPP (Heinsch et al. 2003b). First, the algorithm relies heavily on an underlying land-cover layer from which biome-specific parameters are used to calculate NPP in combination with remotely sensed data. It is assumed that the underlying land-cover layer is accurate. In addition, although these biome-specific parameters are updated based on empirical data collected from ground stations, they do not vary spatially or temporally to account for within-biome variations and seasonal variations. For example, within this model, a semiarid grassland in Kenya is treated the same as a tall-grass prairie in the Midwestern United States. Second, the leaf area index (LAI) and the fraction of photosynthetically absorbed radiation (FPAR) are required to calculate GPP. These values are produced with the MOD15 algorithm (another MODIS product) and are calculated based on an eight-day composite, using selection criteria whereby for more than the eight days, the maximum FPAR is used. This day is then used to measure the LAI value for the respective pixel. Thus, although primary productivity is calculated daily, it is assumed that FPAR and LAI do not vary over the eight days. The MOD17 algorithm also requires daily meteorological data, including average minimum temperature, incident photosynthetically active radiation and specific humidity. These data are estimated based on a global circulation model, incorporating both ground and satellite data and provided through NASA's Data Assimilation Office. The resolution of these data is at 1.00° x 1.25°. It is assumed that this resolution does not vary over the extent of each cell and thus can be reasonably scaled to a finer resolution for the MODIS algorithm.

The end product requires the conversion of the SPAM production data to appropriate units compatible with the MODIS NPP data. The model for conversion uses a number of parameters estimated for each crop and assumes spatial and temporal homogeneity of each parameter for each crop. Although the values of each parameter for each crop are relatively well established in the literature (Appendix Table A.2), there is variation that cannot be accounted for. For example, the harvest index will vary based on available technology and increases with improved practices. Likewise, moisture content of crops may vary with growing condition. Even across a regional scale, such as Africa, it is likely that these parameters will vary.

Despite simplifying assumptions and data limitations, these are generally considered the most accurate models available. Both datasets are evolving to incorporate the most up-to-date and accurate parameters as accuracy assessments and validation continues.

3. RESULTS

Aggregated at the continent level, Africa's terrestrial ecosystems produced a total of 12 billion tons of carbon in 2005 (Table 3.1), agreeing with earlier estimates of NPP (Haberl et al. 2007). Of this, crop production accounted for approximately 484 million tons of removable carbon at harvest, equivalent to 4 percent AANPP or one-third of the global share. Aggregated by country, AANPP ranged from less than 1 to 93 percent, with a mean of 9 percent (Table 3.1).

Table 3.1 Net primary productivity (total + crop) and agricultural appropriation of net primary productivity in Africa by country

Country	Crop production (kg carbon)	NPP (kg carbon)	AANPP (%)
Algeria	13,077,044,224	132,080,093,649	9.90
Angola	5,300,852,736	1,042,959,105,489	0.51
Benin	4,361,645,056	39,621,687,894	11.01
Botswana	95,556,384	174,172,273,781	0.05
Burkina Faso	5,910,040,064	36,279,922,934	16.29
Burundi	4,085,306,112	25,527,699,364	16.00
Cameroon	13,525,407,744	384,820,836,678	3.51
Central African Rep.	1,354,560,000	343,709,644,023	0.39
Chad	3,507,989,248	56,678,896,697	6.19
Congo	1,114,149,632	381,559,624,776	0.29
Côte d'Ivoire	21,768,419,328	234,442,106,720	9.29
Dem. Rep. Congo	14,313,029,632	2,371,659,366,486	0.60
Djibouti	3,597,960	1,243,812,793	0.29
Egypt	55,513,710,592	59,549,155,673	93.22
Eq. Guinea	312,696,352	27,921,238,580	1.12
Eritrea	447,789,824	7,518,212,914	5.96
Ethiopia	26,429,771,776	617,336,788,033	4.28
Gabon	585,660,544	304,018,441,917	0.19
Gambia	450,204,128	2,892,236,341	15.57
Ghana	19,901,229,056	134,498,789,552	14.80
Guinea	7,545,819,648	82,206,859,210	9.18
Guinea-Bissau	767,772,544	7,217,255,262	10.64
Kenya	11,987,146,752	252,914,150,553	4.74
Lesotho	199,639,600	20,075,829,922	0.99
Liberia	1,113,280,384	83,840,736,894	1.33
Libya	1,992,906,752	37,189,949,453	5.36
Madagascar	10,329,387,008	766,060,973,532	1.35
Malawi	5,710,752,768	77,500,375,221	7.37
Mali	6,518,140,928	27,893,521,413	23.37
Mauritania	268,296,384	5,928,146,469	4.53
Morocco	19,751,047,168	107,540,151,632	18.37
Mozambique	5,727,201,280	644,540,290,987	0.89
Namibia	330,185,248	196,132,626,678	0.17
Niger	5,367,151,104	17,591,344,831	30.51

Table 3.1 Continued

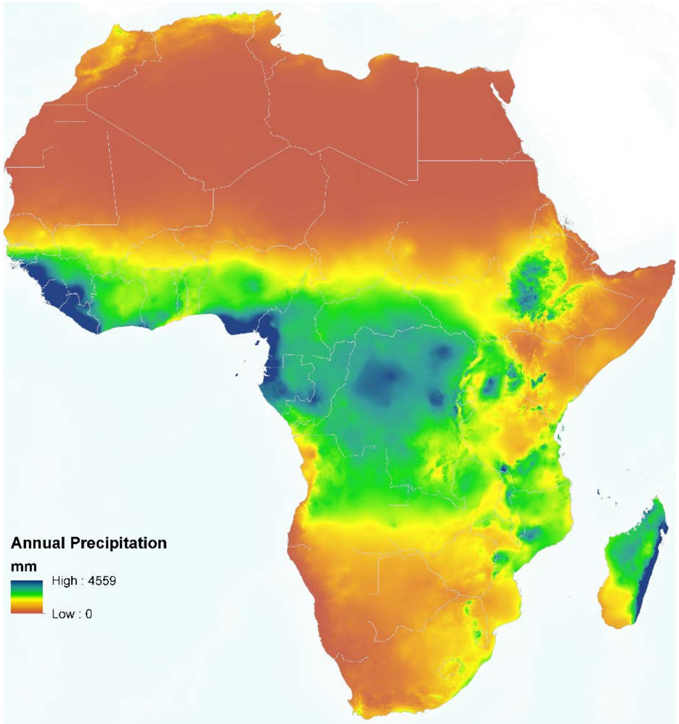
Country	Crop production (kg carbon)	NPP (kg carbon)	AANPP (%)
Nigeria	100,701,831,168	311,159,702,323	32.36
Rwanda	5,424,345,088	28,108,194,807	19.30
South Sudan	1,399,053,568	272,566,157,058	0.51
Sao Tome and Principe	91,992,520	720,119,138	12.77
Senegal	3,292,512,256	27,577,470,221	11.94
Sierra Leone	2,926,090,496	35,140,375,865	8.33
Somalia	934,867,328	85,449,769,763	1.09
Somaliland	55,293,608	15,035,099,721	0.37
South Africa	29,474,162,688	650,183,059,805	4.53
Sudan	10,730,852,352	98,726,721,538	10.87
Swaziland	740,992,192	16,895,793,362	4.39
Tanzania	18,338,957,312	723,911,352,578	2.53
Togo	2,363,777,280	25,183,465,263	9.39
Tunisia	7,712,226,816	43,389,964,858	17.77
Uganda	23,644,829,696	242,385,250,092	9.76
Zambia	2,738,928,128	610,680,089,053	0.45
Zimbabwe	3,567,263,232	225,212,272,661	1.58
Africa Total	483,805,363,688	12,117,447,004,455	3.99

Source: Authors.
Notes: AANPP = agricultural appropriation of net primary productivity; NPP = net primary productivity.

The spatial distribution of NPP in Africa is largely determined by rainfall (Thornton 2014), as shown in Figure 3.1a and 3.1b. NPP was greatest south of the Sahel and north of the Tropic of Capricorn, particularly in Central Africa. In more arid areas, such as Southern and North Africa and across the plains of East Africa, NPP was relatively low, as expected. The spatial distribution of crop NPP, on the other hand, is patchier throughout the continent (Figure 3.1b). Crop NPP was relatively high along the coastline and inner coastal regions of West Africa, across the southern edges of the Sahel, throughout the African Great Lakes region, and down the East African Rift. In some areas where total NPP was high, crop NPP was low, such as in Central Africa, most notably in the Democratic Republic of the Congo.

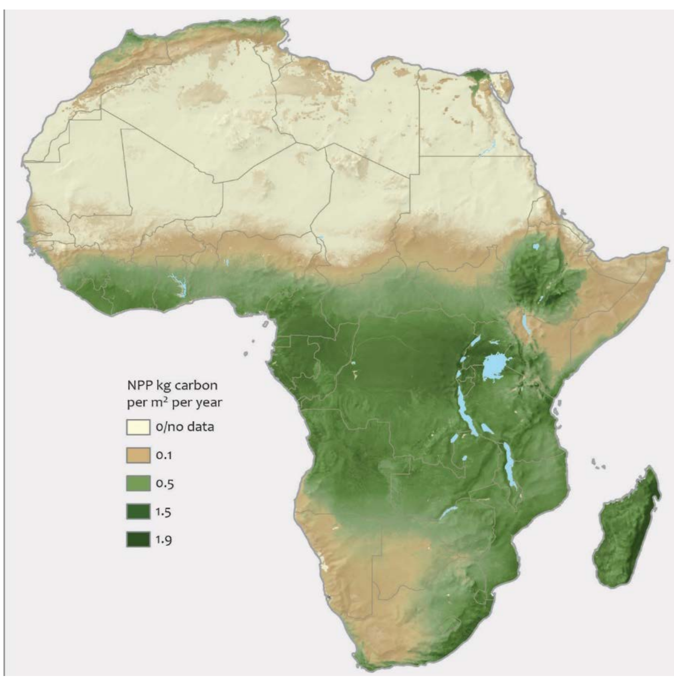
AANPP values were largely moderate to low throughout the continent, with a spatial pattern closely resembling crop NPP (Figure 3.1c). Relatively high AANPP was most notably concentrated throughout West African countries and continued in a diluted effect across the continent along the Sahel, with patchier clusters in the African Great Lakes region and along the East African Rift. In Southern and Central Africa and many countries in the east, such as in the Horn of Africa, AANPP was low to moderate as compared with other regions in Africa. Several arid countries in North and West Africa along the Nile River and in the Sahel had high AANPP despite relatively low regional rainfall—for example, in Egypt, AANPP approached 100 percent and exceeded all other country values by dozens of percentage points (Table 3.1 and Figure 3.1c). In other words, NPP in Egypt and in many of the more northern African countries is almost entirely, or majorly, for crop allocation and human consumption.

Figure 3.1a Annual precipitation gradient



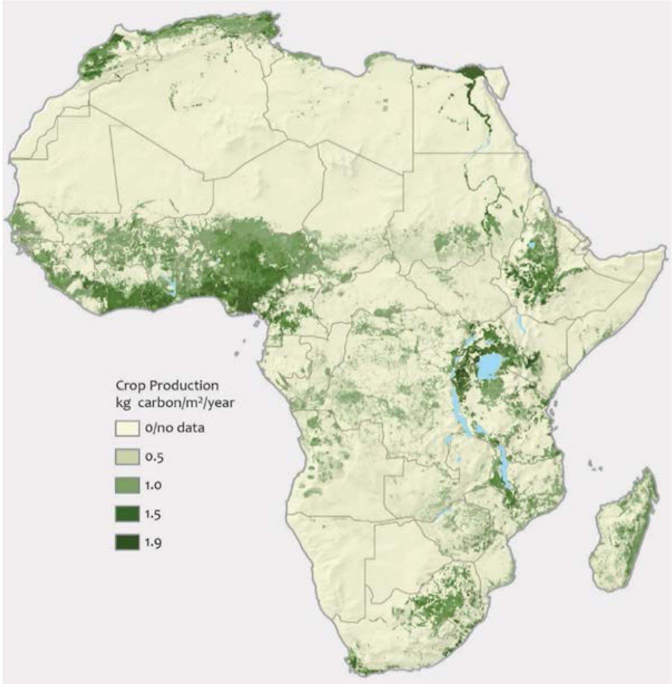
Source: You et al. 2014; Hijmans et al. 2005.

Figure 3.1b Subnational MODIS estimates of total



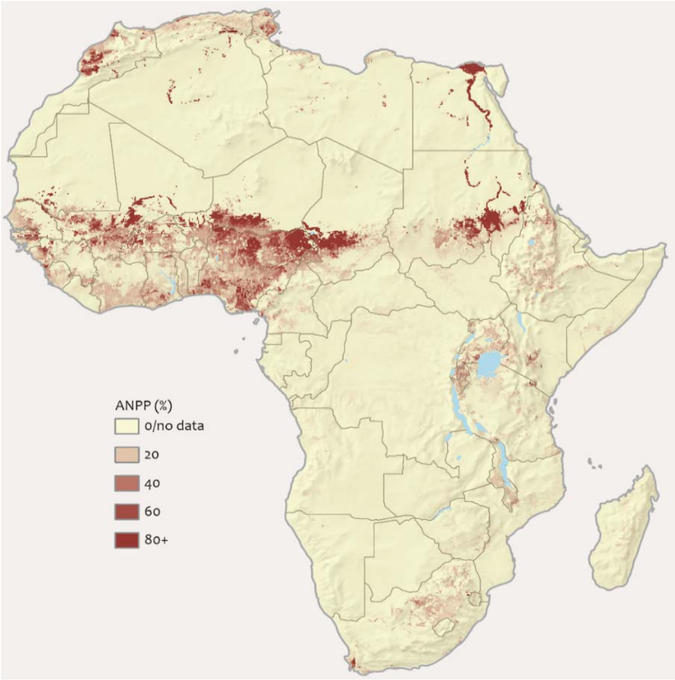
Source: Authors.
Notes: MODIS = moderate-resolution image spectrometer.

Figure 3.1c Net primary productivity



Source: Authors.

Figure 3.1d The percentage of NPP appropriated by agricultural harvest (AANPP)

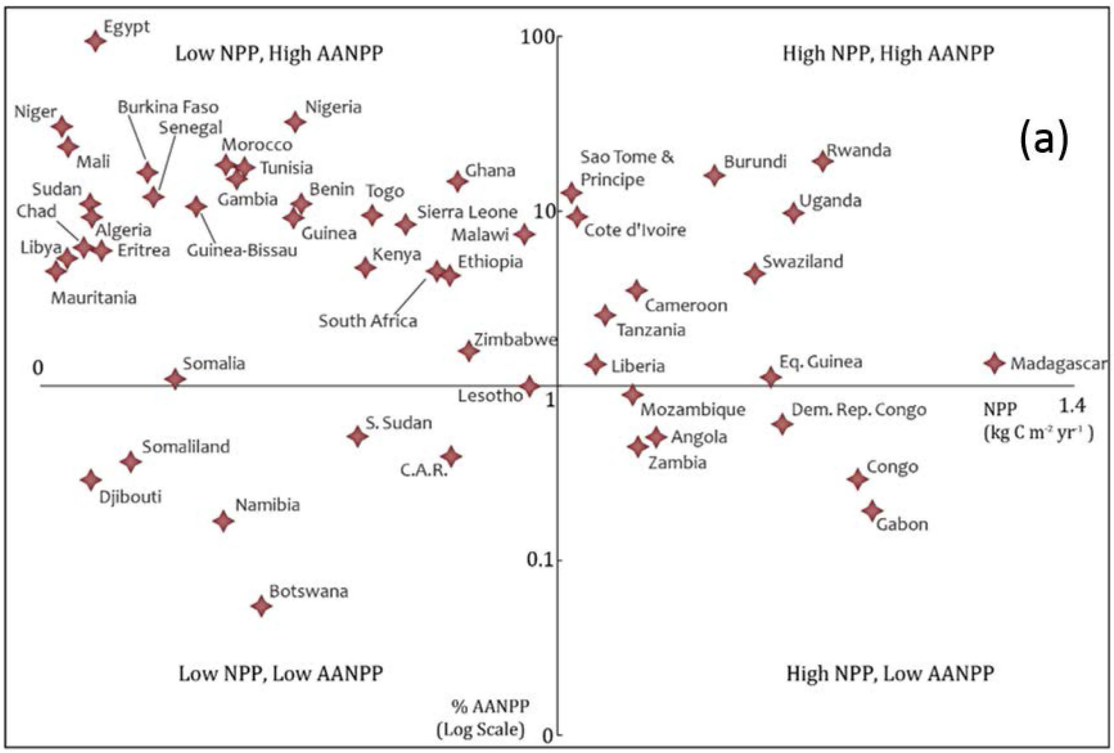


Sources: Authors.

Notes: AANPP = agricultural appropriation of net primary productivity; NPP = net primary productivity. Crop production data are from the spatial production allocation model (SPAM; You et al. 2014) converted to NPP and expressed in kilograms of carbon per square meter (kg/m^2) per year. AANPP is calculated as the percentage of total NPP appropriated by agriculture in a given pixel of 10 square kilometers (5 arc-minute) resolution. SPAM data include approximately 80 (circa 2000) to 99 percent (circa 2005) of the earth's total crop production (FAO 2015). These data embed economic assumptions such as population and market prices. We only included data for crops that were represented in both versions of SPAM.

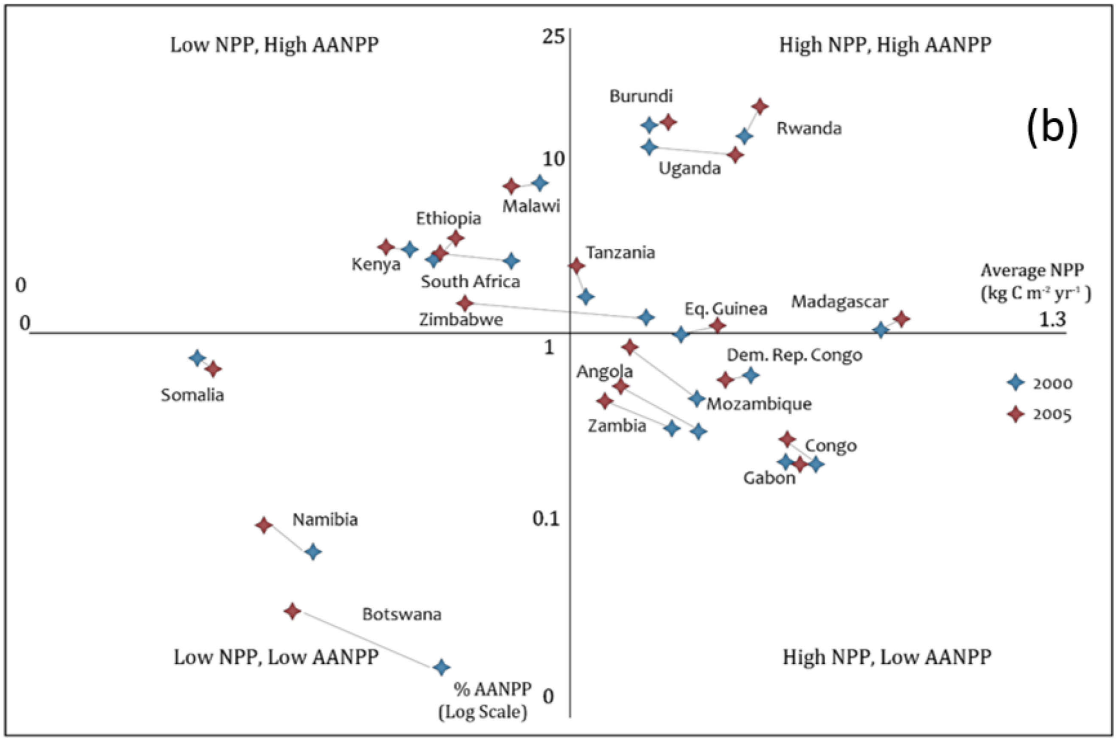
For a more complete picture of the direction and magnitude of AANPP, we plotted countries according to four quadrants of varying levels of relatively high and low total NPP and AANPP (Figure 3.2a). Most countries landed in the upper right quadrant: low NPP/high AANPP. Moreover, most countries skewed toward low total NPP. A comparison of 2000 and 2005 data for selected African countries south of the Sahara shows trends of increasing AANPP at variable rates, though some increases were slight (Figure 3.2b). Several countries (Mozambique, Angola, and Zambia) experienced substantial AANPP increases while NPP declined. Indeed, although AANPP was on the rise, NPP supply was largely stable or decreased considerably across Africa south of the Sahara during the five-year period studied. This pattern is especially evident at the subnational level (zone) in Ethiopia (Figure 3.2c). For example, with the exception of Sidama and Gedio, where AANPP declined considerably at slight increases in NPP, most zones in Ethiopia increased AANPP relative to NPP.

Figure 3.2a Comparisons of agricultural appropriation of net primary productivity (percent log scale) versus net primary productivity (kg C m–2 yr–1) by quartile at the country level across Africa



Source: Authors.
Notes: AANPP = agricultural appropriation of net primary productivity; NPP = net primary productivity. Data points reflect annual means centered around 2005 data.

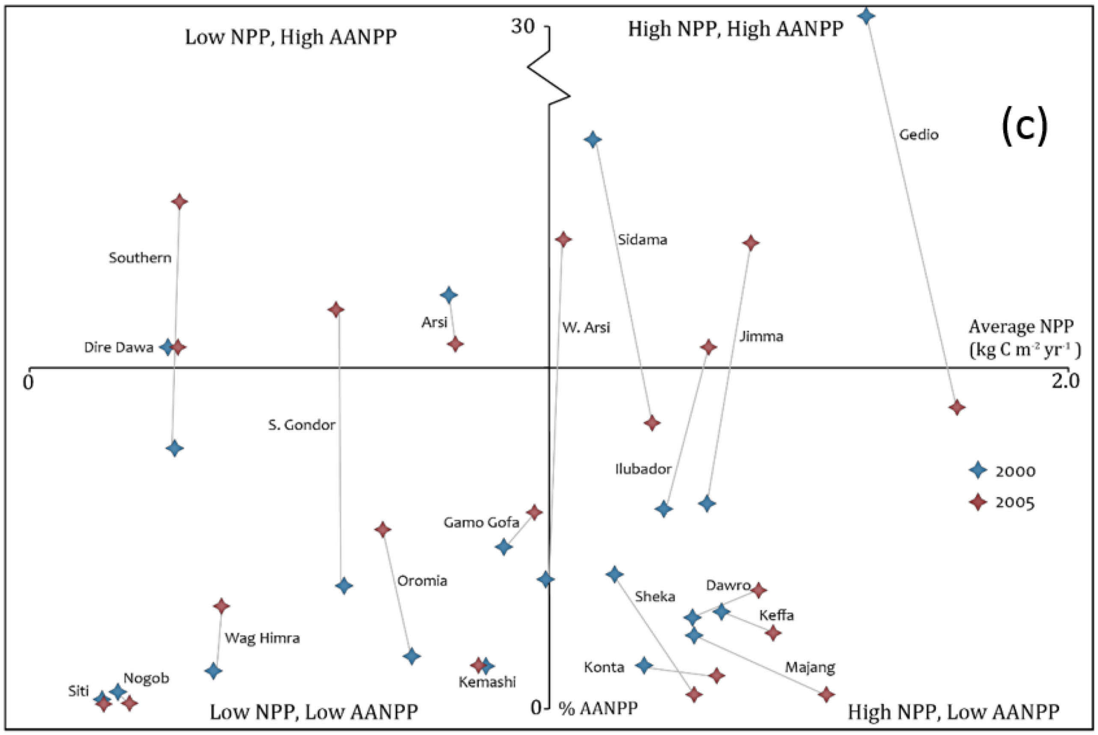
Figure 3.2b Comparison of 2000 and 2005 agricultural appropriation of net primary productivity (percent log scale) data versus net primary productivity (kg C m–2 yr–1) by quartile for selected African countries south of the Sahara



Source: Authors.

Notes: AANPP = agricultural appropriation of net primary productivity; NPP = net primary productivity. Disaggregated by year for 2000 (blue) and 2005 (red).

Figure 3.2c Comparison of 2000 and 2005 agricultural appropriation of net primary productivity (percent log scale) data versus net primary productivity (kg C m–2 yr–1) by quartile for select zones at the subnational, administration level 2 in Ethiopia



Source: Authors.

Notes: AANPP = agricultural appropriation of net primary productivity; NPP = net primary productivity. Disaggregated by year for 2000 (blue) and 2005 (red).

4. DISCUSSION

Improved efficiencies in crop production and technological changes can result in considerable NPP increases overtime (Foley et al. 2011) and not necessarily at the expense of increased AANPP (Krausmann et al. 2013). For example, large-scale farmer adoption of perennial crops, agroforestry, doubled-up legumes, rotations and intercropping, and other sustainable intensification practices currently promoted in multiple Feed the Future countries and beyond (such as Africa RISING[4] and Cereal Systems Initiative for South Asia[5]) would presumably, collectively, increase NPP both spatially and temporally, while also enhancing yield improvements. Evidence of the use of global NPP from literature is scant, however, because NPP measurements have not been traditionally considered in international program assessments.

In the present study, we contribute to the literature by introducing a new methodology and illustrating the utility of NPP data within a development framework for the African continent using remotely sensed NPP data and spatially explicit agricultural production data from 2000 and 2005. We did not include livestock or below-ground NPP data in our calculations, as they are more challenging to quantify. More research is needed because both are important to ecosystems and sustainability and, thus, would undoubtedly spike regional AANPP or NPP estimates (Roy, Mooney, and Saugier 2001; Haberl et al. 2004, 2007; Glover, Reganold, and Cox 2012). Moreover, although we did not consider ex ante modeling analysis, projections of NPP and AANPP at large scale in response to different treatments of sustainable intensification practices are undoubtedly feasible and may provide more on-the-ground decision-making support.

Our results illustrate the dominance of cropping systems as spatial drivers of NPP across many regions in West and East Africa and in the fertile river valleys across North Africa and the Sahel, where access to irrigation and other technological inputs is inflating AANPP relative to NPP. Overall, Africa's crop production accounts for approximately 484 million tons of removable carbon at harvest, equivalent to 4 percent AANPP, or one-third of the global share. In other words, Africa is producing one-third of the global NPP harvest. Lower AANPP estimates in Africa, particularly evident south of the equator, likely stem from prevailing low-intensity farming systems and poor below-ground plant productivity common in the region (Roy, Mooney, and Saugier 2001; Haberl et al. 2007; Niedertscheider et al. 2016).

Trade-offs between NPP and AANPP represent a delicate balancing act that defines the sustainability and production potential of a place. For example, in areas with adequate rainfall where crop NPP falls below the natural potential and AANPP is also low, such as in Central African Republic, increases in both NPP and AANPP are necessary to meet desirable sustainable intensification outcomes (such as food and ecological security). On the other hand, in countries where AANPP and NPP are both relatively high on the continuum (high AANPP/high NPP), such as Rwanda and Burundi, agricultural intensification may be undermining sustainability, because the removal of biomass (energy) is keeping pace with NPP supply. In other words, natural capital in the form of plant biomass is essentially almost entirely diverted to human consumption. In a third scenario, where overall AANPP is high relative to NPP (high AANPP/low NPP), such as in Malawi and Ethiopia, energy availability is more constrained because agricultural demands are extracting from less-productive land (indicated by low overall NPP). In this scenario, ecosystem services may be enhanced by large-scale innovations that increase NPP without concurring a similar rate of increasing AANPP. This last example is an illustration of why both NPP and human derivatives of NPP are important to measure. In more extreme examples within this scenario, however, where rainfall is near negligible and cropping systems are highly dependent on external inputs (such as irrigation), as in Egypt, the choice of practices and innovations within a sustainable intensification framework is limited. The low AANPP/high NPP scenario is common in heavily forested Central Africa where, depending on land use, crop production is low compared to timber. That being said,

[4] For more information on Africa Research in Sustainable Intensification for the Next Generation, see https://africa-rising.net/.

[5] For more information on Cereal Systems Initiative for South Asia, see http://csisa.org/.

poorly reported crop production statistics are common in such regions of instability, highlighting the perennial need for ground-truthing. Although we cannot identify a particular sweet spot on the continuum, agrarian landscapes that fall within more productive and sustainable ranges will have relatively higher NPP to AANPP ratios (for example, in Madagascar). However, lower values of AANPP should be treated as a red flag as this may signal critical yield gaps and the need to intensify agriculture production.

From 2000 to 2005, with few exceptions, changes in AANPP trended upward (albeit, sometimes slightly), whereas NPP either held stable or decreased considerably across Africa south of the Sahara. Several countries (Mozambique, Angola, and Zambia) experienced substantial AANPP increases while NPP declined. This pattern was especially evident subnationally in Ethiopia. For example, with the exception of Sidama and Gedio, where AANPP declined considerably at slight increases in NPP, most zones in Ethiopia increased AANPP relative to NPP. In other words, the magnitude of change in AANPP was appreciably larger than the mostly negative changes in NPP. Such trends in NPP and AANPP highlight increasing vulnerability of populations to food and ecological insecurity. Decision makers and other stakeholders need to carefully consider such trends when designing and supporting conservation and agricultural policies; these decisions makers include FAO, World Bank, and other nongovernmental organizations, as well as major donors and governmental bodies.

Global NPP and agricultural appropriation of energy are critical indicators of sustainability if we are to adopt a radical rethinking of our food systems, particularly in the face of climate change and other global environmental challenges. We may not know Earth's AANPP capacity for a sustainable future, but we do know that ensuring "a sustainable future entails sharing NPP with a great host of other species" (Field 2001). Such a paradigm shift requires an equally radical shift in data capacity and analyses. Large-scale spatial datasets (such as www.harvestchoice.org) are increasingly available to the public, though they are grossly underused, especially the georeferenced socioeconomic data (Azzarri et al. 2016). By taking advantage of open-source datasets, the bang for the investment buck can be better realized in the form of progress toward sustainable development, particularly in highly impacted regions of the world where "good data" are harder to come by.

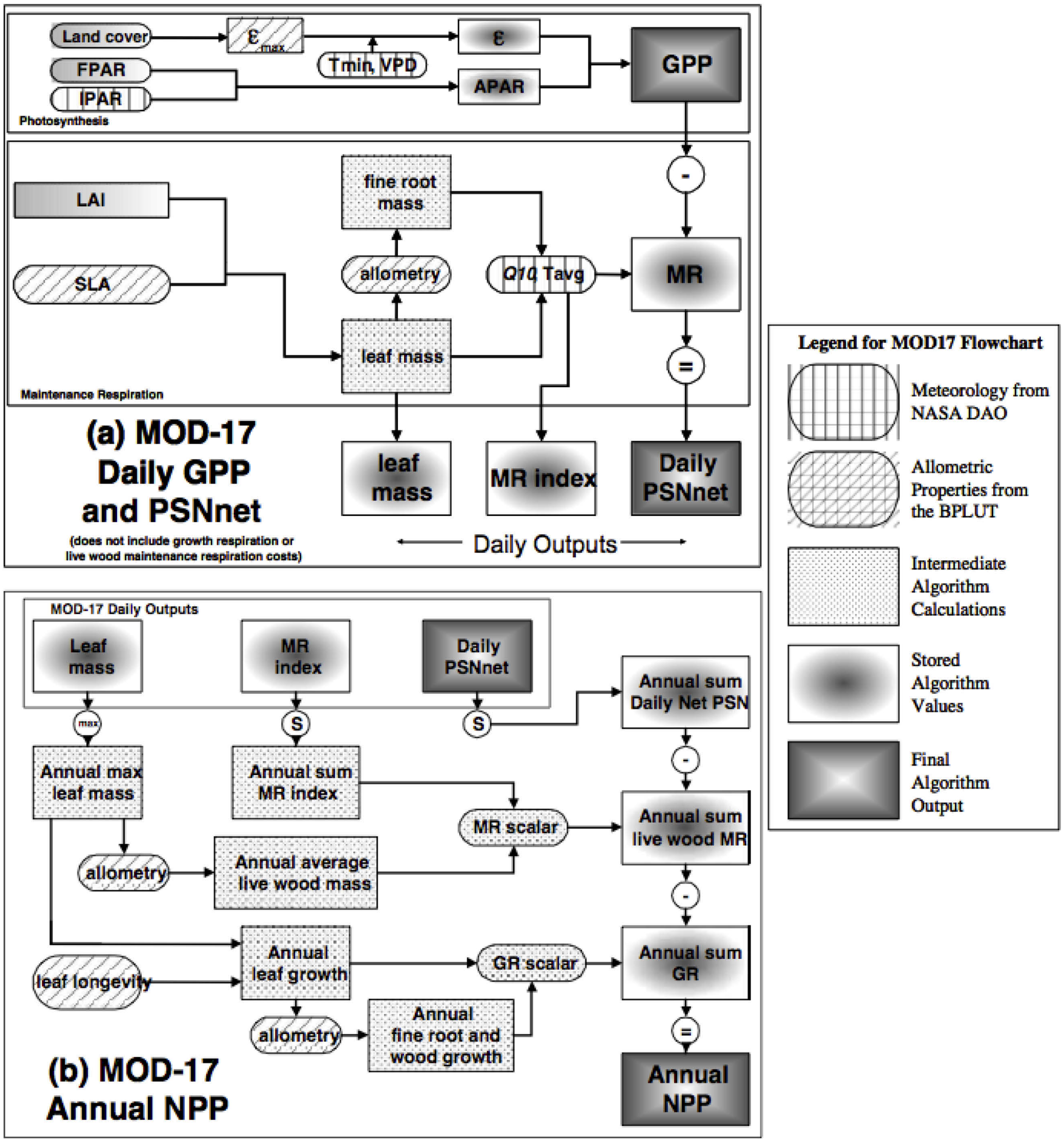
APPENDIX: SUPPORTING INFORMATION: MATERIALS AND METHODS

Box A.1 Detailed MOD17A3 product

The MODIS (Moderate-Resolution Imaging Spectrometer) is a sensor onboard the Terra and Aqua Earth Observation System (EOS) satellites. The sensors acquire data in 36 spectral bands from .4μm to 14.4μm, at varying spectral resolutions from 250m2 to 1km2, and at a daily temporal resolution. A variety of products are derived from the MODIS data and are free and publicly available. The MOD17A2/A3 algorithm combines MODIS remote sensing data, large-scale meteorological data, and carbon cycle processing models (Fig. S1). Gross primary productivity (GPP) and net primary productivity (NPP) are estimated using the MOD17A2/A3 algorithms for the entire terrestrial surface at 1 km2 spatial resolution. For each cell, GPP is calculated daily and averaged over 8-day periods while NPP is calculated annually. In essence, within this algorithm NPP is a function of the absorbed photosynthetically-active radiation (APAR), and the light-use efficiency (ε) for different vegetation biomes. APAR is derived from the fraction of incident photosynthetically active radiation absorbed by the surface (FPAR) and the incident photosynthetically active radiation on the vegetative surface (PAR). The derivation is straightforward (APAR = IPAR * FPAR). FPAR data is acquired from the MODIS sensors while IPAR data is acquired from large-scale meteorological data. The light-use efficiency (ε), or conversion efficiency is highly variable based on vegetation type. Thus, ε is derived based on biome specific estimated values as well as temperature and vapor pressure deficit constraints. APAR and ε are combined to calculate daily estimates of GPP (kg C day-1). The maintenance respiration costs (MR) for leaves and roots are also calculated on a daily basis and subtracted from GPP to calculate an estimate for net photosynthesis. This product is then combined with annual maintenance respiration estimates for woody material estimates and annual growth respiration (GR) estimates to compute annual NPP. NPP = (annual sum of daily net photosynthesis) – (Livewood MR) – (Leaf GR) – (Root GR) – (Livewood GR) – (Deadwood GR). (See (Heinsch et al., 2003) for a full description of the algorithms and explanations of individual parameters.). The MOD17A2/A3 algorithms heavily rely on a Biome Parameter Look-UP Table (BPLUT), with the biomes generated from the MODIS land cover product, MOD12Q1. This product employs Boston University's UMD classification scheme (Table A.1). Each 1 km2 grid cell has a calculated NPP value in Kg C km-2 yr-1. The MODIS sensor was launched on the Terra EOS satellite in 1999 and on the Aqua EOS satellite in 2002. Thus, data is available from 2000 onwards. Furthermore, the MOD17 product is an evolving dataset, and as improvements are made to the algorithms, the series is re-run in its entirety. The current version is 5.0. The MODIS land team is currently working on methods that integrate higher resolution land cover data, where available, to improve NPP estimates.

Source: Authors.

Figure A.1 Conceptual model of the MOD17 algorithm



Source: Heinsch et al., (2003).

Table A.1 Land cover classification scheme

Class value	Class description
0	Water
1	Evergreen Needleleaf Forest
2	Evergreen Broadleaf Forest
3	Deciduous Needleleaf Forest
4	Deciduous Broadleaf Forest
5	Mixed Forest
6	Closed Shrubland
7	Open Shrubland
8	Woody Savanna
9	Savanna
10	Grassland
12	Cropland
13	Urban or Built Up
16	Barren or Sparsely Vegetated
254	Unclassified
255	Missing Data

Source: Heinsch et al., (2003).

Box A.2 Detailed SPAM processing methods

The general model to convert crop production statistics from the Spatial Allocation Production Model (SPAM) to equivalent units in carbon was:

$$P = \sum_i \frac{PC_i * MRY_i * (1 - MC_i) * C}{HI_i \bullet fAG_i}$$

In this equation, P is the production in units of carbon and i represents the individual crop production system. PC_i is the total amount of crop produced in each cell, and was reported as a weight or volume. MRY_i is a multiplier that converts the reported crop production amount to units of mass. MC_i represents the percent moisture for the given crop, and subtracting from one gave the dry mass percent. C is a simple constant to convert dry plant mass to carbon, estimated as .45 g C g-1. HI_i is the harvest index for the given crop and accounts for the portion of the crop lost as result of harvest. fAG_i is the above ground fraction of the plant and used to account for root mass. Many of these parameters are crop specific and found from the literature (Table A.2). The raster calculator was used to convert the SPAM production statistic for each crop into kilograms of carbon removed from the landscape using the parameters. These calculations were done for both the 2000 and 2005 datasets. For a comparison between 2000 and 2005, the 2005 dataset was modified to match the 2000 dataset by removing crops and crop types not present in the 2000 SPAM dataset.

Source: Authors.
Notes: Equation is adapted from Monfreda et al., (2008) and Prince et al., (2001).

Table A.2 Parameters for converting SPAM to units of carbon removed from the landscape at harvest

	Parameters				
Crop	**MRY**	**MC**	**C**	**HI**	**fAG**
Banana	1000000	0.74	0.45	0.1	1
Barley	1000000	0.1	0.45	0.4	0.8
Beans	1000000	0.79	0.45	0.5	0.5
Cassava	1000000	0.65	0.45	0.6	0.75
Chickpea	1000000	0.75	0.45	0.5	0.5
Cocoa	1000000	0.6	0.45	0.03	1
Coconut	1000000	0.1	0.45	0.35	1
Coffee Arabica	1000000	0.11	0.45	0.012	1
Coffee Robusta	1000000	0.11	0.45	0.012	1
Cotton	1000000	0.08	0.45	0.4	0.8
Cowpea	1000000	0.77	0.45	0.5	0.5
Groundnut	1000000	0.09	0.45	0.4	0.8
Lentil	1000000	0.75	0.45	0.5	0.5
Maize	1000000	0.11	0.45	0.45	0.85
Millet pearl	1000000	0.09	0.45	0.45	0.75
Millet small	1000000	0.09	0.45	0.45	0.75
Oil palm	1000000	0.1	0.45	0.35	0.94
Other cereals	1000000	0.1	0.45	0.4	0.8
Other fibers	1000000	0.1	0.45	0.5	0.5
Other oil crops	1000000	0.1	0.45	0.35	0.94
Other pulses	1000000	0.75	0.45	0.5	0.5
Other roots and tubers	1000000	0.75	0.45	0.5	0.8
Pigeon pea	1000000	0.75	0.45	0.5	0.5
Plantain	1000000	0.74	0.45	0.1	1
Potato	1000000	0.75	0.45	0.5	0.9
Rape seed	1000000	0.1	0.45	0.35	0.94
Rest of crops	1000000	0.5	0.45	0.5	0.5
Rice	1000000	0.09	0.45	0.4	0.8
Sesame seed	1000000	0.1	0.45	0.35	0.94
Sorghum	1000000	0.1	0.45	0.4	0.8
Soybean	1000000	0.1	0.45	0.4	0.87
Sugar beet	1000000	0.75	0.45	0.5	1
Sugarcane	1000000	0.85	0.45	0.93	0.92
Sun flower	1000000	0.1	0.45	0.35	0.94
Sweet potato	1000000	0.77	0.45	0.55	0.9
Tea	1000000	0.77	0.45	0.05	1
Temperate fruit	1000000	0.85	0.45	0.03	1
Tobacco	1000000	0.85	0.45	0.5	0.5
Tropical fruit	1000000	0.85	0.45	0.03	1
Vegetable	1000000	0.85	0.45	1	0.5
Wheat	1000000	0.11	0.45	0.4	0.83
Yam	1000000	0.77	0.45	0.55	0.9

Sources: Lobell et al. (2002); Martin et al. (1976); Monfreda et al. (2008).

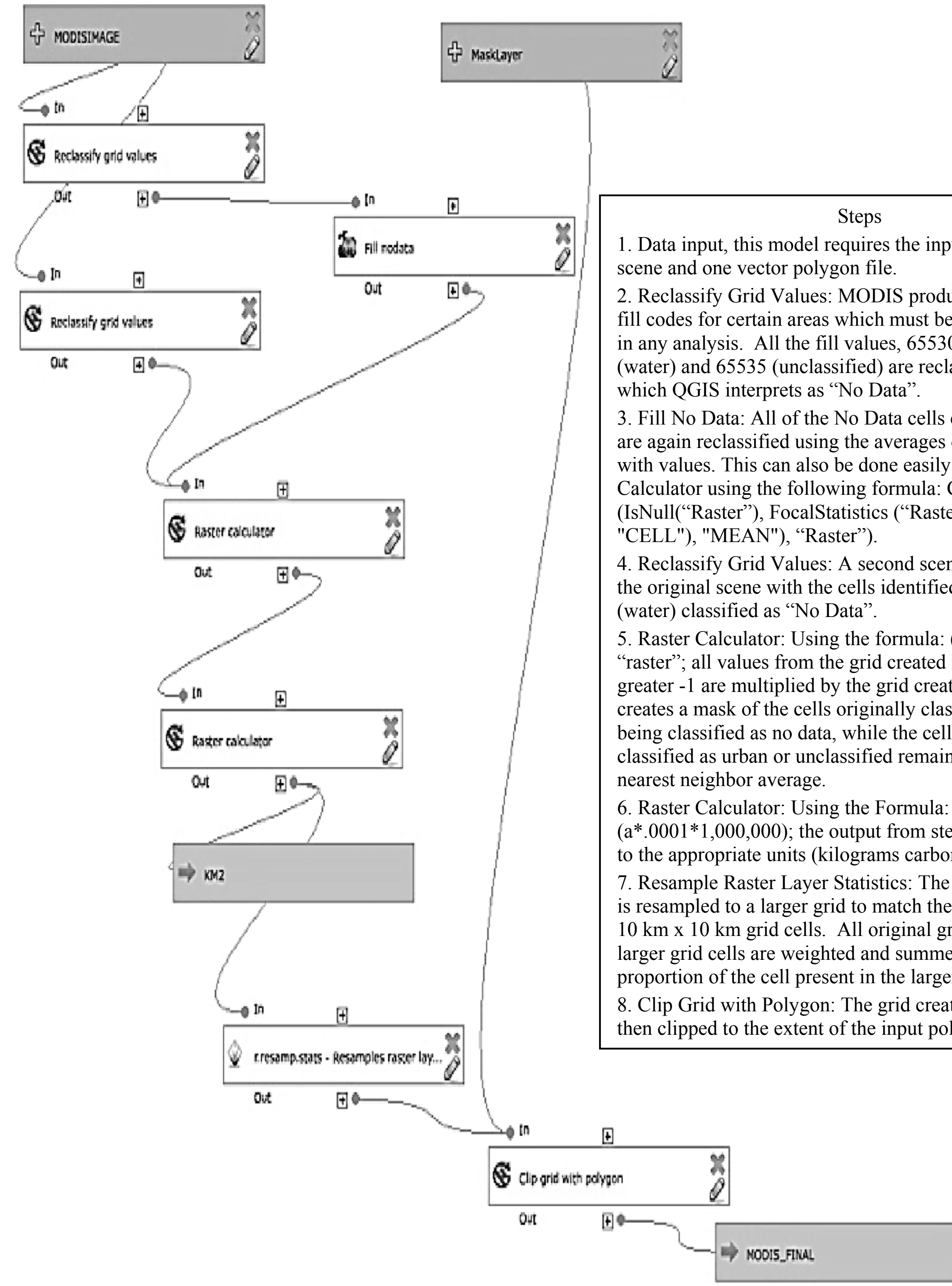
Notes: MRY_i is a multiplier that converts the reported crop production amount to units of mass. MC_i represents the percent moisture for the given crop, and subtracting from one gave the dry mass percent. C is a simple constant to convert dry plant mass to carbon, estimated as .45 g C g-1. HI_i is the harvest index for the given crop and accounts for the portion of the crop lost as result of harvest. fAG_i is the above ground fraction of the plant and used to account for root mass.

Box A.3 Processing MODIS and SPAM data and estimating AANPP

We developed a spatially-explicit estimate of the agricultural appropriation of net primary productivity (AANPP) for countries across Africa by combining global NPP data derived from MODIS (moderate-resolution image spectrometer) sensors and crop distribution and production statistics from SPAM. There was a substantial amount of data pre-processing required in order to seamlessly integrate the two data sets. For this study, MODIS data was downloaded from the USGS EarthExplorer (earthexplorer.usgs.gov). Thirty-eight MODIS tiles encompass the continent of Africa (Path 16, Rows 6-8; Path 17, Rows 5-8; Path 18, Rows 5-9; and Path 19, Rows 5-12; Path 20, Rows 5-12; Path 21, Rows 6-11; and Path 22, Rows 7-10). Each of the tiles for the years 2004 and 2005 were downloaded for the MOD17A2 product. Original data were in the Integerized Sinusoidal (ISIN) projection in HDF format. Few GIS products or image processing products have the capacity to reproject these file types out of the ISIN projection. Thus, the MODIS reproject tool (MRT) was used to reproject the MODIS files from the ISIN projection into the Geographic Projection with the WGS 84 Datum. This tool was also used to conveniently mosaic the tiles together for each of the years. The MRT is available for free from the USGS website along with a detailed instruction manual for installation and use (https://lpdaac.usgs.gov/tools/modis_reprojection_tool). The MODIS data, once reprojected into the proper projection, still required substantial pre-processing. The mosaic tiles were opened in GIS (QGIS). The MOD17 product had several fill codes that mask specific areas. Extremely low productive/barren areas had the code 65533, water had the code 65534 and urban/built up areas had the code 65530. These pixels were reclassified to achieve uniformity within the images. Water was reclassified as ‘nodata’, urban areas were reclassified as ‘0’ and pixels of low productivity scattered throughout the image were reclassified based on the average value of neighboring pixels. Furthermore, the original MODIS data was scaled by a factor of .0001 to obtain the correct units. Pixel values over the two years, 2004 and 2005, were then averaged to produce an estimate of NPP that matches the time-span of the SPAM data. The MODIS grid with 1 km x 1 km cells was then resampled into a grid with 10 km x 10 km cells to match the SPAM data. The data were resampled into the larger grid and the weighted values of the original cells within the larger cells were summed. The result was a raster of NPP values in kg C m-2 yr-1 at the same spatial resolution and over the same time period as the SPAM crop production data. A graphical representation of this workflow is shown in Figure B.3 along with a step-by-step explanation.

Source: Authors.

Figure A.2 Conceptual model of the MODIS data processing



Steps

1. Data input, this model requires the input of one MODIS scene and one vector polygon file.
2. Reclassify Grid Values: MODIS products utilize several fill codes for certain areas which must be modified to work in any analysis. All the fill values, 65530 (urban), 65534 (water) and 65535 (unclassified) are reclassified to -99999 which QGIS interprets as “No Data”.
3. Fill No Data: All of the No Data cells created in step 2 are again reclassified using the averages of the closest cells with values. This can also be done easily using the Raster Calculator using the following formula: Con (IsNull(“Raster”), FocalStatistics (“Raster”, NbrCircle(10, "CELL"), "MEAN"), “Raster”).
4. Reclassify Grid Values: A second scene is created from the original scene with the cells identified with 665534 (water) classified as “No Data”.
5. Raster Calculator: Using the formula: (“raster” >= 0) * “raster”; all values from the grid created in step 4 that are greater -1 are multiplied by the grid created in step 3. This creates a mask of the cells originally classified as water being classified as no data, while the cells originally classified as urban or unclassified remain classified as the nearest neighbor average.
6. Raster Calculator: Using the Formula: (a*.0001*1,000,000); the output from step 5 is converted to the appropriate units (kilograms carbon per sq km).
7. Resample Raster Layer Statistics: The result from step 6 is resampled to a larger grid to match the SPAM data with 10 km x 10 km grid cells. All original grid cells within the larger grid cells are weighted and summed based on the proportion of the cell present in the larger grid.
8. Clip Grid with Polygon: The grid created in step 7 is then clipped to the extent of the input polygon from Step 1.

Source: Authors.

Notes: MODIS = moderate-resolution image spectrometer.

REFERENCES

Azzarri, C., M. Bacou, C. M. Cox, Z. Guo, and J. Koo. 2016. "Subnational Socio-economic Dataset Availability." *Nature Climate Change* 6: 115–116.

Binder, C. R., G. Feola, and J. K. Steinberger. 2010. "Considering the Normative, Systemic and Procedural Dimensions in Indicator-Based Sustainability Assessments in Agriculture." *Environmental Impact Assessment Review* 30: 71–81.

Campbell, B. M., P. Thornton, R. Zougmoré, P. van Asten, and L. Lipper. 2014. "Sustainable Intensification: What Is Its Role in Climate Smart Agriculture?" *Current Opinion in Environmental Sustainability* 8: 39–43.

Crabtree, R., C. Potter, R. Mullen, J. Sheldon, S. Huang, J. Harmsen, A. Rodman, and C. Jean. 2009. "A Modeling and Spatio-temporal Analysis Framework for Monitoring Environmental Change Using NPP as an Ecosystem Indicator." *Remote Sensing of Environment* 113 (7): 1486–1496.

Cramer, W., D. W. Kicklighter, A. Bondeau, B. Moore III, G. Churkina, B. Nemry, A. Ruimy, et al., and the participants of the Potsdam NPP Model Intercomparison. 1999. "Comparing Global Models of Terrestrial Net Primary Productivity (NPP): Overview and Key Results." *Global Change Biology* 5: 1–15.

Davis, A., Z. Matthews, S. Szabo, and H. Fogstad. 2015. "Measuring the SDGs: A Two-Track Solution." *The Lancet* 386: 221–222.

FAO (Food and Agriculature Organization of the United Nations). 2015. FAOSTAT Statistics Database. Accessed October 26, 2015. http://faostat.fao.org.

FAO (Food and Agriculature Organization of the United Nations). 2016. *Save and Grow in Practice: Maize, Rice, Wheat. A Guide to Sustainable Cereal Production*. 120. Rome.

Field, C. B. 2001. "Sharing the Garden." *Science* 294: 2490–2491.

Foley, J. A. 2005. "Global Consequences of Land Use." *Science* 309: 570–574.

Foley, J. A., N. Ramankutty, K. A. Brauman, E. S. Cassidy, J. S. Gerber, M. Johnston, N. D. Mueller, et al. 2011, October 20. "Solutions for a Cultivated Planet." *Nature* 478: 337–342.

Garnett, T., M. C. Appleby, A. Balmford, I. J. Bateman, T. G. Benton, P. Bloomer, B. Burlingame, et al. 2013. "Sustainable Intensification in Agriculture: Premises and Policies." *Science* 341 (6141): 33–34.

Glover, J. D., J. P. Reganold, and C. M. Cox. 2012. "Agriculture: Plant Perennials to Save Africa's Soils." *Nature* 489: 359–361.

Haberl, H., K. H. Erb, F. Krausmann, V. Gaube, A. Bondeau, C. Plutzar, S. Gingrich, W. Lucht, and M. Fischer-Kowalski. 2007. "Quantifying and Mapping the Human Appropriation of Net Primary Production in Earth's Terrestrial Ecosystems." *Proceedings of the National Academy of Sciences* 104 (31): 12942–12947.

Haberl, H., N. B. Schulz, C. Plutzar, K. H. Erb, F. Krausmann, W. Loibl, D. Moser, N. Sauberer, H. Weisz, H. G. Zechmeister, and P. Zulka. 2004. "Human Appropriation of Net Primary Production and Species Diversity in Agricultural Landscapes." *Agriculture, Ecosystems, and Environment* 102 (2): 213–218.

Heinsch, F., M. Reeves, P. Votava, and S. Kang. 2003a. "GPP and NPP (MOD17A2/A3) Products NASA MODIS Land Algorithm." MOD17 User's Guide, 1–57. Missoula, MT, US: Numerical Terradynamic Simulation Group.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones and A. Jarvis, 2005. "Very High Resolution Interpolated Climate Surfaces for Global Land Areas." *International Journal of Climatology* 25: 1965–1978.

Houghton, R. A., J. I. House, J. Pongratz, G. R. van der Werf, R. S. DeFries, M. C. Hansen, C. Le Quére, and N. Ramankutty. 2012. "Carbon Emissions from Land Use and Land-Cover Change." *Biogeosciences* 9: 5125–5142.

Joppa, L. N., B. O'Connor, P. Visconti, C. Smith, J. Geldmann, M. Hoffmann, J. E. M. Watson, et al. 2016. "Filling in Biodiversity Threat Gaps." *Science* 352 (6284): 416–418.

Krausmann, F., K.-H. Erb, S. Gingrich, H. Haberl, A. Bondeau, V. Gaube, C. Lauk, C. Plutzar, and T. D. Searchinger. 2013. “Global Human Appropriation of Net Primary Production Doubled in the 20th Century.” *Proceedings of the National Academy of Sciences* 110: 10324–10329.

Lal, R. 2004. “Soil Carbon Sequestration Impacts on Global Climate Change and Food Security.” *Science* 304: 1623–1627.

Lambin, E. F., and P. Meyfroidt. 2011. “Global Land Use Change, Economic Globalization, and the Looming Land Scarcity.” *Proceedings of the National Academy of Sciences of the United States of America* 108: 3465–3472.

Lobell, D. B., J. A. Hicke, G. P. Asner, C. B. Field, C. J. Tucker, and S. O. Los. 2002.” Satellite Estimates of Productivity and Light Use Efficiency in United States Agriculture, 1982-98.” *Global Change Biology* 8 (8):722–735.

Martin, J. H., W. H. Leonard, and D. L. Stamp. 1976. *Principles of Field Crop Production.* 3rd ed. New York, NY: Macmillan Publishing Co.

Monfreda, C., N. Ramankutty, and J. A. Foley. 2008. “Farming the Planet: 2. Geographic Distribution of Crop Areas, Yields, Physiological Types, and Net Primary Production in the Year 2000.” *Global Biogeochemical Cycles*, 22.

Niedertscheider, M., T. Kastner, T. Fetzel, H. Haberl, C. Kroisleitner, C. Plutzar, and K.-H. Erb. 2016. “Mapping and Analysing Cropland Use Intensity from a NPP Perspective.” *Environmental Research Letters* 11: 14008.

Pretty, J, C. Toulmin, and S. Williams. 2011. “Sustainable Intensification in African Agriculture.” *International Journal of Agricultural Sustainability* 9: 5–24.

Prince, S. D., J. Haskett, M. Steininger, H. Strand, and R. Wright. 2001. “Net Primary Production of US Midwest Croplands from Agricultural Harvest Yield Data.” *Ecological Applications* 11: 1194–1205.

Roy, J., H. A. Mooney, and B. Saugier, eds. 2001. *Terrestrial Global Productivity*. Orlando, FL: Academic Press.

Thornton, P. 2014. “Rainfall and Rainfall Variability.” In *Atlas of African Agriculture Research and Development: Revealing Agriculture’s Place in Africa,* edited by K. Sebastian, 38–39. Washington, DC: International Food Policy Research Institute.

You, L., and S. Wood. 2006. “An Entropy Approach to Spatial Disaggregation of Agricultural Production.” *Agricultural Systems* 90: 329–347.

You, L., S. Wood, and U. Wood-Sichra. 2009. “Generating Plausible Crop Distribution Maps for Sub-Saharan Africa Using a Spatially Disaggregated Data Fusion and Optimization Approach.” *Agricultural Systems* 99: 126–140.

You, L, U. Wood-Sichra, Z. Guo, L. See, and J. Koo. 2014. “Spatial Production Allocation Model (SPAM) 2005 v2.0.” Accessed October 26, 2015. http://mapspam.info.

RECENT IFPRI DISCUSSION PAPERS

For earlier discussion papers, please go to www.ifpri.org/pubs/pubs.htm#dp.
All discussion papers can be downloaded free of charge.

1583. *Effects of agricultural mechanization on smallholders and their self-selection into farming: An insight from the Nepal Terai.* Hiroyuki Takeshima, Rudra Bahadur Shrestha, Basu Dev Kaphle, Madhab Karkee, Suroj Pokhrel, and Anjani Kumar, 2016.

1582. *The agricultural sector as an alternative to illegal mining in Peru: A case study of Madre de Dios.* Valeria Piñeiro, Jenny Thomas, and Pablo Elverdin, 2016.

1581. *What drives diversification of national food supplies?: A cross-country analysis.* Samira Choudhury and Derek Headey, 2016.

1580. *Identity, household work, and subjective well-being among rural women in Bangladesh.* Greg Seymour and Maria S. Floro, 2016.

1579. *Youth employment, agricultural transformation, and rural labor dynamics in Nigeria.* Margaret Adesugba and George Mavrotas, 2016.

1578. *Farm size and effects of chemical fertilizer price on farm households: Insights from Nepal terai.* Hiroyuki Takeshima, Sabnam Shivakoti, Binod Bhattarai, Madhab Karkee, Suroj Pokhrel, and Anjani Kumar, 2016.

1577. *Energy use and rural poverty: Empirical evidence from potato farmers in northern China*. Zihan Li, Yazhen Gong, and Kevin Z. Chen, 2016.

1576. *Does a "blue revolution" help the poor?: Evidence from Bangladesh.* Shahidur Rashid, Nicholas Minot, and Solomon Lemma, 2016.

1575. *Do development projects crowd out private-sector activities?: A survival analysis of contract farming participation in northern Ghana.* Isabel Lambrecht and Catherine Ragasa, 2016.

1574. *Strong democracy, weak state: The political economy of Ghana's stalled structural transformation.* Danielle Resnick, 2016.

1573. *Storage and handling among smallholder potato farmers in southwestern Uganda.* Bjorn Van Campenhout, Senne Vandevelde, Wiberforce Walukano, and Piet Van Asten, 2016.

1572. *What drives input subsidy policy reform?: The case of Zambia, 2002–2016.* Danielle Resnick and Nicole M. Mason, 2016.

1571. *Using household consumption and expenditure surveys to make inferences about food consumption, nutrient intakes and nutrition status: How important is it to adjust for meal partakers?* John L. Fiedler and Dena M. Mwangi, 2016.

1570. Improving *household consumption and expenditure surveys' food consumption metrics: Developing a strategic approach to the unfinished agenda.* John L. Fiedler and Dena M. Mwangi, 2016.

1569. *Microcredit in Viet Nam: Does it matter?* Jonathan Haughton and Shahidur R. Khandker, 2016.

1568. *Micronutrient policy process in Malawi.* Suresh C. Babu, Steven Haggblade, Elizabeth Mkandawire, Flora Nankhuni, and Sheryl Hendriks, 2016.

1567. *Framework to assess performance and impact of pluralistic agricultural extension systems: The best-fit framework revisited.* Guy Faure, Kristin E. Davis, Catherine Ragasa, Steven Franzel, and Suresh C. Babu, 2016.

1566. *Food markets and nutrition in the Democratic Republic of the Congo (2004–2005).* Wim Marivoet, 2016.

1565. *Learning from China?: Manufacturing, investment, and technology transfer in Nigeria.* Yunnan Chen, Irene Yuan Sun, Rex Uzonna Ukaejiofo, Tang Xiaoyang, and Deborah Brautigam, 2016.

1564. *Using cognitive interviewing to improve the Women's Empowerment in Agriculture Index survey instruments: Evidence from Bangladesh and Uganda.* Hazel Malapit, Kathryn Sproule, and Chiara Kovarik, 2016.

1563. *New modalities for managing drought risk in rainfed agriculture: Evidence from a discrete choice experiment in Odisha, India*. Patrick S. Ward and Simrin Makhija, 2016.

1562. U*sing zero tillage to ameliorate yield losses from weather shocks: Evidence from panel data in Haryana, India*. Md. Tajuddin Khan, Avinash Kishore, Divya Pandey, and P. K. Joshi, 2016.

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

www.ifpri.org

IFPRI HEADQUARTERS

2033 K Street, NW
Washington, DC 20006-1002 USA
Tel.: +1-202-862-5600
Fax: +1-202-467-4439
Email: ifpri@cgiar.org