Economics of global yield gaps: A spatial analysis

Uris Lantz C. Baldos and Thomas W. Hertel

Department of Agricultural Economics
Purdue University
West Lafayette, IN 47907-2056
E-mail: ubaldos@purdue.edu

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Abstract

In this paper, we contribute to the existing literature of global yield gap analysis by using geo-spatial dataset on crop yields, agro-climatic factors and selected socio-economic variables. In line with the literature, we link yield gaps to technical efficiencies. By treating each grid-cell as a farm unit, we employ data envelopment analysis to calculate relative farm efficiencies with respect to a technically efficient global production frontier. We then apply spatial econometric techniques to relate the calculated efficiency scores to population, irrigation, fertilizer use, market access, institutional strength and market influence. We find that the effects of the socio-economic variables on the efficiency scores are not consistent and will typically vary by geographic region, crop type and on the scope of analysis (all areas, irrigated areas only, rainfed areas only). However, we can see some general trends. Most of the total impacts of socio-economic variables on efficiency scores are positive. For example, across all crops, regions and all areas, estimates of the total impact of irrigation, fertilizer use, institutional strength and market influence are generally positive. In regions wherein efficiency scores are low, the key variables which positively affect these scores are market influence and fertilizer use. By changing the coverage from all areas to either rainfed or irrigated areas, we generally see changes in the statistical significance of some variables.

I. Background and Motivation

Over the past fifty years, most of the growth in global crop production has been driven by greater cropping intensity and, especially, growth in crop yields (Bruinsma, 2009). However, some authors have recently raised concerns that agricultural yield growth may be slowing in critical parts of the world (Fischer, Byerlee, & Edmeades, 2009; FAO, 2006; Ramankutty, 2010; Tweeten & Thompson, 2009). Since there are limits to increasing crop yields in areas wherein intensive agriculture is already being practiced, global average yields can only be increased significantly if the differences in crop yields within and among countries are narrowed down.

The causes of yield differences, or yield gaps[1], can be attributed to several factors. Physical factors which directly influence crop growth include temperature, humidity, soil conditions and solar radiation (van Ittersum & Rabbinge, 1997). Biophysical factors such as pests, weeds, crop varieties and diseases also contribute to these gaps (Duwayri, Tran, & Nguyen, 2000). There are also socio-economic factors which influence crop yields. These include supply and demand conditions, commodity and input prices, access to transportation systems as well as farm extension services and technologies (Fageria, 1992). Other socio-economic factors include labor shortages, welfare conditions and the farmer's prevailing knowledge and skills (Duwayri et al., 2000). Depending on its causes, some yield gaps are more challenging to understand than others. In addition, it is not always commercially beneficial to

[1]Yield gaps have at least two components namely yield potential and actual yields. The actual yields are typically based on the average yield observed from a sample of farmers in a specific location and season (Lobell, Cassman, & Field, 2009; Singh et al., 2009). On the other hand, yield potential has several definitions. It can be the yields attained in experimental stations, yields which are economically profitable for farmers, yields from mathematical crop models or the maximum value of observed yields (De Datta, 1981; Evans, 1993; Fageria, 1992; Singh et al., 2009). Some of these definitions have limitations. For example, crop yields from mathematical simulation models may be generated under unrealistic assumptions of perfect management and lack of natural constraints to crop growth. Maximum observed yields are only applicable in yield gap analysis if these are attained via intensive farming, generally with irrigation present (Lobell et al., 2009).

close these gaps, especially if input costs are high, farmers have poor access to markets, and if they face significant production risks (Evans, 1993; Herdt, 1979).Given these complications, understanding the causes of yield gaps is critical.

In the literature, studies typically use crop production data collected at country, state or regional level (Bravo-Ureta et al., 2006; FAO, 2000; Liu & Myers, 2008; Nisrane et al., 2011; Sekhon et al., 2010; Singh et al., 2009). However, national level data can only provide information on average yields even though there is great heterogeneity in yields within a country. More recently, the availability of global data sets on crop yields at a grid cell level permits the assessment of global yield gaps at a highly disaggregated level (Licker et al., 2010; Neumann et al., 2010). However, to our knowledge, only the paper of Neumann et al (2010) use satellite data in calculating and explaining yield gaps across the world. The authors used stochastic frontier analysis (SFA) which is an econometric technique that has been widely used in estimating and explaining farm inefficiencies which are directly related to crop yields gaps. The authors then attributed the estimated inefficiencies to differences in land management practices. Proxy variables used to capture the effects of land management practices include slope, irrigation, population in the agricultural sector, as well as distance to markets (i.e. market accessibility) and spatially disaggregated purchasing power parity (i.e. market influence).

Despite being innovative, the paper has some limitations. Some of the economic variables considered in the study might not be appropriate proxy variables for land management practices. For example, the authors defined market influence as measure of the suitability of yield-improving investments in agriculture; hence, areas with greater market influence have higher yields. The authors constructed the proxy for market influence using national data on purchasing power parity (PPP) and distances to nearest markets (i.e. market access). However, PPP can only provide information on the purchasing power of different currencies and it might not be a good measure of farm investment suitability.

In addition, the authors did not take advantage of the spatial nature of the data. The authors used the maximum likelihood technique proposed by Battese and Coelli (1995) in order to estimate the production frontier and technical efficiencies. This approach which is tailored to panel data assumes that the efficiency terms are independently distributed. However, given the spatial nature of the data it is possible that the efficiency terms are correlated across space. As a solution for this problem, the authors used an ad-hoc approach by extracting a random sample of 10% from the grid cells with at least 3% cropping area to ensure that each observation are independent (i.e. reduced spatial autocorrelation). A better alternative is to model the spatial autocorrelation in the data as a spatial stochastic process. Once modeled, the spatial interaction of one location to other location can be used as an explanatory variable (Anselin, 2007).

The main goal of this paper is to contribute to the existing literature on yield gap analysis by using updated geo-spatial data and spatial econometric techniques in explaining the nature of yield gaps across geographic groups. Specifically, we use spatially-disaggregated production data for maize, wheat and rice as well as satellite data on agro-climatic and socio-economic factors at 0.5 degree resolution (around 50 km. x 50 km. at the equator). We employ a two-stage approach. In the first stage, we calculate technical efficiency scores using data envelopment analysis (DEA), a non-parametric technique. These calculated scores which represent the gap between observed yields and technically efficient yields are determined for all areas and across irrigated and rainfed areas. In the second stage, we examine the relationship between these efficiency scores and key socio-economic factors via the spatial Durbin Tobit model. We estimate the spatial model for 8 geographic groups to highlight the regional differences in the impacts of the socio-economic factors on the calculated efficiency scores.

II. Data and Methods

Methods: Crop yield, a partial measure of farm productivity, is related to the concept of technical efficiency. Technical efficiency is associated with firms which produce more output given a set of inputs (Coelli et al., 2005; Farrell, 1957). In this context of this paper, yield gaps can be attributed to the existing inefficiencies across farms. To determine relative efficiencies across producer, researchers map out all possible input-output combination given existing technologies via a production frontier. In the literature, the production frontier is typically estimated using DEA or SFA. DEA, a non-parametric approach, uses mathematical programming in constructing the frontier and in calculating relative firm efficiencies (Banker, Charnes, & Cooper, 1984). In contrast, SFA, a parametric approach, relies on econometric methods (Battese & Coelli, 1995; Coelli, 1995). As summarized by Odeck (2007), the main advantages of using DEA are 1) it does not require an explicit functional form when estimating the production frontier and 2) relative efficiencies are calculated by looking at the most efficient firms within the dataset. However, DEA is heavily influenced by sampling errors and/or errors in data measurement.

In the literature, DEA models have been geared towards calculating inefficiencies in either input use or output production. Input-oriented models aim to maximize the reduction in input use while still maintaining the same optimal level of output. On the other hand, output-oriented models maximize the potential increase in output given a set of input (Murillo-Zamorano, 2004). Because it deals with inefficiencies in output production, output-oriented models are more suitable in yield gap analysis. Aside from input/output orientation, it also is necessary to impose assumptions regarding the returns to scale in production. Initial studies on DEA assume constant returns to scale technology (CRS). Following Charnes, Cooper and Rhodes (1978), an output-oriented optimization model with CRS technology can be written as:

$$Max_{\theta,\mu}\ \theta^0$$

$$s.t. \quad \theta^0 y^0 \leq \sum_{j=1}^{n} y_j \mu_j$$

$$x_i^0 \geq \sum_{j=1}^{n} x_{ij} \mu_j$$

In the optimization problem above, there is a single output and multiple inputs. The efficiency factor is (θ^0) maximized given the observed output and inputs for each observation in the dataset (y^0, x_i^0) and the constraints in the convex combinations of output and inputs levels. The input-output weight for each observation is defined by μ. Once solved, the efficiency factors can be used to calculate the efficiency scores ($\varphi = 1/\theta$) wherein efficient firms have scores closer to 1 (or to 100 if scaled). These scores represent how far the observed output is from the technically efficient frontier given its observed input use.

Under CRS technology, it is implicitly assumed that firms are operating at an optimal scale. However, this assumption might be too restrictive given actual data and can lead to efficiency scores which are biased by returns to scale. A solution for this problem is to impose variable returns to scale in production (VRS). This is operationalized by imposing an additional constraint in the optimization problem above such that the input-output weights would sum to 1 ($\sum_{j=1}^{n} \mu_j = 1$) (Färe, Grosskopf, & Lovell, 1983). With VRS technology, each firm is compared to firms with similar scale; thus, efficiency scores tend to be higher and more firms are efficient under VRS than in CRS. For this reason, we calculate the efficiency scores under VRS.

The efficiency scores are calculated for all areas as well as separately for irrigated and rainfed areas. Imposing separate production frontiers for irrigated and rainfed areas is important since irrigated areas are typically more productive than rainfed areas. Moreover, it allows us to check if the impacts of the socio-economic variables on the efficiency scores are similar or divergent across irrigated and rainfed areas. In line with Neumann et al, we use agro-climactic variables in the calculation of farm efficiencies. Output per grid-cell is measured by crop yields while inputs include precipitation, temperature, terrain constraint, and soil constraint.

Once calculated, we then relate the efficiency scores to selected socio-economic factors via the Tobit model. In the literature, this is the most commonly used model in explaining the DEA scores (Begum et al., 2011; Odeck, 2007; Ramalho, Ramalho, & Henriques, 2010; Speelman et al., 2008; Thiam, Bravo-Ureta, & Rivas, 2005). A generalized Tobit model can be expressed using the following equation:

$$\varphi = \begin{cases} \varphi^*; & 0 \leq \varphi^* \leq 1 \\ 0; & \varphi^* < 0 \\ 1; & 1 < \varphi^* \end{cases} \qquad \varphi^* = x\beta + \Omega$$

wherein $\varphi^*$is the latent dependent variable (i.e. efficiency scores), x is a vector of explanatory variable and Ω is the error term which is independent and normally distributed with mean zero and positive variance. The main argument for using the Tobit model is that the efficiency scores follow a censored data generating process with values in the interval [0, 1]. However, DEA scores typically have values equal to 1 but none with zeroes (McDonald, 2009). This can lead to misspecification issues since the Tobit model requires that there should be positive probabilities of observing both corner values. Despite the lack of zero observations, this model still provide reasonable estimates of DEA scores when compared to other estimation methods (Hoff, 2007).

However, we cannot directly use the Tobit model because it is likely that the calculated efficiency scores are correlated across space. It is also likely that the socio-economic variables that will be used to explain the efficiency scores are spatially correlated due to the nature of the data. As noted by McMillen (1992), heteroskedasticity is generally associated with the presence of spatial autocorrelation in the data and which in turn can lead to inconsistent estimates for limited dependent variable models.

A generalized spatial regression model which takes into account both the influence of the neighboring values of the dependent variable and those of the independent variables is the spatial Durbin model (Anselin, 1988). This model builds on the traditional spatial autoregressive model and is expressed by the following equation:

$$\varphi^* = \rho W \varphi^* + x\beta + Wx\lambda + \Omega$$

wherein ρ is the spatial correlation parameter, $W$is the spatial weight matrix and xW represent the neighboring values of the explanatory variables. Note that the estimates of the parameter $\lambda = -\rho\beta$ capture the marginal effects of the neighboring values of the explanatory variables on the dependent variable.

In order to account for the spatial interaction among the efficiency scores and the explanatory variables, we use the Spatial Durbin Tobit model (SDT) developed by LeSage (2000). LeSage proposed a Gibbs sampling method for estimating spatial models with autoregressive limited dependent variables. This method replaces the censored unobserved observations on the dependent variable using estimated values. With these non-censored values, it is possible estimate the model parameters via maximum likelihood or Bayesian techniques. Furthermore, this method can account for heteroskedasticity issues and also creates posterior distributions regarding the model's parameters which in turn permit statistical inferences regarding their mean and dispersion. To implement the model, we use the code provided by LeSage in his Spatial Econometrics Toolbox (2010) for Matlab.

We estimate the model for 8 world regions in order to see the differences in the significance and marginal impacts of each socio-economic variable to the efficiency scores. For each world region, the spatial weights matrices are constructed using row-standardization and using neighborhood contiguity based on Euclidean distance. We assumed that the relevant neighbors for each observation are within a distance of 100 km. It is required that all observations have at least 1 neighbor in order for the model to solve; thus, we drop the observations which do not meet this requirement.

Data: We collected a variety of geo-spatial and national level data from several sources (Table 1). Most of the geo-spatial data represent the 2000-2001 period. We use yield data for maize, wheat and rice from Monfreda et al. (2008). Temperature and precipitation data were taken from Worldclim (Hijmans et al., 2005) while soil fertility, terrain and slope constraints were collected from Global Agro-Ecological Zones (GAEZ) model (Fischer et al., 2002). Socio-economic variables used in this study include population, fertilizer use, irrigation, market access and proxy variables for market influence and institutional strength. Population is based on the Gridded Population of the World, Version 3 (2005). Fertilizer application rates is taken from Potter et al. (2010) while area of irrigated land is collected from MIRCA (Portmann, Siebert, & Döll, 2010). For market access, we use the global accessibility maps by Nelson (2008) which measures the travel time in minutes to the nearest city with population of 50,000 or more for each grid cell. A proxy for market influence is the Gross Cell Product (GCP) maps by Nordhaus (2006). It is a spatially disaggregated measure of GDP and it is mostly based on detailed economic data collected at the state or province level. To measure institutional strength, we combine the national-level data on the ranges of Corruption Perception Index (CPI) by Transparency International and the urban extent maps from the Global Rural-Urban Mapping

Project, Version 1 (2004). We assumed that, within a country, areas which have high concentration of urban extents have stronger local institutions (high scores of Corruption Perception) compared to areas which are more rural.

To separate rainfed from irrigated systems, we used the data on irrigation. Specifically we assumed that irrigated (rainfed) systems have irrigated land areas which are greater than or equal to (less than) 5000 hectares. In addition, we only focus on grid-cells which have more than 5% cropland area in order to exclude the effect of marginal lands using the Global Cropland and Pasture Data maps by Ramankutty (2011).

III. Results and Discussions

Distribution of Efficiency Scores: The DEA scores are mapped to show the global distribution of technical efficiency scores (Figures 1 to 9). From the maps, we see that areas which have (low) high efficiencies are typically adjacent to each other together which suggests spatial clustering. To formally quantify the degree of spatial clustering in the efficiency scores, the Moran's I test is conducted. The Moran's I test provides a global measurement of spatial autocorrelation among neighboring observations (Anselin, 1996). We implemented the Moran's I test on the efficiency scores for each geographic region. The results confirm that there is clustering in the efficiency scores. Specifically, there is statistically significant and positive spatial autocorrelation among the calculated efficiency scores (Table 2).

Scores which considers all areas are illustrated in Figures 1 to 3. Looking at maize, we see that high scores (≥ 70%) are generally situated in North America, the European Union and in the northeastern China. At a glance, we see that even at country-level, the distribution of technical efficiency scores is quite heterogeneous. For example, scores in North America tend to decline in areas situated near the eastern coast while scores in China are generally lower in the southern than in the northern regions. Regions with low efficiency scores (≤ 30%) include Central America, Sub-Saharan Africa (excluding South Africa), South and South East Asia. This implies that these regions generally have large maize yield gaps due to technical inefficiency. Efficiency scores in Russia, Latin America and Australia are generally less than in North America but are still relatively high compared to the rest of the world. Unlike maize, efficiency scores for wheat are more dispersed. High scores are generally located in the European Union, North America and northeastern China. There are also some patches of technically efficient areas in Africa and South Asia although these regions are still dominated by areas with low efficiency scores. In Russia, areas near the Black Sea are more efficient compared to the rest of the country. Looking at rice, we see that most efficient areas are located in China and in parts of the European Union. Within South East Asia, Viet Nam and parts of Thailand and Indonesia have high efficiency scores compared to other countries in the same region. Despite large concentration of low efficiency scores, there are still some areas in India and Pakistan which have relatively high scores. In Latin America, areas in Argentina are technically more efficient than those in Brazil. Similar to the previous maps, rice efficiency scores in Africa are generally low which is indicative of large yield gaps for this crop in this region.

Efficiency scores generated for rainfed and irrigated areas are also mapped separately. In general, the distribution of rainfed efficiency scores is quite similar to the case wherein all areas are considered especially for maize and wheat (Figures 4 to 6). Rainfed maize and wheat areas with high scores are again situated in North America and in the European Union. Central America, Africa and South East Asia are generally dominated by low efficiency scores which indicate significant yield gaps in rainfed maize and wheat for these regions. Relative to these regions, Latin America and Russia generally have high scores. For rainfed rice, the improvement in efficiency scores is more visible. We can see improvements in the efficiency scores in parts of Argentina, Indonesia and Ukraine. This occurs because we are excluding the majority of technically efficient areas (namely in northeast China) which in turn alters the technically efficient set of observable rice yields.

Similar to the case of rainfed areas, it is difficult to distinguish if there are changes in the distribution of scores for irrigated areas versus all areas (Figures 7 to 9). The maps show that most irrigated areas are located in South Asia, South East Asia and in China. For maize and wheat, high scores are located in North America, the European Union and in northern China while low efficiency scores are observed in South and South East Asia and in southern China. For irrigated rice, high efficiency scores are again located in China and in parts of the European Union while low efficiency scores are situated in South Asia and in parts of South East Asia.

To clearly illustrate the changes in the distribution of technical efficiency scores for all areas, rainfed areas and irrigated areas, we use cumulative histograms (Figures 10 to 12). We plot the cumulative distribution of efficiency scores for 8 geographic regions. We also include the global distribution as a baseline such that distributions to the left (right) of the global distribution have relatively low (high) efficiency scores. Starting with maize, we see that the global distribution does not change dramatically if we separate irrigated and rainfed areas (Figure 10). Roughly 50% of global scores are in the interval [1, 20] for all cases which suggest large yield gaps for this crop globally. Among the regions, scores in N & C America are always on the right of these graphs which indicates that this region generally have high efficiency scores compared to the rest of the world. It is interesting to note that there are some regions which show changes in the distribution of scores when irrigated and rainfed areas are separated. For example, in the case of all areas we see that the distribution for the EU & Russia and C & E Asia are close to the global distribution. However, in the case of rainfed areas the distribution for C & E Asia approaches that of N & C America. Under this case, more that 50% of rainfed areas in C & E Asia have scores in the interval [1, 30] while it is higher for EU & Russia (75%). In the case of irrigated areas, the distribution for EU & Russia is closer to N & C America while the distribution for C & E Asia approaches the global distribution. Regions which have distributions on the left of the global distribution include L America, SS Africa, M East & N Africa, S Asia and SE Asia & Oceania. For these regions, greater than 75% of the all areas and rainfed areas have efficiency scores in the interval [1, 30] which suggests that these regions are generally inefficient compared to other world regions. There are some notable changes in the distribution of scores under the case of irrigated area in particular for M East & N Africa and for L America. For L America (M East & N Africa), the distribution shifts to the left (right) and moves away from (closer to) the global distribution.

Compared to maize, the distribution of scores is less dispersed in the case of wheat (Figure 11). Globally, around 25% of the efficiency scores are in the interval [1, 20] for all cases. This implies that yield gaps in wheat are generally smaller relative to maize since more observed wheat yields are closer to the technically efficient frontier. Similar to maize, we see that the distribution of scores for N & C America is always on the right for these graphs. The distribution of scores for EU & Russia is close to the global distribution for all cases. For C & E Asia, the distribution is closer to N & C America in the case of all areas and irrigated areas while it is close to EU & Russia in the case of rainfed areas. Distribution of efficiency scores for S Asia, L America, and SE Asia & Oceania are always on the left of the global distribution. At least 75% of the scores in these regions are within the interval [1, 30] which implies large inefficiencies in wheat production for these regions. We can also observe this for M East & N Africa and SS

Africa in the case of all areas and for rainfed areas. However, we see that if we focus on irrigated areas the distribution of scores in these regions shifts to the right. This is indicative that in these regions irrigated areas have relatively high efficiency scores. In all cases, the distribution for SE Asia & Oceania region is always on the right which suggest that wheat production in this region is relatively inefficient compared to the rest of the world.

Efficiency scores for rice are more dispersed compared to maize and wheat (Figure 12). More importantly, there are notable changes in the global distribution of scores between rainfed and irrigated areas. If all areas are considered, roughly 50% of global scores are within the interval [1, 30] while this increases to at least 60% if we look at rainfed areas. However, we see a sizable decline in the case of irrigated areas (at least 30%). This implies greater efficiency in observed irrigated rice yields compared to rainfed rice yields. The distribution for C & E Asia is always on the right relative to other regions which suggests that rice production in this region is quite efficient. Other regions on the right of the global distribution are N & C America and EU & Russia. Looking at all areas, we see that regions to the left of the global distribution include M East & N Africa, SS Africa, S Asia and SE Asia & Oceania. If we focus only at rainfed areas, S Asia and SE Asia & Oceania shifts and moves closer to the global distribution while the distributions for M East & N Africa and SS Africa remain unchanged. In the case of irrigated areas, the distribution of scores for S Asia and for SE Asia & Oceania shifts to the left (becomes more inefficient). In general, L America always follows the global distribution for rice.

Estimation results: We estimate the SDT model for all areas, rainfed areas and irrigated areas for each world regions (Tables 3 to 5). Explanatory variables for the calculated efficiency scores include population (POP), fertilizer use (FERT), irrigation (IRRIG), market accessibility (ACCESS) and proxy variables for market influence (GCP) and an index for institutional strength (INSTI). Interpretation of the parameter estimates is not straight forward since the spatial model takes into account the neighboring values of the efficiency scores and the neighboring values of the explanatory variables. Given this, the marginal effect of an explanatory variable in a grid-cell will not only affect the efficiency scores in that location but also the scores in neighboring grid-cells.

As discussed by LeSage and Fischer (2007), in models with spatial lags the changes in the explanatory variables result in direct impacts in its own region as well as indirect impacts to other regions. A formal method for calculating summary measures of the direct, indirect and total impacts and their corresponding statistical measures of dispersion was introduced by Pace and LeSage (2006). The authors defined the direct impact as the average impact of changes in a variable within a region such that the feedback effects from neighboring regions are accounted for. On the other hand, the total effect measures the average impact in a typical region if we change a variable in all regions. This measure includes both the direct and indirect impacts. Finally, the indirect effects which capture the spill-over effects across space can be calculated from the difference between the total and direct impacts. The methods used to calculate these summary impacts are in the Spatial Econometrics Toolbox by LeSage.

Estimates of total impacts are shown in Tables 6 to 8. We focus our discussion on geographic regions which have large distribution of low efficiency scores based on the maps and on the cumulative histograms (i.e. L America, SS Africa, SE Asia & Oceania, S Asia). Starting with maize, we see that in L America population (-) and irrigation (+) are key factors affecting the efficiency scores when all areas are considered. If we focus on rainfed areas, population, irrigation and institutional strength have negative total impacts on efficiency. None of the socio-economic variables have statistically significant total impacts on irrigated maize in this region.

Looking at all areas in SS Africa, we see that all variables except market access have statistically significant and positive total effect on efficiency. In the case of rainfed areas, population, market access, institutional strength and market influence have increasing total effects on efficiency scores for this region. In S Asia, market influence has positive total impacts on efficiencies for both rainfed and irrigated areas. For irrigated areas, institutional strength negatively affects efficiency for this region. For SE Asia & Oceania for both all areas and rainfed areas, variables which significantly affect the efficiency scores are fertilizer use (+), institutional strengths (+), market influence (+) and market access (-). If we focus only on irrigated areas, fertilizer use and institutional strength positively impacts efficiency.

In the case of wheat production, we see that in L America key drivers of efficiency scores include fertilizer use (-), market access (-), and institutional strength (+) when all areas are considered. The same factors plus market influence (-) are the main contributors to efficiency under rainfed areas. Institutional strength (+) is the only statistically significant variable in the case of irrigated areas in this region. In SS Africa, only population (-) is statistically significant for both all areas and rainfed areas. Likewise, fertilizer use (+) is the only statistically significant variable under the case of irrigated areas. In rainfed and irrigated areas in S Asia, main contributors to efficiency scores are institutional strength (-) and market influence (+). Irrigation also increases efficiency scores for irrigated areas in this region. In SE Asia & Oceania, only the case of irrigated areas has statistically significant coefficients. For this region, the total effect on efficiency of population and institutions are negative while it is positive for market influence.

For rice production, we see that most of the statistically significant variables are in L America, S Asia and SE Asia & Oceania. If all areas are considered, irrigation contributes positive to efficiency scores in L America while fertilizer use has an adverse impact. For rainfed areas, institutional strength has an adverse effect while market access has a positive impact on efficiency scores under irrigated areas. Efficiency scores for rice are positively affected by market influence for all cases in S Asia. Variables which have negative impacts on scores for rainfed areas in this region include institutional strength and irrigation. In SE Asia & Oceania, key drivers of efficiency scores are fertilizer use (+) institutional strength (-). For both rainfed and all areas, market influence contributes positively to efficiency scores in this region. Market access also contributes to efficiency scores in the case of all lands (-) and irrigated lands (+).

The results discussed above show that the effects of the socio-economic variables on the efficiency scores are not always consistent and will typically vary by geographic region, crop type and scope of analysis (all areas, rainfed areas, irrigated areas). For example, the impact of fertilizer in maize is consistently positive across all regions but for wheat and rice, its impacts are mixed. In the case of rice, the total impact of irrigation on the efficiency scores are either zero or negative for all areas, rainfed areas and irrigated areas. However, we can also see some general trends. Most of the total impacts of socio-economic variables on efficiency scores are positive. For example, across all crops and regions the total impact of irrigation, fertilizer use, institutional strength and market influence are generally positive in the case of all areas. For rainfed areas, fertilizer use and market influence are the key drivers of efficiency. These are also the drivers for irrigated areas plus market access. If we look at each crop for all cases and regions, we see that irrigation, fertilizer use, institutional strength and market influence are the important factors affecting efficiency scores for maize. For wheat and rice, the main contributors to efficiencies are fertilizer use and market influence. At regional level and for all crops and cases, we see that in L America, institutional strength (+) and market access (-) generally have statistically significant total impacts. For S Asia, market influence (+) and institutional strength (-) are the key drivers.

For SE Asia & Oceania, market influence (+) and fertilizer use (+) are important contributors to efficiency. In the case of SS Africa, all except population generally have positive total impact on efficiency. The results also indicate that by changing the coverage from all areas to either rainfed or irrigated areas, we generally see that some variables become statistically significant while some become insignificant. However, as long as the estimate is statistically significant in the case of all areas we see that the signs of these estimates are generally consistent if we focus on either rainfed or irrigated areas.

Finally, we explore the results of the model by isolating the direct and indirect effects of the socio-economic variables on the efficiency scores (Tables 9 and 10). In general, these results indicate that there are variables which do not have statistically significant total effect but have statistically significant direct/indirect effects. For example, for rainfed maize in L America, we see that irrigation (-) and market influence (+) become statistically significant in terms of its direct effect. This is also true for the direct effects of fertilizer use (+), institutional strength (+) and market influence (+) on efficiency scores of rainfed rice in SS Africa. In most cases, the indirect effect is generally larger than direct effect. Examples of these include fertilizer use (-) and market access (-) for rainfed wheat in L America and institutional strength (+) for rainfed maize in S Asia. However, there are some instances wherein the signs of the direct and indirect impacts are different. This is true in the case of fertilizer use and market access for rainfed maize in S Asia and in irrigation in SE Asia & Oceania.

IV. Conclusion

In this study, we revisit global yield gap analysis by examining technical efficiencies in global crop production and by relating these to selected socio-economic variables. To calculate these efficiencies across the world, we apply data envelopment analysis on geo-spatial data on crop yields and agro-climatic factors. This non-parametric approach allows us to generate scores which represent how far the observed crop yields are from the technically efficient frontier given its observed agro-climatic inputs. We then relate these efficiency scores to selected socio-economic variables namely population, irrigation, fertilizer use, market access, institutional strength and market influence. We apply spatial econometric techniques in our estimation to account for the spatial correlation in the data and in the calculated scores. Specifically, we estimated the spatial Durbin Tobit model using the methods outlined by LeSage (2000). The results of the study show that the global distribution of calculated efficiency scores varies among countries. More importantly, these scores vary within countries and this highlights the importance of using spatial data on global yield gap analysis. We find that the effects of the socio-economic variables on the efficiency scores are not always consistent and will typically vary depending on region, crop and scope. However, we can also see some general trends. Most of the total impacts of socio-economic variables on efficiency scores are positive. For example, across all crops and regions the total impact of irrigation, fertilizer use, institutional strength and market influence are generally positive if we look at all areas. By changing the coverage from all areas to either rainfed or irrigated areas, we generally see that some variables become statistically significant while some become insignificant. However, the signs of these estimates are generally consistent if we examine all areas or if we limit our focus on rainfed or irrigated areas. Given the spatial model, we can also explore the direct and indirect impacts of the socio-economic variables on the efficiency scores. In some cases, there are variables which do not have statistically significant total effect but have statistically significant direct/indirect effects. The indirect effect is generally larger than direct effect which shows the importance of using spatial econometric techniques to account for the spatial interaction in the data.

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Figure 1. Efficiency Scores of Maize: All Areas

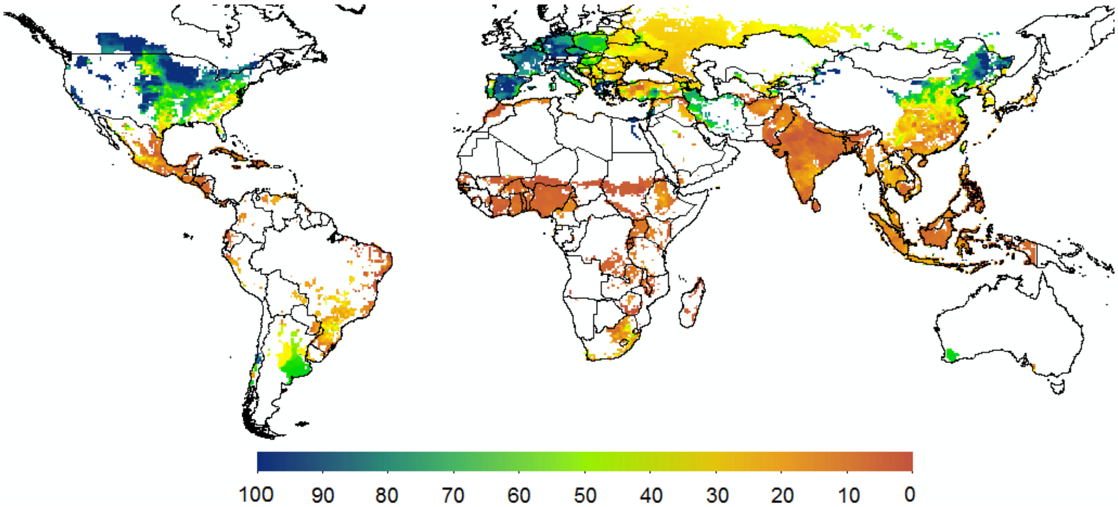


Figure 2. Efficiency Scores of Wheat: All Areas

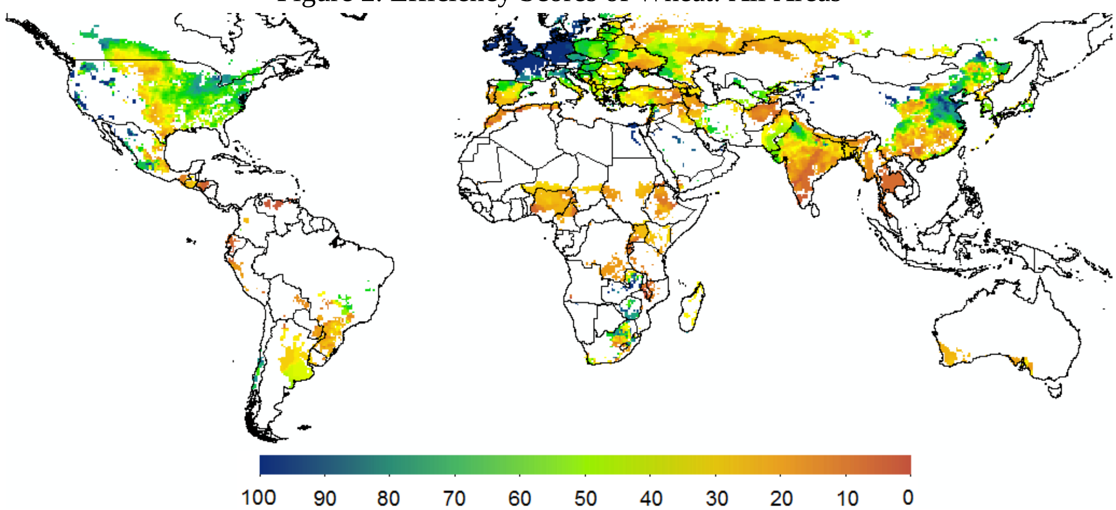


Figure 3. Efficiency Scores of Rice: All Areas

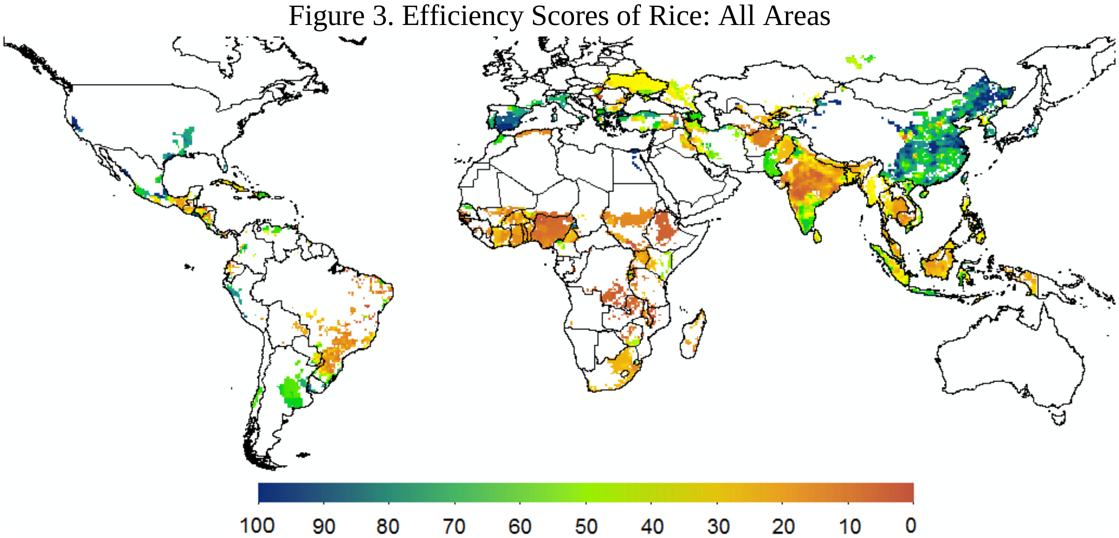


Figure 4. Efficiency Scores of Maize: Rainfed Areas

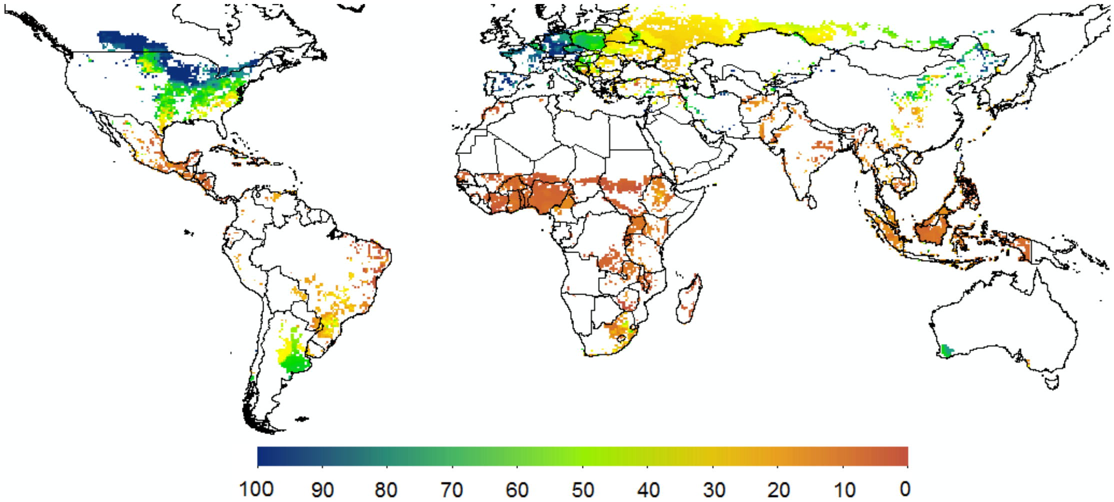


Figure 5. Efficiency Scores of Wheat: Rainfed Areas

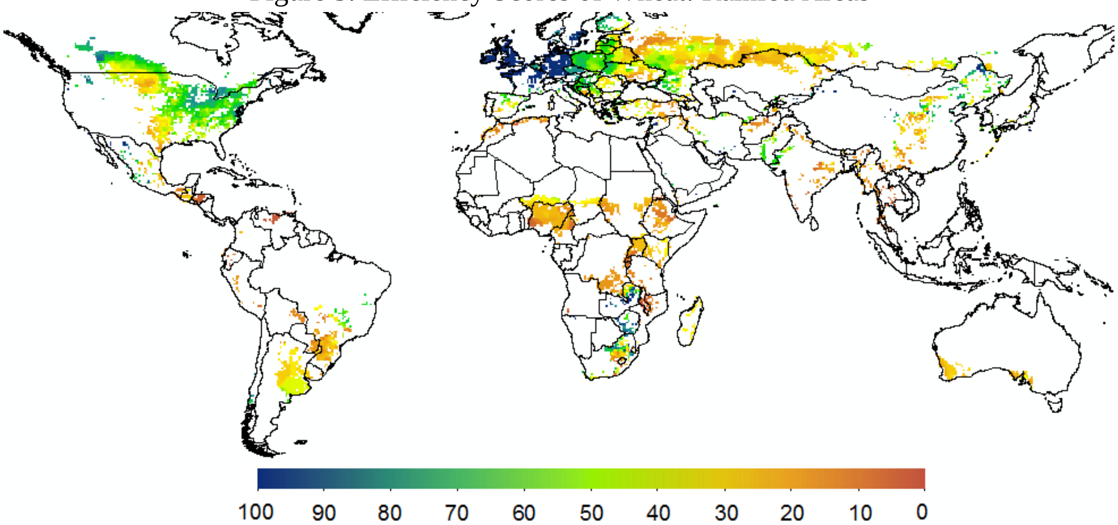


Figure 6. Efficiency Scores of Rice: Rainfed Areas

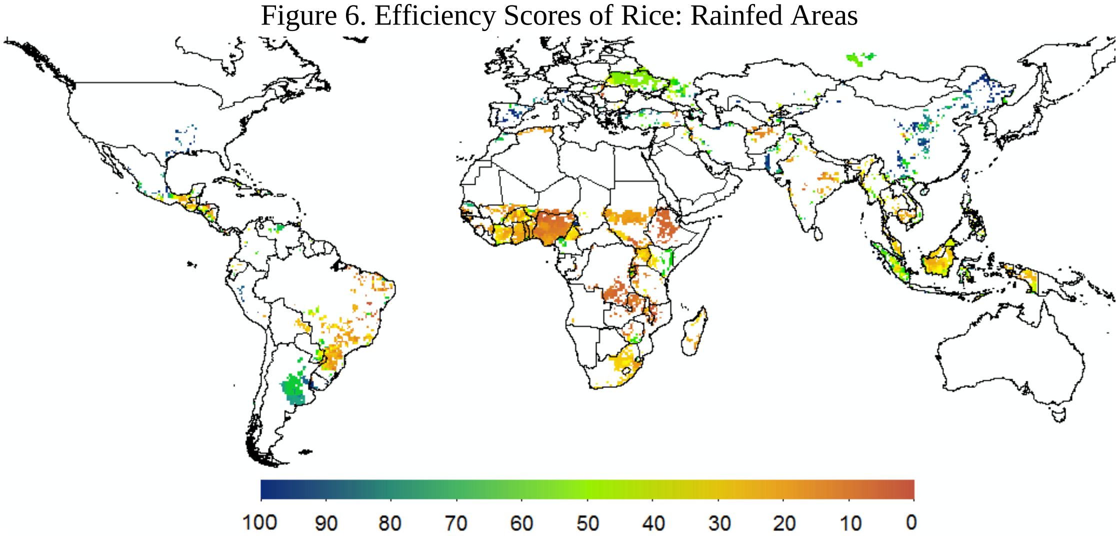


Figure 7. Efficiency Scores of Maize: Irrigated Areas

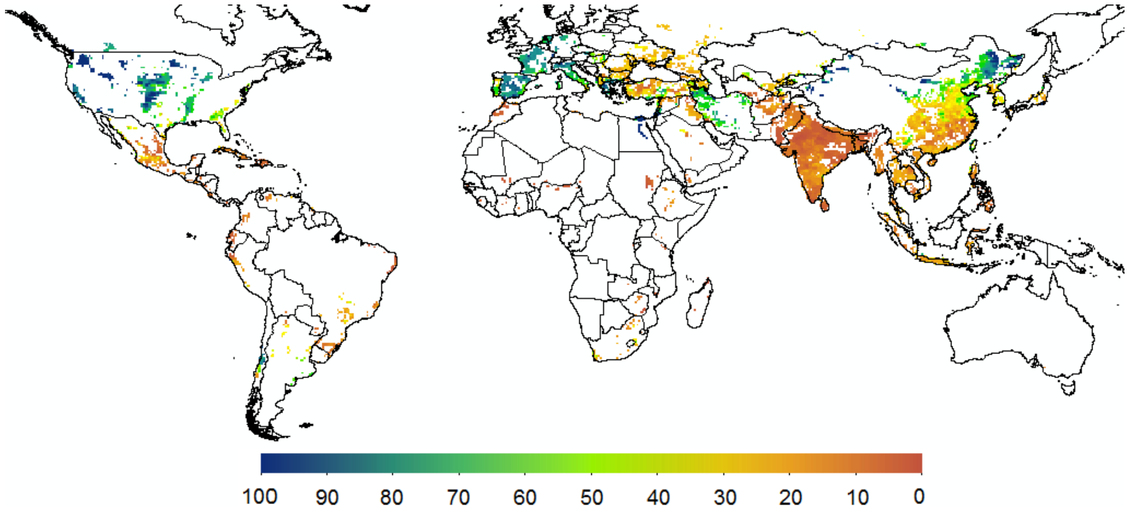


Figure 8. Efficiency Scores of Wheat: Irrigated Areas

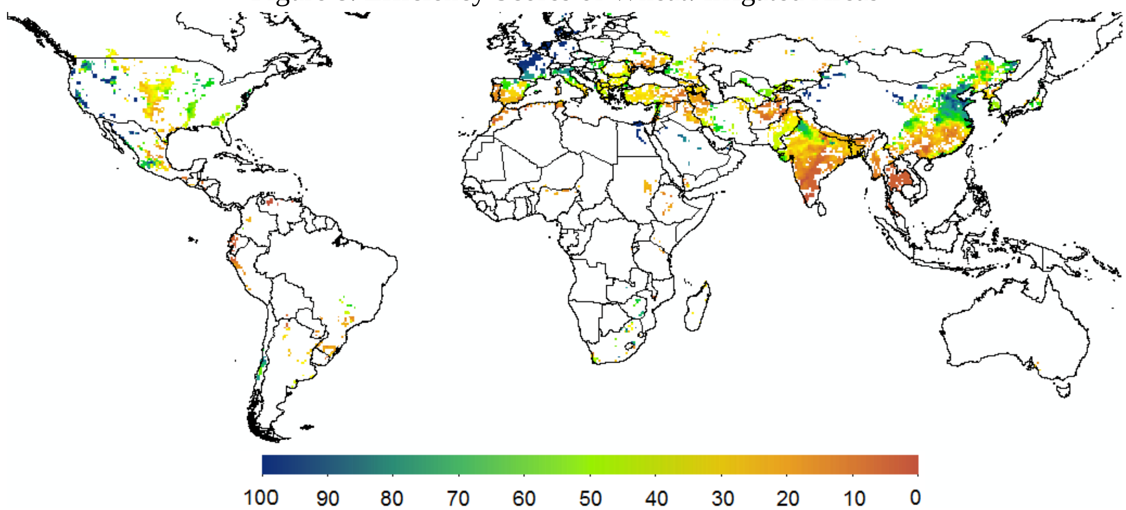
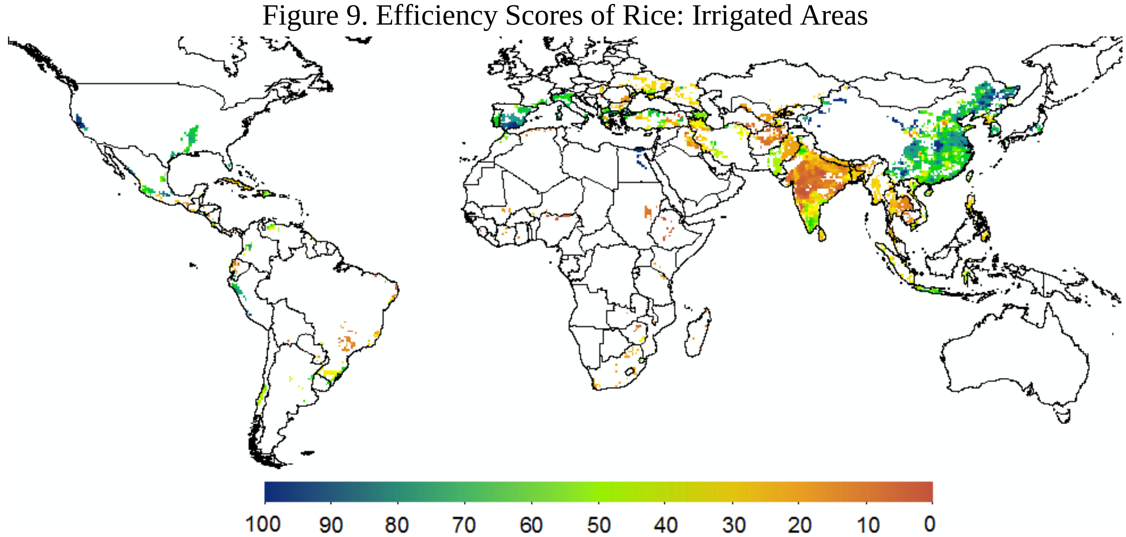


Figure 9. Efficiency Scores of Rice: Irrigated Areas



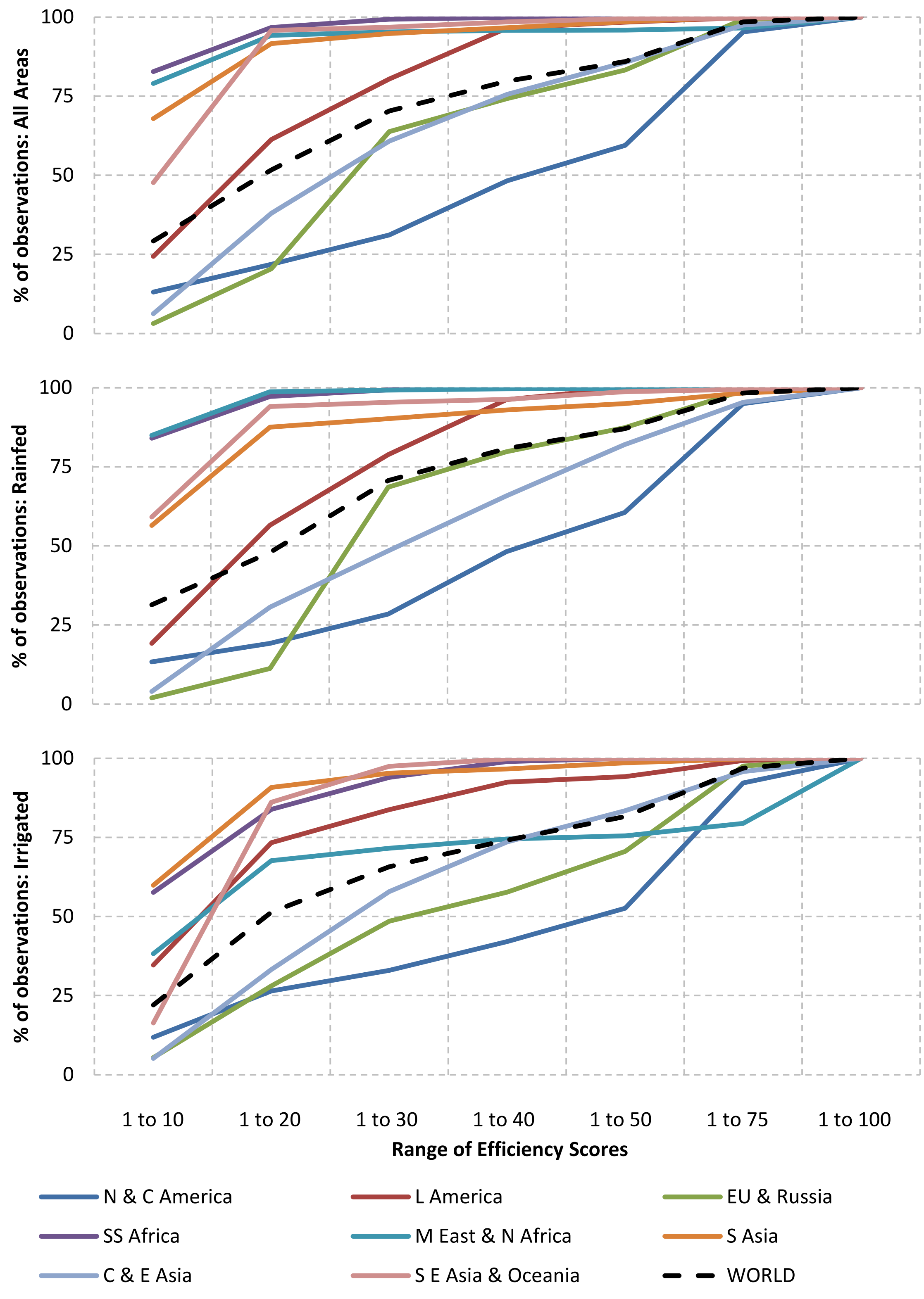


Figure 10. Cumulative distribution of Maize efficiency scores

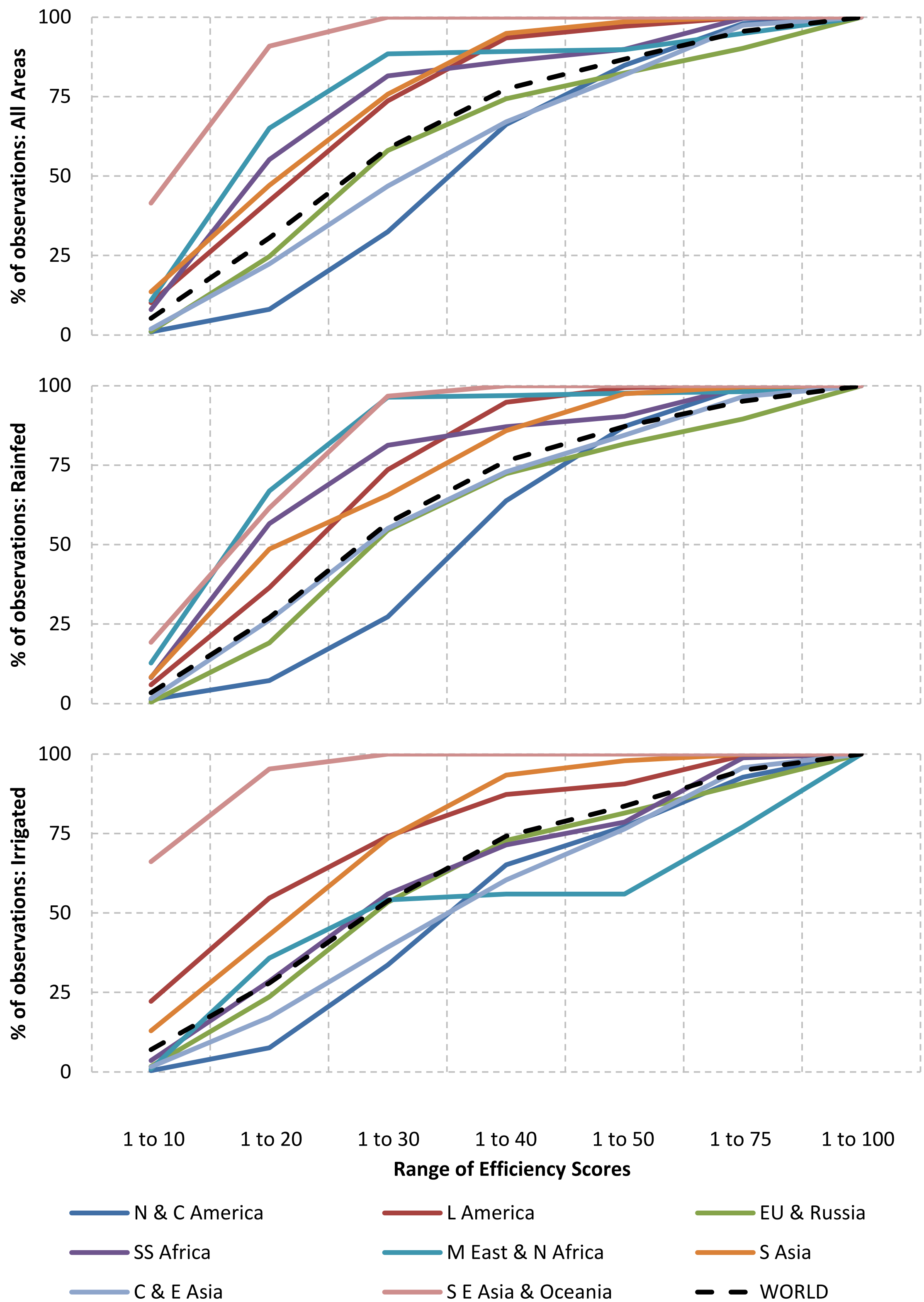


Figure 11. Cumulative distribution of Wheat efficiency scores

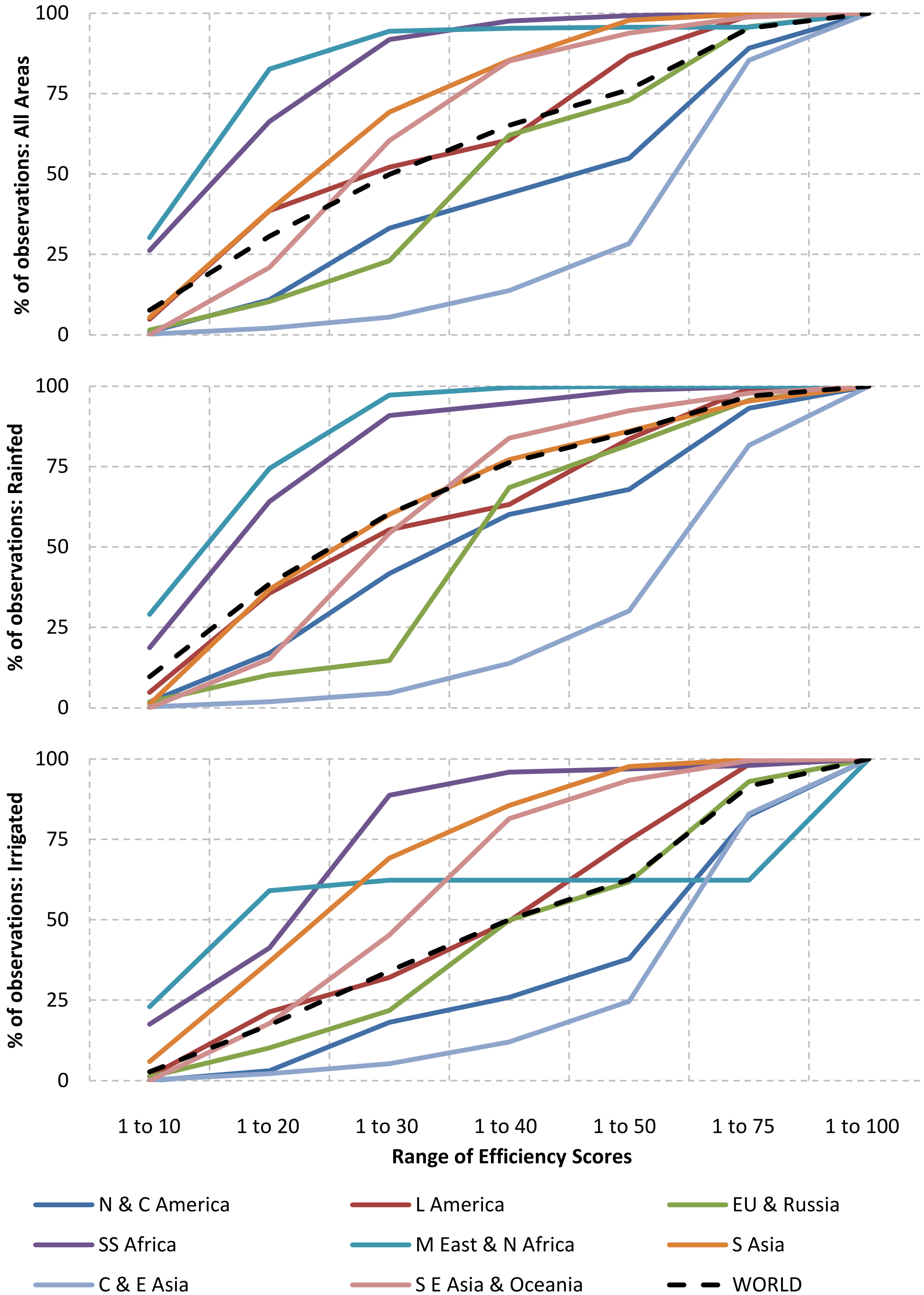


Figure 12. Cumulative distribution of Rice efficiency scores

Table 1. Data description

Variables	Data Description	Source
Crop yields	Yields for maize, rice and wheat (metric tons per hectare)	Monfreda et al. (2008)
Temperature	Sum of monthly temperature in Fahrenheit	Worldclim (Hijmans et al., 2005)
Precipitation	Sum of monthly precipitation in millimeters	
Soil constraint	Scale [1-100] 100 – no constraint 1 – not suitable for agriculture	Global Agro-Ecological Zones model (Fischer et al., 2002)
Terrain slope		
Irrigation	Total area equipped for irrigation (1000 hectares)	MIRCA (Portmann, Siebert, & Döll, 2010)
Population	in 1000	Gridded Population of the World, Version 3 (2005)
Gross cell product	2005 US $ per capita at purchasing power parity exchange rates	Nordhaus (2006)
Land accessibility	Travel times in hours	Nelson (2008)
Fertilizer use	Kilogram per hectare	Potter et al. (2010)
Institutional strength	Scale [1-100]	Calculated from of Corruption Perception Index by Transparency International & from the Global Rural-Urban Mapping Project, Version 1 (2004)

Table 2. Moran's I statistics of the efficiency scores

Geographic Regions	Maize			Wheat			Rice		
	All Areas	Irrigated Areas	Rainfed Areas	All Areas	Irrigated Areas	Rainfed Areas	All Areas	Irrigated Areas	Rainfed Areas
N & C America	0.93*	0.92*	0.94*	0.87*	0.86*	0.89*	0.86*	0.86*	0.81*
L America	0.89*	0.82*	0.93*	0.88*	0.83*	0.93*	0.88*	0.83*	0.89*
EU & Russia	0.87*	0.81*	0.84*	0.95*	0.92*	0.94*	0.88*	0.84*	0.89*
SS Africa	0.80*	0.79*	0.79*	0.83*	0.77*	0.85*	0.75*	0.42*	0.80*
M East & N Africa	0.88*	0.86*	0.85*	0.93*	0.95*	0.85*	0.92*	0.89*	0.91*
S Asia	0.94*	0.86*	0.91*	0.86*	0.77*	0.89*	0.80*	0.76*	0.83*
C & E Asia	0.89*	0.80*	0.87*	0.88*	0.82*	0.87*	0.79*	0.78*	0.75*
S E Asia & Oceania	0.47*	0.41*	0.55*	0.93*	0.85*	0.93*	0.57*	0.71*	0.54*

* Statistically significant at 5% level of significance

Table 3. Estimation results of the spatial Durbin Tobit model: All Areas

Regions	N & C America	L America	EU & Russia	SS Africa	M East & N Africa	S Asia	C & E Asia	S E Asia & Oceania
Maize								
Constant	-12.686*	2.617*	2.545*	-0.277	-6.370*	0.199	4.932*	1.837*
POP	-0.002*	-0.002*	-0.001*	-0.001*	-0.002	-2E-04	4E-04	-0.001*
IRRIG	-0.011	-0.044*	-0.035*	0.026	-0.022	0.006*	-0.039*	-0.004
FERT	0.250*	0.054	0.032*	0.084*	0.081*	0.003	0.043*	0.049*
ACCESS	0.387*	-0.165*	1.064*	-0.015	0.134	0.246*	0.413*	-0.033
INSTI	0.633*	-0.091	0.209*	0.044*	0.247*	-0.043	0.053	0.032
GCP	0.189*	0.225*	0.193*	0.255*	0.437*	-0.243*	0.126	-0.003
W*POP	0.012*	-0.003	-0.001	0.001*	0.005*	1E-04	-0.003*	9E-06
W*IRRIG	0.047*	0.094*	0.038*	0.051*	0.033	-0.005	0.048*	0.031
W*FERT	-0.092*	-0.055	0.012	-0.082	-0.059	-0.001	-0.030	-0.005
W*ACCESS	0.556	0.096	-0.634*	0.061	0.033	-0.239*	-0.665*	-0.010
W*INSTI	-0.408*	0.076	-0.093*	-0.011	-0.007	0.044	-0.063	0.068
W*GCP	-0.367*	-0.144	0.004	-0.136	-0.526*	0.335*	-0.164	0.144
ρ	0.870*	0.894*	0.665*	0.811*	0.829*	0.960*	0.912*	0.506*
Wheat								
Constant	-4.543*	3.892*	1.813*	1.584	1.503	3.688	-4.543	3.892*
POP	-0.001	0.001	-1E-04	-0.001	0.001*	-1E-04	-0.001*	0.001
IRRIG	0.027*	-0.064*	-0.021*	0.129*	-0.012	0.037*	0.027*	-0.064
FERT	0.115*	0.041	0.047*	-0.249*	0.072*	0.094*	0.115*	0.041
ACCESS	0.081	-0.179*	0.728*	0.015	-0.085	0.100	0.081	-0.179*
INSTI	0.328*	-0.163*	0.294*	-0.081	0.102*	-0.099	0.328*	-0.163
GCP	0.047	-0.023	0.114*	0.044	-0.016	0.144	0.047*	-0.023
W*POP	0.011*	-0.002	0.002*	-0.001	-0.001	9-E05	0.011	-0.002
W*IRRIG	-0.004	0.093*	-0.024*	0.004	0.027*	-0.026*	-0.004	0.093
W*FERT	-0.055*	-0.203*	0.031*	0.405*	-0.025	-0.099*	-0.055*	-0.203
W*ACCESS	0.487*	-0.114	-0.751*	-0.012	0.205	-0.120	0.487	-0.114
W*INSTI	-0.271*	0.23*	-0.261*	0.135	-0.133*	0.010	-0.271	0.230*
W*GCP	-0.072	-0.103	-0.110*	-0.185	0.171	-0.055	-0.072*	-0.103
ρ	0.918*	0.860*	0.877*	0.865*	0.886*	0.929*	0.918*	0.860*
Rice								
Constant	27.837*	5.582*	1.872	1.744*	-3.511	8.023*	5.238*	14.325*
POP	0.004*	-0.001	-0.002	0.001	1E-04	4E-04	2E-04	-0.001*
IRRIG	0.041	0.081*	-0.017	-0.130*	-0.018	0.048*	0.018	-0.022
FERT	-0.016	0.157*	0.010	0.039	0.051	0.004	-0.002	0.136*
ACCESS	-0.886*	-0.111	1.097*	-0.017	-0.038	1.099*	0.238	-0.161*
INSTI	0.509*	-0.200*	0.542*	0.058	0.020	-0.463*	0.303*	-0.254*
GCP	0.376*	0.195	0.417*	0.249	0.399	-0.046	0.249	1.015*
W*POP	-0.015*	-0.001	0.002	-0.001	0.001	1E-04	-0.001	0.001
W*IRRIG	-0.004	0.022	0.017	0.311*	0.011	-0.043*	-0.070*	-0.003
W*FERT	0.131	-0.302*	-0.049	-0.079	0.019	-0.028	0.075*	0.001
W*ACCESS	-1.178	0.110	-0.557	0.019	0.163	-1.062*	-0.350	0.107*
W*INSTI	-0.848*	0.161	-0.466*	-0.031	0.212	0.249	-0.185*	0.046
W*GCP	0.221	-0.144	-0.281*	-0.113	-0.437	0.303	-0.332	-0.702*
ρ	0.711*	0.885*	0.839*	0.829*	0.834*	0.902*	0.844*	0.666*

[*] Statistically significant at 5% level of significance

Table 4. Estimation results of the spatial Durbin Tobit model: Rainfed Areas

Regions	N & C America	L America	EU & Russia	SS Africa	M East & N Africa	S Asia	C & E Asia	S E Asia & Oceania
Maize								
Constant	-15.061*	4.944*	5.234*	-0.312	1.356	-4.397	14.078*	1.384
POP	-0.005*	-0.002*	-4E-04	-0.001*	-0.001	-0.001*	0.003	-0.001
IRRIG	-0.051	-0.286*	-0.140	0.185*	-0.209	-0.094	0.027	-0.190
FERT	0.291*	0.095*	0.056*	0.056	0.034	0.004	-0.029	0.032
ACCESS	0.545*	-0.074	1.103*	0.010	-0.036	0.346*	0.453*	-0.038
INSTI	0.738*	-0.148	0.310*	0.024	-0.016	0.044	0.783*	-0.016
GCP	0.181*	0.158*	0.407*	0.264*	0.035	0.201	-0.316	0.033
W*POP	0.019*	-0.005*	2E-04	0.002*	-0.004	4E-04	-0.019*	-0.004
W*IRRIG	0.419	0.047	-0.444*	-0.212	0.527	-0.450*	0.223	0.513
W*FERT	-0.039	-0.080	0.018	-0.049	0.023	-0.049*	0.068	0.025
W*ACCESS	0.478	-0.053	-0.463*	0.039	-0.021	-0.007	-0.519*	-0.019
W*INSTI	-0.423*	0.088	-0.119*	0.016	0.162*	0.111	-0.831*	0.160*
W*GCP	-0.459*	-0.085	-0.143*	-0.116	0.100	1.342*	0.089	0.105
ρ	0.786*	0.887*	0.463*	0.797*	0.474*	0.744*	0.723*	0.474*
Wheat								
Constant	-1.922	4.172*	2.638*	2.126*	4.751*	28.479*	5.448*	2.721*
POP	-0.001	1E-04	-1E-04	2E-04	0.001	0.001	0.004	-0.002
IRRIG	0.223	0.101	-0.123	0.401*	-0.217	-0.182	-0.523	-0.049
FERT	0.128*	-0.004	0.077*	-0.617*	0.024	0.014	0.005	0.012
ACCESS	0.331*	-0.020	0.736*	0.056	-0.069	-0.012	0.286*	0.005
INSTI	0.389*	-0.079	0.397*	-0.158*	0.206	-0.318*	1.054*	-0.154*
GCP	0.064*	0.015	0.204*	-0.052	0.666	-0.098	-1.042*	0.001
W*POP	0.013*	-0.004	0.003*	-0.002	-0.002	-0.002	-0.011*	-2E-04
W*IRRIG	-0.720	0.055	0.288	-0.120	-0.594	-0.458	0.669	-0.010
W*FERT	-0.041*	-0.147*	0.060*	0.790*	0.018	-0.095*	0.079	-0.059
W*ACCESS	0.300	-0.251*	-0.662*	-0.035	0.179	-0.054	-0.124	-0.089
W*INSTI	-0.382*	0.135*	-0.320*	0.194*	-0.249*	-0.396*	-1.025*	0.161*
W*GCP	-0.028	-0.187	-0.178*	0.003	-0.097	0.516	0.951*	0.018
ρ	0.893*	0.883*	0.775*	0.862*	0.729*	0.756*	0.748*	0.858*
Rice								
Constant	22.154*	7.765*	6.314*	1.720*	-2.599	67.861*	-9.460	19.874*
POP	-0.003	-1E-05	-0.002	0.001	-0.001	0.001	-0.006	-0.001
IRRIG	1.212	0.352	0.176	0.093	-1.144*	-0.909*	0.102	-1.638*
FERT	0.250	0.122	-0.121*	0.206*	0.102	-0.045	-0.184	0.187*
ACCESS	-0.490	0.094	1.419*	0.059	-0.014	0.676*	0.174	-0.159*
INSTI	0.550*	-0.144	0.501*	0.156*	1.232*	-0.919*	2.417*	-0.277*
GCP	0.649*	0.248	0.314	0.256	0.070	-0.127	-0.223	0.946*
W*POP	-0.006	-0.002	-0.004	-0.001	0.001	-0.001	-0.010	0.003
W*IRRIG	0.163	-0.524	-0.356	-0.023	0.149	-1.042	-0.771	1.055
W*FERT	0.071	-0.163	-0.006	-0.228*	0.084	-0.093	0.304	0.369*
W*ACCESS	-1.174	-0.084	-0.878	-0.066	0.104	-0.367	-0.345	0.138*
W*INSTI	-0.793*	0.043	-0.374*	-0.134*	-0.964*	-0.975*	-1.379*	-0.027
W*GCP	0.149	-0.149	-0.081	-0.115	0.194	1.133	0.714	-0.662
ρ	0.596*	0.865*	0.708*	0.864*	0.759*	0.622*	0.633*	0.478*

[*] Statistically significant at 5% level of significance

Table 5. Estimation results of the spatial Durbin Tobit model: Irrigated Areas

Regions	N & C America	L America	EU & Russia	SS Africa	M East & N Africa	S Asia	C & E Asia	S E Asia & Oceania
Maize								
Constant	-8.739*	-2.115	3.022	-4.051	-6.396	12.472*	4.488*	6.112*
POP	-0.002	-0.003	-0.002*	0.002	-1E-04	-1E-04	-0.002*	-0.001*
IRRIG	0.005	-0.043	-0.045*	-0.092	-0.018	0.004	-0.087*	-0.038*
FERT	0.115*	-0.010	0.016	-0.055	0.057	0.049*	0.098*	0.124*
ACCESS	-0.185	-0.351	-0.283	0.209	0.592	1.518*	0.006	-0.244*
INSTI	0.567*	-0.090	-0.045	-0.435	0.052	0.011	0.109*	-0.009
GCP	0.360*	0.550	0.363*	0.747*	1.244*	-0.193*	0.099	0.364*
W*POP	0.002	0.003	-0.001	-4E-04	0.007*	-3-E03	-4E-04	1E-04
W*IRRIG	0.045*	0.138*	0.040	0.173	0.005	-0.001	0.086*	0.056*
W*FERT	-0.150*	-0.122	0.021	0.240	-0.032	-0.088*	-0.082*	-0.071*
W*ACCESS	1.295*	0.531	1.444*	-0.272	-0.484	-1.677*	-0.242	0.163
W*INSTI	-0.349*	0.151	0.106	0.641	0.210	-0.349*	-0.075	0.004
W*GCP	-0.345*	-0.012	-0.053	-0.589	-1.241*	0.500*	-0.109	0.106
ρ	0.777*	0.723*	0.680*	0.546*	0.774*	0.881*	0.884*	0.469*
Wheat								
Constant	5.193	2.340	9.126*	2.182	2.403	9.867*	4.118	16.223*
POP	-4E-04	0.001	-1E-04	-0.006	0.001	-5E-05	-2E-04	-2E-04
IRRIG	0.040*	-0.083*	-0.043*	0.230	-0.014	0.040*	-0.015	0.001
FERT	0.076*	0.035	0.086*	0.794	0.085*	0.118*	0.078*	-0.023
ACCESS	-0.265	-0.581*	-0.167	0.405	0.094	1.426*	0.050	-0.001
INSTI	0.255*	0.012	0.339*	-0.361	0.268*	-0.044	0.064	-0.236*
GCP	-0.063	0.058	0.266*	0.453	0.121	0.155	0.107	-0.007
W*POP	0.002	-0.002	-4E-04	0.004	0.001	-1E-04	-2E-04	-0.008*
W*IRRIG	0.027	0.092	-0.003	0.335	0.022	-0.008	0.050*	0.004
W*FERT	-0.149*	-0.081	0.030	0.463	-0.029	-0.150*	-0.055*	0.072
W*ACCESS	0.083	-0.137	-1.528*	-1.983*	0.228	-1.436*	0.160	-0.658*
W*INSTI	-0.245*	0.260	-0.350*	0.721	-0.347*	-0.234	-0.127	-0.044
W*GCP	0.092	-0.301	-0.216	-1.683*	0.197	0.039	0.109	0.777*
ρ	0.828*	0.611*	0.810*	0.491*	0.851*	0.859*	0.863*	0.645*
Rice								
Constant	29.967*	7.898	3.237	0.655	-4.661	8.983*	6.701*	14.983*
POP	0.004*	-0.002	-0.002	0.005	0.001	0.001*	7E-05	-0.001*
IRRIG	0.056	0.031	-0.042*	-0.386*	-0.016	0.050*	0.010	-0.003
FERT	-0.083	-0.034	0.018	-0.896	0.059	0.009	-0.001	0.066*
ACCESS	-0.526	-0.45	0.294	-0.240	0.738	2.056*	0.355	-0.111
INSTI	0.372*	-0.074	0.538*	-1.219	-0.023	-0.542*	0.393*	-0.014
GCP	0.401*	0.143	0.546*	0.696	0.709	0.057	0.218	0.808*
W*POP	-0.005	0.002	0.002	-0.010	0.003	-0.001	4E-04	0.002*
W*IRRIG	0.005	0.017	0.032	0.489	-0.022	-0.038*	-0.073*	0.005
W*FERT	0.193	-0.355	-0.042	1.706*	0.065	-0.036	0.073*	0.015
W*ACCESS	-1.030	1.336*	0.224	0.370	0.888	-2.207*	-0.272	0.481*
W*INSTI	-0.740*	0.154	-0.397*	1.540	0.270	0.340	-0.276*	-0.289*
W*GCP	0.271	-0.156	-0.450*	-0.123	-0.704	0.169	-0.243	-0.143
ρ	0.597*	0.716*	0.767*	0.214*	0.739*	0.873*	0.811*	0.637*

* Statistically significant at 5% level of significance

Table 6. Estimated total effects from the spatial Durbin Tobit model: Maize

Regions	N & C America	L America	EU & Russia	SS Africa	M East & N Africa	S Asia	C & E Asia	S E Asia & Oceania
All Areas								
POP	0.078*	-0.048*	-0.004	0.004*	0.02*	-0.003	-0.029*	-0.001
IRRIG	0.279*	0.48*	0.009	0.408*	0.07	0.016	0.106	0.055
FERT	1.235*	-0.006	0.129*	0.007	0.128	0.037	0.158	0.09*
ACCESS	7.381*	-0.661	1.29*	0.245*	1.007	0.199	-2.868*	-0.087*
INSTI	1.762*	-0.139	0.346*	0.177*	1.432*	0.014	-0.115	0.202*
GCP	-1.391*	0.76	0.589*	0.631*	-0.531	2.35	-0.433	0.289*
Rainfed Areas								
POP	0.065*	-0.064*	-0.000287	0.004*	-0.01	-0.002	-0.058*	-0.01
IRRIG	1.768	-2.103	-1.088*	-0.135	0.614	-2.12	0.915	0.623
FERT	1.194*	0.132	0.137*	0.035	0.108*	-0.18	0.141	0.11*
ACCESS	4.785*	-1.133*	1.194*	0.238*	-0.109*	1.333	-0.246	-0.11*
INSTI	1.489*	-0.538*	0.358*	0.198*	0.278*	0.609	-0.174	0.276*
GCP	-1.319*	0.656	0.492*	0.727*	0.26*	6.143*	-0.82	0.265*
Irrigated Areas								
POP	0.002	0.00011	-0.007	0.003	0.03*	-0.004	-0.019*	-0.002
IRRIG	0.233*	0.351	-0.014	0.194	-0.053	0.032	-0.012	0.035
FERT	-0.16	-0.477	0.119	0.412	0.113	-0.337	0.145	0.101*
ACCESS	5.025*	0.64	3.648*	-0.143	0.493	-1.389	-2.067	-0.156
INSTI	0.99*	0.22	0.194*	0.461	1.187*	-2.907*	0.3	-0.01
GCP	0.065	1.969	0.972*	0.349	0.014	2.627*	-0.086	0.897*

Table 7. Estimated total effects from the spatial Durbin Tobit model: Wheat

Regions	N & C America	L America	EU & Russia	SS Africa	M East & N Africa	S Asia	C & E Asia	S E Asia & Oceania
All Areas								
POP	0.128*	-0.011	0.018*	-0.015*	0.005	-0.004	-0.006	-0.01
IRRIG	0.278*	0.209	-0.363*	0.982	0.137	0.165	0.5*	-0.059
FERT	0.747*	-1.184*	0.637*	1.161	0.415*	-0.061	0.055	-0.258
ACCESS	7.052*	-2.129*	-0.187	0.023	1.071	-0.278	2.071	-0.658
INSTI	0.7*	0.488*	0.273*	0.408	-0.285	-1.3	0.439	-0.201
GCP	-0.307	-0.916	0.035	-1.044	1.396*	1.283	-0.192	0.561
Rainfed Areas								
POP	0.108*	-0.033	0.011*	-0.019*	-0.003	-0.006	-0.031*	-0.016
IRRIG	-4.694	1.365	0.723	2.029	-3.023	-2.617	0.595	-0.423
FERT	0.83*	-1.313*	0.605*	1.257	0.158	-0.334	0.332*	-0.345
ACCESS	6.021*	-2.363*	0.335	0.151	0.407	-0.31	0.641	-0.618
INSTI	0.072	0.489*	0.343*	0.267	-0.16	-3.001*	0.123	0.056
GCP	0.342	-1.503*	0.115	-0.359	2.118*	1.754*	-0.366	0.142
Irrigated Areas								
POP	0.007	0.000187	-0.003	-0.004	0.014*	-0.001	-0.004	-0.026*
IRRIG	0.394*	0.02	-0.242*	1.145	0.049	0.237*	0.259	0.017
FERT	-0.431*	-0.111	0.617*	2.54*	0.382*	-0.237	0.169	0.149
ACCESS	-1.065	-1.88	-8.933*	-3.171	2.202	-0.085	1.561	-1.991
INSTI	0.061	0.718*	-0.058	0.721	-0.54	-2.006*	-0.457	-0.845*
GCP	0.16	-0.633	0.274	-2.479	2.163*	1.413*	1.597	2.328*

[*] Statistically significant at 5% level of significance

Table 8. Estimated total effects from the spatial Durbin Tobit model: Rice

Regions	N & C America	L America	EU & Russia	SS Africa	M East & N Africa	S Asia	C & E Asia	S E Asia & Oceania
All Areas								
POP	-0.04*	-0.019	0.002	-0.002	0.009	0.007	-0.006	-0.000165
IRRIG	0.131	0.902*	-0.004	1.064*	-0.043	0.053	-0.338*	-0.077
FERT	0.405	-1.268*	-0.244	-0.241	0.427*	-0.24	0.474*	0.416*
ACCESS	-7.339*	-0.025	3.373	0.012	0.776	0.397	-0.714	-0.163*
INSTI	-1.199*	-0.348	0.474*	0.16	1.412*	-2.243	0.77	-0.632*
GCP	2.115*	0.438	0.855*	0.808	-0.231	2.713*	-0.554	0.952*
Rainfed Areas								
POP	-0.021	-0.018	-0.019	-0.003	-0.003	0.001	-0.044*	0.005
IRRIG	3.361	-1.248	-0.624	0.483	-4.145	-5.252*	-1.862	-1.128
FERT	0.804	-0.3	-0.437*	-0.166	0.781	-0.374	0.332	1.075*
ACCESS	-4.257	0.085	1.896	-0.057	0.369	0.826	-0.476	-0.038
INSTI	-0.619	-0.758*	0.44*	0.167	1.126	-5.063*	2.864*	-0.587*
GCP	2.03	0.733	0.8*	1.045	1.106	2.668*	1.355	0.547*
Irrigated Areas								
POP	-0.001	-0.000244	0.001	-0.007	0.016	0.003	-0.003	0.003
IRRIG	0.154	0.181	-0.045	0.134	-0.152	0.093	-0.339*	0.004
FERT	0.285	-1.411	-0.1	1.048	0.487*	-0.217	0.383*	0.226*
ACCESS	-3.948	3.196*	2.261	0.177	6.391	-1.222	0.431	1.042*
INSTI	-0.932*	0.28	0.614*	0.415	0.96	-1.614	0.618	-0.85*
GCP	1.703*	-0.038	0.412	0.749	0.014	1.828*	-0.135	1.88

* Statistically significant at 5% level of significance

Table 9. Estimates of direct and indirect impacts of selected variables on efficiency scores: Rainfed Areas

Regions		N & C America	L America	EU & Russia	SS Africa	M East & N Africa	S Asia	C & E Asia	S E Asia & Oceania
Maize									
Direct	POP	-0.004*	-0.006*	-4E-04	-4-E04	-0.002	-0.001	-0.004	-0.002
	IRRIG	-0.009	-0.413*	-0.189	0.161	-0.173	-0.303	0.133	-0.154
	FERT	0.312*	0.098*	0.059*	0.054	0.037	-0.015	-0.008	0.036
	ACCESS	0.640*	-0.147	1.109*	0.026	-0.040	0.450*	0.367	-0.041
	INSTI	0.754*	-0.174*	0.313*	0.036	-0.002	0.104	0.670*	-0.003
	GCP	0.147*	0.192*	0.411*	0.297*	0.045	0.823*	-0.379	0.044
Indirect	POP	0.069*	-0.057*	1-E04	0.005*	-0.008	-0.001	-0.054*	-0.008
	IRRIG	1.777	-1.690	-0.899*	-0.296	0.787	-1.817	0.782	0.777
	FERT	0.882*	0.035	0.078*	-0.019	0.071	-0.165	0.149	0.074
	ACCESS	4.145*	-0.986*	0.085	0.212*	-0.070	0.883	-0.613	-0.069
	INSTI	0.734*	-0.364*	0.045	0.163*	0.280*	0.505	-0.845*	0.279*
	GCP	-1.466*	0.463	0.081	0.43*	0.215	5.319*	-0.441	0.221*
Wheat									
Direct	POP	0.001	-0.002	5E-04	-0.002	0.001	-2E-04	0.001	-0.003
	IRRIG	0.133	0.171	-0.070	0.523	-0.586	-0.442	-0.426	-0.074
	FERT	0.141*	-0.080*	0.109*	-0.480*	0.042	-0.023	0.034	-0.013
	ACCESS	0.439*	-0.154*	0.711*	0.063	-0.009	-0.049	0.321*	-0.038
	INSTI	0.383*	-0.046	0.394*	-0.128	0.159	-0.608*	0.974*	-0.139*
	GCP	0.069*	-0.073	0.198*	-0.070	0.858*	0.097	-0.986*	0.009
Indirect	POP	0.108*	-0.032	0.01*	-0.017*	-0.004	-0.006	-0.031*	-0.013
	IRRIG	-4.827	1.195	0.793	1.507	-2.437	-2.175	1.021	-0.348
	FERT	0.689*	-1.233*	0.496*	1.737*	0.116	-0.311*	0.298*	-0.332
	ACCESS	5.582*	-2.209*	-0.376	0.088	0.416	-0.261	0.320	-0.580
	INSTI	-0.311	0.536*	-0.051	0.395	-0.319	-2.392*	-0.851*	0.195
	GCP	0.273	-1.430*	-0.083	-0.289	1.260*	1.657*	0.620	0.134
Rice									
Direct	POP	-0.004	-0.001	-0.004	4E-04	-0.002	0.001	-0.010	-0.001
	IRRIG	1.369	0.231	0.101	0.120	-1.433*	-1.352*	-0.081	-1.618*
	FERT	0.285*	0.090	-0.151*	0.179*	0.169	-0.079	-0.138	0.231*
	ACCESS	-0.755	0.096	1.469*	0.051	0.023	0.692*	0.114	-0.153*
	INSTI	0.471*	-0.194	0.496*	0.157*	1.225*	-1.341*	2.455*	-0.292*
	GCP	0.740*	0.290	0.357*	0.308*	0.158	0.163	-0.090	0.931*
Indirect	POP	-0.017	-0.017	-0.016	-0.003	-0.001	7E-05	-0.034	0.006
	IRRIG	1.993	-1.480	-0.724	0.363	-2.712	-3.900	-1.782	0.490
	FERT	0.518	-0.390	-0.286	-0.346	0.612	-0.295	0.469	0.845*
	ACCESS	-3.502	-0.011	0.427	-0.108	0.346	0.134	-0.590	0.115
	INSTI	-1.090	-0.563	-0.056	0.010	-0.099	-3.722*	0.409	-0.295
	GCP	1.290	0.443	0.443	0.736	0.948	2.505*	1.445	-0.384

[*] Statistically significant at 5% level of significance

Table 10. Estimates of direct and indirect impacts of selected variables on efficiency scores: Irrigated Areas

Regions		N & C America	L America	EU & Russia	SS Africa	M East & N Africa	S Asia	C & E Asia	S E Asia & Oceania
Maize									
Direct	POP	-0.002	-0.003	-0.002*	0.002	0.002	-2E-04	-0.002*	-0.001*
	IRRIG	0.017	-0.001	-0.042*	-0.045	-0.021	0.005	-0.085*	-0.035*
	FERT	0.101*	-0.055	0.026	0.021	0.062	0.041*	0.100*	0.123*
	ACCESS	0.079	-0.247	0.068	0.155	0.591	1.450*	-0.066	-0.240*
	INSTI	0.588*	-0.055	-0.025	-0.293	0.149	-0.056	0.115*	-0.008
	GCP	0.347*	0.700*	0.416*	0.686	1.142*	-0.130	0.091	0.383*
Indirect	POP	0.004	0.003	-0.005	0.001	0.028*	-0.004	-0.017*	-0.001
	IRRIG	0.216*	0.353	0.028	0.239	-0.033	0.027	0.072	0.070*
	FERT	-0.261	-0.422	0.093	0.390	0.051	-0.378*	0.045	-0.022
	ACCESS	4.945*	0.887	3.581*	-0.297	-0.098	-2.840*	-2.001	0.084
	INSTI	0.401	0.275	0.218	0.755*	1.039*	-2.851*	0.185	-0.002
	GCP	-0.282	1.269	0.556*	-0.337	-1.128	2.757*	-0.178	0.513
Wheat									
Direct	POP	-1E-04	0.001	-4E-04	-0.006	0.002	-8-E05	-4E-04	-0.001
	IRRIG	0.058*	-0.073	-0.061*	0.372	-0.009	0.045*	-0.005	0.002
	FERT	0.050	0.021	0.133*	1.058*	0.110*	0.109*	0.081*	-0.018
	ACCESS	-0.310	-0.705*	-0.955	-0.153	0.275	1.391*	0.106	-0.055
	INSTI	0.246*	0.078	0.305*	-0.192	0.199*	-0.090	0.045	-0.252*
	GCP	-0.053	-0.008	0.267*	-0.005	0.293*	0.186	0.161	0.056
Indirect	POP	0.007	-0.001	-0.003	0.002	0.012	-0.001	-0.003	-0.025*
	IRRIG	0.337*	0.093	-0.181*	0.773	0.057	0.192*	0.264*	0.015
	FERT	-0.481*	-0.132	0.483*	1.481	0.272*	-0.346	0.088	0.167
	ACCESS	-0.755	-1.176	-7.978*	-3.018	1.927	-1.476	1.455	-1.935
	INSTI	-0.186	0.640*	-0.363*	0.913	-0.738*	-1.916*	-0.502	-0.593
	GCP	0.213	-0.624	0.007	-2.474*	1.870*	1.226	1.436	2.272*
Rice									
Direct	POP	0.004	-0.002	-0.002	0.004	0.002	0.001*	-2E-04	-0.001
	IRRIG	0.062	0.047	-0.042	-0.344	-0.029	0.051*	-0.004	-0.003
	FERT	-0.059	-0.182	0.008	-0.746	0.100	0.003	0.013	0.073*
	ACCESS	-0.762	-0.064	0.481	-0.208	1.273	1.977*	0.359	-0.056
	INSTI	0.287*	-0.038	0.543*	-1.079	0.070	-0.565*	0.403*	-0.052
	GCP	0.488*	0.119	0.535*	0.707	0.642	0.097	0.204	0.858*
Indirect	POP	-0.005	0.002	0.003	-0.011	0.014	0.002	-0.002	0.004
	IRRIG	0.092	0.134	-0.003	0.478	-0.124	0.042	-0.335*	0.007
	FERT	0.344	-1.229	-0.108	1.794*	0.388	-0.220	0.369*	0.153
	ACCESS	-3.186	3.260*	1.779	0.386	5.117	-3.200	0.072	1.098*
	INSTI	-1.219*	0.318	0.071	1.494	0.889	-1.049	0.216	-0.798*
	GCP	1.215*	-0.158	-0.123	0.042	-0.627	1.731	-0.339	1.022

* Statistically significant at 5% level of significance