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Agriculture Production and Transport Infrastructure in East Africa

An Application of Spatial Autoregression

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Abstract

Africa is estimated to have great potential for agricultural production, but there are a number of constraints inhibiting the development of that potential. Spatial data are increasingly important in the realization of potential as well as the associated constraints. With crop production data generated at 5-minute spatial resolution, the paper applies the spatial tobit regression model to estimate the possible impacts of improvements in transport accessibility in East Africa. It is found that rural accessibility and access to markets are important to increase agricultural production. In particular for export crops, such as coffee, tea, tobacco, and cotton, access to ports is crucial. The elasticities are estimated at 0.3–4.6. In addition, the estimation results show that spatial autocorrelation matters to the estimation results. While a random shock in a particular locality would likely affect its neighboring places, the spatial autoregressive term can be positive or negative, depending on how fragmented the current production areas are.

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AGRICULTURE PRODUCTION AND TRANSPORT INFRASTRUCTURE IN EAST AFRICA: AN APPLICATION OF SPATIAL AUTOREGRESSION

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I. Introduction

Africa has great potential for agriculture. Together with agribusiness, it is estimated that agriculture currently generates $31 billion or nearly half of the GDP of the region. This is projected to continue growing to $1 trillion by 2030 (World Bank 2013). However, the potential has not been fully explored yet. For instance, the ratios of potential to actual agricultural outputs are estimated at 1.5 for cassava, 1.9 for rice, 2.7 for maize and 5 for wheat in West Africa (World Bank 2012). Importantly, from the agro-ecological point of view, Africa can feed itself if proper inputs, such as improved seeds and fertilizer, are used. But Africa is currently importing considerable quantities from outside the region.[1] Given rapid urbanization and strong population growth, Africa needs to produce more agricultural products.

There are a number of constraints: Africa's agriculture is mostly small-scale subsistence farming. Irrigation and fertilizer are among the most important missing inputs (e.g., Gyimah-Brempong, 1987; Bravo-Ortega and Lederman, 2004; Xu et al., 2009; Dillon, 2011). Access to markets is also important, for farmers to take advantage of advanced technologies and market opportunities. In Africa, rural accessibility is particularly limited.[2] Transport accessibility — regardless of mode — has a crucial role to play to reduce input prices and boost agricultural production (Khandker, Bakht and Koolwal, 2009; Donaldson, 2010). A growing literature also suggests the importance of access to information and communication technology to obtain market information (Kiiza and Pederson, 2012, Zanello 2012).

Spatial techniques are becoming an increasingly popular tool to identify potential economic opportunities and possible bottlenecks in unlocking them. On the agriculture side, there are several important international initiatives to examine current land use and potential crop

[1] Africa imported $15 billion of cereals in 2008, out of which only 5 percent originated from the African region (World Bank 2012).

[2] In Africa, rural accessibility measured by the proportion of the rural residents within a 2-km walking distance from an all-weather road is less than 30 percent (Gwilliam 2011).

productivity in connection to climate and soil conditions (e.g., Global Agro-ecological Zones (GAEZ) system developed by the FAO and the International Institute for Applied Systems Analysis (IIASA)). These data provide information on crop suitability at the detailed spatial level. On the infrastructure side, the new economic geography literature is building a solid body of knowledge on regional distribution and disparity of infrastructure endowments, identifying missing links and bottlenecks (see, for instance, World Bank (2009) and (2010)).

There are however only a few empirical studies that statistically link these two different sources of spatial data on the agriculture and infrastructure sides, excepting a number of more recent works, such as Dorosh, Wang, You and Schmidt (2012). This paper examines the agricultural potential of East Africa, namely, Burundi, Kenya, Rwanda, Tanzania and Uganda, through an examination of the two different sources of spatial data. Despite the currently high international commodity prices, in particular in the traditional export crops, such as coffee and cotton, these East African countries are still struggling to improve agricultural productivity. This paper specifically aims at: (i) generating spatial agricultural production and potential data for the region; (ii) developing spatial data to show transport accessibility in each locality; and (iii) developing an empirical model to link these data and analyze the relationship between agriculture production and transport infrastructure investment.

The remaining sections are organized as follows: Section II describes our spatial agriculture data. Section III develops an empirical model and describes our infrastructure data. Section IV discusses our main estimation results and some policy implications. Section V concludes.

II. Spatial Production Allocation Model (SPAM) Update

The current paper relies on a spatial production allocation model (SPAM) developed by the International Food Policy Research Institute (IFPRI) for generating highly disaggregated crop-specific production data. The SPAM is a spatial model to allocate crop production

derived from large statistics reporting units, such as country, province and district, to a raster grid at a spatial resolution of 5 minutes of arc (approximately 9 km at the equator (normally referred to as 10km x10km pixel for simplicity). To infer likely production locations, the model uses a cross-entropy method (Shannon 1948). Given initial allocations, the cross-entropy method minimizes the cross-entropy distance—entropy is referred to as a measurement of uncertainty of expected information—between different probability distributions of the variables in the analysis, under different spatial constraints. As a result, the SPAM allows the simulation of the most plausible agricultural production locations given all available data at different levels.

Various input data are taken into account in the cross-entropy procedure, such as sub-national crop production statistics, satellite data on land cover, maps of irrigated areas, biophysical crop suitability assessments, population density, secondary data on irrigation and rainfed production systems, cropping intensity, and crop prices. Specifically in the SPAM, we start with crop production statistics at the large administrative (geopolitical) units (Figure 1).[3] These are typically national or sub-national. Key information to determine where and how much agricultural land exists at the pixel level comes from the existing land cover imagery, which is divided into crop land and non-crop land. With this crop land combined with the crop suitability data based on local climate, terrain and soil conditions, the crop-specific land areas can be obtained (e.g., maize in the figure). Note that the SPAM model disaggregates crop areas and yields into four different management intensities: (i) irrigated; (ii) high-input rain-fed; (iii) low-input rain-fed; and (iv) subsistence. Together with all these data, the SPAM applies the cross entropy method to obtain the final estimation of each crop distribution.

For the current paper, the SPAM was updated for five member countries of the East Africa Community. The model was rerun for 42 crops around 2010 with the latest available crop statistics and other new spatial data included. In the previous SPAM, i.e., SPAM 2000, which

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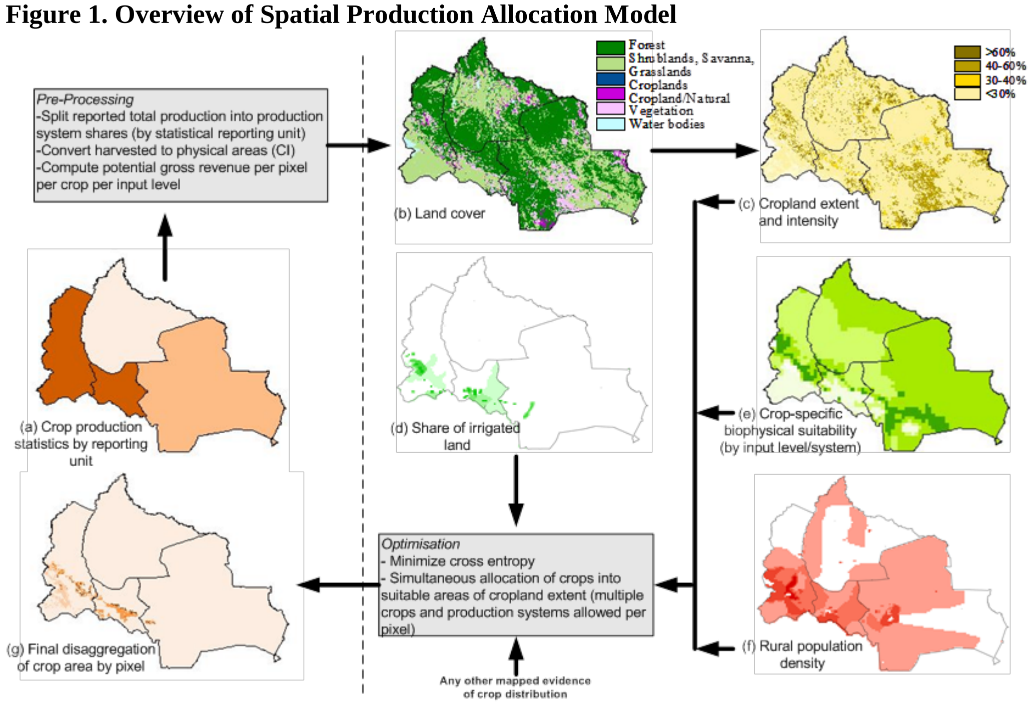
[3] See You and Wood (2006), You *et al.* (2009), and You et al. (2014) for further details.

is available on the Internet at MapSpaM.info, only 20 major crops were allocated. In the current application, the base year is changed to 2010, and the coverage of crops was increased to 42. In addition, some other updated inputs, such as land cover, are also used (see Annex Table 1). Therefore, the SPAM 2010 provides more precise estimates of crop production at each locality.

Data sources for subnational crop statistics differ across countries (Annex Table 2). Ideally, the data should cover the same period of time around 2010. However, data is not always available. In such a case, the spatial distribution of crop production is assumed to be the same as the year for which the latest data is available, and the data is scaled to FAO average 2009-2011 values.

In the following empirical analysis, only eight major crops that are produced in East Africa are used for analytical purposes: maize, rice, bananas (and plantains), cassava, coffee, tea, cotton, and tobacco. But the same types of data are available for other crops as well.

Figure 1. Overview of Spatial Production Allocation Model



Source: Authors' illustration.

III. Empirical Model and Data

In the literature, the traditional approach to investigating the linkage between agricultural production and infrastructure investment is to estimate a production function (see for instance Gyimah-Brempong (1987) and Bravo-Ortega and Lederman (2004) for literature reviews). Besides infrastructure conditions (often represented by transport accessibility), at least four other inputs are considered essential: labor, land, fertilizer and irrigation. The literature suggests that the output elasticities are relatively high for labor, reflecting the fact that agriculture production is labor-intensive. The elasticities associated with land are often modest, reflecting the relative abundance of land in Africa.

Fertilizer and irrigation seem to be critical to improve production, but the statistical significance varies across studies (Bravo-Ortega and Lederman, 2004). A growing literature suggests their importance: In Zambia, timely availability of fertilizer could increase maize yields by 11 percent on average (Xu et al., 2009). Improved availability of irrigation could nearly double agricultural productivity in Mali (Dillon, 2011).

Transport infrastructure has multiple implications for agricultural production. Better market access can reduce input prices. Khandker, Bakht and Koolwal (2009) find that farm-gate fertilizer prices were lowered by rural road investment in Bangladesh. Better transport infrastructure also provided more opportunities for farmers to engage in cash crop production and market transactions. Agriculture output prices increased by 2 percent and the volume of production was boosted by 22 percent (ditto).

To examine the infrastructure impacts on agricultural production, the following simple production function is considered:

$$y_i = \beta_0 + \beta_z z_i + \sum_k \beta_k x_{ik} + u_i \qquad (1)$$

where y is the amount of a crop produced at location i, which depends on an exogenous agro-ecological factor and the amounts of inputs used. u_i is an error term. z is a measurement of crop suitability or productivity of land. x's are production inputs: $k = \{L, R, I, F, T\}$. L denotes labor. Land is divided into two types: rain-fed (R) and irrigated (I). F and T denote fertilizer and transport accessibility, respectively. The logarithms are taken for all dependent and independent variables.[4]

As is often discussed, spatial autocorrelation is an important empirical issue for estimating the equation. Our primary data is spatial, and the unit of analysis is approximately10 x 10 km parcels of land for each crop. Therefore, one observation may not be independent of another, i.e., $Cov(u_t, u_s) \neq 0$. By nature, agricultural land is a continuum of various characteristics, such as soil fertility and water availability. Weather conditions are continuous across locations. On the infrastructure side, public infrastructure, such as transport networks, is a typical network industry, which also creates autocorrelation among neighboring areas.

Another issue is that our agricultural production data are censored. As in many empirical spatial studies, an actual value for the dependent variable—in our case, crop production y—is only available for a subset of the observations. As discussed below, some crops are grown everywhere, and others are produced in specific areas. As a result, there are a large number of locations (i.e., 10 x 10 km of land parcels) with zero production of a given crop.

To deal with these two problems, the spatial tobit (SPTobit) regression model is used. Denoting the latent variable of the output produced by y^*, the following censoring mechanism is considered:

$$y_i = \begin{cases} y_i^* = \lambda \sum_j w_{ij} y_j + \beta_z z_i + \sum_k \beta_k x_{ik} + u_i & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

[4] A small positive number (one) is added if the amount of input used is zero to avoid taking the logarithm of zero. For instance, fertilizer is not used in many observations of our sample.

$$u_i = \rho \sum_j w_{ij} u_j + \varepsilon_i \qquad (3)$$

where w is an element of the spatial-weighting matrix. λ and ρ are spatial autoregressive parameters in the dependent variable and error term, respectively. ε is an idiosyncratic error distributed independently and identically. Under the normality assumption, this can be estimated by the conventional maximum likelihood estimation procedure (e.g., Anselin, 1988; Amaral and Anselin, 2011).[5]

For the spatial weighting matrix, inverse distances between two locations s and t are used. The distance is calculated using the Euclidean distance between the two locations. The intuition is that two locations are more closely related to each other, if they are located closely. This follows the Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things (Tobler 1970)."

Our primary data source is the SPAM 2010 update. As discussed above, the SPAM is basically a model to disaggregate the national and subnational production data into the 10 x 10 km plots (pixels) using a number of different spatial data types. Therefore, it is critical to control for spatial autocorrelation in our analysis.

The analysis focuses on eight major crops that are produced in East Africa: maize, rice, bananas (and plantains), cassava, coffee, tea, cotton, and tobacco (Figure 2). The selection aims at examining both domestic food crops, such as maize and bananas, and export crops, such as tea and coffee. These eight crops account for about 40 percent of total agricultural commodities produced in the region.[6] The current productivity of these crops is generally low by regional standards, though it exceeds the African average in some cases (Figure 3).

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[5] For estimation we rely on a STATA command ***sptobitsac*** developed by Shehata and Michaiel (2013).

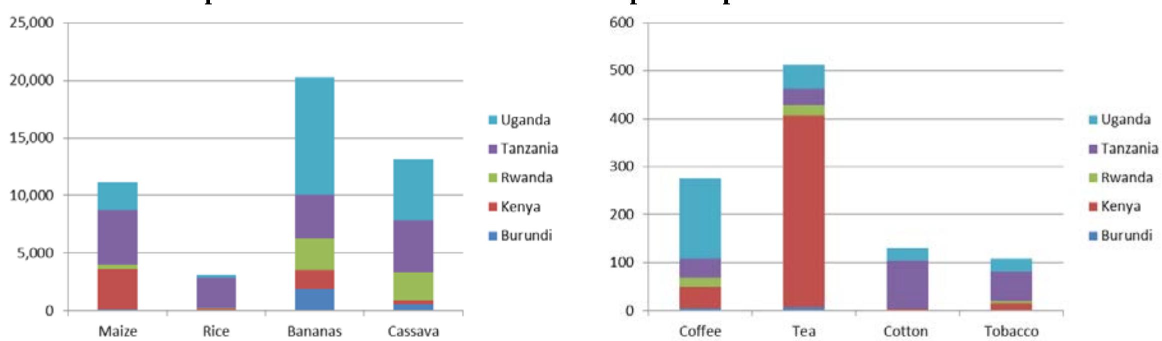
[6] According to FAOSTAT, the East Africa Community member countries produced about $25 billion of agricultural commodities in 2011. The eight commodities examined amount to $9.3 billion in total.

As shown in Annex Figure 1, the spatial distribution of agricultural production differs significantly across commodities.

Agricultural production depends crucially on agro-climatic conditions at each locality. While recognizing that various constraints exist in reality, such as absence of infrastructure and environmental protection (e.g., national parks), the current agricultural production does not seem to fully exploit its biophysical potential in the region (also see Annex Figure 1). We use the crop suitability developed by FAO and IIASA to measure agricultural potential of each crop at each location, *z*. This is defined by the amount of crops that could technically be produced given the underlying biophysical, climatic and landscape characteristics under the "low input and subsistence" assumption, which is more or less the same as the technology currently available in the region.

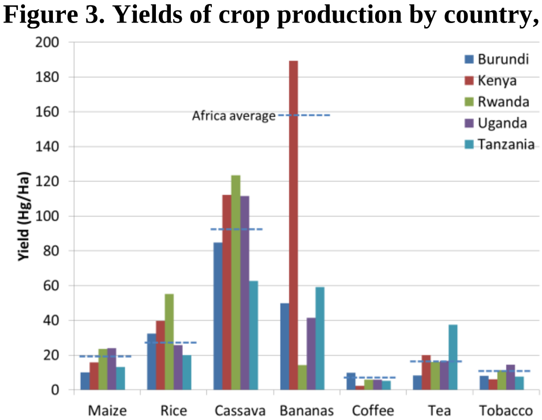
Figure 2. Major crops produced in East Africa, 2010 (1,000 tons)

Domestic food crops **Export crops**



Source: FAOSTAT (accessed in December 2013).

Figure 3. Yields of crop production by country, 2011



Source: FAOSTAT (accessed in December 2013).

For production factors, various spatial and other data are used. For labor, the number of population engaged in crop *j* production at location *i* is calculated from the rural population estimate and the probability of household's engagement in crop production. The latter comes from the national statistics of each country, and the level of aggregation differs across countries.[7] The pixel-level rural population data is taken from the Global Rural-Urban Mapping Project (GRUMP).[8]

$$x_L = ruralpop_i * \Pr(household\ working\ on\ crop\ j) \qquad (4)$$

The land data comes from the same source as the output variable, i.e., SPAM. It provides an estimate of land use for each crop at each location. Land has two types: rain-fed (*R*) and irrigated (*I*). There is little irrigated area in East Africa (Figure 4). According to the SPAM data, there is no irrigated land in the region for bananas, for which the variable *I* is omitted from the model.

The fertilizer variable represents the quantity of plant nutrients applied to the land area for each crop. This is calculated by multiplying the land area (ha) where fertilizer is used by the national average fertilizer consumption (kg per ha). The land area with fertilizer application is derived from SPAM, which generates the land area for each crop depending on

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[7] For Tanzania, the district-level share of households engaged in each crop production is calculated with the 2010 LSMS data. For Uganda, the LSMS 2010 is similarly used to calculate the shares at the first sub-national level. For Rwanda, the subnational statistics are available at the 30-district level. For Burundi, the national-level data are directly used because no subnational data are available. For Kenya, household-level agriculture production data are not available, either. In this paper it is assumed that the average plot size per household is the same across crops in each administrative unit. As in other countries in the region, the vast majority of farmers are small landholders with an average of 2.5 ha in Kenya. While some wealthy households sometimes own a significant amount of land, the variation of land per household is relatively small (Jayne et al. 2006; Salami et al. 2010). Thus, our assumption may not always hold but can generate a reasonable proxy.

[8] The Global Rural-Urban Mapping Project (GRUMP) is a derivative product of the Gridded Population of the World (GPW) data, which is based on 2000 round census data and has actual 1990, 1995, and 2000 population grids and projected 2005, 2010, and 2015 grids at a 2.5 minute resolution (approximately 5km at the equator). GRUMP is at a 30 arc-second (1km) resolution (the same as Landscan) and includes an urban-rural reallocation.

technologies, i.e., low-input, high-input and irrigated production systems. The last two figures are used for our calculation of areas with fertilizer application.

The average fertilizer consumption is calculated based on IFA/IFDC/IPI/PPI/FAO (2002) and Liu et al. (2010). Our fertilizer variable is the sum of three major elements of fertilizer: nitrogenous (N), phosphate (P2O5) and potash (K2O), because the actual mix and content of N, P and K varies across fertilizers. They are simply the sum of all the three elements for each crop.

Transport connectivity is also a crucial input for agricultural production. Farmers need to go to the markets to purchase necessary inputs and sell their products. Transport connectivity can be measured at different levels. First, the distance to the nearest road—denoted by T_0—is fundamental regardless of the type of crop, because farmers need to get to the road network no matter which crop is produced and where the products are transported to. In East Africa, rural accessibility is still a challenge and the accessibility indices are estimated at about 25-35 percent (Figure 5). Using the spatial data of road networks, the distance to the nearest road is calculated from the centroid of each location *i*. This varies from less than 1km to over 100 km, depending on location (Figure 6).

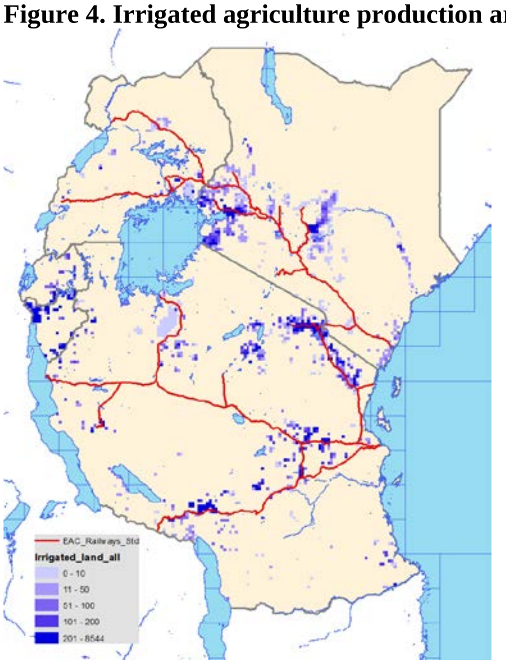
Beyond the local accessibility, required transport connectivity may differ depending on the destination of the products. For domestically consumed food crops, such as maize and bananas, the destination is assumed to be a large town/ city, which is defined by the nearest populated area with more than 50,000 inhabitants.[9] Under the cost minimization assumption, the transport network cost is calculated by summing up the transport unit costs of road, railway and port along the optimal path from the production area to the city (Figure 7). This is denoted by T_1. Note that the unit road transport costs vary, depending on type and class of road, and road conditions. In addition, not only road user costs and transport tariffs, but also

[9] For small countries, such as Burundi, some other cities below this threshold are also included, because there would otherwise be only one domestic market in the country, i.e., the capital city, Bujumbura.

waiting time costs at transport nodes, such as stations, inland ports and seaports, are included. The transport costs to the nearest large town/city vary from several dollars to over \$50 per ton. This can be significant in remote areas, compared to the regional market prices (Table 1).

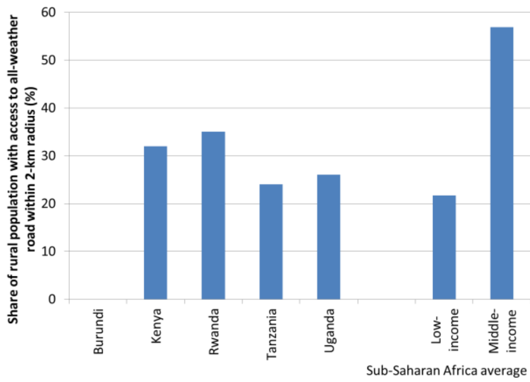
For export crops, the destination is assumed to be one of the regional ports: Dar es Salaam and/or Mombasa. Again, the transport cost, T_2, is calculated from the production location to the port based on the lowest cost criteria. Transport costs to the ports are significant: Port handling costs and fees are included, which amount to about \$96 and \$78 at the ports of Dar es Salaam and Mombasa, respectively. Thus, the total transport cost to a port can be over \$150 per ton in inland areas and land-locked countries (Figure 8).

Figure 4. Irrigated agriculture production areas (ha)



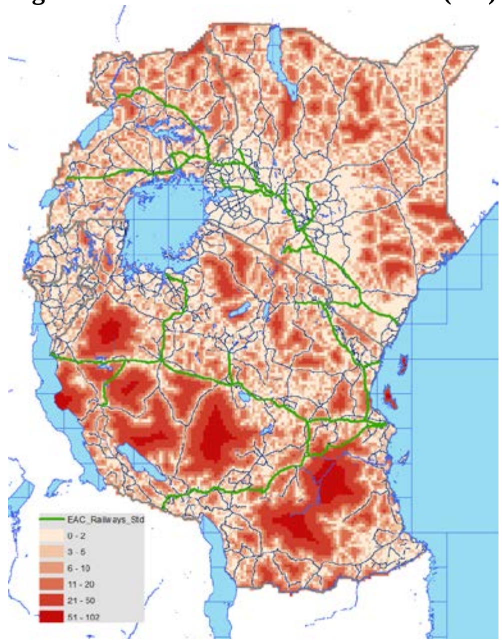
Source: SPAM Update 2010.

Figure 5. Rural Accessibility Index



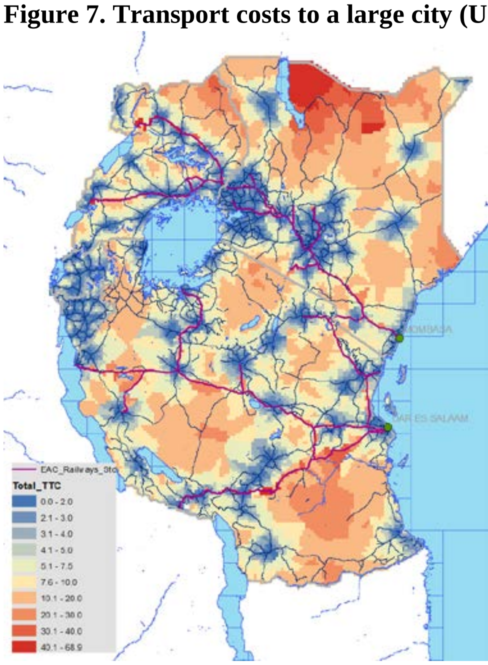
Source: Gwilliam (2011).

Figure 6. Distance to the nearest road (km)



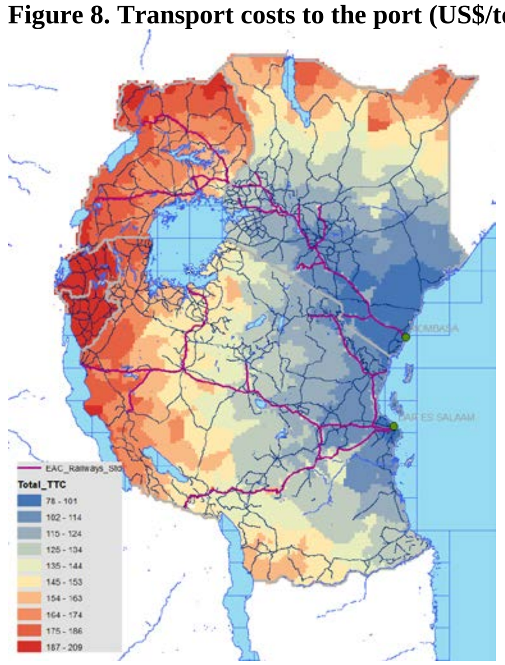
Source: World Bank calculation.

Figure 7. Transport costs to a large city (US$/ton)



Source: World Bank calculations.
Note: The transport cost to the nearest city is calculated based on unit road user costs, transport tariffs, waiting time at stations, inland ports and seaports.

Figure 8. Transport costs to the port (US$/ton)



Source: World Bank calculations.
Note: The transport cost to the nearest port is calculated based on unit road user costs, transport tariffs, waiting time at stations, inland ports and seaports.

Table 1. Regional crop prices of selected commodities

Food crop	$/ton	Export crop	$/ton
Maize	260	Coffee	3,192
Rice	856	Tea	1,506
Bananas	536	Cotton	1,429
Plantain	240	Tobacco	1,365
Cassava	294		

Source: Calculated based on FAOSTAT.

IV. Estimation Results and Policy Implications

The spatial tobit (SPTobit) regression is performed for each crop and each geographic group. Since the amount of data points is significant from the computational point of view, the entire region is separated into 6 areas for food crop calculations and 3 areas for export crop calculations (Figure 9).[10] The three landlocked countries comprise the first group. Kenya is the second group, but the analysis is focused only on the western half of the country, because there is little variation in agricultural production in the other half.

Tanzania is a large country, which is composed of over 9,000 10 x 10 km pixels. This would cause significant computational difficulties without disaggregation of the country. Food crops are produced in many places. Therefore, the sample data is divided into four areas: "Tabora", "Mbeya", "Arusha", and "Coastal." For export crops, the production takes place in very limited places (compared to the size of the country). Thus, the sample data are trimmed down to focus on the areas where major production takes place.

All the estimation results are shown in Annex Tables. The ordinary least squares (OLS) estimates are also included as references. The results are broadly consistent with *a priori* expectations. First of all, regarding the autocorrelation parameters, i.e., λ and ρ, they indicate

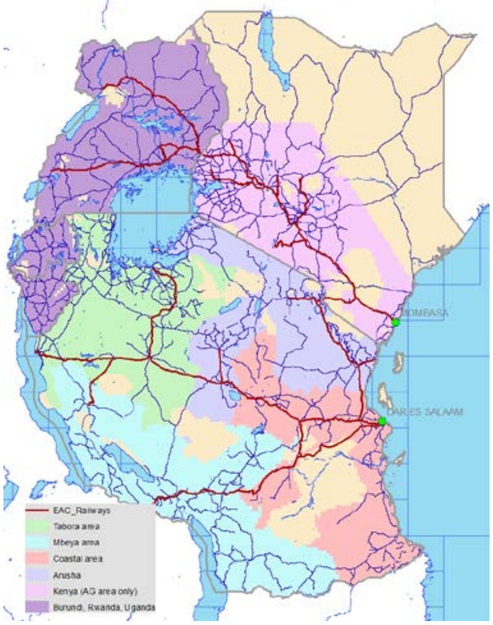
[10] Major national parks are also excluded from our analysis, because these areas are environmentally protected and not supposed to be used for agriculture production purposes.

that the OLS estimation is likely biased. The hypothesis that the spatial autocorrelation parameters are zero can easily be rejected. Therefore, not surprisingly, spatial autocorrelation matters to our data. Because of this autocorrelation, some estimated coefficients are significantly different from the SPTobit results, although the coefficients tend to be broadly similar (see Annex Tables).

An important finding is that the spatial autoregressive term λ is almost always significant but can be positive or negative. This implies that spatial concentration varies across crops and areas. For tobacco production, for instance, the estimated spatial autoregressive term is positive at 0.502 in Kenya. It means that if tobacco is produced in one place, the neighboring places are also likely to grow tobacco in Kenya. On the other hand, the same parameter is estimated at -0.246 in Tanzania, which is also statistically significant. It means that if tobacco production takes place in one locality, the neighboring places are less likely to grow tobacco in Tanzania. The evidence indicates certain fragmentation or agglomeration diseconomies in tobacco production in Tanzania. This is consistent with the maps depicting production areas at the same scale: Production areas are more dispersed in Tanzania than in Kenya (Figure 10).

Unlike the spatial autoregressive term, the autocorrelation coefficient in the errors, ρ, is almost always positive at 0.8-0.95 and highly significant. This can be interpreted to mean that an exogenous shock—for example, drought and flood—in a given location has a substantial spillover effect on its neighboring areas. Obviously, this is plausible because there must be various shocks that affect agricultural production in a wider area than our unit of analysis (10 x 10 km). Because of this, it is important to control spatial autocorrelation in the analysis.

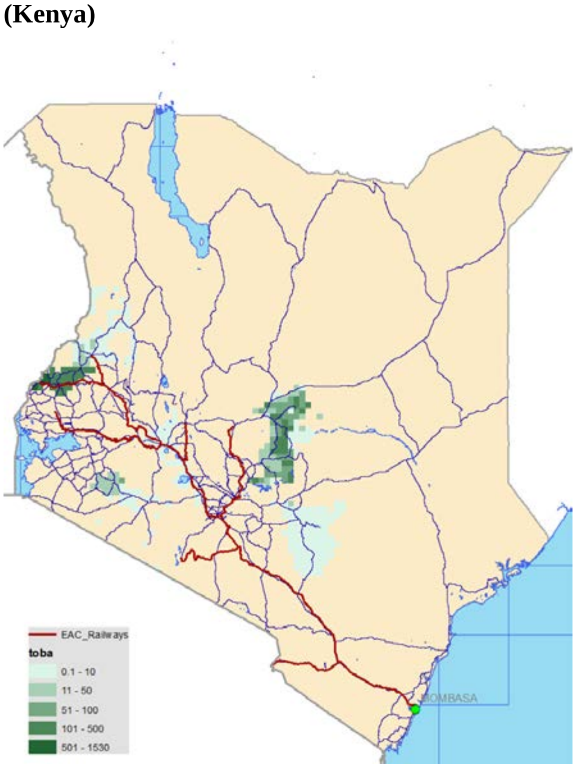
Figure 9. Regional groups for analytical work



Source: Authors' illustration.

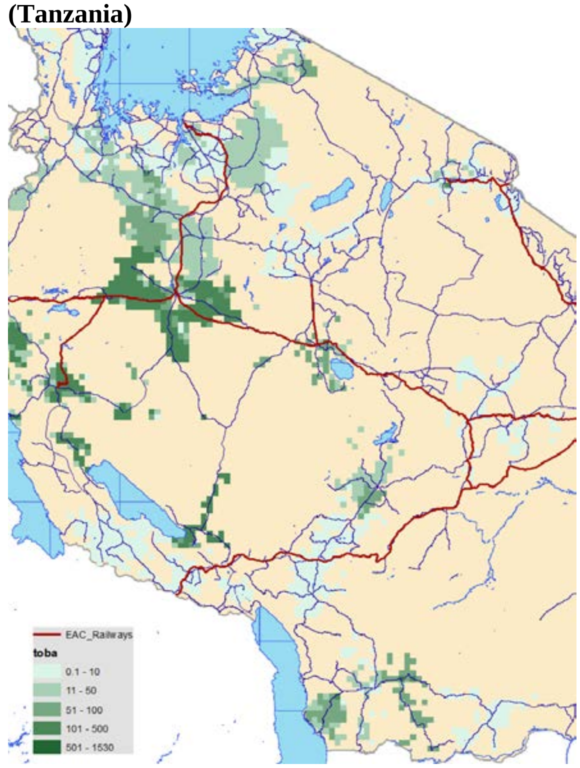
Figure 10. Difference in spatial concentration of tobacco production

(Kenya)



Source: SPAM Update 2010.

(Tanzania)



Source: SPAM Update 2010.

Regarding the impacts of transport accessibility on agricultural production, the main results from the SPTobit models are shown in Table 2. Despite the autocorrelation discussed above, these are considered unbiased and consistent. The estimated elasticities vary across areas and crops but are broadly consistent with our prior expectation: Both rural accessibility and market access are important factors in stimulating agriculture production. Figures 11 and 12 depict the predicted changes in each crop production under the assumption that each element of transport accessibility is improved by 10 percent.[11] Recall that while our rural accessibility is measured by the distance to the nearest road (km), market accessibility is measured by the economic transport cost ($ per ton) to the nearest city or port, depending on the type of crop.

Our estimation results suggest that market accessibility is generally more important than rural accessibility. Particularly, for export crops, access to maritime port is found to be crucial: In some cases (e.g., coffee in the landlocked countries, tea in Kenya and tobacco in Tanzania), a 10-percent reduction in transport costs to the maritime port could boost export crop production by more than 10 percent. These are considered as high-yield crops from the infrastructure investment point of view.

Notably, however, this does not underplay the importance of rural accessibility. For instance, there is no evidence showing that banana production is constrained by market access in Burundi, Kenya, Rwanda and Uganda. But improving rural accessibility would likely result in some increases in banana production. While a 10-percent rural accessibility improvement could increase coffee production by 0.5 percent in Tanzania, the same amount of improvement in port access could increase the production by 4 percent. Thus, both are important to improve, and the relative importance varies across countries.

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[11] The predicted changes are shown only in case the estimated elasticity is statistically significant. In several cases, the predicted impacts are counter-intuitive. For instance, the evidence implies that an improvement in rural accessibility would result in less production of tobacco. This may be interpreted to mean that rural roads are well developed in the tobacco producing area of Kenya. At the same time, there may be a statistical issue that over- or under-estimate the impact, particularly when a large number of observations are censored, as in the case of tobacco in Kenya.

For the landlocked countries, access to a port is found to be most important. The expected impact is largest on coffee production, followed by tobacco and cotton. For domestic food crops, access to a large city is also a significant determinant of production, particularly for rice. The result indicates that rice production areas are not well connected to major consumption areas.

For Kenya, cotton and tobacco production could benefit greatly from transport cost reductions to the port. Expected benefits to tea and coffee production are also likely significant. To stimulate coffee production, rural accessibility is also found to be important. For food crops, there would be some gains by improving market access to cassava, maize and rice producers.

The expected impacts of improved connectivity to the port look relatively modest in Tanzania. The obvious reason is that the country has the port of Dar es Salaam and major export crop production areas seem to be well connected to the port by the trunk road network. Of course, cotton and tobacco production, which takes place largely in inland areas, such as Tabora and Mwanza, could still be stimulated by improved transport access to the port. But rural accessibility and access to domestic markets are expected to be relatively important in the case of Tanzania. Expected benefits are large for rice production in Mbeya Area, maize in Arusha, and cassava in Tabora and Coastal Areas.

Regarding other production inputs, it is commonly found that land, regardless of whether rain-fed or irrigated, is among the most important production factors. It can be interpreted to mean that agricultural production in East Africa is and still can be dependent on extensification (more land), rather than improving technological level (intensification). For instance, the land elasticity is estimated at 0.74 to 0.98 for food crops, such as rice, maize and cassava in Burundi, Rwanda and Uganda. For cash crops, such as tea and cotton, the land elasticity is also large at 0.85 to nearly 1 (see Annex Tables).

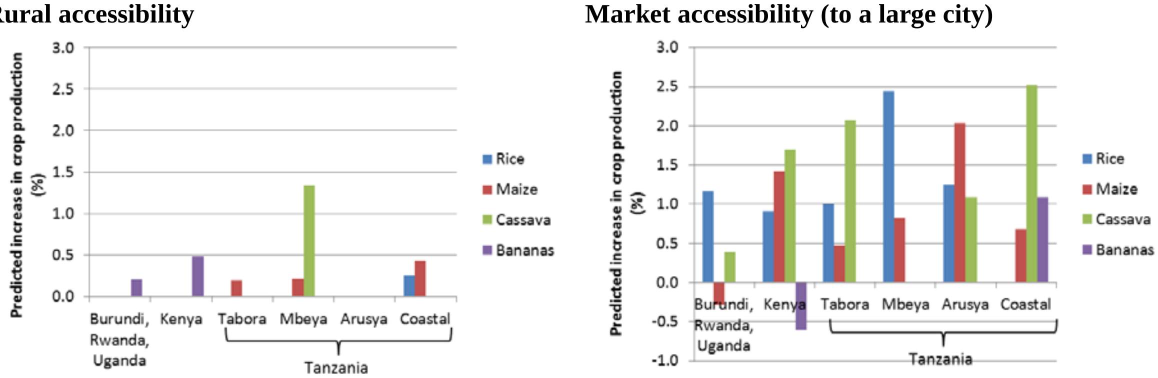
Other advanced inputs are also found productive. As discussed above, irrigation use is still limited. But the irrigated land elasticity is estimated at 0.77 for rice in Burundi, Rwanda and Uganda. In Kenya, this is estimated at 1.13, an indication of more significant potential of irrigation use.

Fertilizer is also found to be productive: The estimated elasticities range from 0.01 to 0.3 in most cases. In Kenya, for instance, the fertilizer elasticity is 0.074 for maize, while the same is estimated at 0.23 for tea. Thus, fertilizer use is more effective for the latter. In Tanzania, the fertilizer elasticity for maize is 0.06 to 0.11, depending on areas, while it is estimated at 0.12 for tea, 0.19 for rice and 0.51 for tobacco. Those export crops may need more fertilizer use.

In contrast, labor seems to be less productive and sometimes unproductive. This is particularly observed in the estimation results for food crop production. One possible reason is that our labor variable is poor, because there is no agricultural labor statistics at the location level: We allocated labor using the sub-national statistics. But the evidence may be consistent with the common view in the region: Labor is abundant in the agriculture sector. It is important to increase the adoption of more advanced technologies and promote the shift of production towards more valuable commodities.

Figure 11. Predicted changes in food crop production by a 10% reduction of transport connectivity

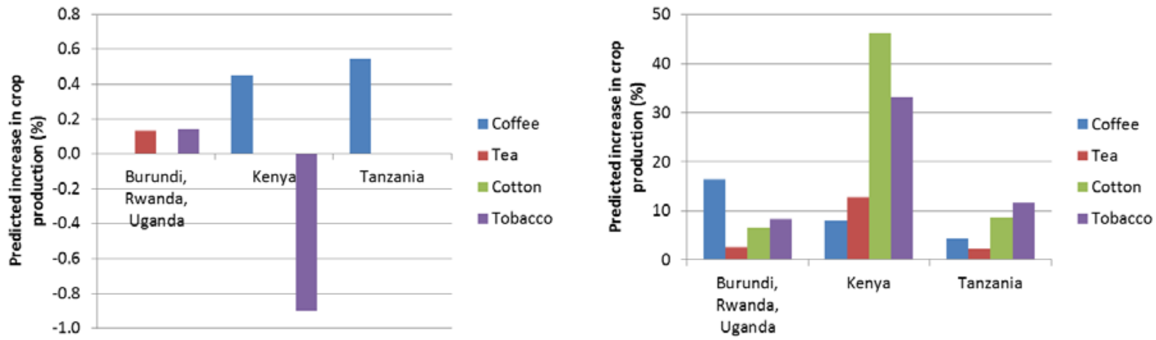
Rural accessibility **Market accessibility (to a large city)**



Source: Authors' illustration based on the SPTobit estimation results (shown in Annex Tables).

Figure 12. Predicted changes in export crop production by a 10% reduction of transport connectivity

Rural accessibility **Market accessibility (to a seaport)**



Source: Authors' illustration based on the SPTobit estimation results (shown in Annex Tables).

From the policy point of view, the question that may be raised is where governments should invest. First, as discussed above, the estimated elasticities are already indicative of expected returns on infrastructure investment. More investment should be made where the elasticities are high, such as coffee in the landlocked countries, cotton and tea in Kenya and tobacco in Kenya and Tanzania. All these export crops are likely to benefit from transport cost reductions at the ports for instance. Therefore, the ports seem to be the priority areas to improve efficiency and lower costs. For the same reason, priority should also be placed on the regional and national transport networks in Kenya and Tanzania, to improve market access within the countries. It would also seem that both countries would benefit from further support to improve rural accessibility for specific crops, such as cassava in Mbeya Area, and coffee in Kenya and Tanzania.

Second, infrastructure investment has a spillover effect. One single investment in transport infrastructure can benefit all the countries in the region. But the magnitude of the benefits is different across countries. For instance, suppose that the waiting time cost at Dar es Salaam could be halved. The average waiting time is currently estimated at 327 hours for gate waiting, yard storage, customs and ship handling. By halving this, the total port costs, including handling and waiting costs, could be reduced by about 40 percent from $96 to $59 per ton. As discussed above, export crop production would likely be increased. The predicted impacts differ across locations, depending on elasticity, current transport costs to the port,

and the level of production. The expected benefits range from $10 million to $170 million, which account for 0.2-0.6 percent of current GDP (Table 3).

Finally, there exist many other investment options: Because of the expected spillover effects and the significance of investment requirements, strategic prioritization and coordination are called for not only within a country but also in the East African region. For instance, consider an alternative investment option that would halve the waiting time at the port of Mombasa from 260 hours to 130 hours.[12] The total port costs would decline from $78 to $49 per ton. Kenya would greatly benefit from this investment, but benefits would also be accrued to Uganda and the northern part of Tanzania (Table 4). Burundi and Rwanda could also benefit to a certain extent. From the regional point of view, this investment choice would be more cost-effective than the above-mentioned port improvement project at Dar es Salaam, "if" everything else, including investment costs, remained the same.

[12] Kenya embarked upon a significant expansion project at the port of Mombasa in 2013. The first phase of the terminal is expected to be completed by 2016 and the whole project will be completed by 2020, increasing the port capacity from 750,000 TEU to 1.2 million TEU. The project cost is estimated at $366 million.

Table 2. Estimated output elasticities with respect to transport accessibility

	Burundi, Rwanda & Uganda		Kenya		Tanzania							
					Tabora		Mbeya		Arusha		Coastal	
	T_0	T_1	T_0	T_1	T_0	T_1	T_0	T_1	T_0	T_1	T_0	T_1
Rice	-0.010	-0.117 ***	0.019	-0.091 *	-0.013	-0.100 ***	0.000	-0.244 ***	0.005	-0.125 ***	-0.025 *	-0.037
	(0.017)	(0.024)	(0.032)	(0.053)	(0.010)	(0.021)	(0.020)	(0.035)	(0.021)	(0.044)	(0.014)	(0.028)
Maize	0.011	0.028 *	0.020	-0.142 ***	-0.019 **	-0.048 ***	-0.021 **	-0.082 ***	-0.008	-0.203 ***	-0.043 ***	-0.068 **
	(0.011)	(0.017)	(0.013)	(0.023)	(0.008)	(0.016)	(0.010)	(0.019)	(0.012)	(0.027)	(0.012)	(0.028)
Cassava	-0.005	-0.039 **	0.022	-0.169 ***	-0.002	-0.207 ***	-0.134 ***	0.047	-0.001	-0.109 ***	-0.024	-0.252 ***
	(0.013)	(0.019)	(0.017)	(0.028)	(0.016)	(0.037)	(0.018)	(0.029)	(0.013)	(0.030)	(0.020)	(0.038)
Bananas	-0.020 **	-0.013	-0.049 **	0.060 *	-0.011	0.005	-0.040	-0.042	0.008	0.041	0.010	-0.109 ***
	(0.009)	(0.013)	(0.019)	(0.032)	(0.025)	(0.041)	(0.037)	(0.071)	(0.015)	(0.028)	(0.022)	(0.034)

	Burundi, Rwanda & Uganda		Kenya		Tanzania (all regions)	
	T_0	T_2	T_0	T_2	T_0	T_2
Coffee	-0.003	-1.644 ***	-0.045 **	-0.804 ***	-0.055 **	-0.437 ***
	(0.007)	(0.097)	(0.018)	(0.094)	(0.023)	(0.076)
Tea	-0.013 **	-0.254 ***	0.029	-1.270 *	-0.005	-0.218 ***
	(0.007)	(0.030)	(0.024)	(0.767)	(0.032)	(0.060)
Cotton	0.004	-0.647 ***	-0.020	-4.623 ***	-0.009	-0.853 ***
	(0.009)	(0.027)	(0.021)	(0.340)	(0.012)	(0.077)
Tobacco	-0.014 **	-0.831 ***	0.090 ***	-3.312 ***	0.004	-1.157 ***
	(0.007)	(0.262)	(0.030)	(0.634)	(0.008)	(0.039)

Source: Based on the SPTobit estimation results (shown in Annex Tables).

Table 3. Predicted production increases by halving the port waiting time at Dar es Salaams

	Increase in production value ($ million)					% of GDP
	Coffee	Tea	Cotton	Tobacco	Total	(2010)
Burundi	17.1	0.5	0.4	0.3	18.3	0.90
Kenya	0.0	0.0	0.0	0.0	0.0	0.00
Rwanda	12.4	1.4	0.0	1.0	14.8	0.26
Tanzania	13.1	2.7	72.2	29.8	117.7	0.51
Uganda	0.9	0.2	0.2	0.2	1.4	0.01
Total	43.4	4.8	72.8	31.2	152.2	0.19

Source: Authors' calculation based on the SPTobit estimation results.

Table 4. Predicted production increases by halving the port waiting time at Dar es Salaams

	Increase in production value ($ million)					% of GDP
	Coffee	Tea	Cotton	Tobacco	Total	(2010)
Burundi	14.3	0.4	0.3	0.2	15.3	0.75
Kenya	109.8	181.9	128.9	19.1	439.6	1.37
Rwanda	10.9	1.3	0.0	0.9	13.0	0.23
Tanzania	12.4	1.7	69.7	20.3	104.1	0.45
Uganda	167.4	2.9	13.4	4.8	188.4	1.10
Total	314.8	188.1	212.3	45.3	760.4	0.95

Source: Authors' calculation based on the SPTobit estimation results.

V. CONCLUSION

Africa has great potential for agriculture. However, the potential has not been fully explored yet. It is important to accelerate agricultural growth further, because Africa is currently importing significant amounts of food from abroad, though Africa can feed itself from the agro-ecological point of view.

The literature suggests a lot of constraints, from fertilizer use to public infrastructure availability. The current paper focuses on the relationship between major crop production and transport connectivity in the East Africa Community. Unlike the existing literature, the paper generates new agricultural production data for each crop at the detailed spatial resolution. In addition, spatial data is also developed to measure transport connectivity from each production location to the destination, either domestic market or port to export crops.

To deal with autocorrelation and censoring in data, the spatial tobit regression model was used in the paper. The results are consistent with prior expectation. Spatial autocorrelation matters, presumably because our agricultural production data are spatially connected to neighboring areas. In addition, transport infrastructure is a typical network industry. Therefore, it is methodologically important to take autocorrelations into account: OLS estimation is likely biased.

It is also found that the impacts of transport accessibility on agriculture production vary across areas and crops. However, the results suggest that both rural accessibility and market access are important to stimulate agriculture production. Particularly, for export crops, access to port is found to be crucial: In some cases (e.g., coffee in the landlocked countries, tea in Kenya and tobacco in Tanzania), the estimated elasticities exceed one, implying that public investments to improve transport connectivity for these crops are highly profitable from the economic point of view.

There are many possible investment options to improve transport connectivity in the region. For illustration purposes, the paper examined two particular scenarios under the assumption that the waiting time costs at the two regional ports, Mombasa and Dar-es-Salaam, would be halved. The expected impacts are different, depending on estimated elasticity and the current level of production. But the results indicate that infrastructure investment tends to have a spillover effect in the region. Therefore, strategic prioritization and coordination may be important not only within a country but also in the whole East African region.

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ANNEX

Annex Table 1. Comparison between SPAM 2000 and SPAM 2010

Data type	Resolution	SPAM2000	SPAM2010
Number of crops allocated	N/A	20 crops and calculated rest (excluding pastures)	42 crops (excluding pastures and fodder)
Subnational crop statistics	Level 1 or level 2 administrative units	Centered around 2000	Country statistics available on the web or from direct country sources; centered around 2010, or earlier year if not available
National crop statistics	Country level	FAOSTAT average 1999-2001 last downloaded in May 2011 [1]	FAOSTAT average 2009-2011, downloaded in August 2013
Production system shares	Country level or Level 1 administrative units	Various literature and expert judgments	Same as for SPAM2000
Irrigated areas (areas equipped for irrigation)	5 deg min pixels	Siebert, S., Döll, P., Hoogeveen, J. (2002). "Global map of irrigated areas version 2.1." Center for Environmental Systems Research, University of Kassel, and FAO.	Same as for SPAM2000
Landcover, agricultural areas	5 deg min pixels	Ramankutty et al. (2008), "Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000", Global Biogeochemical Cycles, Vol. 22, GB1003, doi:10.1029/2007GB002952.	S. Fritz and Linda See (2013). Ag-land surface, IIASA.
Crop suitabilities (area and yield)	5 deg min pixels	GAEZ 2000, FAO/IIASA	IIASA/FAO (2010). Global Agro-ecological Zones (GAEZ v3.0). IIASA and FAO, and HarvestChoice (2010)
Rural population density	5 deg min pixels	Global Rural-Urban Mapping Project (GRUMP), v1.Center for International Earth Science Information Network (CIESIN), Columbia University; IFPRI; The World Bank; and Centro Internacional de Agricultura Tropical (CIAT). 2004.	Same as for SPAM2000
Crop distribution	5 deg min pixels	CG centers, expert knowledge	Same as for SPAM2000
Crop prices	Country level	FAO International $ PPP avg (1999-2001), calculated from FAOSTAT in 2003	FAO International $ PPP avg (2004-2006), calculated from FAOSTAT in 2013
Boundaries of administrative units	Country, level 1 and level 2	GADM	GAUL2008, version 2009

1/ FAOSTAT updates its production time series not only for new years, but sometimes also backwards for past years.

Annex Table 2. Data sources of sub-national crop statistics

Country	Source	Year
Burundi	Downloaded from CountrySTAT on May 7, 2013. Only production at Level 1 administrative units. Yield taken from FAO.	Avg 2004-2006
Kenya	The Kenya Agricultural Sector Data Compendium, Vol2, Jan 2009. Area and production at Level 1 and level 2 administrative units.	Avg 2004-2006 for main crops, and avg 2009-2011 for horticulture
Rwanda	Downloaded from CountrySTAT in October 2012. Only production at Level 1 administrative units. Yield taken from FAO.	Avg. 2006-2008
Tanzania	MoAG Tanzania, Agricultural area, production and yield by region and district (level 1 and level 2).	Avg 2006-2009
Uganda	Uganda Census of Agriculture 2008-2009. Level 1 and level 2.	Sum of last season in 2008 and first season in 2009

Annex Table 3. OLS and spatial autocorrelation tobit estimation: Food crops, Burundi, Rwanda and Uganda

	Rice		Maize		Cassava		Bananas	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln$A$	-0.011	0.002	0.300 ***	0.269 ***	0.016 ***	0.044 ***	0.036 ***	0.058 ***
	(0.013)	(0.011)	(0.017)	(0.014)	(0.004)	(0.006)	(0.005)	(0.005)
ln$L$	0.005	0.004	0.117 ***	0.104 ***	0.013	0.004	0.062 ***	0.061 ***
	(0.014)	(0.014)	(0.015)	(0.012)	(0.013)	(0.013)	(0.015)	(0.010)
ln$R$	0.629 ***	0.738 ***	0.960 ***	0.939 ***	0.986 ***	0.983 ***	0.957 ***	0.921 ***
	(0.021)	(0.020)	(0.007)	(0.006)	(0.009)	(0.010)	(0.011)	(0.012)
ln$I$	0.582 ***	0.768 ***	3.209 ***	0.001 ***				
	(0.031)	(0.034)	(0.341)	(0.000)				
ln$F$	0.002	0.007	-1.713 ***	0.226 ***	-0.003	-0.018 ***	0.056 ***	0.068 ***
	(0.011)	(0.011)	(0.210)	(0.040)	(0.005)	(0.007)	(0.003)	(0.004)
lnT_0	0.001	-0.010	0.019	0.011	-0.003	-0.005	-0.017 *	-0.020 **
	(0.024)	(0.017)	(0.013)	(0.011)	(0.013)	(0.013)	(0.010)	(0.009)
lnT_1	-0.152 ***	-0.117 ***	0.100 ***	0.028 *	-0.058 ***	-0.039 **	-0.009	-0.013
	(0.032)	(0.024)	(0.018)	(0.017)	(0.020)	(0.019)	(0.015)	(0.013)
constant	3.923 ***	5.823 ***	0.948 ***	-32.599	2.208 ***	38.318	1.265 ***	42.531
	(0.133)	(1.861)	(0.356)	(29.313)	(0.105)	(36.096)	(0.093)	(40.470)
Obs.	964	2860	1669	2860	1409	2860	1486	2860
Censored		1899		1341		1453		1396
Uncensored		961		1519		1407		1464
R-squared	0.7256	0.9009	0.9568	0.9486	0.9188	0.9692	0.9673	0.9901
F-stat	139.72	3703.942	3942.42	7520.8	3402.56	14971.8	8586.94	47610.5
auto-correlation parameters:								
lambda		-0.208 **		0.194 ***		-0.059		-0.059 *
		(0.102)		(0.050)		(0.055)		(0.032)
rho		0.714 ***		0.977 ***		0.974 ***		0.987 ***
		(0.114)		(0.022)		(0.026)		(0.013)

Annex Table 4. OLS and spatial autocorrelation tobit estimation: Export crops, Burundi, Rwanda and Uganda

	Coffee		Tea		Cotton		Tobacco	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln*A*	0.084 ***	0.169 ***	0.129 ***	0.148 ***	0.295 ***	0.316 ***	0.147 ***	0.135 ***
	(0.022)	(0.020)	(0.019)	(0.017)	(0.019)	(0.020)	(0.027)	(0.021)
ln*L*	-0.098 ***	-0.079 ***	0.039 ***	0.020 **	0.033 ***	0.041 ***	0.058 ***	0.035 ***
	(0.011)	(0.009)	(0.010)	(0.009)	(0.007)	(0.008)	(0.009)	(0.011)
ln*R*	0.715 ***	0.349 ***	1.069 ***	1.062 ***	0.973 ***	0.998 ***	1.130 ***	0.852 ***
	(0.044)	(0.035)	(0.022)	(0.020)	(0.011)	(0.018)	(0.043)	(0.175)
ln*I*								
ln*F*	0.182 ***	0.724 ***	-0.003	-0.043 ***			-0.215 ***	0.228
	(0.051)	(0.040)	(0.004)	(0.004)			(0.058)	(0.154)
lnT_0	-0.032 ***	-0.003	0.008	-0.013 **	0.004	0.004	0.010	-0.014 **
	(0.010)	(0.007)	(0.008)	(0.007)	(0.010)	(0.009)	(0.009)	(0.007)
lnT_2	-0.089	-1.644 ***	-0.318 *	-0.254 ***	-0.103	-0.647 ***	-0.375	-0.831 ***
	(0.287)	(0.097)	(0.172)	(0.030)	(0.155)	(0.027)	(0.278)	(0.262)
constant	-0.166	204.128	0.916	2.392 ***	-1.527 *	9.255	2.213	1.735 ***
	(1.694)	(224.014)	(0.927)	(0.244)	(0.837)	(7.020)	(1.371)	(0.280)
Obs.	927	2860	1010	2860	753	2860	1160	2860
Censored		1943		1856		2127		1754
Uncensored		917		1004		733		1106
R-squared	0.9265	0.4341	0.8297	0.789	0.9531	0.9779	0.8839	0.1565
F-stat	3043.82	364.7999	655.98	1778.1	2972.94	25219.4	1245.18	88.2
auto-correlation parameters:								
Lambda		-0.766 ***		-0.674 ***		-0.649 ***		0.240
		(0.121)		(0.054)		(0.084)		(0.295)
rho		0.988 ***		0.318 ***		0.903 ***		-1.276 ***
		(0.014)		(0.091)		(0.084)		(0.101)

Annex Table 5. OLS and spatial autocorrelation tobit estimation: Food crops, Kenya

	Rice		Maize		Cassava		Bananas	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln*A*	-0.035 **	-0.058 ***	0.037 ***	-0.050 ***	-0.013 *	-0.023 **	0.046 ***	0.046 ***
	(0.017)	(0.020)	(0.014)	(0.009)	(0.008)	(0.010)	(0.008)	(0.010)
ln*L*	-0.161 *	-0.186 ***	0.175 ***	-0.172 ***	0.013	0.015	-0.088 ***	-0.090 ***
	(0.092)	(0.071)	(0.028)	(0.019)	(0.012)	(0.014)	(0.020)	(0.023)
ln*R*			0.962 ***	0.806 ***	1.067 ***	1.005 ***	1.061	1.034 ***
			(0.029)	(0.025)	(0.018)	(0.025)	(0.016)	(0.015)
ln*I*	1.134 ***	1.127 ***						
	(0.024)	(0.023)						
ln*F*			0.024 **	0.074 ***				
			(0.011)	(0.011)				
lnT_0	0.016	0.019	0.065 ***	0.020	0.029 *	0.022	-0.049 **	-0.049 **
	(0.042)	(0.032)	(0.017)	(0.013)	(0.018)	(0.017)	(0.021)	(0.019)
lnT_1	-0.137 **	-0.091 *	-0.155 ***	-0.142 ***	-0.199 ***	-0.169 ***	0.005	0.060 *
	(0.069)	(0.053)	(0.033)	(0.023)	(0.028)	(0.028)	(0.035)	(0.032)
constant	1.900 **	7.162	-1.122 ***	81.113	1.820 ***	21.615	2.823 ***	36.163
	(0.648)	(6.661)	(0.221)	(81.678)	(0.069)	(17.618)	(0.101)	(26.167)
Obs.	87	2471	1611	2471	830	2471	733	2471
Censored		2385		870		1645		1762
Uncensored		86		1601		826		709
R-squared	0.9552	0.9078	0.8183	0.9455	0.8943	0.9271	0.9148	0.8509
F-stat	807.66	4851.845	2153.27	7130.38	1746.07	6274.23	1897.69	2813.3
auto-correlation parameters:								
lambda		0.854 ***		0.861 ***		0.295 **		-0.171
		(0.132)		(0.043)		(0.118)		(0.126)
rho		0.735 ***		0.994 ***		0.949 ***		0.947 ***
		(0.231)		(0.006)		(0.042)		(0.039)

Annex Table 6. OLS and spatial autocorrelation tobit estimation: Export crops, Kenya

	Coffee		Tea		Cotton		Tobacco	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln*A*	0.307 ***	0.287 ***	0.291 ***	0.374 ***	0.229 ***	0.280 ***	0.282 ***	0.234 ***
	(0.084)	(0.051)	(0.083)	(0.050)	(0.035)	(0.036)	(0.040)	(0.045)
ln*L*	0.021	0.018	0.023	0.014	0.113 ***	0.061 **	0.020	0.114 ***
	(0.031)	(0.028)	(0.017)	(0.016)	(0.028)	(0.026)	(0.032)	(0.038)
ln*R*	0.776 ***	0.673 ***	0.526 ***	0.585 ***	1.233 ***	1.172 ***	0.773 ***	0.709 ***
	(0.022)	(0.026)	(0.053)	(0.048)	(0.027)	(0.030)	(0.024)	(0.032)
ln*I*	0.186 ***	0.200 ***	0.107 ***	0.151 ***			0.324 ***	0.205 ***
	(0.019)	(0.022)	(0.017)	(0.021)			(0.033)	(0.029)
ln*F*	0.058 ***	0.067 ***	0.237 ***	0.233 ***				
	(0.014)	(0.010)	(0.044)	(0.037)				
$\ln T_0$	-0.070 ***	-0.045 **	0.019	0.029	-0.019	-0.020	0.045 *	0.090 ***
	(0.025)	(0.018)	(0.030)	(0.024)	(0.021)	(0.021)	(0.027)	(0.030)
$\ln T_2$	-1.304 **	-0.804 ***	-0.652	-1.270 *	-4.697 ***	-4.623 ***	0.524	-3.312 ***
	(0.642)	(0.094)	(1.019)	(0.767)	(0.351)	(0.340)	(0.543)	(0.634)
constant	4.345	3.608 *	3.197	6.710 *	19.140 ***	14.963 ***	-3.251	16.443 ***
	(3.406)	(1.899)	(4.818)	(4.008)	(1.707)	(1.638)	(2.619)	(2.828)
Obs.	579	2471	300	2471	454	2471	352	2471
Censored		1984		2177		2032		2243
Uncensored		487		294		439		228
R-squared	0.9137	0.8555	0.8837	0.3395	0.9059	0.6033	0.9313	0.174
F-stat	886.46	2083.836	165.03	180.826	858.63	749.749	852.04	86.4852
auto-correlation parameters:								
lambda		0.257		-0.484 **		0.843 ***		0.502 *
		(0.162)		(0.233)		(0.132)		(0.264)
rho		0.489		0.124		-0.320 ***		0.133
		(0.347)		(0.303)		(0.044)		(0.096)

Annex Table 7. OLS and spatial autocorrelation tobit estimation: Food crops, Tabora Area, Tanzania

	Rice		Maize		Cassava		Bananas	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln*A*	0.251 ***	0.104 ***	0.131 ***	0.111 ***	0.238 ***	0.089 ***	0.154 ***	0.030
	(0.045)	(0.018)	(0.029)	(0.023)	(0.037)	(0.014)	(0.037)	(0.034)
ln*L*	-0.004	-0.054 ***	-0.005	-0.055 **	0.031 *	0.006	-0.090 *	-0.097 **
	(0.016)	(0.020)	(0.017)	(0.026)	(0.018)	(0.016)	(0.048)	(0.044)
ln*R*	0.885 ***	0.977 ***	0.782 ***	0.756 ***	0.927 ***	0.934 ***	1.010 ***	1.042 ***
	(0.021)	(0.020)	(0.027)	(0.028)	(0.017)	(0.017)	(0.018)	(0.020)
ln*I*								
ln*F*	0.088 ***	-0.046 **	0.075 ***	0.059 **				
	(0.024)	(0.022)	(0.026)	(0.027)				
lnT_0	-0.008	-0.013	-0.020 **	-0.019 **	0.017	-0.002	-0.019	-0.011
	(0.010)	(0.010)	(0.008)	(0.008)	(0.016)	(0.016)	(0.025)	(0.025)
lnT_1	-0.067 ***	-0.100 ***	-0.011	-0.048 ***	-0.153 ***	-0.207 ***	0.128 ***	0.005
	(0.019)	(0.021)	(0.014)	(0.016)	(0.036)	(0.037)	(0.046)	(0.041)
constant	-1.227 ***	13.291	-0.240	18.985	-0.011	26.927	0.519 *	10.106
	(0.395)	(12.155)	(0.336)	(17.524)	(0.354)	(19.760)	(0.322)	(6.630)
Obs.	1116	2338	1134	2338	1123	2338	430	2338
Censored		1247		1205		1217		1925
Uncensored		1091		1133		1121		413
R-squared	0.9513	0.9877	0.7943	0.9933	0.7957	0.9661	0.9518	0.9636
F-stat	2253.05	31151.22	489.34	58032.2	1508.85	13274.3	1697.27	12335.3
auto-correlation parameters:								
lambda		-0.223 ***		-0.281 ***		-0.334 ***		-0.503 ***
		(0.042)		(0.037)		(0.051)		(0.131)
rho		0.964 ***		0.977 ***		0.968 ***		0.847 ***
		(0.036)		(0.023)		(0.025)		(0.110)

Annex Table 8. OLS and spatial autocorrelation tobit estimation: Food crops, Mbeya Area, Tanzania

	Rice		Maize		Cassava		Bananas	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln*A*	0.256 ***	0.053 ***	0.381 ***	0.232 ***	0.182 ***	0.155 ***	0.082 ***	0.252 ***
	(0.052)	(0.019)	(0.016)	(0.019)	(0.016)	(0.010)	(0.019)	(0.029)
ln*L*	0.206 ***	0.063 **	0.024 *	-0.222 ***	-0.190 ***	-0.212 ***	0.024	-0.116 ***
	(0.033)	(0.025)	(0.014)	(0.028)	(0.025)	(0.026)	(0.040)	(0.034)
ln*R*	0.842 ***	0.770 ***	0.925 ***	0.742 ***	0.997 ***	0.968 ***	0.819 ***	0.727 ***
	(0.025)	(0.027)	(0.018)	(0.028)	(0.019)	(0.021)	(0.015)	(0.019)
ln*I*								
ln*F*	0.055 ***	0.045 ***	0.060 ***	0.082 ***				
	(0.009)	(0.014)	(0.009)	(0.012)				
lnT_0	0.029	0.000	0.001	-0.021 **	-0.150 ***	-0.134 ***	-0.039	-0.040
	(0.019)	(0.020)	(0.009)	(0.010)	(0.019)	(0.018)	(0.038)	(0.037)
lnT_2	-0.210 ***	-0.244 ***	0.025 *	-0.082 ***	0.072 ***	0.047	0.073	-0.042
	(0.030)	(0.035)	(0.015)	(0.019)	(0.028)	(0.029)	(0.081)	(0.071)
constant	-1.388 ***	17.903	-3.106 ***	22.991	0.809 ***	21.577	1.795 ***	3.852 *
	(0.512)	(16.913)	(0.211)	(22.467)	(0.165)	(19.933)	(0.222)	(2.127)
Obs.	630	2675	856	2675	606	2675	296	2675
Censored		2058		1826		2079		2393
Uncensored		617		849		596		282
R-squared	0.9086	0.9868	0.9355	0.9949	0.8942	0.9863	0.9214	0.8388
F-stat	876.26	33322.05	1692.47	87072.8	1006.54	38501.6	963.44	2778.21
auto-correlation parameters:								
lambda		0.283 ***		0.203 ***		-0.444 ***		0.668 ***
		(0.089)		(0.070)		(0.097)		(0.208)
rho		0.943 ***		0.971 ***		0.946 ***		0.484
		(0.054)		(0.028)		(0.052)		(0.303)

Annex Table 9. OLS and spatial autocorrelation tobit estimation: Food crops, Arusha Area, Tanzania

	Rice		Maize		Cassava		Bananas	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln*A*	0.139 ***	-0.157 ***	0.465 ***	0.244 ***	0.301 ***	0.211 ***	-0.036 ***	-0.069 ***
	(0.049)	(0.035)	(0.015)	(0.021)	(0.023)	(0.009)	(0.007)	(0.009)
ln*L*	0.192 ***	-0.029	0.074 ***	-0.188 ***	-0.050 ***	-0.144 ***	0.058 ***	-0.026 *
	(0.029)	(0.051)	(0.011)	(0.021)	(0.010)	(0.018)	(0.014)	(0.014)
ln*R*	0.565 ***	0.591 ***	0.777 ***	0.755 ***	0.888 ***	0.846 ***	1.024 ***	1.018 ***
	(0.038)	(0.036)	(0.017)	(0.022)	(0.013)	(0.016)	(0.016)	(0.015)
ln*I*								
ln*F*	0.354 ***	0.318 ***	0.111 ***	0.066 ***				
	(0.050)	(0.041)	(0.013)	(0.016)				
$\ln T_0$	0.006	0.005	0.004	-0.008	0.009	-0.001	0.001	0.008
	(0.022)	(0.021)	(0.009)	(0.012)	(0.015)	(0.013)	(0.017)	(0.015)
$\ln T_1$	0.042	-0.125 ***	-0.006	-0.203 ***	-0.084 ***	-0.109 ***	0.024	0.041
	(0.040)	(0.044)	(0.017)	(0.027)	(0.028)	(0.030)	(0.037)	(0.028)
constant	-1.890 ***	27.605	-3.677 ***	23.680	0.084	21.548	1.466 ***	11.370
	(0.493)	(24.998)	(0.158)	(23.728)	(0.204)	(21.563)	(0.083)	(9.465)
Obs.	632	1979	772	1979	599	1979	370	1979
Censored		1358		1216		1382		1609
Uncensored		621		763		597		370
R-squared	0.8064	0.9506	0.9522		0.9414	0.9844	0.97	0.9475
F-stat	460.46	6323.41	1884.51		2807.05	24904.5	3398.25	7126.0
auto-correlation parameters:								
lambda		0.052		0.239 ***		0.385 ***		0.894 ***
		(0.140)		(0.058)		(0.085)		(0.072)
rho		0.958 ***		0.975 ***		0.962 ***		0.900 ***
		(0.038)		(0.025)		(0.038)		(0.081)

Annex Table 10. OLS and spatial autocorrelation tobit estimation: Food crops, Coastal Area, Tanzania

	Rice		Maize		Cassava		Bananas	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln*A*	0.161 ***	0.017	0.333 ***	0.166 ***	0.210 ***	0.141 ***	0.165 ***	0.241 ***
	(0.031)	(0.015)	(0.025)	(0.026)	(0.025)	(0.017)	(0.016)	(0.033)
ln*L*	-0.036 *	-0.045 **	-0.058 ***	-0.172 ***	-0.032	-0.089 ***	-0.078	-0.140 ***
	(0.021)	(0.020)	(0.019)	(0.030)	(0.022)	(0.023)	(0.056)	(0.045)
ln*R*	0.942 ***	0.968 ***	0.787 ***	0.703 ***	0.892 ***	0.883 ***	1.028 ***	1.032 ***
	(0.017)	(0.018)	(0.019)	(0.022)	(0.022)	(0.021)	(0.022)	(0.019)
ln*I*								
ln*F*	0.001	-0.019 *	0.107 ***	0.112 ***				
	(0.009)	(0.011)	(0.013)	(0.017)				
lnT_0	-0.008	-0.025 *	-0.001	-0.043 ***	-0.002	-0.024	-0.002	0.010
	(0.013)	(0.014)	(0.011)	(0.012)	(0.021)	(0.020)	(0.018)	(0.022)
lnT_2	0.007	-0.037	0.023	-0.068 **	-0.196 ***	-0.252 ***	-0.033	-0.109 ***
	(0.023)	(0.028)	(0.025)	(0.028)	(0.033)	(0.038)	(0.036)	(0.034)
constant	-0.204	18.761	-1.991 ***	40.590	0.661 **	13.058	1.134 ***	3.125 **
	(0.237)	(16.346)	(0.251)	(39.552)	(0.267)	(8.874)	(0.278)	(1.426)
Obs.	837	2073	824	2073	845	2073	279	2073
Censored		1239		1252		1233		1845
Uncensored		834		821		840		228
R-squared	0.9228	0.977	0.8808	0.9896	0.7679	0.9749	0.979	0.1515
F-stat	1482.31	14625.73	1395.82	32883.4	450.25	16088.1	3914.71	73.7963
auto-correlation parameters:								
lambda		-0.261 ***		-0.305 ***		-0.412 ***		-0.685 ***
		(0.063)		(0.048)		(0.055)		(0.173)
rho		0.965 ***		0.985 ***		0.908 ***		0.534 **
		(0.032)		(0.015)		(0.073)		(0.269)

Annex Table 11. OLS and spatial autocorrelation tobit estimation: Export crops, Tanzania

	Coffee		Tea		Cotton		Tobacco	
	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT	OLS	SPTOBIT
ln*A*	0.193 ***	0.107 ***	-0.024	0.072 **	0.437 ***	0.374 ***	0.365 ***	0.346 ***
	(0.024)	(0.029)	(0.016)	(0.032)	(0.023)	(0.045)	(0.017)	(0.017)
ln*L*	-0.111 ***	-0.176 ***	-0.086	-0.111 *	0.012	0.056 ***	0.171 ***	0.137 ***
	(0.021)	(0.030)	(0.065)	(0.064)	(0.009)	(0.010)	(0.010)	(0.012)
ln*R*	0.770 ***	0.581 ***	1.082 ***	0.900 ***	0.956 ***	0.959 ***	0.339 ***	0.521 ***
	(0.019)	(0.039)	(0.036)	(0.038)	(0.011)	(0.020)	(0.020)	(0.020)
ln*I*								
ln*F*	0.146 ***	0.193 ***	0.083 ***	0.120 ***			0.852 ***	0.507 ***
	(0.015)	(0.022)	(0.008)	(0.011)			(0.037)	(0.030)
lnT_0	-0.064 ***	-0.055 **	0.009	-0.005	0.006	-0.009	-0.009	0.004
	(0.021)	(0.023)	(0.026)	(0.032)	(0.012)	(0.012)	(0.010)	(0.008)
lnT_2	0.038	-0.437 ***	1.668 ***	-0.218 ***	-0.040	-0.853 ***	0.291 ***	-1.157 ***
	(0.028)	(0.076)	(0.250)	(0.060)	(0.075)	(0.077)	(0.042)	(0.039)
constant	-1.642 ***	29.206	-8.151 ***	4.312 ***	-3.016 ***	14.075	-8.579 ***	49.392
	(0.241)	(30.413)	(1.233)	(1.655)	(0.418)	(10.155)	(0.318)	(45.470)
Obs.	687	2740	264	1882	1166	2721	1458	2816
Censored		2169		1625		1587		1545
Uncensored		571		257		1134		1271
R-squared	0.8804	0.7536	0.8588	0.9471	0.9392	0.9479	0.9299	0.9139
F-stat	1587.21	1392.791	160.72	5590.71	3457.67	9879.11	2058.46	4971.93
auto-correlation parameters:								
lambda		0.341 **		-0.871 ***		-0.430 ***		-0.246 ***
		(0.156)		(0.206)		(0.060)		(0.047)
rho		0.949 ***		0.603 ***		0.946 ***		0.989 ***
		(0.053)		(0.209)		(0.042)		(0.010)

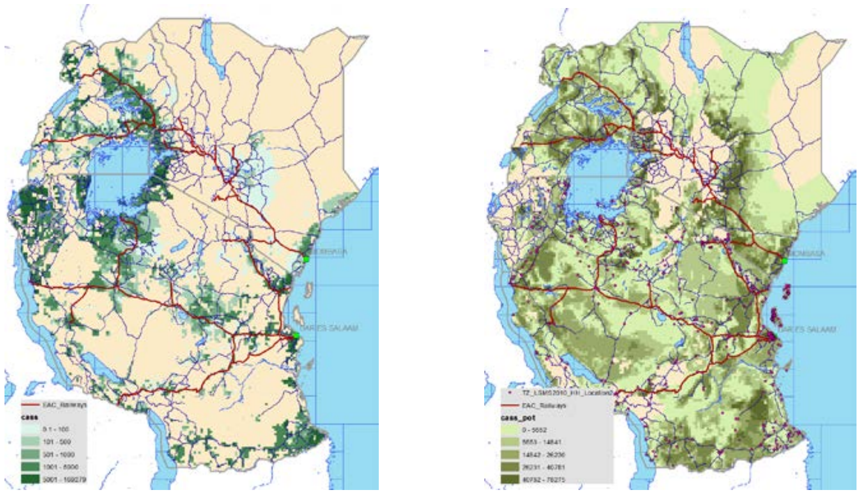
Annex Figure 1. Comparison between actual and potential crop production areas (MT)

(Actual) **(Potential)**

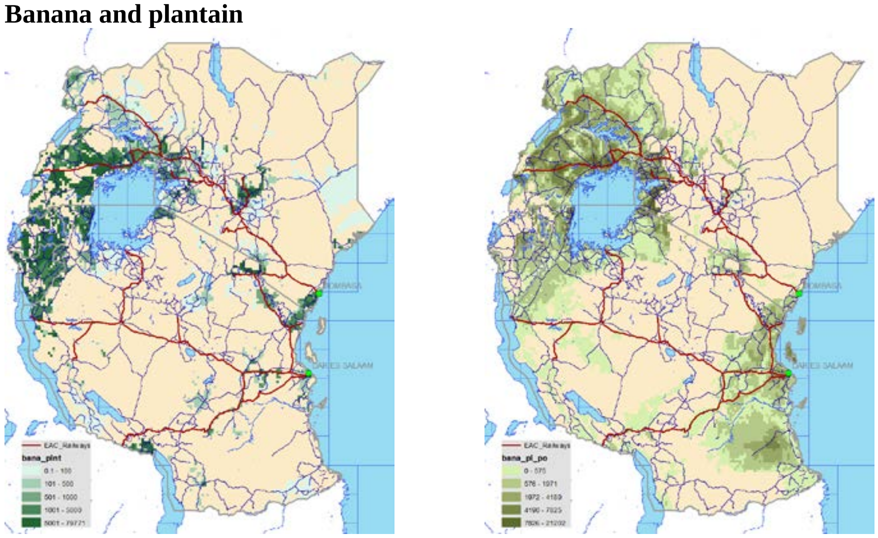
Maize

Rice

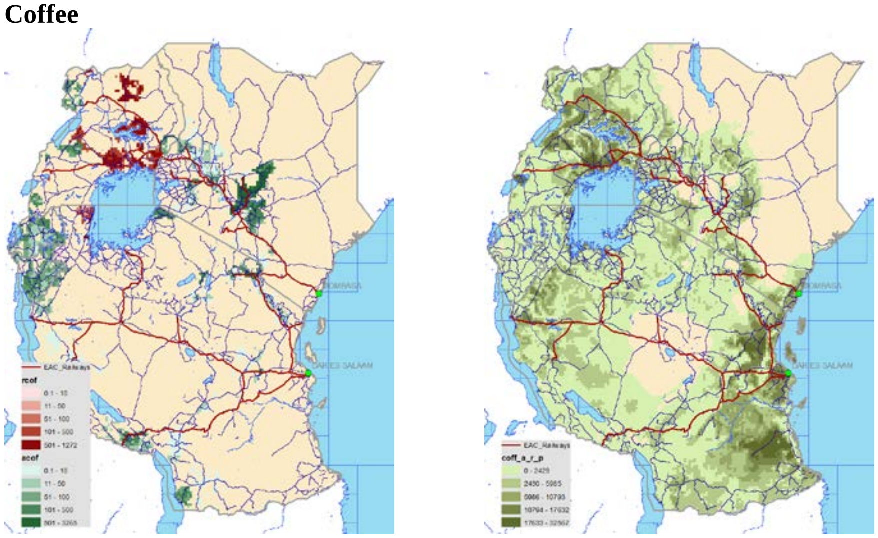
Cassava



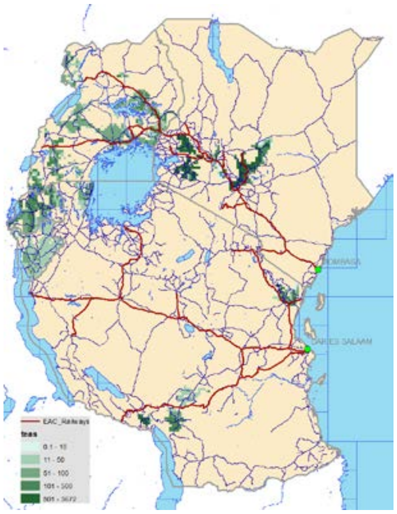
Banana and plantain



Coffee



Tea



Tobacco

Cotton