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October 2007

Generating Plausible Crop Distribution and Performance Maps for Sub-Saharan Africa Using a Spatially Disaggregated Data Fusion and Optimization Approach

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ABSTRACT

Agricultural production statistics reported at country or sub-national geopolitical scales are used in a wide range of economic analyses, and spatially explicit (geo-referenced) production data are increasingly needed to support improved approaches to the planning and implementation of agricultural development. However, it is extremely challenging to compile and maintain collections of sub-national crop production data, particularly for poorer regions of the world. Large gaps exist in our knowledge of the current geographic distribution and spatial patterns of crop performance, and these gaps are unlikely to be filled in the near future. Regardless, the spatial scale of many sub-national statistical reporting units remains too coarse to capture the patterns of spatial heterogeneity in crop production and performance that are likely to be important from a policy and investment planning perspective. To fill these spatial data gaps, we have developed and applied a meso-scale model for the spatial disaggregation of crop production. Using a cross-entropy approach, our model makes plausible pixel-scale assessment of the spatial distribution of crop production *within* geopolitical units (e.g. countries or sub-national provinces and districts). The pixel-scale allocations are performed through the compilation and judicious fusion of relevant spatially explicit data, including production statistics, land use data, satellite imagery, biophysical crop "suitability" assessments, population density, and distance to urban centers, as wells as any prior knowledge about the spatial distribution of individual crops. The development, application and validation of a prior version of the model using data from Brazil strongly suggested that our spatial allocation approach shows considerable promise. This paper describes efforts to generate crop distribution maps for Sub-Saharan Africa for the year 2000 using this approach. Apart from the empirical challenge of applying the approach across many countries, the application includes three significant model improvements, namely (1) the ability to cope with production data sources that provided different degrees of spatial disaggregation for different crops within a single country; (2) the inclusion of a digital map of irrigation intensity as a new input layer; and (3) increased disaggregation of rainfed production systems. Using the modified spatial allocation model, we generated 5-minute (approximately 10-km) resolution grid maps for 20 major crops across Sub-Saharan Africa, namely barley, dry beans, cassava, cocoa, coffee, cotton, cowpeas, groundnuts, maize, millet, oil palm, plantain, potato, rice, sorghum, soybeans, sugar cane, sweet potato, wheat, and yam. The approach provides plausible results but also highlights the need for much more reliable input data for the region, especially with regard to sub-national production statistics and satellite-based estimates of cropland extent and intensity.

Keywords: Sub-Saharan Africa, cross-entropy, satellite image, spatial allocation, agricultural production, crop suitability

1. INTRODUCTION

Enlightened approaches to agricultural development in Sub-Saharan Africa recognize that policymakers must consider the extreme heterogeneity of production conditions that exist across the sub-continent (Pender et al. 2006, CAADP 2006). Since location is particularly important from a crop production perspective, obtaining a better understanding of the spatial patterns of crop production systems should allow better targeting of related policies and investments (Wood et al. 1999). In addition, such spatially explicit insights are needed to assess the potential human welfare and natural resource impacts of much-needed improvements in crop productivity. Thankfully, the increased availability of geo-referenced data and more accessible geographic information systems (GISs) now support the management and analysis of spatial data, and provide better opportunities for researchers to help meet these needs. Recently, numerous agricultural economists have extended their analytical methods to capitalize on more disaggregated production insights (Nelson 2002; Staal, et al. 2002; Luijten 2003; Bell and Irwin 2002; Anselin 2002).

The ideal scenario would be for consistent, highly disaggregated production data to be made available through national statistical and survey agencies. In many countries of Sub-Saharan Africa, however, chronic under-funding of these agencies often means that crop production data are compiled only infrequently and with limited geographic disaggregation. Furthermore, even where such data exist, it remains a challenge to compile and maintain regional and global collections of sub-national crop production data. Large gaps exist in our knowledge of the current geographic distribution and spatial patterns of crop performance, and these gaps are unlikely to be filled in the foreseeable future. Regardless of these limitations, however, the physical size of many sub-national statistical reporting units remains too large to reveal important patterns of spatial heterogeneity in crop production and performance that are likely to be relevant from a policy and investment planning perspective. To fill these disaggregated data gaps, we previously developed a meso-scale model for the spatial allocation of crop production and applied this model to data from Brazil (You and Wood 2003, You and Wood 2006). Using a cross-entropy approach, our spatial allocation model allows us to spatially disaggregate crop statistics to individual pixels *within* the larger geopolitical units for which the statistics are reported (e.g. countries or provinces). The pixel-scale allocations are performed through the compilation and judicious fusion of relevant spatially explicit data, such as production statistics, land use data, satellite imagery, biophysical crop "suitability" assessments, population density, distance to urban centers and any available knowledge of crop distribution. The development, application and validation of a prior version of the model using data from Brazil (You and Wood 2006) strongly suggested that our spatial allocation approach shows considerable promise.

This paper describes the generation of crop distribution maps for Sub-Saharan Africa (SSA) for the year 2000. The application includes three significant model improvements: the ability to cope with production data sources that provided different degrees of spatial disaggregation for different crops within a single country; the inclusion of a digital map of irrigation intensity as a new input layer; and the increased disaggregation of rainfed production systems. Among these three improvements, the first is the most complex from a modeling perspective.

In the Brazil study, we constructed a consistent state-level crop production database (yield, area and production) for all crops and all 28 states in the country, and ran independent spatial allocations for each state. Notably, within any given geopolitical unit, the spatial distribution of each crop is jointly and simultaneously determined (i.e. all crops compete for production space within the available irrigated and rainfed cropland, each crop having its own likelihood of being irrigated and its unique spatial patterns of yield potential determined by local agroecological conditions). Thus, in order for our approach to function accurately, it is important to have all crop statistics compiled at a common sub-national scale. In the case of SSA, however, there is a good deal of inconsistency regarding the availability of sub-national production statistics for different crops. In any given country, production statistics may be reported at strictly the national level for most crops. Major food staple production statistics can often be obtained at the first sub-national level of disaggregation (e.g. regions or states), and even greater levels of disaggregation may occasionally be available for a limited number of commodities (e.g. important export crops). This situation made it impossible for us to apply the methodology used in our study of the Brazilian data (You and Wood 2006), which requires all production statistics to be compiled at the same level of sub-national disaggregation. For example, if we choose the state as the sub-national unit within which the pixel level allocation is made, we face two problems: first, we have no satisfactory way to perform state-level disaggregation of crop statistics reported at the strictly national level; and second, we have no way to include the desirable finer resolution statistical data that may exist for some other crops. Thus, we sought to modify the allocation methodology such that the nation always serves as the primary geographic allocation domain wherein the pixel scale allocation takes place, while still including the additional detail available from sub-national crop statistics reported at different levels of disaggregation for different crops. This methodological advance significantly improves the flexibility of the allocation methodology and extends its range of applicability in the face of disparate sources of production data for individual crops. Applying the modified spatial allocation model, we are able to generate grid maps of area, yield and production of 20 major crops across SSA at five-minute (approximately 10-km) resolution.

In the present paper, we first describe the various types and sources of data included in the allocation model. Second, we describe the revised spatial allocation model itself. Third, the modified approach is applied across SSA to generate pixel-scale crop distribution maps for the selected crops. This is followed by a (partial) validation of the allocation results. We conclude by discussing the significance and application of the results, and examine various dimensions of the data and approach that require further development.

2. DATA

The SSA region is dominated by humid or sub-humid tropical zones with heterogeneous vegetation cover, such as mixed forest and pasture, as well as permanent and annual crops. In 2000, agricultural land occupied some 903 million hectares, representing about 40 percent of the land surface and making agriculture the most dominant land use in the region. The majority of agricultural land, about 82 percent, is permanent pasture while the total land area under annual and permanent crops is only about 161 million hectares (FAOSTAT 2006). The vast majority of farming is practiced by smallholders and subsistence farmers.

We specified 2000 as our base year, in part because regionally consistent land cover and land use datasets exist for this period. Where possible, production estimates were derived as annual means for the three years 1999-2001, so as to reduce the influence of atypical years on the production allocation results. The following 20 crops are included in the spatial allocation for SSA: barley, beans, cassava, cocoa, coffee, cotton, cow peas, groundnuts, maize, millet, oil palm, plantain, potato, rice, sorghum, soybeans, sugar cane, sweet potato, wheat, and yam. These crops include the top 15 crops (by harvested areas) in SSA, as well as traditional export crops such as cocoa, coffee and cotton. These 20 crops occupy more than 90 percent of SSA cropland, and their total output makes up almost 40 percent of regional agricultural GDP.

Production Statistics

Country-level production data are available from FAO (Food and Agricultural Organization of United Nations), and these data are augmented with sub-national data[1] compiled by the authors from a variety of sources, including data from the agro-maps (FAO, IFPRI, SAGE 2006). Figure 1 shows the sub-national data coverage for the 20 selected crops. Only Benin, Cameroon, D.R. Congo, Uganda, Zambia and Mozambique have more than 10 crops reported at the sub-national scale. For some other countries, such as Angola, the Republic of Congo, Gabon and the Ivory Coast, production data was only available at the national level. Cowpeas, beans, maize and cassava have the most complete sub-national data coverage, with data available for over 70 percent of total sub-national units. Over all crops and countries, there is an approximately 40 percent coverage of sub-national data. As an example, Table 1 shows the sub-national area data for 10 crops in Uganda.

[1] In this paper, sub-national unit refers to the first geopolitical level under country, such as districts in Uganda, regions in Nigeria, and provinces in South Africa. Very little second level sub-national data are available for SSA.

Figure 1. Sub-national data coverage

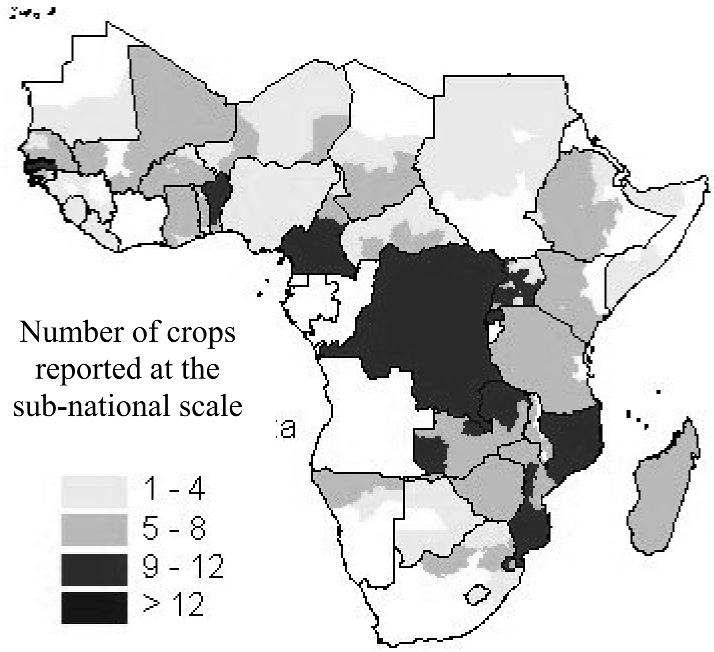


Table 1. Harvested areas of major crops in Uganda (2000/2001)

District Code	District Name	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpea	Bean	Groundnut	Maize	Millet
							(Hectares)				
UG00	UGANDA	0	401000	13717	300991	250000	64000	699000	199000	629000	384000
UG26	Apac	0	24671	-999	0	26509	76	43842	12369	7467	26101
UG27	Arua	0	24418	-999	674	2283	177	26908	15968	13464	16667
UG28	Bundibugyo	0	2221	-999	3112	0	0	4504	464	1110	26
UG29	Bushenyi	0	3876	-999	7262	4048	0	12969	2665	1394	9087
UG30	Gulu	0	20822	-999	0	1949	-999	34323	18284	-999	-999
UG31	Hoima	0	2977	-999	4149	1291	125	19375	3035	4327	4183
UG68	Iganga	0	29554	-999	12448	7833	229	17170	8621	71020	28628
UG33	Jinja	0	3248	-999	6224	0	-999	18631	384	12980	1325
UG34	Kabale	0	3391	-999	0	0	0	32974	450	15659	815
UG35	Kabarole	0	16695	-999	4149	571	93	31211	6420	7913	9115
UG36	Kalangala	0	24083	-999	1037	0	-999	219	145	-999	-999
UG37	Kampala	0	0	-999	0	0	-999	0	0	-999	-999
UG38	Kamuli	0	18824	-999	5187	13678	0	24911	6660	64985	18074
UG39	Kapchorwa	0	569	-999	8299	50	0	58714	933	26803	251
UG40	Kasese	0	3223	-999	4668	19733	0	4165	206	4710	413
UG41	Kibaale	0	2320	-999	5187	350	-999	5237	3578	-999	-999
UG42	Kiboga	0	0	-999	12967	75	-999	0	0	-999	-999
UG43	Kisoro	0	0	-999	0	0	-999	5492	0	-999	-999
UG44	Kitgum	0	23645	-999	0	10792	-999	30053	18860	-999	-999
UG45	Kotido	0	169	-999	0	0	-999	983	2846	-999	-999
UG46	Kumi	0	20453	-999	0	2270	-999	15628	14266	-999	-999
UG47	Lira	0	20669	-999	0	43128	372	40916	9382	7593	34381
UG70	Luwero	0	3432	-999	20747	655	0	10371	3132	6074	340
UG71	Masaka	0	4404	-999	45644	0	8	13349	3270	6759	236
UG50	Masindi	0	4922	-999	2593	7275	0	32085	4690	22756	3329
UG51	Mbale	0	29694	-999	18673	7434	16	47055	9965	21083	4460
UG52	Mbarara	0	11097	-999	0	0	235	31977	8607	16944	10176
UG53	Moroto	0	207	-999	0	125	-999	1992	419	-999	-999
UG72	Moyo	0	3096	-999	0	300	-999	617	2704	-999	551
UG55	Mpigi	0	12598	-999	36308	0	139	12006	1294	2787	10
UG56	Mubende	0	3262	-999	22822	4	0	8680	2473	17900	1525
UG57	Mukono	0	14062	-999	56018	35	101	17205	1801	17802	6455
UG58	Nebbi	0	17596	-999	2075	33271	-999	9421	8533	11091	813
UG60	Pallisa	0	18308	-999	13486	42870	-999	8867	3324	-999	-999
UG61	Rakai	0	4278	-999	3112	0	33	21659	2879	13398	581
UG62	Rukungiri	0	1070	-999	0	0	0	6157	2158	4658	6101
UG75	Soroti	0	14803	-999	0	3330	-999	16367	9477	-999	-999
UG76	Tororo	0	12346	-999	4149	20615	783	32967	8737	9952	53529
UG59	Ntungamo	0	0	-999	0	500	26	0	0	2210	3262

Source: IFPRI Sub-national Database. This entry is derived from UBOS (2002). (2) –999 indicates missing data.
Note: (1)

Production System Disaggregation

There are many reasons why farmers plant specific crops, including the need to satisfy subsistence food needs, or the desire to produce for high-risk, high-payoff export markets. There are also many ways in which any given crop commodity might be produced, with variables including the accessibility and use of inputs such as labor, animal power, improved seeds, supplementary water, fertilizers, and pesticides. Different production systems can exhibit quite different levels of crop productivity, and from a development perspective, may be susceptible to common threats or amenable to specific enhancement opportunities. From a research and policy perspective, therefore, there are distinct advantages in attempting to disaggregate reported shares of crop production into (at a minimum) the major categories of production systems, as a means of increasing the utility of the allocation results for development purposes.

However, it is not just the search for practical relevance of the results that drives the potential utility of an *ex ante* disaggregation of production into key production systems. Since the crop allocation is explicitly spatial, its reliability would be improved by discrimination between, for example, the distinct location and yields of irrigated and rainfed production. Furthermore, high-input rainfed production systems are usually only found in more favorable production environments where they support intermediate yield levels, and the production of basic foodstuffs in homestead plots- often with relatively low yields- might be better predicted on the basis of population density rather than agroecological suitability alone.

We are able to estimate crop production shares by production systems and to perform the spatial allocation on the basis of the production system components thanks to three things: the availability of biophysical production (area and yield) *potential* maps for most of the 20 target crops under irrigated, high-input rainfed and low-input rainfed conditions (Fischer et al. 2001) (see Section 2.6); access to unpublished estimates of the average areas and yields of both rainfed and irrigated production of crops by country that, when aggregated, are consistent with FAO-published national average areas and yields for the entire national crop output (Bruinsma 2000); and the authors' compilation and interpretation of a wide range of other background data (e.g. farm size structure, adoption of modern varieties, and fertilizer use) that provide insights into the overall structure of crop production systems within each country.

We allow for the sub-division of total national production into up to four production systems for each crop: irrigated, high-input rainfed, low-input rainfed, and subsistence. Allocation of the irrigated share of production must be made within the mapped extent of irrigated areas, while high and low input rainfed shares are allocated within rainfed croplands in accordance with (amongst other factors) the different agroecological conditions that best match the needs of each system. While biophysical crop suitability or potential revenue is generally used to estimate a prior distribution for each crop production system (see Section 3 on "modified spatial allocation model"), population density also drives the spatial allocation of the subsistence share of crop production.

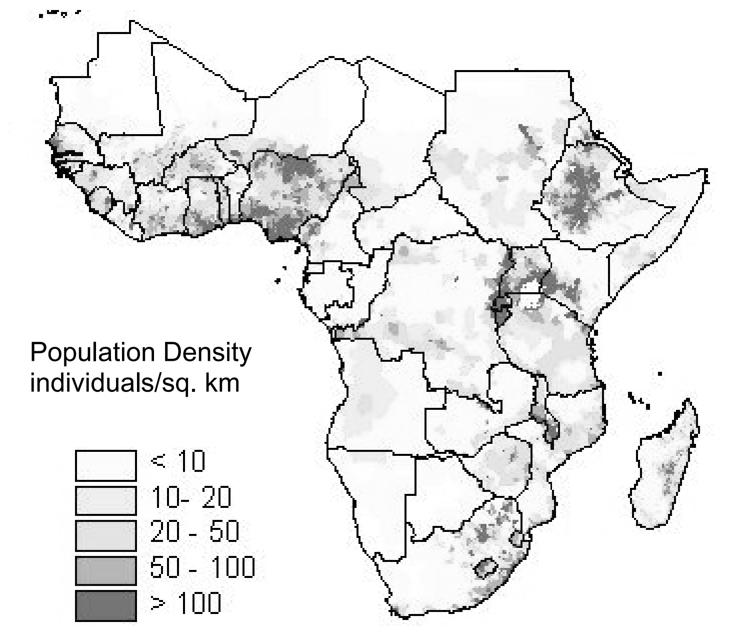
Appendix Table A1 provides an assessment of the overall breakdown of crops by production system for the SSA region. Rice and sugar cane are identified as the two major irrigated crops in the region, with the remaining 18 crops having quite limited irrigation. The major staple crops, such as cassava, maize, millet, sweet potato, rice and sorghum, are largely grown for subsistence purposes (Table A1), while the export crops such as cocoa, coffee and cotton – largely grown by smallholders – are classified as low-input rainfed commodities. The percentages for high-input rainfed areas vary from country to country, but generally do not exceed 50 percent (Table A1). Overall, the crop-based production systems in Sub-Saharan Africa are dominated by low-input rainfed (including subsistence) production.

Transaction Costs and Market Access

There is a rich literature on the extent to which the selection, productivity, and profitability of various crops in different locations are linked to the distance to product markets (von Thunen 1966), market-related transactions costs (Jayne 1994, Omamo 1998, Obare et al. 2003, Renkow et al. 2004), and a wide range of market imperfections (Kherallah et al. 2000). Furthermore, since many subsistence households are also net buyers of food staples, these factors are also important to subsistence producers (Jayne 1994, Omamo 1998). Market access affects production costs by constraining access to production-related information, services and inputs, and further affects gross revenue by impacting the effective farm-gate price of outputs (e.g. through transport and other transaction costs). For this study, rather than using a measure of physical market access derived from a very incomplete and inconsistent regional road network map and database, we elected to adopt population density as a proxy of market access and transactions costs, since higher population densities imply higher access to markets and lower transaction costs. This use of population density has been established in the literature (Deichmann 1996, CIESIN, IFPRI and WRI 2000).

The Gridded Population of the World (GPW) Version 2 provides global estimates of population counts and population densities (persons per square kilometer) for 1990 and 1995 (CIESIN, IFPRI and WRI 2000). National figures have been reconciled to be consistent with United Nations population estimates for those years in this GPW database. Figure 2 illustrates the variation in population density across SSA extracted from this global map.

Figure 2. Population density for Sub-Saharan Africa



Our market access proxy ($Access_i$) is estimated by using the normalized population density measure:

$$Access_i = \frac{Pop_i - MinPop_k}{MaxPop_k - MinPop_k} \tag{2.3}$$

where $MinPop_k$ and $MaxPop_k$ are the population densities at 20 percent and 90 percent of a given country k's cumulative population density distribution curve[2], and Pop_i is the population density for pixel i.

Land Cover Images

Satellite-based land cover images play an important role in the allocation model, as they provide detailed spatial information on cropland extent, allowing us to distinguish cropland from other forms of land cover such as forest, grassland, and water bodies, and helping us delineate the geographical boundaries within which crop production must be allocated. Thus, the reliability of the cropland cover data can have significant implications for the overall reliability of the allocation. As more and better remotely sensed data become available through technological advances in remote sensing and improvements in our ability to interpret satellite imagery for agricultural applications, the reliability of such crop production allocation

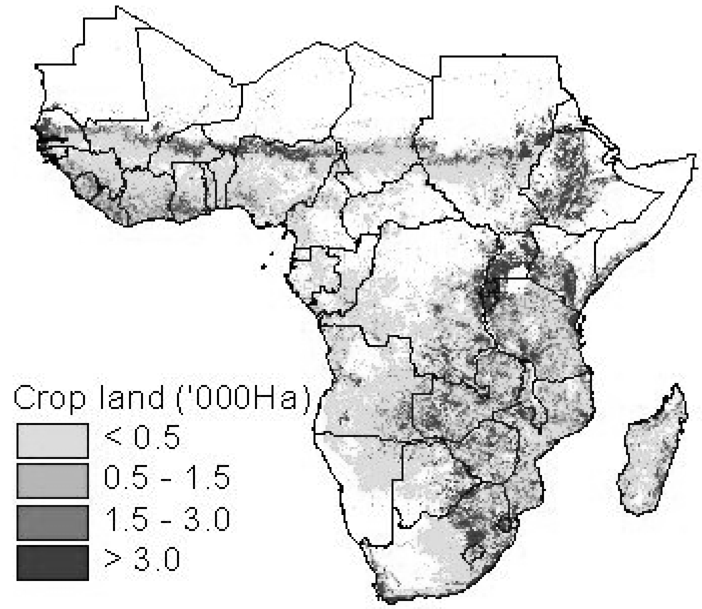
[2] In fact, $MinPop_k$ = Max($MinPop_k$, 5). If $MinPop_k$ is less than 5 people per square kilometer, the region may be just forest with little agricultural land.

will increase. For SSA, medium- to high-resolution land cover datasets are available from three (global data) sources: NOAA-AVHRR (Hansen et al. 2000; Loveland et al. 2000), TERRA-MODIS (Friedl et al. 2002), and SPOT-VEGETATION (JRC 2003). Each land cover dataset has its own pros and cons, and some researchers (e.g., Jung et al. 2006) are exploring the option of merging individual remote sensing products in order to provide high-quality, integrated land cover datasets. For our present purposes, data availability is a factor in choosing which land cover dataset to use, and the time period of the satellite-based estimates of cropland cover should coincide, as closely as possible, with the reference period for the allocation (1999-2001).

Based on evaluation of the two global land cover datasets available for the year 2000, we elected to use the Africa Land Cover 2000 from the Global Land Cover 2000 project (GLC2000). GLC2000 makes use of the VEGA 2000 dataset comprising 14 months (November 1, 1999 – December 31, 2000) of pre-processed daily global data acquired by the VEGETATION instrument on board SPOT 4, made available through a sponsorship from members of the **VEGETATION** program (http://vegetation.cnes.fr/).

There are twenty-two land cover classes in GLC2000, ranging from bare land to tree cover. Cropland is contained in only three classes: cultivated and managed areas; mosaic, crop land/tree cover/other natural vegetation; and mosaic, crop land/shrub/grass. While the 'cultivated and managed areas' class obviously contains all crop land, only some of the areas under the two mosaic classes actually correspond to crop land. Consultation with GLC2000 teams indicates that 80 percent of each pixel under the two crop land mosaic classes actually corresponds to crop land. Since the exact percentage of crop land within a given pixel of these two classes varies from continent to continent, and thus continent-specific percentages should be used when available. Figure 3 shows the crop land cover of Sub-Saharan Africa in 2000. The crop land shows considerably spatial heterogeneity across SSA, with intensive and widespread crop land seen in Uganda, Tanzania, Zambia, Zimbabwe and Mozambique, while cultivated land is spatially concentrated in the Sahelian countries, as well as Angola, Sudan, Ethiopia, and D. R. Congo.

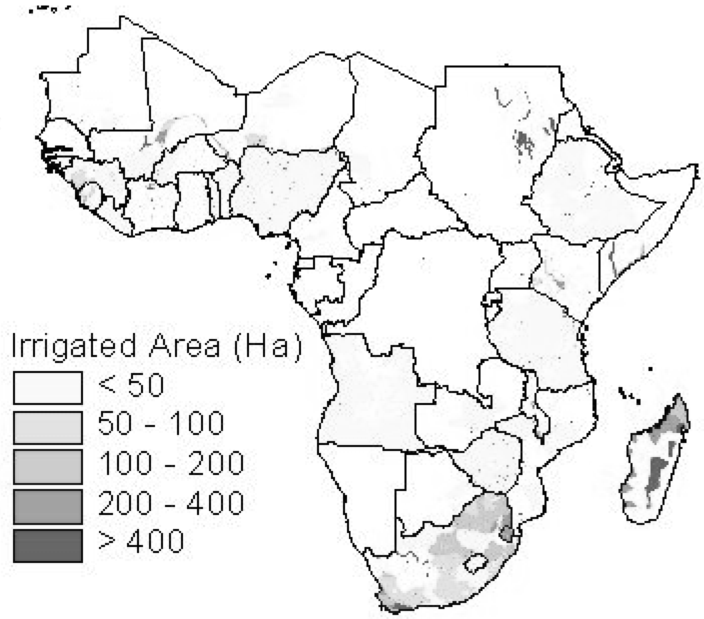
Figure 3. Crop land in Sub-Saharan Africa, 2000



Irrigation Map

The Land and Water Development Division of the Food and Agriculture Organization of the United Nations (FAO) and the Center for Environmental Systems Research of the University of Kassel, Germany, have developed a global irrigation map showing the amount of area equipped for irrigation in the 1990s as a percentage of the total pixel area, with a resolution of five minutes (about 10 x 10 km^2 along the equator). Because the map was generated uniformly across countries, the quality and accuracy of the mapped irrigated area is not uniform and is highly dependent on the individual quality of the data for the different countries (Siebert et al. 2001). There was no dramatic expansion of irrigation in crop production in Africa during the late 1990s, allowing us use this irrigation map as the base data for year 2000. In our spatial allocation, the irrigation map provides another layer of information the model can use to decide where to allocate the irrigated areas. In Sub-Saharan Africa, rainfed agriculture dominates, with relatively little irrigation seen (Figure 4). South Africa and Madagascar are the only two countries having extensive irrigated cropland, with about 1.43 million hectares and 1.15 million hectares of irrigated cropland, respectively. Irrigation is quite limited in the rest of SSA, with countries such as Mauritania, Chad, D.R. Congo, and Namibia having very little irrigation.

Figure 4. Irrigation map



Agroclimatic Crop Suitability

Different crops have different thermal, moisture, and soil requirements, particularly under rainfed conditions. FAO, with the collaboration of the International Institute for Applied Systems Analysis (IIASA), has developed the Agro-ecological Zones (AEZ) methodology based on an inventory of land resources and evaluation of biophysical limitations and potentials. AEZ methodology provides a standardized framework for the characterization of climate, soil, and terrain conditions relevant to agricultural production. Crop modeling and environmental matching procedures are used to identify crop-specific limitations of prevailing climate, soil, and terrain resources, under assumed levels of inputs and management conditions. This methodology provides information pertaining to maximum potential, agronomically attainable crop yields, and suitable crop areas for basic land resource units (usually grid-cells in the recent digital databases) (Fischer et al. 2001, FAO 2003). In the present work, we use three production system types from the FAO/IIASA suitability datasets: irrigated – high input (we simply call it "irrigated"), rainfed – high input, and rainfed – low input[3]. For each crop grown with these physical input levels, we define our suitable land as the sum of the area held by the 'very suitable,' 'suitable,' 'moderately suitable,' and 'marginally suitable' classes in the AEZ model. The yield is then calculated as the area-weighted average of these four suitability classes (FAO 1981). Some crops have many types,

[3] There three types correspond to the three production patterns defined on page 8. The forth one, subsistence, always corresponds to low-input rainfed production.

such as highland and lowland maize germplasm, sub-divided by maturity class. Thus, the crop surface of “maize” in this work is a composite of pixels corresponding to the most suitable variety for each location.

Figure 5 shows the suitability surfaces for maize in SSA, offering both potential yield and suitable area distributions under high input and low input rainfed conditions. Obviously, maize is widely suitable in Sub-Saharan African except in the extremely northern countries of Mauritania, Mali, Niger, Chad, and the extremely southern countries of Angola, Botswana and South Africa. Maize normally does not require irrigation, which is shown by the relative scarcity of areas suitable for irrigated maize (Figure 5 (c)). However, irrigated maize has a much higher potential yield than rainfed maize.

Figure .5. Crop suitability surfaces – suitable areas

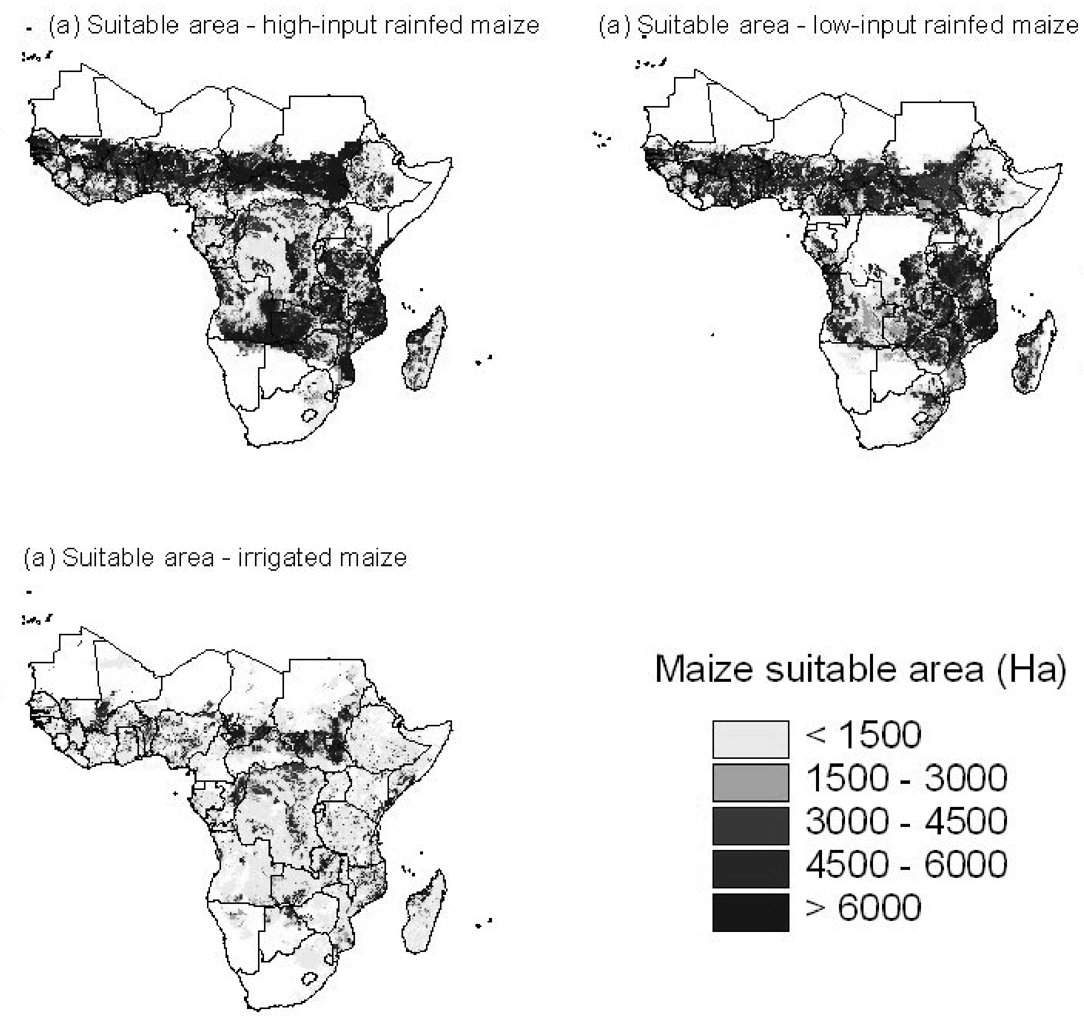
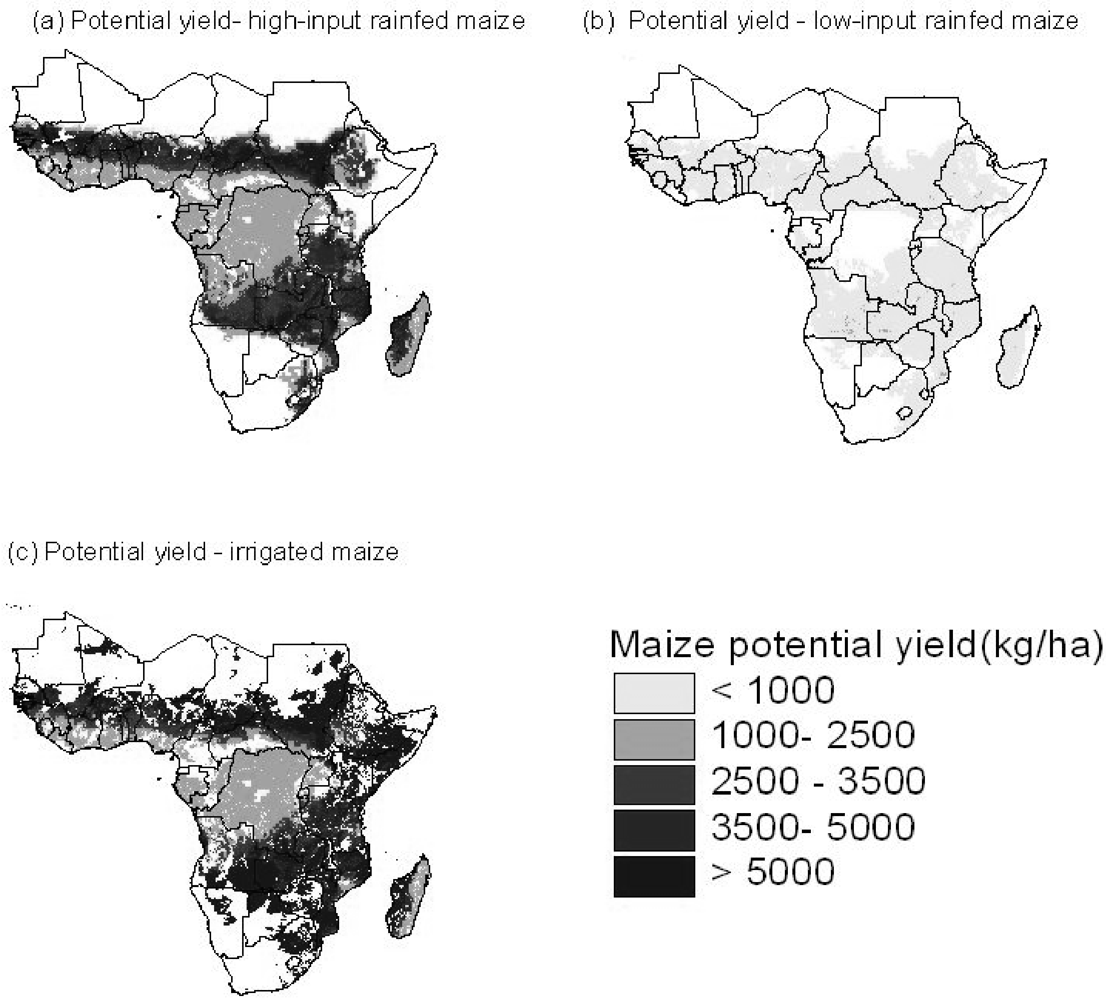


Figure 6. Crop suitability surfaces – potential yield



3. MODIFIED SPATIAL ALLOCATION MODEL

Cross-Entropy Approach

Entropy, which goes back to Boltzmann's distribution law in thermodynamics (Jaynes 1979), is a measure of the "disorder" of molecules in a system. One of the fundamental laws of nature is the second law of thermodynamics, which says the entropy of a closed system never decreases and increases whenever possible. Shannon (1948) introduced the term 'information entropy' as a way to measure the uncertainty (state of knowledge) of expected information, giving rise to information theory. According to Shannon's definition, information is a statistical property of a message. Any probability distribution p_i, $i = 1, 2, \ldots, n$, of a random variable provides some *information* about that variable. Shannon defined entropy $H(p)$ as a weighted sum of the information $-lnp_i$, $i= 1,2,\ldots,n$, with the respective probabilities as weights:

(3.1) $$H(p) = -\sum_{i=1}^{n} p_i \ln p_i = -E(\ln p)$$

under the convention that $0ln0=0$, and $E(lnp)$ is expected value of lnp.

Jaynes (1957) proposed the maximum entropy principle in statistical inference, which states that the least informative probability distribution p_i can be found by maximizing the entropy $H(p)$. In (3.1), the solutions are: $p_i = 1/n$, $i= 1, 2, \ldots, n$, $H(p) = ln\ n$. In other words, in the absence of information to the contrary, all possible states of system are equally likely. The generalized maximum entropy (GME) approach is based upon this principle.

Following (3.1), the cross-entropy of one probability distribution $p=\{p_1, p_2, \ldots, p_n\}$ with respect to another probability distribution $q=\{q_1, q_2, \ldots, q_n\}$ can be defined

(3.2) $$CE(p,q) = -\sum_{i=1}^{n} p_i \ln p_i / q_i = E(\ln p) - E(\ln q)$$

This is actually a measure of distance between two probability distributions p and q. If we choose the non-informative q, i.e., $q = \{1/n, 1/n, \ldots, 1/n\}$, then $CE(p, q)$ becomes:

(3.3) $$CE(p,q) = \sum_{i=1}^{n} p_i \ln p_i - \ln n = -H(p) - \ln n$$

Therefore, maximizing entropy is actually a special case of minimizing cross-entropy with respect to a uniform distribution. The cross-entropy (CE) approach can be stated as a minimization problem where the cross-entropy (objective function) is minimized subject to applicable constraints and prior knowledge.

Since the publication of the comprehensive book on this topic by Golan, Judge and Miller (1996), numerous groups have sought to apply the entropy approach to various estimation problems (Lencer and Miller 1998; Paris and Howlitt 1998; Robinson, Cattaneo and El-Said 2000; Zhang and Fan 2001). A unique feature of the entropy approach is its ability to overcome two empirical problems that hamper traditional econometrics: multi-collinearity and ill-posed problems (particularly due to underdetermined or incomplete data) (Paris and Caputo 2001; Golan, Judge and Miller 1996). The idea is to remove irrelevant information at the beginning of a problem rather than taking pains to make dubious assumptions. Preckel (2001) compares least squares and entropy methods from a penalty function perspective and concludes that the differences between these two approaches boil down to how the supports for errors and coefficients are defined in a generalized cross-entropy approach. When the supports are specified to be symmetric, wide, and centered on zero for the residual errors, the coefficient estimates are essentially indistinguishable (Preckel 2001). Shen and Perloff (2001) estimate a ratio of parameters using different methods and concludes that GME (and the Bayesian method of moments) estimator has much smaller mean square errors and average biases than do ordinary least squares (OLS). Bera and Bilias (2002) report an excellent synthesis of different estimation approaches, including the strategies of method of moments, maximum entropy, maximum likelihood, empirical likelihood, estimating function, and generalized methods of moments. The paper compares many of these estimation techniques with a unified framework and puts these techniques in an interesting historical perspective. Our production allocation problem is underdetermined with quite incomplete data, and the entropy approach is ideally suited for our spatial allocation model.

Modified Spatial Allocation Model

This section describes the spatial allocation model using the cross entropy approach with partial sub-national data and new irrigation maps. We first let s_{ijl} be the area share allocated to pixel i and crop j at input level l with a given country (country **X**) in SSA. $CropArea_{jl}$ is the total physical area for crop j at input level l for a certain spatial allocation unit, and A_{ijl} is the area allocated to pixel i for crop j at input level l in country **X.** Therefore:

(3.4) $$s_{ijl} = \frac{A_{ijl}}{CropArea_{jl}}$$

If we let π_{ijl} be the prior area shares (see below) for pixel i and crop j at input level l in country **X,** the modified spatial allocation model can be written as follows:

(3.5) $$\underset{\{s_{ijl}\}}{MIN} \quad CE(s_{ijl}, \pi_{ijl}) = \sum_i \sum_j \sum_l s_{ijl} \ln s_{ijl} - \sum_i \sum_j \sum_l s_{ijl} \ln \pi_{ijl}$$

subject to:

(3.6) $$\sum_i s_{ijl} = 1 \quad \forall j \, \forall l$$

(3.7) $$\sum_j \sum_l CropArea_{jl} \times s_{ijl} \le Avail_i \quad \forall i$$

(3.8) $$CropArea_{jl} \times s_{ijl} \le Suitable_{ijl} \quad \forall i \, \forall j \forall l$$

(3.9) $$\sum_{i \in k} \sum_l CropArea_{jl} \times s_{ijl} = SubCropArea_{jk} \quad \forall k \forall j \in J$$

(3.10) $$\sum_{l \in L} CropArea_{jl} \times s_{ijl} \le IRRArea_i \quad \forall i$$

(3.11) $$1 \ge s_{ijl} \ge 0 \quad \forall i, j, l$$

where:

i = 1, 2, 3, … is the pixel identifier within the allocation unit,

j = 1, 2, 3, … is the crop identifier (such as maize, cassava, rice, etc.) within the allocation unit,

l = irrigated, rainfed-high input, rainfed-low input, subsistence represents the management and input levels for crops,

k = 1, 2, 3, … is the identifier for the sub-national geopolitical unit,

J is the set of commodities for which sub-national production statistics exist,

L is the set of commodities that are irrigated within pixel *i*,

$Avail_i$ is the total agricultural land in pixel *i*, which is equal to total agricultural area estimated from land cover satellite image as described in the previous section,

$Suitable_{ijl}$ is the suitable area for crop *j* at input level *l* in pixel *i*, which comes form FAO/IIASA suitability surfaces as introduced in the previous section, and

$IRRArea_i$ is the irrigation area in pixel *i* from global map of irrigation (Siebert et al. 2001).

Compared to our original spatial allocation model (You and Wood 2006), the present work includes two new constraints, namely equations (3.9) and (3.10). Constraint (3.9) sets the sum of all allocated areas within those sub-national units that have existing statistical data to be equal those corresponding sub-national statistics. Constraint (3.10) includes the irrigation information and states that the sum of all allocated irrigated crop areas in any pixel must not exceed the total area identified by Siebert et al. (2001) as being equipped for irrigation within that pixel. The objective function and all other equations are similar to those found in the original model. The modified model is capable of disaggregating across mixed scales of production data, giving it a broader range of practical application and increasing its reliability by allowing it to use the highest level of production data disaggregation available for each crop.

Obviously, an informed prior (π_{ijl}) is very important for the success of the model. We create the prior based upon a range of available evidence. First, for each pixel we calculate the potential revenue per pixel as:

(3.12) $$Rev_{ijl} = Price_j \times Access_i \times SuitYield_{ijl} \times SuitArea_{ijl}$$

where $Price_j$ is the price for crop *j* in country X, $SuitYield_{ijl}$ is the agro-climatically suitable yield for crop *j* at input level *l* and pixel *i*, and $Access_i$ is the previously described proxy of physical market accessibility for pixel *i*. In the case of subsistence production, we replace the revenue measure with population density because we assume the crops are grown primarily for food security reasons and as an expression of preference for certain food staples, even at relatively low levels of biophysical suitability. We then pre-allocate the available statistical crop areas (at various geopolitical scales) into pixel-level areas by simple weighting:

$$Area_{ijl} = SubCropArea_{jk} \times Percent_{jl} \times \frac{\mathrm{Re}\,v_{ijl}}{\sum_{i \in k} \mathrm{Re}\,v_{ijl}} \quad \forall j \forall i \forall l \tag{3.13}$$

where $Areai_{jl}$ is the area pre-allocated to pixel *i* for crop *j* at level *l*, and $Percent_{jl}$ is the area percentage of crop *j* at input level *l* (see Table A1). Geopolitical units without crop area statistics are combined, and a total crop area for the merged unit is derived by subtracting the sum of available sub-national areas from the national total. After this pre-allocation, we calculate the prior by normalizing the allocated areas over the whole country:

$$\pi_{ijl} = \frac{Area_{ijl}}{\sum_{i} Area_{ijl}} \quad \forall j \forall i \forall l \tag{3.14}$$

4. RESULTS

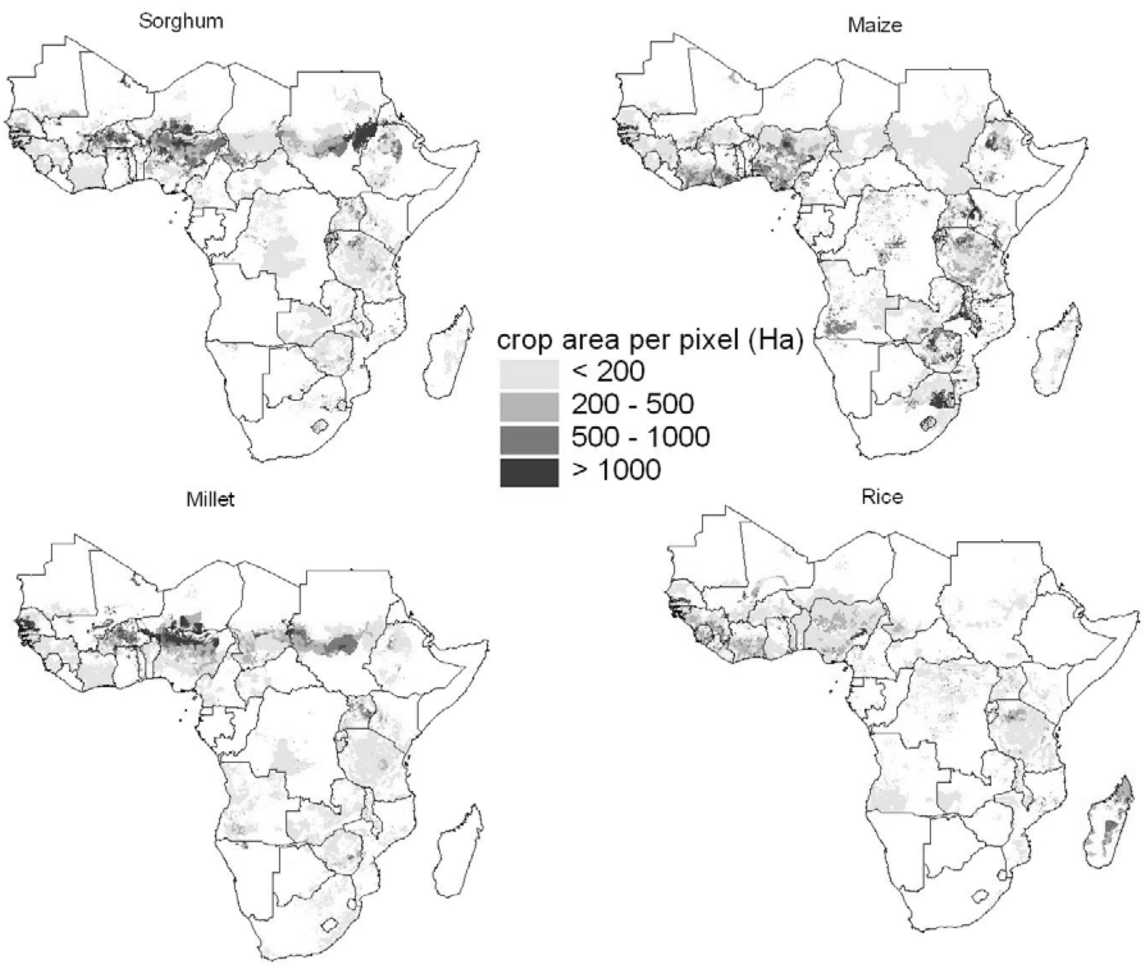
The application of the spatial allocation model faces two major challenges. The first is inconsistency among the various constraints due to imperfect data. For example, the sum of all the statistical crop areas may be even larger than the cropland available from satellite images at either the national or sub-national levels, meaning that constraint (3.7) in the model may directly conflict with constraint (3.6) (at the national level) or with constraint (3.9) (at a sub-national level), and the optimization problem becomes infeasible. Similar conflicts may appear among the rest of the constraints; for example, there may be less available irrigated area than the sum of statistical irrigated crops areas [(3.6) or (3.9) vs. (3.10)], less cropland than the irrigated area [(3.7) vs. (3.10)], or less suitable area than the statistical crop areas [(3.8) vs. (3.6) or (3.9)]. These conflicting constraints, which must be solved before the model is run, are found for every SSA country in the current application. Accordingly, we develop computer programs in FoxPro language to deal with these conflicts, using a set of rules to solve the conflicts. Although it is unknown whether the statistics (either national or sub-national) are more reliable than the other datasets (e.g. satellite images), such statistics are widely used and recognized, and we therefore set the statistics as a benchmark to make the results more comparable. Two rules are used: first, we scale up cropland areas, irrigated areas and suitable areas if they are less than the corresponding statistical areas; and second, we set cropland areas equal to the irrigated areas for pixels having zero cropland but positive irrigated areas.

The second challenge is the size of the optimization problem, in particular for big countries. With the utilized grid resolution of five minutes, a middle-sized country such as South Africa has about 10,000 pixels with nonzero agricultural land (pixels with zero agricultural land are excluded from the model run). South Africa produces 16 of the 20 crops considered, and each crop has four input levels. Therefore the total number of unknowns for South Africa is in the range of 600,000, which is relatively large for a nonlinear programming problem. Large countries, such as Angola and D.R. Congo, have even larger problems. In addition, the objective function with logarithms is a challenge for any nonlinear programming solver. These issues lead to the issue of sheer computer power. In the present work, we use GAMS (2003) to solve the model. The requirement for CPU time depends on the specific country in question, ranging from a few minutes to over 50 hours on a Dell desktop with 3.2 GHz CPU and 1GB RAM. We run the modified spatial allocation model country-by-country for all 51 countries[4] in Sub-Saharan Africa, yielding the allocated crop areas at the pixel level. A post-processing program takes the results from GAMS and calculates both the harvest areas and productions by pixels. Figure 7 shows the crop area distribution maps for the four cereal crops (sorghum, maize, millet and rice) examined herein.

[4] Some island countries, such as Mayotte and Seychelles, have little or no agricultural production.

The maps for the remaining 16 crops are shown in Appendix Figure A1. These are the five-by-five-minute (about 8,500 hectares in Africa) crop distribution maps.

Figure 7. Estimated crop distribution maps of Sub-Saharan Africa



5. PARTIAL MODEL VALIDATION

In order to assess the performance of our modified approach, we undertake the huge effort of collecting census data from 1,317 second-level administrative units in 17 countries, including statistics for maize, millet, sorghum and cassava. Table 2 shows the data availability for these countries. While not all countries have complete data for all four crops, the countries and crops are quite diverse in terms of geographical coverage. We use these datasets as a benchmark to assess model performance.

Table 2. Data availability for second-level administrative units

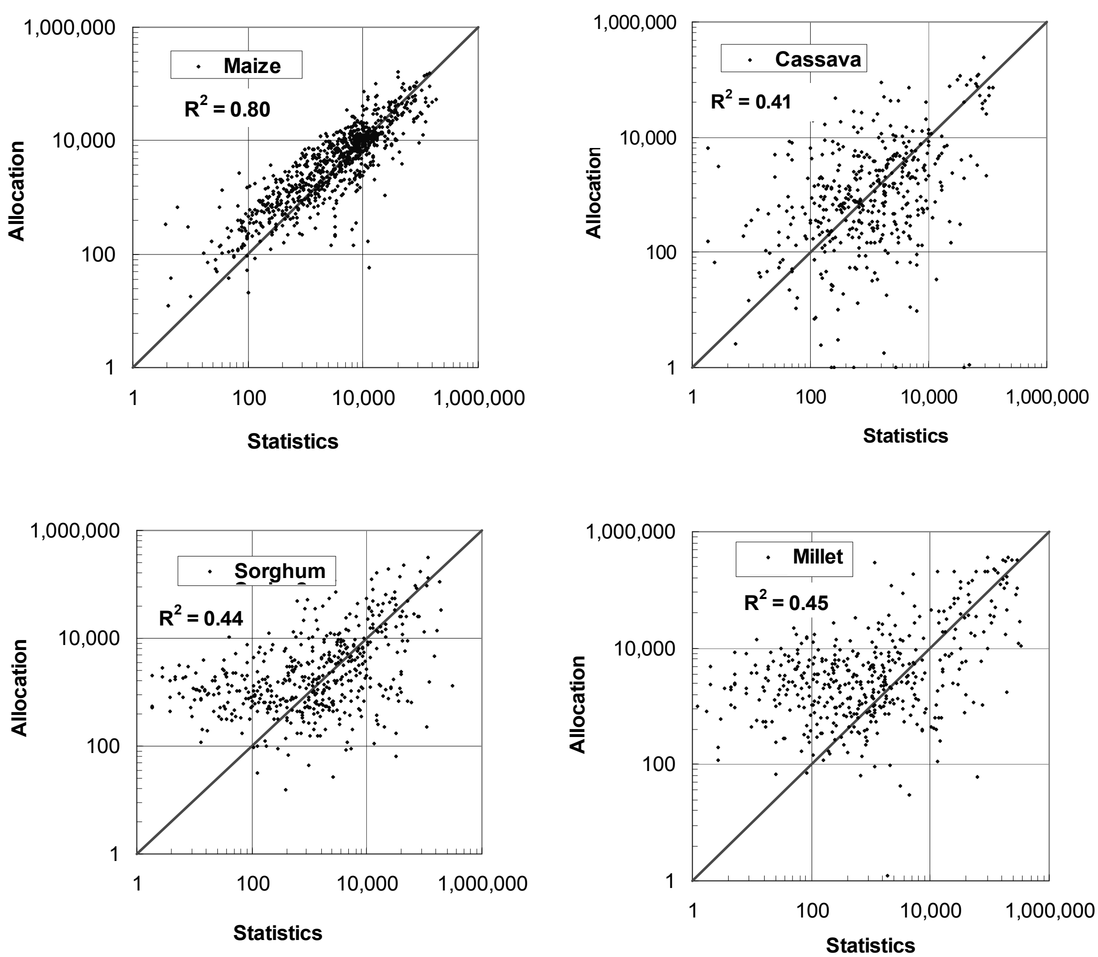
Country	Number of admin. units	Maize	Millet	Cassava	Sorghum
Benin	77	complete	partial	complete	partial
Botswana	26	complete	complete	complete	complete
Ethiopia	81	complete	partial	complete	complete
Gambia	37	complete	complete	none	complete
Guinea	33	complete	none	complete	None
Guinea Bissau	63	complete	complete	complete	complete
Kenya	46	complete	none	none	none
Madagascar	111	complete	complete	complete	none
Malawi	173	complete	partial	complete	partial
Mali	49	partial	complete	complete	complete
Niger	35	none	complete	none	complete
Senegal	29	partial	complete	complete	partial
South Africa	378	partial	none	complete	none
Togo	21	complete	complete	complete	complete
D. R. Congo	40	complete	none	complete	none
Zambia	58	complete	complete	complete	complete
Zimbabwe	60	complete	complete	none	complete

Note: complete: data for all administrative units are available; partial: only part of administrative units have data; none: all data are missing

We aggregate the allocated areas by pixels into the 1,317 second-level administrative units of the 17 countries. We then compare these synthetic area estimates with the actual census data we collected. Figure 8 shows the graphical results of this comparison. Most of data points cluster around the 45^o line of perfect correlation. Maize is the best performer among the four crops, with a R^2 around 0.8, while the other three crops have a R^2 around 0.45. If the four crops are representative of the rest of the examined crops, we could expect the R^2 values for the other 16 crops to lie between 0.45 and 0.8.

There are several reasons for the differences between the observed and predicted crop areas. From a methodological perspective, the most fundamental reason is the simplicity of the method used to estimate the prior, relative to the complex factors involved in a given farmer's decisions regarding crop choices, crops mixes and the type and scale of production. We have used nominal gross revenues (except in the case of subsistence production) as a basis to generate the prior allocation. However, empirical evidence shows that profit is the driving force behind crop production decisions, for both commercial farmers and smallholders alike(Kherallah et al. 2000, Renkow et al. 2004). Many other factors such as culture, tradition and food security concern also affects farmers' production decisions. However, it is difficult to obtain such data on a regional scale in regions such as Africa, and since our goal is to develop a framework that can applied on a regional and even global scale, we have sought to minimize the reliance on such fragmentary and expensive data. Beyond the methodological reason, there are many data accuracy issues that may affect our results. First, crop production in Sub-Saharan Africa is mainly performed by smallholders sparsely scattered within large areas of forest or grassland. This poses a range of challenges for satellite classification, as described in Section 2.4. Secondly, the suitability surfaces may have different site accuracies for different crops. Third, we treat the census data as the "truth" for the model validation purpose. However, it is important to recognize that the accuracy of such data is often questionable, due to weak capacity of many local statistical bureaus.

Figure 8. Correlation of area statistics and model predictions: SSA, 2000



6. CONCLUSION

We propose a spatial allocation model of crop production based on a cross-entropy approach (CE). The approach utilizes information from various sources, including the best available production statistics, satellite imagery, biophysical crop suitability assessments, irrigation maps, and population density, in order to generate plausible, disaggregated estimates of the distribution of crop production on a pixel basis. With this spatial allocation model we obtain five-by-five-minute resolution maps for the 20 major crops in Sub-Saharan Africa. A partial data comparison with second level administrative statistics yields correlation coefficients between 0.45 and 0.8 for maize, millet, cassava and sorghum. We briefly discuss the factors affecting the accuracy of the model predictions and possible error sources. We also find that new technologies such as remote sensing and image processing are useful tools for exploring the spatial heterogeneity of agricultural production, infrastructure and natural resources. On the other hand, working at the spatial scale of individual pixels creates many data management and computational challenges. Some of these challenges will need to be addressed in the future through improved numerical methods and the use of mathematical optimization software.

Though the current model provides what appear to be reasonable results, at least in the absence of "truth" regarding the real distribution of production, we are currently working to improve its performance. One obvious means for advancement is to improve the underlying quality of the parameters currently included in the model, since the end results can only be as accurate as the input information. Thus, we seek to include better approximations of the extent of agriculture, more realistic crop suitability surfaces, and more research on the association between crop production and population density. In addition, we could also add new types of information into the model. For example, household or agricultural survey information on the location and quantity of crop production would provide a direct, sampled calibration of the entire crop distribution surface. If such information exists and it is of reasonable quality, it will definitely improve the estimation accuracy. We could also add some other behavioral assumptions. For example, it seems reasonable to assume that farmers would opt to plant higher revenue crops in any given location, all other things being equal. But potential revenue is in reality a proxy for potential profitability, and some could argue that risk minimization might also play a role. Thus, there are several options for further work in exploring alternative drivers of crop choice, both individually and in crop combinations, in each location.

APPENDIX

Table A1: Crop production systems in Sub-Saharan Africa

Country	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpeas	Bean	Groundnut	Maize	Millet
	(% by area)									
Angola										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	35.0	0.0	0.0	0.0	0.0	20.0
low input rainfed	100.0	10.0	100.0	100.0	65.0	30.0	30.0	10.0	10.0	40.0
subsistence	0	90.0	0.0	0.0	0.0	70.0	70.0	90.0	90.0	40.0
Total	100	100	100	100	100	100	100	100	100	100
Benin										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	20.0	0.0	20.0	20.0	35.0	35.0	20.0	0.0	20.0
low input rainfed	100.0	40.0	100.0	80.0	80.0	40.0	40.0	40.0	30.0	40.0
subsistence	0	40.0	0.0	0.0	0.0	25.0	25.0	40.0	70.0	40.0
Total	100	100	100	100	100	100	100	100	100	100
Botswana										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	20.0	20.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	100.0	100.0	100.0	40.0	40.0	10.0	10.0	10.0
subsistence	0	0.0	0.0	0.0	0.0	40.0	40.0	90.0	90.0	90.0
Total	100	100	100	100	100	100	100	100	100	100
Burkina Faso										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	35.0	35.0	35.0	20.0	20.0	20.0
low input rainfed	100.0	10.0	100.0	100.0	65.0	40.0	40.0	40.0	40.0	40.0
subsistence	0	90.0	0.0	0.0	0.0	25.0	25.0	40.0	40.0	40.0
Total	100	100	100	100	100	100	100	100	100	100
Burundi										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	37.4	0.0
high input rainfed	0.0	20.0	0.0	35.0	0.0	35.0	35.0	0.0	0.0	35.0
low input rainfed	100.0	40.0	100.0	65.0	100.0	40.0	40.0	30.0	18.8	40.0
subsistence	0	40.0	0.0	0.0	0.0	25.0	25.0	70.0	43.8	25.0
Total	100	100	100	100	100	100	100	100	100	100
Cameroon										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	35.0	0.0	20.0	35.0	35.0	35.0	0.0	55.0	20.0
low input rainfed	100.0	40.0	100.0	80.0	65.0	40.0	40.0	10.0	30.0	40.0
subsistence	0	25.0	0.0	0.0	0.0	25.0	25.0	90.0	15.0	40.0
Total	100	100	100	100	100	100	100	100	100	100
Cape Verde										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100	100	100	100	100	100	100	100	100	100

Table A1. Continued

Country	Oil Palm	Banana	Potato	Rice	Sorghum	Soybean	Sugar Cane	Sweet Potato	Wheat	Yam
					(% by area)					
Angola										
irrigated	0.0	0.0	0.0	72.7	0.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	35.0	35.0	20.0	0.0	0.0	0.0	0.0	0.0	35.0	0.0
low input rainfed	65.0	40.0	40.0	2.7	100.0	100.0	0.0	30.0	40.0	100.0
subsistence	0.0	25.0	40.0	24.5	0.0	0.0	0.0	70.0	25.0	0.0
Total	100	100	100	100	100	100	100	100	100	100
Benin										
irrigated	0.0	0.0	0.0	58.8	0.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	35.0	55.0	0.0	8.2	20.0	20.0	0.0	35.0	0.0	0.0
low input rainfed	65.0	30.0	100.0	16.5	40.0	40.0	0.0	40.0	100.0	30.0
subsistence	0.0	15.0	0.0	16.5	40.0	40.0	0.0	25.0	0.0	70.0
Total	100	100	100	100	100	100	100	100	100	100
Botswana										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	35.0	0.0
low input rainfed	100.0	100.0	100.0	100.0	10.0	100.0	100.0	100.0	40.0	30.0
subsistence	0.0	0.0	0.0	0.0	90.0	0.0	0.0	0.0	25.0	70.0
Total	100	100	100	100	100	100	100	100	100	100
Burkina Faso										
irrigated	0.0	0.0	0.0	42.9	0.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	20.0	20.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	100.0	5.7	40.0	40.0	0.0	30.0	100.0	100.0
subsistence	0.0	0.0	0.0	51.4	40.0	40.0	0.0	70.0	0.0	0.0
Total	100	100	100	100	100	100	100	100	100	100
Burundi										
irrigated	0.0	0.0	0.0	100.0	34.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	35.0	0.0	0.0	0.0	13.2	0.0	0.0	0.0	0.0	0.0
low input rainfed	65.0	10.0	10.0	0.0	26.4	100.0	0.0	30.0	10.0	30.0
subsistence	0.0	90.0	90.0	0.0	26.4	0.0	0.0	70.0	90.0	70.0
Total	100	100	100	100	100	100	100	100	100	100
Cameroon										
irrigated	0.0	0.0	0.0	57.1	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	35.0	0.0	15.0	20.0	0.0	0.0	0.0	20.0	0.0
low input rainfed	65.0	40.0	10.0	17.1	40.0	10.0	100.0	30.0	40.0	30.0
subsistence	0.0	25.0	90.0	10.7	40.0	90.0	0.0	70.0	40.0	70.0
Total	100	100	100	100	100	100	100	100	100	100
Cape Verde										
irrigated	0.0	0.0	0.0	15.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	15.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100	100	100	100	100	100	100	100	100	100

Table A1. Continued

Country	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpeas	Bean	Groundnut	Maize	Millet
					(% by area)					
Central African Rep										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	35.0	0.0	55.0	55.0	20.0	0.0	20.0
low input rainfed	100.0	10.0	100.0	65.0	100.0	30.0	30.0	40.0	30.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	15.0	15.0	40.0	70.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Chad										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	35.0	35.0	20.0	0.0	20.0
low input rainfed	100.0	10.0	100.0	100.0	100.0	40.0	40.0	40.0	30.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	25.0	25.0	40.0	70.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Comoros										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Congo, R.										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	55.0	20.0	0.0	35.0	35.0	35.0	0.0	0.0
low input rainfed	100.0	30.0	45.0	80.0	100.0	40.0	40.0	40.0	10.0	100.0
subsistence	0.0	70.0	0.0	0.0	0.0	25.0	25.0	25.0	90.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Djibouti										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Equatorial Guinea										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Eritrea										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.1	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	35.0	35.0	20.0	0.0	20.0
low input rainfed	10.0	100.0	100.0	100.0	100.0	40.0	40.0	40.0	9.3	40.0
subsistence	90.0	0.0	0.0	0.0	0.0	25.0	25.0	40.0	83.6	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Oil Palm	Banana	Potato	Rice	Sorghum	Soybean	Sugar Cane	Sweet Potato	Wheat	Yam
					(% by area)					
Central African Rep										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	0.0	0.0	20.0	20.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	65.0	10.0	10.0	40.0	40.0	100.0	100.0	30.0	100.0	30.0
subsistence	0.0	90.0	90.0	40.0	40.0	0.0	0.0	70.0	0.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Chad										
irrigated	0.0	0.0	0.0	14.1	0.0	0.0	100.0	0.0	100.0	0.0
high input rainfed	0.0	0.0	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	40.0	8.6	30.0	100.0	0.0	30.0	0.0	10.0
subsistence	0.0	0.0	40.0	77.3	70.0	0.0	0.0	70.0	0.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Comoros										
irrigated	0.0	0.0	0.0	15.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	15.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Congo, R.										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	4.5	0.0	0.0	0.0
high input rainfed	35.0	35.0	20.0	0.0	0.0	0.0	19.1	0.0	0.0	35.0
low input rainfed	65.0	40.0	40.0	10.0	100.0	100.0	76.4	30.0	100.0	40.0
subsistence	0.0	25.0	40.0	90.0	0.0	0.0	0.0	70.0	0.0	25.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Djibouti										
irrigated	0.0	0.0	0.0	15.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	15.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Equatorial Guinea										
irrigated	0.0	0.0	0.0	15.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	15.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Eritrea										
irrigated	0.0	0.0	100.0	0.0	3.8	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	19.2	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	0.0	100.0	38.5	100.0	100.0	100.0	10.0	30.0
subsistence	0.0	0.0	0.0	0.0	38.5	0.0	0.0	0.0	90.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpeas	Bean	Groundnut	Maize	Millet
					(% by area)					
Ethiopia										
irrigated	0.0	0.0	0.0	0.0	100.0	0.2	0.2	0.0	1.4	0.0
high input rainfed	0.0	0.0	0.0	35.0	0.0	34.9	34.9	35.0	34.5	20.0
low input rainfed	10.0	100.0	100.0	65.0	0.0	39.9	39.9	40.0	39.4	40.0
subsistence	90.0	0.0	0.0	0.0	0.0	25.0	25.0	25.0	24.6	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Gabon										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	17.6	0.0	0.0
high input rainfed	0.0	0.0	0.0	20.0	0.0	35.0	35.0	16.5	35.0	0.0
low input rainfed	100.0	10.0	100.0	80.0	100.0	40.0	40.0	32.9	40.0	100.0
subsistence	0.0	90.0	0.0	0.0	0.0	25.0	25.0	32.9	25.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Gambia, The										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	35.0	20.0	20.0
low input rainfed	100.0	10.0	100.0	100.0	100.0	30.0	30.0	40.0	40.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	70.0	70.0	25.0	40.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Ghana										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	35.0	0.0	20.0	20.0	0.0	0.0	20.0	20.0	20.0
low input rainfed	100.0	40.0	100.0	80.0	80.0	10.0	10.0	40.0	40.0	40.0
subsistence	0.0	25.0	0.0	0.0	0.0	90.0	90.0	40.0	40.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Guinea										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	20.0	20.0	35.0	35.0	35.0	20.0	0.0	20.0
low input rainfed	100.0	30.0	80.0	80.0	65.0	40.0	40.0	40.0	30.0	40.0
subsistence	0.0	70.0	0.0	0.0	0.0	25.0	25.0	40.0	70.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Guinea-Bissau										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Ivory Coast										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	20.0	0.0	35.0	35.0	35.0	20.0	0.0	20.0
low input rainfed	100.0	10.0	80.0	100.0	65.0	40.0	40.0	40.0	10.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	25.0	25.0	40.0	90.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Oil Palm	Banana	Potato	Rice	Sorghum	Soybean	Sugar Cane	Sweet Potato	Wheat	Yam
	(% by area)									
Ethiopia										
irrigated	0.0	20.0	0.0	0.0	1.7	57.1	100.0	0.0	0.0	0.0
high input rainfed	0.0	44.0	20.0	0.0	34.4	23.6	0.0	0.0	20.0	35.0
low input rainfed	100.0	24.0	40.0	100.0	39.3	12.9	0.0	15.0	40.0	40.0
subsistence	0.0	12.0	40.0	0.0	24.6	6.4	0.0	85.0	40.0	25.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Gabon										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	20.0	0.0	55.0	0.0	20.0	35.0	0.0	0.0	0.0
low input rainfed	65.0	40.0	100.0	30.0	100.0	40.0	65.0	30.0	100.0	30.0
subsistence	0.0	40.0	0.0	15.0	0.0	40.0	0.0	70.0	0.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Gambia, The										
irrigated	0.0	0.0	0.0	12.5	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	0.0	0.0	17.5	20.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	65.0	100.0	100.0	35.0	40.0	100.0	100.0	100.0	100.0	100.0
subsistence	0.0	0.0	0.0	35.0	40.0	0.0	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Ghana										
irrigated	0.0	0.0	0.0	10.3	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	20.0	0.0	17.9	20.0	0.0	20.0	35.0	0.0	20.0
low input rainfed	65.0	40.0	100.0	35.9	40.0	100.0	80.0	40.0	100.0	40.0
subsistence	0.0	40.0	0.0	35.9	40.0	0.0	0.0	25.0	0.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Guinea										
irrigated	0.0	0.0	0.0	13.2	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	20.0	0.0	35.0	0.0	0.0	0.0
low input rainfed	100.0	10.0	100.0	26.1	40.0	100.0	65.0	30.0	100.0	30.0
subsistence	0.0	90.0	0.0	60.8	40.0	0.0	0.0	70.0	0.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Guinea-Bissau										
irrigated	0.0	0.0	0.0	15.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	15.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Ivory Coast										
irrigated	0.0	0.0	0.0	6.8	0.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	35.0	35.0	0.0	18.6	0.0	35.0	0.0	35.0	0.0	0.0
low input rainfed	65.0	40.0	100.0	37.3	10.0	40.0	0.0	40.0	100.0	10.0
subsistence	0.0	25.0	0.0	37.3	90.0	25.0	0.0	25.0	0.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpeas	Bean	Groundnut	Maize	Millet
	(% by area)									
Kenya										
irrigated	0.0	0.0	0.0	3.4	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	20.0	0.0	19.3	0.0	0.0	0.0	0.0	35.0	20.0
low input rainfed	50.0	40.0	100.0	77.2	100.0	30.0	30.0	30.0	40.0	40.0
subsistence	50.0	40.0	0.0	0.0	0.0	70.0	70.0	70.0	25.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Lesotho										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	35.0	35.0	0.0	0.0	0.0
low input rainfed	50.0	100.0	100.0	100.0	100.0	40.0	40.0	100.0	10.0	100.0
subsistence	50.0	0.0	0.0	0.0	0.0	25.0	25.0	0.0	90.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Liberia										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	20.0	0.0	20.0	20.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	80.0	100.0	40.0	40.0	30.0	100.0	100.0
subsistence	0.0	70.0	0.0	0.0	0.0	40.0	40.0	70.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Madagascar										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	35.0	20.0	55.0	35.0	35.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	65.0	80.0	45.0	40.0	40.0	30.0	10.0	100.0
subsistence	0.0	70.0	0.0	0.0	0.0	25.0	25.0	70.0	90.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Malawi										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	35.0	0.0	35.0	35.0	20.0	20.0	20.0
low input rainfed	100.0	62.0	100.0	65.0	100.0	40.0	15.0	30.0	10.0	10.0
subsistence	0.0	38.0	0.0	0.0	0.0	25.0	50.0	50.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mali										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.4	0.0	1.2
high input rainfed	0.0	20.0	0.0	0.0	35.0	0.0	0.0	19.7	35.0	19.8
low input rainfed	100.0	40.0	100.0	100.0	65.0	30.0	30.0	39.5	40.0	39.5
subsistence	0.0	40.0	0.0	0.0	0.0	70.0	70.0	39.5	25.0	39.5
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mauritania										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	20.0	0.0	0.0
low input rainfed	100.0	100.0	100.0	100.0	100.0	30.0	30.0	40.0	10.0	10.0
subsistence	0.0	0.0	0.0	0.0	0.0	70.0	70.0	40.0	90.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Oil Palm	Banana	Potato	Rice	Sorghum	Soybean	Sugar Cane	Sweet Potato	Wheat	Yam
	(% by area)									
Kenya										
irrigated	0.0	0.0	0.0	100.0	0.0	0.0	50.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	20.0	0.0	17.5	35.0	35.0	0.0
low input rainfed	100.0	10.0	30.0	0.0	40.0	100.0	32.5	40.0	40.0	30.0
subsistence	0.0	90.0	70.0	0.0	40.0	0.0	0.0	25.0	25.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Lesotho										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	20.0	0.0	0.0	0.0	0.0	55.0
low input rainfed	100.0	100.0	100.0	100.0	40.0	100.0	100.0	100.0	10.0	30.0
subsistence	0.0	0.0	0.0	0.0	40.0	0.0	0.0	0.0	90.0	15.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Liberia										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	55.0
low input rainfed	65.0	40.0	100.0	30.0	100.0	10.0	100.0	30.0	100.0	30.0
subsistence	0.0	40.0	0.0	70.0	0.0	90.0	0.0	70.0	0.0	15.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Madagascar										
irrigated	0.0	0.0	0.0	72.3	0.0	0.0	40.9	0.0	0.0	0.0
high input rainfed	35.0	20.0	0.0	9.7	0.0	0.0	11.8	0.0	55.0	0.0
low input rainfed	65.0	40.0	30.0	11.1	10.0	100.0	47.3	30.0	30.0	30.0
subsistence	0.0	40.0	70.0	6.9	90.0	0.0	0.0	70.0	15.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Malawi										
irrigated	0.0	0.0	0.0	31.0	0.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	10.0	40.0	36.0	10.0	90.0	0.0	100.0	10.0	100.0
subsistence	0.0	90.0	40.0	33.0	90.0	10.0	0.0	0.0	90.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mali										
irrigated	0.0	0.0	0.0	63.2	1.8	0.0	100.0	0.0	100.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	19.6	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	100.0	3.7	39.3	100.0	0.0	10.0	0.0	100.0
subsistence	0.0	0.0	0.0	33.1	39.3	0.0	0.0	90.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mauritania										
irrigated	0.0	0.0	0.0	100.0	7.7	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	100.0	0.0	9.2	100.0	100.0	10.0	100.0	100.0
subsistence	0.0	0.0	0.0	0.0	83.1	0.0	0.0	90.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpeas	Bean	Groundnut	Maize	Millet
					(% by area)					
Mauritius										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
subsistence	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mayotte										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mozambique										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0
high input rainfed	0.0	0.0	0.0	35.0	0.0	20.0	20.0	0.0	0.0	20.0
low input rainfed	100.0	10.0	100.0	65.0	100.0	40.0	40.0	10.0	10.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	40.0	40.0	90.0	89.6	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Namibia										
irrigated	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.1	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	40.0	100.0	100.0	99.6	60.0	60.0	10.0	29.9	10.0
subsistence	0.0	60.0	0.0	0.0	0.0	40.0	40.0	90.0	70.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Niger										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0
high input rainfed	0.0	20.0	20.0	35.0	0.0	20.0	20.0	20.0	19.9	20.0
low input rainfed	100.0	40.0	80.0	65.0	100.0	40.0	40.0	40.0	39.8	40.0
subsistence	0.0	40.0	0.0	0.0	0.0	40.0	40.0	40.0	39.8	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Nigeria										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	13.5	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	35.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	10.0	100.0	100.0	65.0	10.0	10.0	8.6	30.0	30.0
subsistence	0.0	90.0	0.0	0.0	0.0	90.0	90.0	77.8	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Reunion										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Oil Palm	Banana	Potato	Rice	Sorghum	Soybean	Sugar Cane	Sweet Potato	Wheat	Yam
	(% by area)									
Mauritius										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	18.3	0.0	0.0	0.0
high input rainfed	0.0	55.0	35.0	0.0	0.0	0.0	28.6	55.0	0.0	20.0
low input rainfed	100.0	30.0	40.0	100.0	100.0	100.0	53.1	30.0	100.0	40.0
subsistence	0.0	15.0	25.0	0.0	0.0	0.0	0.0	15.0	0.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mayotte										
irrigated	0.0	0.0	0.0	57.1	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	12.9	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	30.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mozambique										
irrigated	0.0	0.0	0.0	12.8	0.0	0.0	76.9	0.0	0.0	0.0
high input rainfed	0.0	20.0	35.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	40.0	40.0	8.7	30.0	100.0	23.1	30.0	10.0	30.0
subsistence	0.0	40.0	25.0	78.5	70.0	0.0	0.0	70.0	90.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Namibia										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.1	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	30.0	30.0	60.0	100.0	10.0	57.9	60.0
subsistence	0.0	70.0	70.0	70.0	70.0	40.0	0.0	90.0	40.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Niger										
irrigated	0.0	0.0	20.8	0.4	0.0	0.0	82.6	0.0	35.7	0.0
high input rainfed	20.0	20.0	0.0	34.9	20.0	20.0	3.5	20.0	22.5	20.0
low input rainfed	80.0	40.0	23.8	39.8	40.0	40.0	13.9	40.0	25.7	40.0
subsistence	0.0	40.0	55.4	24.9	40.0	40.0	0.0	40.0	16.1	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Nigeria										
irrigated	0.0	0.0	0.0	50.0	0.0	0.0	100.0	33.3	100.0	0.0
high input rainfed	0.0	0.0	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	40.0	5.0	10.0	100.0	0.0	20.0	0.0	100.0
subsistence	0.0	0.0	40.0	45.0	90.0	0.0	0.0	46.7	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Reunion										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	30.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpeas	Bean	Groundnut	Maize	Millet
					(% by area)					
Rwanda										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	35.0	0.0	35.0	35.0	0.0	0.0	20.0
low input rainfed	100.0	10.0	100.0	65.0	100.0	40.0	40.0	30.0	10.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	25.0	25.0	70.0	90.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sao Tome and Principe										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Senegal										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	20.0	0.0	0.0	20.0	0.0	20.0
low input rainfed	100.0	10.0	100.0	100.0	80.0	30.0	30.0	40.0	10.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	70.0	70.0	40.0	90.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Seychelles										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sierra Leone										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	55.0	0.0	35.0	35.0	20.0	0.0	20.0
low input rainfed	100.0	10.0	100.0	45.0	100.0	40.0	40.0	40.0	30.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	25.0	25.0	40.0	70.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Somalia										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	27.5	0.0
high input rainfed	0.0	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	40.0	100.0	100.0	100.0	30.0	30.0	30.0	7.3	100.0
subsistence	0.0	40.0	0.0	0.0	0.0	70.0	70.0	70.0	65.3	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
South Africa										
irrigated	0.0	0.0	0.0	0.0	24.4	0.0	0.0	0.0	3.0	0.0
high input rainfed	0.0	20.0	0.0	20.0	0.0	0.0	0.0	0.0	35.0	20.0
low input rainfed	100.0	30.0	100.0	80.0	75.6	50.0	75.0	50.0	52.0	30.0
subsistence	0.0	50.0	0.0	0.0	0.0	50.0	25.0	50.0	10.0	50.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Oil Palm	Banana	Potato	Rice	Sorghum	Soybean	Sugar Cane	Sweet Potato	Wheat	Yam
					(% by area)					
Rwanda										
irrigated	0.0	0.0	0.0	50.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	20.0	20.0	10.0	20.0	0.0	20.0	0.0	0.0	0.0
low input rainfed	100.0	40.0	40.0	20.0	40.0	10.0	80.0	30.0	10.0	10.0
subsistence	0.0	40.0	40.0	20.0	40.0	90.0	0.0	70.0	90.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sao Tome and Principe										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	30.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Senegal										
irrigated	0.0	0.0	0.0	47.2	0.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	35.0	0.0	35.0	18.5	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	65.0	100.0	40.0	21.1	30.0	100.0	0.0	10.0	100.0	100.0
subsistence	0.0	0.0	25.0	13.2	70.0	0.0	0.0	90.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Seychelles										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	30.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sierra Leone										
irrigated	0.0	0.0	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	0.0	0.0	0.0	20.0	0.0	55.0	0.0	0.0	0.0
low input rainfed	65.0	10.0	100.0	9.3	40.0	100.0	45.0	10.0	100.0	10.0
subsistence	0.0	90.0	0.0	83.7	40.0	0.0	0.0	90.0	0.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Somalia										
irrigated	0.0	0.0	0.0	100.0	13.2	0.0	100.0	100.0	100.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	100.0	100.0	0.0	8.7	100.0	0.0	0.0	0.0	100.0
subsistence	0.0	0.0	0.0	0.0	78.1	0.0	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
South Africa										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	31.6	0.0	22.7	0.0
high input rainfed	0.0	0.0	0.0	0.0	20.0	0.0	17.5	35.0	35.0	0.0
low input rainfed	100.0	60.0	60.0	70.0	30.0	90.0	50.9	50.0	32.3	90.0
subsistence	0.0	40.0	40.0	30.0	50.0	10.0	0.0	15.0	10.0	10.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpeas	Bean	Groundnut	Maize	Millet
					(% by area)					
St. Helena										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	100.0	100.0	100.0	30.0	30.0	30.0	90.0	10.0
subsistence	0.0	70.0	0.0	0.0	0.0	70.0	70.0	70.0	10.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sudan										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	32.4	26.0	47.8	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	23.7	23.7	0.0	0.0	0.0
low input rainfed	100.0	10.0	100.0	100.0	100.0	59.4	27.0	7.4	5.2	10.0
subsistence	0.0	90.0	0.0	0.0	0.0	16.9	16.9	66.6	47.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Swaziland										
irrigated	0.0	0.0	0.0	0.0	68.8	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	35.0	35.0	35.0	35.0	0.0
low input rainfed	100.0	100.0	100.0	100.0	31.3	40.0	40.0	40.0	40.0	100.0
subsistence	0.0	0.0	0.0	0.0	0.0	25.0	25.0	25.0	25.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Tanzania										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.0
high input rainfed	0.0	20.0	35.0	20.0	0.0	20.0	20.0	0.0	19.8	20.0
low input rainfed	70.0	40.0	65.0	80.0	100.0	40.0	40.0	30.0	39.6	40.0
subsistence	30.0	40.0	0.0	0.0	0.0	40.0	40.0	70.0	39.6	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Togo										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	35.0	20.0	0.0	0.0	0.0	0.0	20.0
low input rainfed	100.0	10.0	100.0	65.0	80.0	30.0	30.0	30.0	30.0	40.0
subsistence	0.0	90.0	0.0	0.0	0.0	70.0	70.0	70.0	70.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Uganda										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	35.0	0.0	20.0	20.0	0.0	0.0	10.0
low input rainfed	100.0	15.0	100.0	65.0	100.0	0.0	10.0	20.0	45.0	5.0
subsistence	0.0	85.0	0.0	0.0	0.0	80.0	70.0	80.0	55.0	85.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Congo, D.R.										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	20.0	0.0	20.0	20.0	0.0	0.0	20.0
low input rainfed	100.0	30.0	100.0	80.0	100.0	40.0	40.0	30.0	10.0	40.0
subsistence	0.0	70.0	0.0	0.0	0.0	40.0	40.0	70.0	90.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Oil Palm	Banana	Potato	Rice	Sorghum	Soybean	Sugar Cane	Sweet Potato	Wheat	Yam
					(% by area)					
St. Helena										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	30.0	30.0	30.0	30.0	50.0	100.0	10.0	30.0	30.0
subsistence	0.0	70.0	70.0	70.0	70.0	50.0	0.0	90.0	70.0	70.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sudan										
irrigated	0.0	100.0	100.0	100.0	7.3	0.0	100.0	0.0	100.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	0.0	0.0	0.0	27.8	100.0	0.0	10.0	0.0	100.0
subsistence	0.0	0.0	0.0	0.0	64.9	0.0	0.0	90.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Swaziland										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	35.0	0.0
low input rainfed	100.0	10.0	10.0	100.0	30.0	100.0	0.0	10.0	40.0	100.0
subsistence	0.0	90.0	90.0	0.0	70.0	0.0	0.0	90.0	25.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Tanzania										
irrigated	0.0	0.0	0.0	7.3	0.0	0.0	100.0	0.0	0.0	0.0
high input rainfed	35.0	35.0	20.0	0.0	20.0	0.0	0.0	0.0	35.0	0.0
low input rainfed	65.0	40.0	40.0	27.8	40.0	10.0	0.0	10.0	40.0	100.0
subsistence	0.0	25.0	40.0	64.9	40.0	90.0	0.0	90.0	25.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Togo										
irrigated	0.0	0.0	0.0	4.3	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	35.0	0.0	33.5	20.0	0.0	0.0	35.0	0.0	0.0
low input rainfed	65.0	40.0	100.0	38.3	40.0	100.0	100.0	40.0	100.0	10.0
subsistence	0.0	25.0	0.0	23.9	40.0	0.0	0.0	25.0	0.0	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Uganda										
irrigated	0.0	0.0	0.0	9.4	0.0	0.0	3.3	0.0	0.0	0.0
high input rainfed	0.0	0.0	20.0	0.0	10.0	25.0	0.0	0.0	35.0	0.0
low input rainfed	100.0	30.0	25.0	40.6	10.0	35.0	86.7	5.0	15.0	100.0
subsistence	0.0	70.0	55.0	50.0	80.0	40.0	10.0	95.0	50.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Congo, D.R.										
irrigated	0.0	0.0	0.0	1.7	0.0	0.0	0.0	0.0	0.0	0.0
high input rainfed	35.0	0.0	20.0	0.0	0.0	0.0	20.0	0.0	20.0	20.0
low input rainfed	65.0	10.0	40.0	9.8	30.0	10.0	80.0	10.0	40.0	40.0
subsistence	0.0	90.0	40.0	88.5	70.0	90.0	0.0	90.0	40.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A1. Continued

Country	Barley	Cassava	Cocoa	Coffee	Cotton	Cowpeas	Bean	Groundnut	Maize	Millet
					(% by area)					
Zambia										
irrigated	0.0	0.0	0.0	0.0	8.7	0.0	0.0	0.0	0.0	0.0
high input rainfed	0.0	0.0	0.0	35.0	32.0	20.0	20.0	0.0	20.0	20.0
low input rainfed	70.0	30.0	100.0	65.0	59.3	40.0	40.0	10.0	40.0	40.0
subsistence	30.0	70.0	0.0	0.0	0.0	40.0	40.0	90.0	40.0	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Zimbabwe										
irrigated	100.0	0.0	0.0	0.0	27.9	0.0	0.0	0.0	0.6	0.0
high input rainfed	0.0	0.0	0.0	35.0	0.0	35.0	35.0	0.0	0.0	0.0
low input rainfed	0.0	10.0	100.0	65.0	72.1	40.0	40.0	10.0	29.8	10.0
subsistence	0.0	90.0	0.0	0.0	0.0	25.0	25.0	90.0	69.6	90.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Country	Oil Palm	Banana	Potato	Rice	Sorghum	Soybean	Sugar Cane	Sweet Potato	Wheat	Yam
					(% by area)					
Zambia										
irrigated	0.0	0.0	0.0	23.1	0.0	0.0	100.0	0.0	100.0	0.0
high input rainfed	0.0	0.0	20.0	0.0	20.0	35.0	0.0	55.0	0.0	0.0
low input rainfed	100.0	10.0	40.0	7.7	40.0	40.0	0.0	30.0	0.0	100.0
subsistence	0.0	90.0	40.0	69.2	40.0	25.0	0.0	15.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Zimbabwe										
irrigated	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	100.0	0.0
high input rainfed	0.0	0.0	35.0	0.0	0.0	35.0	0.0	0.0	0.0	0.0
low input rainfed	100.0	10.0	40.0	100.0	30.0	40.0	0.0	10.0	0.0	100.0
subsistence	0.0	90.0	25.0	0.0	70.0	25.0	0.0	90.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Figure A1. Estimated crop distribution maps of Sub-Saharan Africa

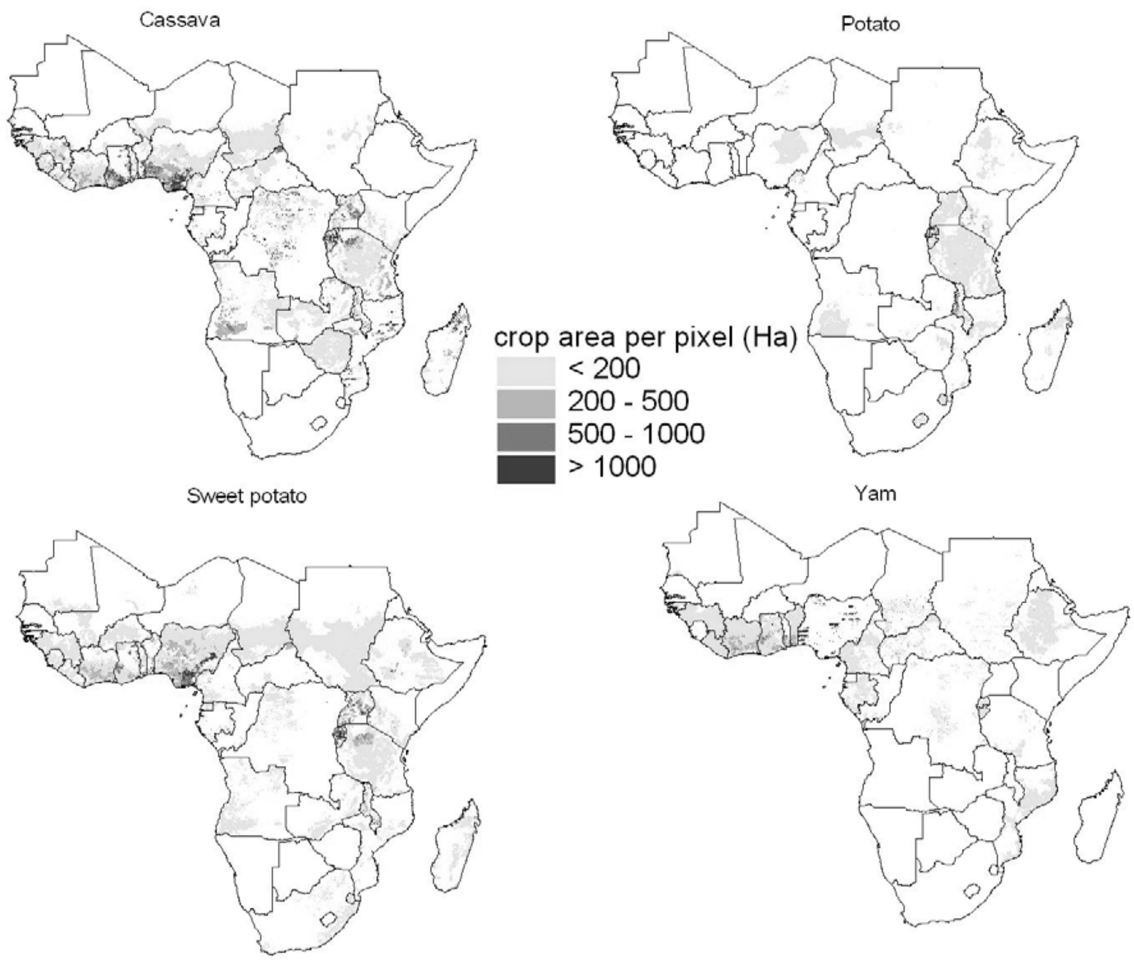


Figure A1. Continued

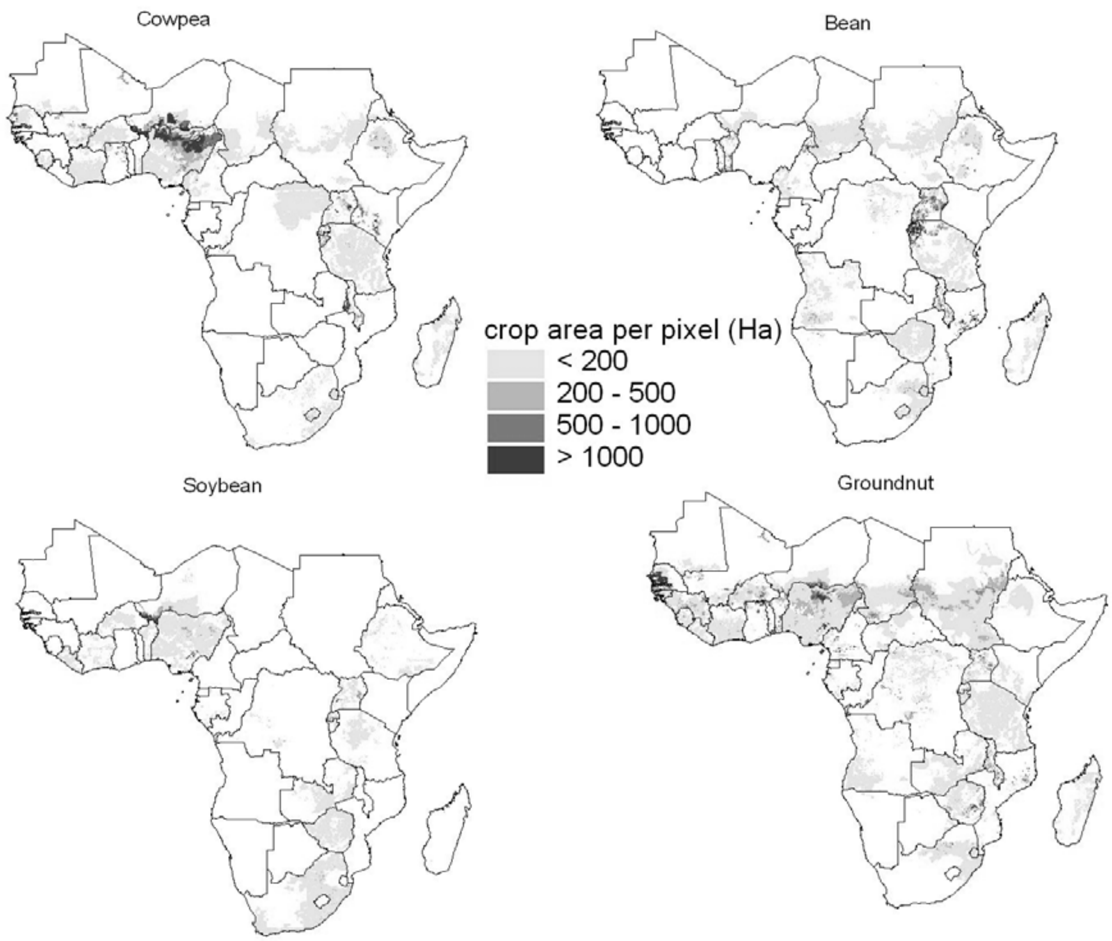


Figure A1. Continued

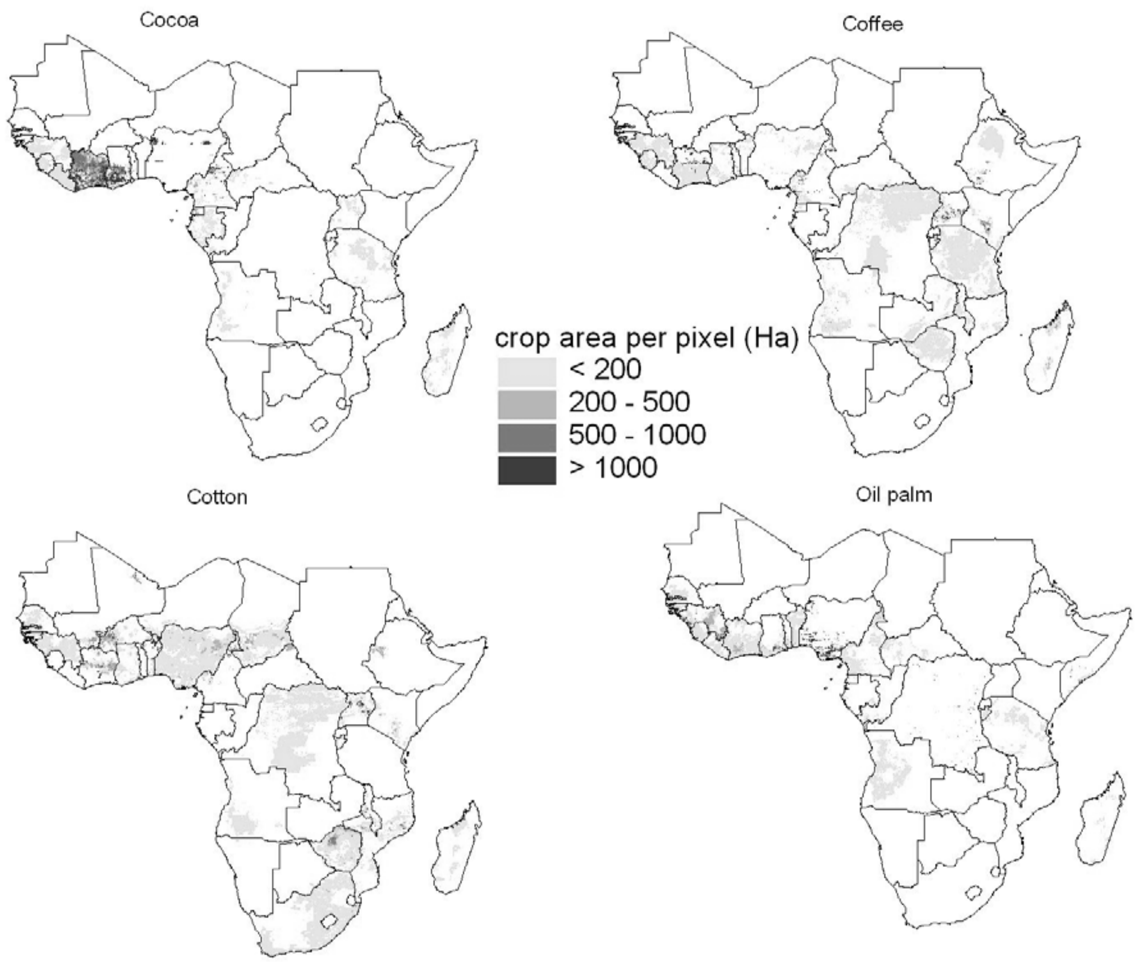
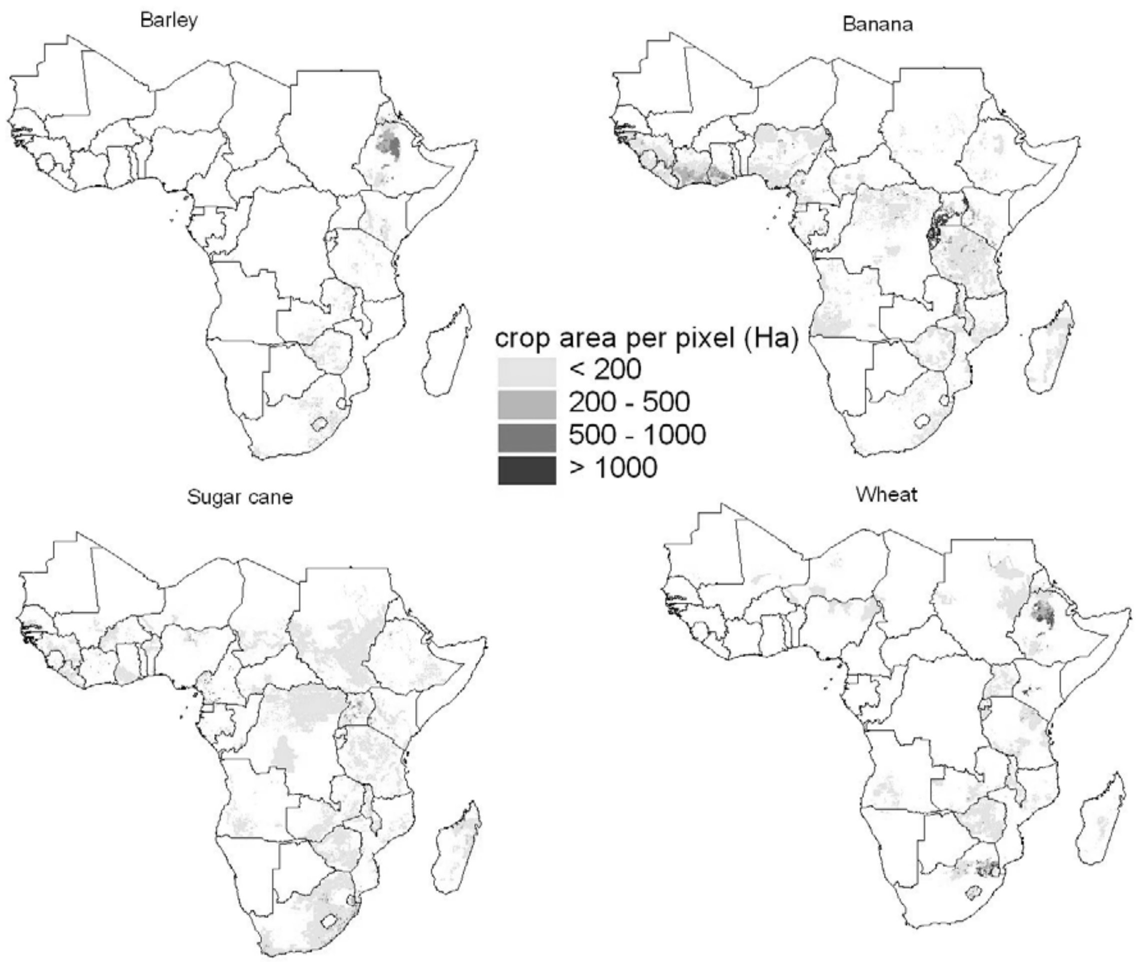


Figure A1. Continued



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