Disentangling agronomic and economic yield gaps: An integrated framework and application

Michiel van Dijk[a,c]*, Tom Morley[a], Roel Jongeneel[a], Martin van Ittersum[b],
Pytrik Reidsma[b] and Ruerd Ruben[a]

[a]Wageningen Economic Research
[b]Plant Production Systems – Wageningen University
[c]International Institute for Applied Systems Analysis (IIASA)

*Corresponding author: michiel.vandijk@wur.nl

Highlights

- A framework is proposed that disentangles agronomic and economic approaches to yield gap measurement.
- The framework is operationalised by combining information from crop models and household surveys.
- Decomposition of the total yield gap shows that the technology yield gap makes up the largest part.
- Closing all the yield gaps will result in a fivefold increase in national maize production.
- The results can be used to inform targeted policy and farming recommendations.

Abstract

Despite its frequent use in policy discussions on future agricultural production, both the concept of the yield gap and its determinants are understood differently by economists and agronomists. This study provides a micro-level framework that disentangles and integrates agronomic and economic approaches to yield gap measurement. It decomposes the conventional yield gap indicator into four components that together provide a better understanding of why actual farm yield falls below potential: (1) the technical efficiency yield gap, (2) the allocative yield gap, (3) the economic yield gap and (4) the technology yield gap. The results can be used to inform targeted policy and farming recommendations at plot, farm household, local and national level. The framework is operationalised and tested by combining results from crop models with detailed farm and plot level survey data for maize production in Tanzania.

Key words
Yield gaps, integrated framework, decomposition, stochastic frontier analysis, Tanzania

1 Introduction

According to recent projections, relative to 2005/07 global agricultural production (in value terms) will have to grow by 60% in 2050 to satisfy increasing demand (Alexandratos & Bruinsma 2012). Due to the limited availability of arable land, the largest share of the projected growth will have to come from an increase in crop yields through better use of inputs. Yield gap estimations and explanations provide important information on the scope for production increases on existing agricultural land through better farming systems, improved farm management practices and enabling policies (van Ittersum & Rabbinge 1997; Lobell et al. 2009; Foley et al. 2011; Mueller et al. 2012). To identify the required changes in systems, management and policy that allow for narrowing yield gaps, the analysis of agricultural productivity and its determinants is crucial.

The notion of 'yield gap' has frequently been used as a framing device for agricultural policy in developing countries because of its rather straightforward and powerful implications. However, in a recent paper Sumberg (2012), who analysed the use of the yield gap notion in a number of high profile policy documents concludes that: *"…while the yield gap of policy discourse provides a simple and powerful framing device, it is most often used without the discipline or caveats associated with the best examples of its use in production ecology and microeconomics. […] In general, the link between the yield gap and issues addressed by the favoured policy options is lacking or at best poorly specified"* (Sumberg 2012, p. 510). One problem is that the definition of yield gap often differs between studies, which makes it difficult to interpret and compare results. Specifically, differences in views between agronomists and economists can be observed, who each use their own interpretation of the yield gap. Broadly speaking, agronomic assessment of the yield gap tends to focus on the bio-physical and physiological determinants of crop production but do not account for socio-economic constraints such as prevailing market conditions, infrastructure, risk attitude and institutions. Economists in contrast, emphasize the role of prices, markets and efficiency as determinants of agricultural production but often fail to take into account the biophysical opportunities and constraints that are highly locally-specific.

The aim of this paper is to provide a micro-level framework that disentangles and integrates agronomic and economic approaches to assess the causes of the yield gap. It builds on the work of De Koeijer et al. (1999) and Hoang (2013), who present similar analytical approaches but with limited or no empirical application (also see Beddow et al. 2015). The framework that is presented in this paper allows for an enhanced understanding of the various types of yield gaps, their sizes and determinants. The results can be used to inform targeted policy and farming recommendations at plot, local and national level.

The framework is operationalised and tested by combining results from crop models with detailed farm and plot level survey data for maize production in Tanzania. With an average gross national income per capita of US$ 570 (2012), Tanzania is classified as a low income country (World Bank 2015). Agriculture, which contributes almost 28 % to the GDP, is the predominant source of income for the 73% of the population that lives in rural areas. The main staple food crop is maize, which is consumed and cultivated throughout the country under varying agro-climatic and socio-economic conditions. An analysis of the maize yield gap in Tanzania is therefore methodologically interesting and relevant from both a poverty and food security perspective.

The structure of this paper is as follows. Section 2 provides a literature review that summarises insights from agronomy and agricultural-economics research regarding the definition and measurement of the yield gap. Section 3 presents the conceptual framework that disentangles and integrates yield gap approaches applied in the two sciences. Section 4 describes the data used for the analysis and Section 5 presents yield gap estimates for maize by zone in Tanzania. Section 6 uses the yield gap estimates to assess the scope to increase maize production at the national level. Finally, Section 7 concludes.

2 Literature review

2.1 Insights from agronomy

The notion of yield gap originates from agronomy and production ecology. It is the difference between the potential yield and the actually observed yield at the farm, field or plot level (Evans & Fisher 1999; van Ittersum & Rabbinge 1997). It can be either expressed as a difference (in tonnes per hectare) or as a fraction. Potential yield is defined as *"the yield of a cultivar when grown in environments to which it is adapted, with nutrients and water non-limiting and with pests, diseases, weeds, lodging, and other stresses effectively controlled"* (Evans & Fisher 1999, p. 1544). It refers to the biophysical maximum production level of a crop with growth only constrained by *growth defining factors*, including atmospheric CO_2 emissions, solar radiation, temperature and plant characteristics (van Ittersum & Rabbinge 1997). Potential yield is time- and location-specific because of spatial differences in growth defining factors and the development of improved cultivars over time.

Four methods are used in the agronomic literature to calculate or estimate potential yield (Lobell et al. 2009): (1) crop model simulations, (2) field experiments, (3) yield contests, and (4) maximum observed (farmer) yield, also sometimes referred to as 'attainable' yield (Hall et al. 2013; Tittonell & Giller 2013). Van Ittersum et al. (2013) present a detailed comparison of these methods for different cropping systems in three countries: Kenya, USA and Australia. They find considerable differences in potential yield estimations and conclude that crop model simulations provide the best opportunities to capture interactions between crops and the environment in yield gap analyses. This requires the use of a well-tested and calibrated crop growth model and best (preferably measured) weather, soil and agronomic data (Grassini et al. 2015). A similar conclusion is reached by Affholder et al. (2013), who compare different methodologies to measure potential yield for several farming systems in selected study areas in Brazil, Senegal and Vietnam.

In practice, actual farmers' yield will be below potential yield because of two factors. *Growth limiting factors*, which refer to the two essential inputs for plant growth: water and nutrients. In large parts of the world, in particular sub-Saharan Africa, agricultural systems mainly comprise rain-fed crops. Under these conditions, water-limited potential yield, is used as a benchmark for potential yield, assuming that yield is limited by water supply and distribution during the crop growth period and there are no other constraints. The second group of factors that constrain crop growth are *growth reducing factors*. These include pests, diseases, weeds, insects and pollutants. Agronomic management practices determine the extent to which growth reducing and growth limiting factors affect yield levels, and hence, the observed yield gap. Examples of practices to manage growth limiting and growth reducing factors are crop rotation, irrigation, fertilisation and pest management (Tittonell & Giller 2013).

The relationship between yield and the growth defining, growth limiting and growth reducing factors can be described by a *yield response function*, defined as:

$$Y = f(D, L, R) \tag{1}$$

where Y is yield and D, are the growth defining factors, L are the growth limiting factors, and R are the growth reducing factors. Traditionally, the functions have been estimated using data from experimental or research station plots on which growth limiting factors vary while growth defining factors are kept constant and growth reducing factors are fully controlled for. The focus lies on estimating the relationship between yield and the essential inputs water and nutrients, while seed characteristics and agronomic management are kept constant. Although there is no agreement in the literature on the functional form of the yield response function, several studies find that linear response and plateau functions (i.e. Mitscherlich-Baule and Von Liebig) give the best results. Such functional forms suggest that plant growth is constrained by a most limiting input (de Wit 1992; Paris 1992). Berck and Helfand (1990) pointed out that it is relevant to distinguish between micro-level (i.e. plant) and aggregated (plot or field) response functions. Aggregated functions model the total output of multiple plants, which are grown under a variety of conditions (e.g. differences in soil quality and management practices within the field). They show that, even if the linear response and plateau model hold at the single plant or homogenous experimental plot level, heterogeneous conditions will result in a smooth aggregate production function such as the Cobb-Douglas and quadratic functions, which allow for substitution between inputs.

Lobell et al. (2009) surveyed a large number of yield-gap studies for maize, wheat and rice cropping systems throughout the world and found that actual farmers' yields plateau at around 80% of their potential. The explanation that is offered for this finding is that it will often not be cost-effective for farmers to achieve potential yield (Fischer et al. 2014; Sadras et al. 2015). As the response to inputs is diminishing, reaching potential yield demands a very large and unprofitable additional amount of fertilizers, pesticides and machinery to fully close the yield gap. The profit maximizing yield level that reflects local economic conditions has been referred to as 'exploitable yield' (van Ittersum et al. 2013), 'attainable yield' (Fischer et al. 2014) and 'economic yield' (Fischer 2015). It is often defined as 70-85% of (water-limited) potential yield on the basis of 'general experience' (van Ittersum et al. 2013; Fischer 2015). However, proper estimations involving information on input and output prices that are needed to determine economic yield are not common in the agronomic literature.

2.2 Insights from agricultural economics

Generally, economics does not take into account the biophysical constraints of agricultural production that are emphasised by agronomic theories of crop growth. For this reason, the concept of potential yield and yield gap are not part of the standard economic approach to agricultural production. Economists use a production function that represents the technology that transforms inputs into outputs to measure the performance of the agricultural sector, farms or plots (Sadoulet & De Janvry 1995). This can be written as:

$$Q = f(X, Z) \tag{2}$$

where Q are outputs (e.g. crop and livestock production), X are variable inputs and Z are fixed inputs. Variable inputs are factors that can be easily purchased or hired in the short run, such as labour, fertilizer, water, pesticides, seeds and hired machinery. Fixed inputs include private capital that constitutes relatively large long-run investments (e.g. land and machinery) but also environmental production conditions (i.e. the growth defining factors from agronomy).

The production function can also be rewritten as a yield response function in which yield (i.e. output per unit of land) depends on variable and fixed inputs per unit of land (indicated by a bar):

$$Y = f(\bar{X}, \bar{Z}) \tag{3}$$

The most common functional forms for Equation 3 are the Cobb-Douglas and translog functions (Sadoulet & De Janvry 1995). Similar to the agronomic yield response function, the economic approach controls for growth defining factors and growth limiting factors by including irrigation and fertilizer, although they are not always considered in empirical work (Sherlund et al. 2002). The main difference is that the economic yield response function also includes (proxy) variables that control for the presence (or prevention) of growth reducing factors, which may differ widely in non-experimental settings. Most common are the use of pesticides to account for pest management and the use of herbicides and weeding to account for weed control. In addition, it also includes general farm-level factors (labour and machinery) that represent overall farm management. Recently, researchers have used economic yield response functions to estimate the response to fertilizer using large household and plot level surveys for several African countries (Xu et al. 2009; Sheahan et al. 2013).

To compare the performance between farmers, the concept of technical efficiency is often used (Coelli et al. 2005). Technical efficiency is defined as the farm’s ability to produce maximum output given a set of inputs and technology. A farm is inefficient if it can produce more output with the same set of inputs. Technical efficiency is measured as the distance to the production or technology frontier, which depicts best-practice performance. It is different from technical change or innovation, which reflects an outward shift of the frontier (Färe et al. 1994). To estimate technical efficiency, the production frontier is estimated using non-parametric data envelopment analysis (DEA) or stochastic frontier analysis

(Coelli et al. 2005). The technical efficiency of farms can differ substantially both within (e.g. Latruffe et al. 2012) and between countries (e.g. Theriault & Serra 2014) and are caused by a wide range of determinants related to farm-level factors (e.g. farm size, experience and age) and the enabling environment (e.g. access to extension services, farmer organisations and institutions) – see Bravo-Ureta (2007) and Ogundari (2014) for reviews.

Apart from technical efficiency, it also possible to evaluate the farm's success in choosing economic optimal input and output quantities.[1] The main assumption in neoclassical economics is that economic actors (e.g. farmers) maximize profits (not production), subject to given input and output market prices and production technology. This can be formalised as follows:

$$Max\, pY - w\bar{X}, \text{s.t.}\, Y = f(\bar{X}, \bar{Z}) \tag{4}$$

The first part of equation 4 is the (per unit of land) profit function (equalling revenues minus costs), where, w and p are the (expected) prices of inputs and outputs, respectively, indicating their scarcity. Profits are maximized subject to the yield response function presented in equation 3. Profit maximization implies that the farm households will demand inputs up to the level that the marginal cost of acquiring an additional unit of input (e.g. fertilizer) is equal to the marginal revenue of producing an additional unit of output (e.g. tons of maize). Under the assumption of perfect markets and full information, the demand for inputs will solely depend on exogenous input and output prices, and production technology. The assumption of perfect markets is not realistic in the context of developing countries because of poor infrastructure that result in high transaction cost, missing credit and insurance markets and lack of information on input and output prices and available technologies (Stiglitz 1989; Dillon & Barrett 2014).

---

[1] A related concept to measure the optimal use of inputs and outputs that is used in the economic production literature is 'allocative efficiency' (Coelli et al. 2005), This is a specific technical measure that relates to the economic optimal use of combinations of multiple inputs given a single output (the input orientation) or combinations of multiple outputs given a single input (the output orientation). Our approach is framed in the literature on optimal fertilizer use that evaluates the economic optimal allocation of one input (nitrogen) and one output (yield) given prices. If price information for other inputs such as labour and capital are available allocative efficiency might be estimated. However, this information is not available in our case.

Under these conditions, the demand for inputs tends to be lower than the economic optimum resulting in lower output and yield (Kelly et al. 2003; Liverpool-Tasie 2016).

3 Analytical framework

Figure 1 combines and extends insights from agronomy and agricultural economics into one figure. It depicts input-output combinations of agricultural units (i.e. plots or farms). For the moment, we assume that the yield response function has only one output y (e.g. maize yield), one variable input x (e.g. nitrogen) and growth defining factors are the same for all observations.[2] All other inputs are fixed. For the purpose of illustration, we also assume that water is not limited and therefore the water-limited potential yield level is not relevant.[3] The *theoretical yield response function* describes the relationship between yield and inputs when growth defining factors are held constant and growth reducing factors are fully controlled for. This is the function that can be estimated using data from experimental research stations. The maximum of the function depicts the potential yield level, which in this study is computed using crop models. The *frontier yield response function* is estimated using actual observations from a sample of farmers in a specific country or region. It measures best-practice performance at different input levels and reflects the available technology and best management practices in the region. It will always be lower than the theoretical yield response function because of the impact of growth reducing factors, the enabling environment and farm level characteristics on actual farmers' yield.

Figure 1: Combined agronomic and economic framework to decompose the yield gap

---

[2] In practice, even within countries, observations will be located in different climatic zones and potential yield cannot to be assumed equal for each observation point. In the empirical example below we use spatially explicit estimates of potential yield and control for differences in agro-ecological conditions in the estimation of the yield response curves.

[3] The water-limited potential yield level can easily be added in the diagram by adding a line below the theoretical yield response curve that accounts for the impact of limited water supply on yield.

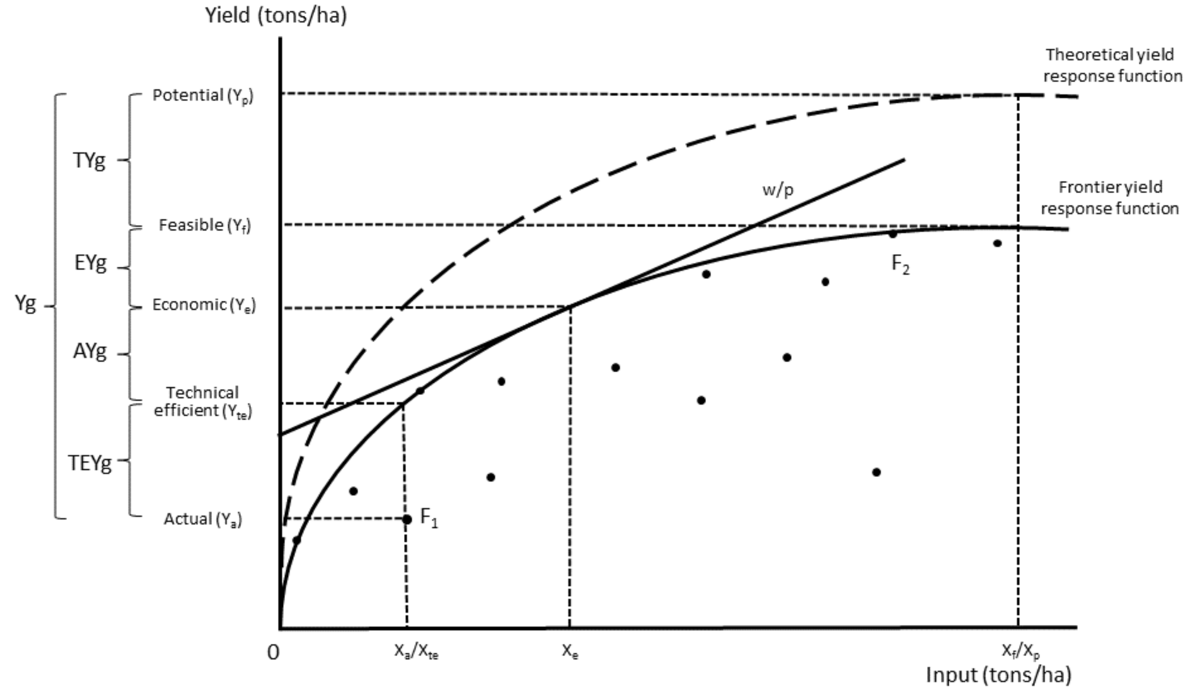


Figure 1 depicts five yield levels. For plot F_1, *actual yield* (Y_a) is determined by input level X_a. F_1 is located below the frontier and therefore a farmer can increase the yield to the *technical efficient yield* (Y_{te}) using the same amount of inputs. At this level of inputs and given output price p and input price w, profit is not maximized. To maximize profits, farmers will have to increase inputs to X_e, which results in the *economic yield level* (Y_e). At this point marginal costs are equal to marginal revenue and the relative market price line (w/p) is tangent to the frontier yield response function. In some cases, it is also possible that farmers are overusing inputs (e.g. plot F_2), for instance because of subsidies or risk behaviour. In this case, the economic yield level will be lower than the technical efficient yield level. Technically, farmers can increase yield to the *feasible yield level* (Y_f) using X_f inputs. This is the point where the frontier function reaches its maximum and additional inputs will no longer result in higher yield.[4] It represents the maximum feasible yield that can be reached on the plot with available technology

---

[4] For ease of explanation we assume that the theoretical and frontier yield response function plateau at the same input level X_f/X_p. X_p defines the input level at which potential yield is reached and, by definition, is therefore always larger or equal to X_f.

and best-practice management but without economic constraints (e.g. free inputs).[5] Finally, under perfect management of e.g. pests and diseases and no limitations in water and (all) nutrients, yield can be further increased to the *potential yield level* (Y_p), which is achieved at the top of the theoretical yield function using inputs X_p.

The total yield gap (Yg) from the agronomic literature can be defined in relative terms (r) and in level form (l). The relative term expresses the gap as a percentage, while the level form measures the gap in tons per hectare.

$$Yg_r = 1 - \frac{Y_a}{Y_p}, \qquad Yg_l = Y_p - Y_a \tag{5}$$

Building on the framework above, we can decompose this into four components. Similar to Yg, each of the components can be expressed in relative terms and in level form.

(1) *The technical efficiency yield gap (TEYg)*, which is defined as:

$$TEYg_r = 1 - \frac{Y_a}{Y_{te}}, \qquad TEYg_l = Y_{te} - Y_a \tag{6}$$

The *TEYg* is the distance to the frontier yield response function and indicates to what extent farmers can increase yield with the same inputs in comparison to best-practice (also see Silva et al. 2016, who apply the same measure in their study on Philippine rice yield gaps). Hence, it is a measure of the technical inefficiency of farmers. As pointed out above, a wide number of factors related to the enabling environment and the farm level explain the *TEYg*.

---

[5] This yield level is sometimes referred to as the ‘potential farm yield’ (De Datta 1981), ‘maximum attainable yield’ (FAO 2004), ‘technical on-farm ceiling yield’ (De Bie 2000) and 'locally attainable yield' (Tittonell & Giller 2013) but does not feature in the conventional agronomic and agro-economic theoretical frameworks described above. In most empirical work this yield level is approximated by the average of the (90 or 95 percentile) highest yield in the sample of observations (Hall et al. 2013), which corresponds with F_2 in Figure 1. We prefer to introduce a new name (i.e. feasible yield) to avoid the confusion between all the different uses of ‘attainable yield’ in the literature.

(2) *The allocative yield gap (AYg)*, which is defined as*:*

$$AYg_r = 1 - \frac{Y_{te}}{Y_e}, \qquad AYg_l = Y_e - Y_{te} \tag{7}$$

The *AYg* is the gap between the technical efficient and the economic optimum yield level, both located on the frontier. It measures whether (efficient) farmers allocate their resources in an economically optimal way. It captures the impact of missing credit and insurance markets, high transaction costs and information asymmetries on production decisions of the farmer. The *AYg* is expected to be larger in developing countries, such as Tanzania, because of pervasive market failures that characterise (agricultural) input and output markets.

(3) *The economic yield gap (EYg)*, which is defined as:

$$EYg_r = 1 - \frac{y_e}{y_f}, \qquad EYg_l = y_f - y_e \tag{8}$$

The *EYg* is the difference between the yield that is economically feasible and the yield that is technically feasible with the available technology but assuming that all inputs (e.g. fertilizer, capital and labour) are available at no costs. Although farmers can technically close this gap by applying more inputs, economic constraints will prevent them from doing so.[6] This gap is also expected to be relatively large in developing countries, where input prices are relatively high because of market poor dealer networks, high transportation costs and small market size (Morris et al. 2007).

(4) *The technology yield gap (TYg)*, which is defined as:

$$TYg_r = 1 - \frac{Y_f}{Y_p}, \qquad TYg_l = Y_p - Y_f \tag{9}$$

---

[6] Apart from economic constraints, there also might be environmental reasons (e.g. uncertainties related to temperature and rainfall) that prevent farmers producing at the feasible yield level (Van Ittersum et al., 2013).

The *TYg* is the distance between the frontier and theoretical yield response curve approximated by the difference between the feasible and potential yield level. This gap cannot be attributed to differences in intensification as the level of inputs (X_f/X_p) is the same for both yield levels. Instead, the main explanation has to be sought in (the lack of) access to and availability of appropriate technologies (Tittonell & Giller 2013). Potential yield reflects the biophysical maximum, which can only be reached using advanced technologies such as precision agriculture and advanced crop management practices as well as the adoption of the latest varieties (i.e. hybrid seeds) that are not yet used by all farmers. To close this gap, the frontier yield function will have to shift upward in the direction of the theoretical yield function. This implies that best-practice farmers adopt advanced technologies, inputs and practices that make it possible to increase their yield to levels that previously could not be attained. For farmers in developing countries that are not using the latest technology, the *TYg* is expected to be larger than in rich countries, which are already operating close to the potential yield level. The cause of the (agricultural) technology gap between rich and poor countries has been the subject of much research and can be related to broader institutional, technological, economic and social factors (Fagerberg 1994; Mekonnen et al. 2015).

Equations 5 to 9 above can be combined in the following way:

$$\frac{Y_a}{Y_p} = \frac{Y_a}{Y_{te}} \times \frac{Y_{te}}{Y_e} \times \frac{Y_e}{Y_f} \times \frac{Y_f}{Y_p} \qquad (10)$$

$$Yg_l = TEYg_l + AYg_l + EYg_l + TYg_l \qquad (11)$$

Our framework described above provides a more elaborate approach to measuring the yield gap than agronomic and economic approaches alone. By decomposing the total yield gap into four components a more accurate picture of the key determinants of yield gaps can be obtained. It shows that the total yield gap is caused by differences in the level of intensification (i.e. the quantity of inputs used) – captured by *AYg* and *EYg* – the efficiency with which inputs are used – measured by *TEYg* – and the technology that is applied to the agricultural production process – reflected by *TYg*. The decomposition enables a more focussed appraisal of the likely effectiveness of possible policy options.

4 Data and Methods

4.1 Data sources

The main data source for the analysis of plot level yield gaps is the 2010-11 and 2012-13 waves of the Tanzania Living Standards measurement Study Integrated Surveys in Agriculture (LSMS-ISA).[7] The LSMS-ISA is a large scale nationally representative survey implemented by the National Bureau of Statistics Tanzania in collaboration with the World Bank. The survey was designed to be representative at the national and geographical zone level and has a strong focus on agriculture. The LSMS-ISA covers a wide range of agricultural variables at the plot, household and community level, including crop-specific production, fertilizer use, labour, and input and output prices. The database also contains the GPS recording for the size of the plot, which are essential to obtain accurate actual yield estimations. The LSMS-ISA also includes the longitude and latitude of each household cluster that was sampled. This makes it possible to link external data including climate, soil and a selection of other spatial data. Each wave of the data is accompanied by a data file with information on a large number of geo-spatial variables from additional sources. For the analysis we use an unbalanced sample of more than 1,100 households per year that own more than 1,600 plots. Annex A provides additional information about the data (sample selection, summary statistics and other data sources).

We augmented the LSMS-ISA data with spatial information from the Africa Soil Information Service (AfSIS, http://africasoils.net) project and the Global Yield Gap Atlas (GYGA, www.yieldgap.org). AfSIS presents soil property maps for Africa at 250m spatial resolution and various depths based on 28 thousand sampling locations (Hengl et al. 2015). We use AfSIS data to derive the soil organic carbon stock and pH for the top 200 cm soil layer. These indicators are frequently used as covariates in yield

---

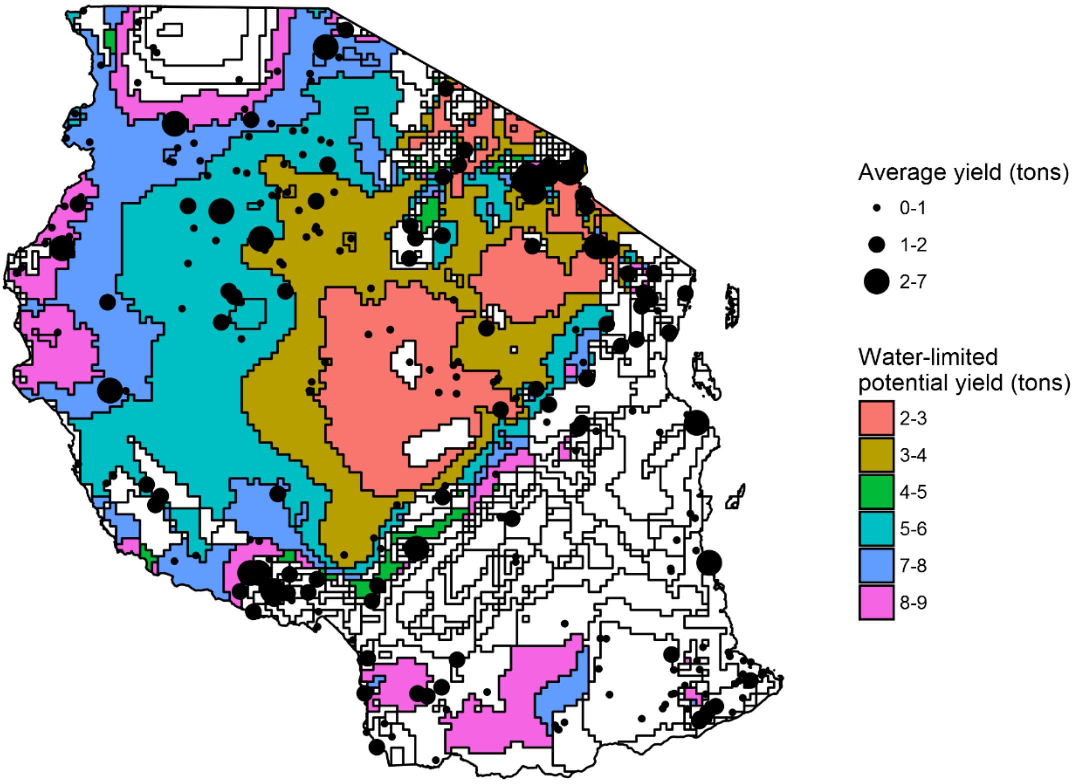
[7] The first wave of the LSMS-ISA for Tanzania was conducted in 2008-09. As the level of GPS recording was very low for this year we decided not to use it.

response function estimates (Marenya & Barrett 2009; Burke 2012) to estimate soil quality. GYGA aims to present consistent estimates of potential yield and yield gaps using a standard protocol combined with a bottom-up approach based on field- data and robust crop simulation models (van Bussel et al. 2015; Grassini et al. 2015). We derived data on water-limited potential yield for maize in Tanzania from GYGA.[8] The map in Figure 2 depicts average actual yield per enumeration area from the LSMS-ISA and water-limited potential yield from GYGA. Clusters of households with high yield can be observed in the Northern and Southern Highlands zones, which constitute the key maize producing regions in Tanzania, while potential yield is highest in parts of the Lake, Southern and Western zones (also see Figure 1 in Annex A).

---

[8] Maize cultivation is predominantly rainfed in Tanzania. This is also confirmed by information in the LSMS-ISA, which indicates that around 2% of maize plots are irrigated.

Figure 2: Water-limited potential maize yield and actual maize yield in Tanzania



Source: Water-limited potential maize yield from GYGA and actual yield by enumeration area from the World Bank LSMS-ISA surveys. Actual yield is based on the pooled sample and weighted by plot size. To reduce the impact of outliers, enumeration areas that contain information for only one plot are not depicted.

4.2 Yield level estimation

Actual yield, defined as total quantity harvested divided by harvested, is taken from the LSMS-ISA. We use stochastic frontier analysis (Meeusen & Broeck 1977; Aigner et al. 1977) to estimate the frontier yield response function and determine the technical efficient yield for each of the plots in our sample. We assume that actual field level yield can be modelled using a Cobb-Douglas function and depends on a vector of bio-physical and socio-economic variables that are specific to each plot. To control for unobserved household and plot-specific effects (e.g. farmer management skills and soil quality), that are likely to be correlated with some of the explanatory variables (e.g. fertilizer application), we apply the correlated random effects (CRE) framework that controls for unobserved farm-level effects (Wooldridge 2010). Further details on the estimation procedure are provided in Annex B.

Ultimately, like potential yield, best-practice performance will be constrained by growth defining factors and we therefore need to control for this in the frontier response function. This is done by adding information on agro-ecological zone (AEZ), slope and a dummy for the use of hybrid seeds. Growth limiting factors are captured by a range of variables. We use two variables for nutrient availability. Nitrogen applied in the form of inorganic fertilizer is computed using information on the chemical composition of fertilizer.[9] As fertilizer is applied on only 18% of the plots, we add a dummy variable to account for structural differences between plots that use fertilizer and those that do not (Battese 1997). We control for organic fertilizer by adding a dummy for the use of manure. Availability of water is measured by means of growing season rainfall data and a dummy variable for irrigation. We control for differences in soil by using information on (farmer-reported) type of soil, soil organic carbon (SOC) stock and pH from the AfSIS dataset. For the latter, we follow Burke (2012) and apply threshold values for pH of 5.5 and 7, which demarcate the optimal conditions for maize growth. Growth reducing factors (or better, activities that prevent those factors) are modelled by adding information on the use of pesticides. Labour, assets and farm size (measured by total plot area) are included to proxy for overall farm management and size. Finally, we add control variables for pure maize plots (sole crop as opposed to multicrop), survey year and CRE averages.

To estimate economic yield we follow equation 4 and assume that farmers maximize profit at the plot level. As we do not have information on the costs of labour and capital (i.e. wages and rental rates), we take a partial approach and only focus on optimal nitrogen use while the remaining inputs remain constant. We believe this is justified approach in the very short-run when it can be assumed that production factors such as land and assets are fixed but is less realistic in the long-run when farmers

---

[9] Urea, followed by DAP and CAN, are the most common types of fertilizer in Tanzania. Nitrogen and phosphate fertilizers are often used in fixed combination resulting in multicollinearity between N and P. The latter is therefore not included in the model.

may decide to purchase more land and equipment to maximize profit. The same approach is also used in the recent literature on optimal fertilizer use (e.g. Sheahan et al. 2013; Liverpool-Tasie 2016). We use the coefficients of the estimated frontier yield response function and information on maize and nitrogen prices to calculate optimal nitrogen use and associated economic yield for each of the plots.

To estimate feasible yield we collected additional information on the amount of nitrogen (X_f/X_p) that is needed to reach potential yield in Tanzania. Fertilizer trials in a large number of regions in Tanzania (Mowo et al. 1993; Kaswende & Akulumuka 1997) show that maximum experimental plot yield is achieved at around 120 to 150 kg N/ha. We calculate feasible yield assuming a uniform rate of 120 kg N/ha for all plots in the estimated frontier yield response function. To reach the feasible yield level also other inputs than fertilizer will have to be increased. As we do not have information on this, we make the assumption that labour and capital use will grow by 50% and that pesticides and hybrid seeds are applied to all maize plots.

Water-limited potential yield is taken from GYGA. As it does not cover the whole country (Figure 2) we assume a potential yield of 9 tons/ha (the maximum water limited potential yield in Tanzania) for regions that are not covered by GYGA but for which we have LSMS-ISA data. Finally, we compare all yield levels with the water-limited potential yield, which we consider as the absolute maximum. Annex C summarises the procedure to estimate all yield levels.

5 Estimation of yield gaps

5.1 Frontier yield response model

The results for the yield response frontier model are presented in Table 1 (see Annex D for detailed information). Since yield and explanatory factors are measured in their logarithmic forms, all the estimated parameters are elasticities of these inputs. Dichotomous variables are transformed following Kennedy (1981) so that they measure percentage impact. The Likelihood ratio statistic indicates that the stochastic frontier model performs better than the corresponding OLS model, which assumes no technical inefficiency.

Of the growth defining factors, only the AEZ variable for Tropic-warm/sub-humid is significant. The use of hybrid seeds does not result in higher yield although the sign is in the expected direction. Of the growth limiting factors, the dummy for no fertilizer application has a large positive and significant effect. The same result was also found for maize plots in Zambia by Burke (2012) and suggests that fertilizer is more likely to be used on plots with depleted soils. For plots that use fertilizer, one percent more nitrogen results in 0.21 percent higher yield. In contrast to expectations, rainfall appears to have a negative but very small effect on yield. An explanation for this finding might be that rainfall is correlated with the AEZ variable that also includes a precipitation component, leading to a spurious reverse relationship. Another reason for this unexpected relationship is that precipitation is measured at a resolution of 0.1 x 0.1 decimal degrees (approximately 11 x 11 km) and therefore might not adequately capture the actual rainfall in the field. Soil type and quality have a high impact on yield. In comparison to sandy soils, maize cultivation on loam and other soils results in 15% to 33% higher maize yield. SOC stock has a significant but very low impact on maize yield, while an ideal pH between 5 to 7 results in 32% more output. Manure and irrigation are not significant. Pesticides, which controls for (the prevention) of growth reducing factors, is also not significant. Of the farm factors, with elasticities of 0.07 and 0.45, the use of capital and labour is positively correlated with maize yield. In line with most of the literature, we find an inverse relationship between farm size and productivity (Eastwood et al. 2010).

Table 1: Technical efficiency yield gap estimation (stochastic frontier model)

	Coef.	Std. error	
Constant	3.58	0.23	***
Growth defining factors			
Hybrid seeds	0.04	0.07	
Slope	0.0002	0.003	
Tropic-warm/sub-humid	-0.21	-0.05	***
Tropic-cool/sub-humid	-0.05	-0.05	
Growth limiting factors			
No nitrogen	0.72	0.19	***
Nitrogen	0.21	0.05	***
Manure	-0.03	-0.07	
Rainfall	-0.0004	-0.0001	***
Irrigation	-0.08	-0.21	
Loam	0.15	0.07	**
Clay	0.12	0.08	
Other soil	0.33	0.16	*
SOC stock	0.01	0.004	**
pH 5.5-7	0.32	0.06	***
pH >7	0.17	0.09	*
Growth reducing factors			
Pesticides	0.06	0.08	
Farm factors			
ln(assets)	0.07	0.01	***
ln(labour)	0.45	0.02	***
ln(area)	-0.08	-0.03	***
Control factors			
Pure maize plot	0.05	0.05	
Year	0.23	0.03	***

CRE variables		Yes	
σ^2	1.61	0.07	***
Γ	0.79	0.02	***
Log-likelihood		-4,699	
Likelihood ratio statistic		137***	
Observations		3,637	

Note: coefficients for dummy variables have been transformed following Kennedy (1981) to measure impact in percentages; * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

5.2 Quantification of yield gaps

Table 2 and Table 3 present the total yield gap and its decomposition into four elements for each of the seven geographic zones in Tanzania, using the level and relative definition, respectively. We divide the yield gaps in level form (equation 11) by Yg_l to obtain shares that sum to 100%. The level and relative yield gap decomposition provide different pieces of information that are relevant for policy formulation. The first shows which of the different yield gap components contributes the most to the total yield gap. The second provides information on the scope for closing the various yield gap components.

At country scale, TYg_l (44%) makes up the largest part of Yg_l, followed by AYg_l (23%), EYg_l (21%) and $TEYg_l$ (11%). A closer look at the results at zonal level, reveal some striking differences. Apart from the Northern and Central zone, TYg_l gap contributes the largest share to the total yield gap in all zones. AYg_l is more than 20% in all zones apart from the Southern Highlands and Southern zone. This finding can be explained by the fertilizer subsidy policy program in Tanzania (see below). EYg_l is more or less the same in all zones. $TEYg_l$ is relatively high in the Central zone in comparison to other regions.

In relative terms, comparing each yield level to its own benchmark, $TEYg_r$ (52%) is the largest at country level, followed AYg_r (47%), EYg_r (34%) and by TYg_r (33%). Again, findings differ across zones. $TEYg_r$ is broadly the same range for all zones, which indicates that constraints to increase technical efficiency prevail throughout the country. AYg_r is lower in two key maize areas in Tanzania:

the Southern Highlands and the Southern zone. These two zones received most of the fertilizer subsidies under the National Agricultural Voucher Scheme (NAIVS), Tanzania's national fertilizer subsidy program, which offers farmers access to fertilizers at half of the market price (World Bank 2014). The actual price that many farmers paid for fertilizer in these zones is much lower than the price we used as market price in our calculation of economic optimal yield and fertilizer. A large number of farmers are therefore using 'too much' fertilizer, resulting in negative AYg_r values. This is confirmed by Figure 3, which shows the distribution of the yield gap measures. TYg_r also varies substantially between regions, ranging from 7% in the Central zone to 59% in the Southern zone.

Our results are broadly in line with other studies. Msuya *et al.* (2008) find an average technical efficiency of 60% among smallholder maize farmers in the Northern and Southern-Highland zones, which is comparable with our $TEYg_r$ results in these regions. Combing survey information and crop model results, Mourice *et al.* (2015) observe a maize yield gap of 79% (relative to water-limited potential yields) in the Wami River sub-basin (Eastern zone), which is somewhat lower than our Yg_r estimate of 92% for the same zone. There are no comparable results in the literature for the other type of yield gaps.

Table 2: Maize yield gap by zone (%) using the level definition as share of total yield gap

Zone	$TEYg_l$	AYg_l	EYg_l	TYg_l	Yg_l
Northern	13	36	22	30	100
Lake	12	33	22	34	100
Western	16	32	26	26	100
Central	27	40	22	11	100
Eastern	9	25	20	46	100
Southern Highlands	10	17	21	51	100
Southern	7	12	18	63	100
Total	11	23	21	44	100

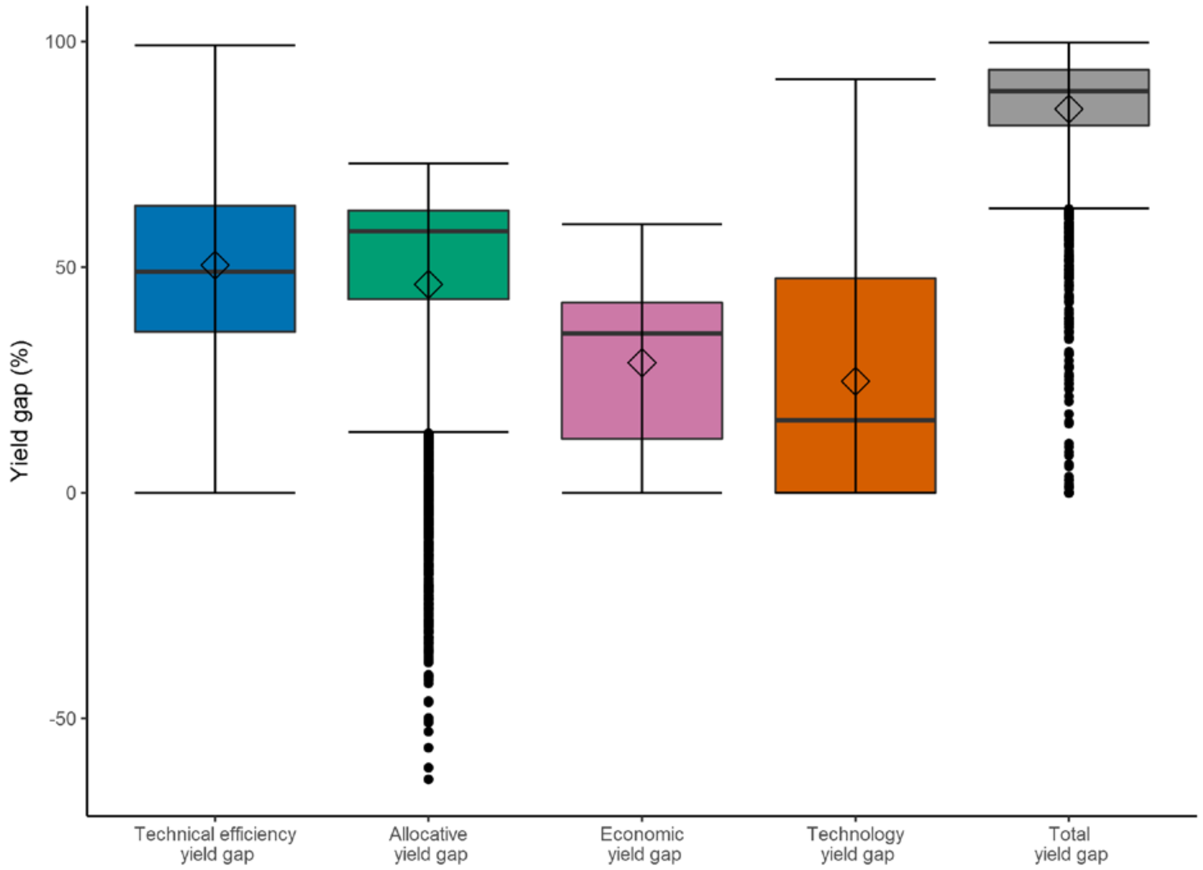
Note: Average for 2010 and 2012. Plot size used as weights. Shares are derived by dividing the yield components by the total yield gap per zone. See Annex D for the yield gap in level form underlying the figures in the table.

Table 3: Maize yield gaps (%) by zone using the relative definition

Zone	$TEYg_r$	AYg_r	EYg_r	TYg_r	Yg_r
Northern	47	54	27	22	86
Lake	60	61	31	30	92
Western	56	50	32	19	88
Central	55	45	18	7	81
Eastern	51	59	35	41	92
Southern Highlands	49	41	38	43	89
Southern	52	40	44	59	93
Total	52	47	34	33	89

Note: Average for 2010 and 2012. Plot size used as weights. Yield gap in percentage form. All values measure a gap, meaning 1 minus the relative yield.

Figure 3: Size and distribution of maize yield gaps using relative definition



Note: Pooled data for 2010 and 2012. The mean yield gap indicated by the diamond symbol are not weighted, and therefore may differ from the weighted values in Table 3.

5.3 Data issues and limitations

It is useful to discuss some of the data issues and limitations related with the yield gap decomposition. First, the results are strongly influenced by the definition of actual yield assumed in the analysis. For comparison, we use the same definition as used by GYGA and FAOSTAT: production per hectare harvested. Reynolds *et al.* (2015) argue that it is better to use production per hectare planted because it accounts for the loss in crop area between planting and harvest. Using planted area in the denominator, will lead to lower yield estimates and a higher yield gaps.

Second, even though we use the same definition for yield, a comparison shows that our estimate of Yg_r for Tanzania (89%) is higher than that presented in GYGA (79%). There are two reasons that might explain this difference. First, as GYGA results do not cover all maize areas defined by the SPAM2005 crop areas mask (You et al., 2014) (Figure 3), we assume that potential yield in areas for which data are missing is equal to the maximum water-limited potential yield in the country. For areas that in reality have lower water-limited potential yield, this results in an overestimation of Yg and TYg. Second, a comparison shows that the actual yield from the LSMS-ISA is lower than the one used by GYGA. It is not clear why the yield measures differ between the two sources. One possible explanation is that LSMS-ISA focuses predominantly on small-scale and subsistence farmers, while GYGA data also covers (a small number of) larger and more specialised farms that might have a higher yield.

Third, in GYGA the Hybrid Maize model was used to estimate (water-limited) potential yield of maize. Even though this is a well-tested model in a broad range of environments, there is inherent uncertainly in estimating yield potential using a single crop growth model, in particular in data scarce environments (Asseng et al. 2013).

A fourth factor that influences the yield gap estimations is the choice of the functional form to estimate the frontier response function (Ackello-Ogutu et al. 1985; Jauregui & Sain 1992). For illustrative purposed we decided to use a relatively simple but tractable Cobb-Douglas function. This functional form is less flexible than the translog model, which is also frequently used in production economics. It would be interesting to compare yield gap outcomes using the Cobb-Douglas and translog functions.

Finally, estimation of the economic yield gap requires certain assumptions on the quantity of inputs needed to reach the associated yield level. Coarse information on optimal fertilizer application can be found in the documentation of field experiments but comparable data on the use of labour, capital and pesticides are not readily available. More precise information can be obtained by organising interviews with farmers, extension agents and researchers, who have in-depth knowledge and expertise of the crop growth process.

Of the four yield gap components, the technology yield gap (TYg) is probably most sensitive to the aforementioned data issues. It is estimated as a residual in our framework and therefore also captures potential measurement errors in the other yield gap components.

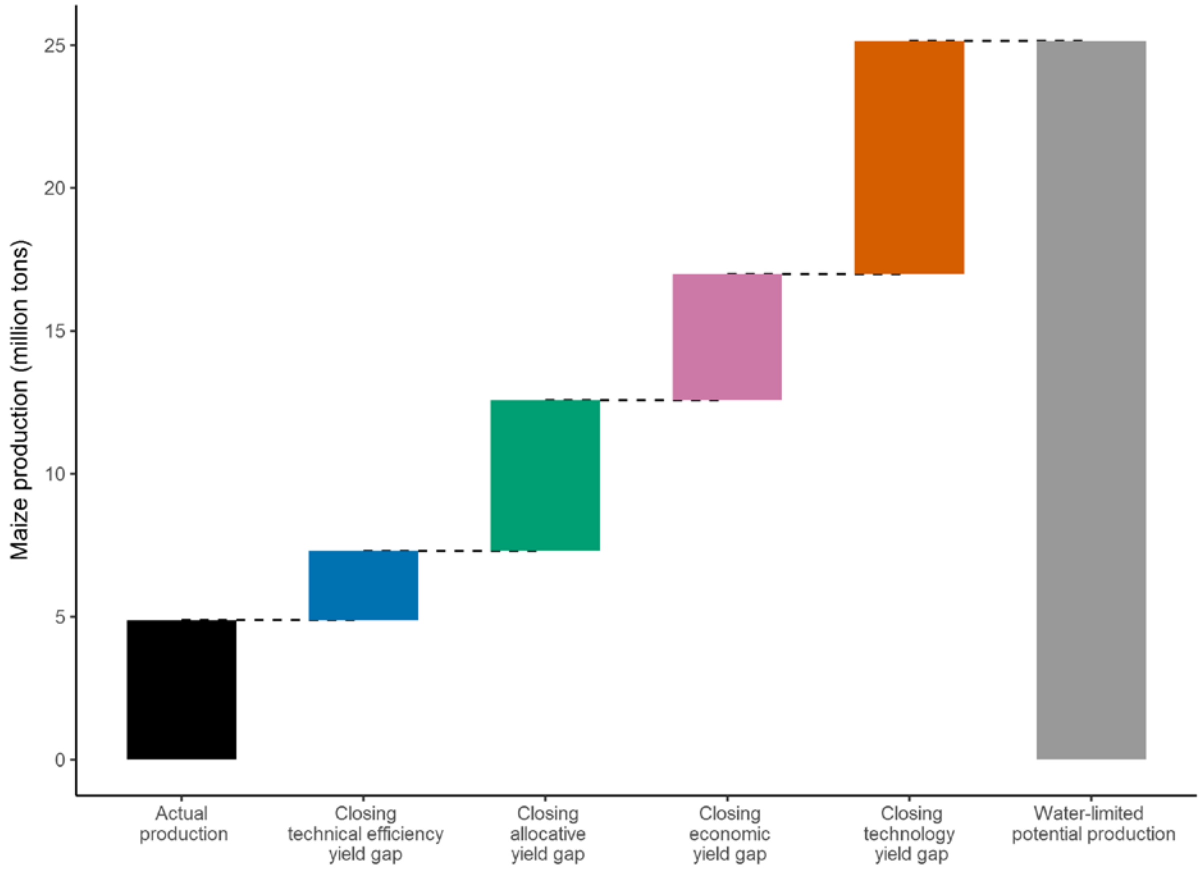
6 Potential to increase maize production in Tanzania

The estimations for the different types of yield gaps can be used to analyse the extent to which maize production in Tanzania can be increased if all gaps could be closed. As the LSMS-ISA sample is stratified by zone, the zonal yield gap decomposition in Table 3 can be considered representative for all farmers that are active in that zone. To estimate (water-limited) potential production for each of the geographical zones, we obtain information on total maize production per zone from SPAM (You et al. 2014), which spatially allocates national production, yield and area data from FAOSTAT for the period 2004-2006. Next, we assume that total production in each of the zones has changed at the same rate as national production and use data on the growth of national maize production to project average production per zone for the period 2010-2013. Finally, we combine production and yield information at zone-level with our relative yield gap estimations and potential yield information from GYGA to compute additional maize production in case all gaps could be closed and aggregate to the national level.

Figure 4 presents the results. The left hand side of the figure presents the average total maize production for the period 2010-2013 (equal to the total production in FAOSTAT). The bars to the right show the additional maize output that would be produced if TEYg, AYg, EYg and TYg could be closed. The final bar represents total maize production if Yg could be closed.

Total maize production in Tanzania can be increased from 4.9 to 7.3 tons if farmers would produce at full technical efficiency. Closing the allocative yield gap will add 5.1 million tons of maize production and closing the economic yield gap, will add another 4.6 million tons. The remainder, the technology yield gap will add a final 8.2 million tons, resulting in a total potential production of over 25 tons.

Figure 4: Decomposition of water-limited potential maize production at national level, 2010-2013



7 Conclusions

This paper attempts to disentangle and integrate agronomic and economic approaches to yield gap measurement. We presented a novel framework that decomposes the conventional total yield gap into a technical efficiency (TEYg), allocative (AYg), economic (EYg) and technology (TYg) yield gap component that provide additional information on why observed farm or plot level yield is lower than the biophysical potential.

We illustrated our framework using a nationally representative database that combines bio-physical and socio-economic data at the farm household and plot-level on maize production in Tanzania. Estimation of the frontier yield response function points out that both agronomic (e.g. agro-ecological zone, soil quality and use of fertilizer) and socio-economic (e.g. labour and capital) determinants have a significant impact on yield and need to be taken into account when undertaking yield and yield gap analysis. Decomposition of the total yield gap shows that the technology yield gap makes up the largest part, followed by the allocative yield gap, the economic yield gap and the technical efficiency yield gap although results differ across geographical zones. We also demonstrated that closing all the yield gaps will result in a fivefold increase in national maize production from 5 to 25 million tons. In practice, however, there will be various (agronomic, economic and environmental) reasons why full closure will not be achieved.

The findings imply that the lack of access to modern technologies is the main cause of the maize yield gap in Tanzania but that also missing markets, economic constraints and technical inefficiencies are important. Closing the technology yield gap demands the transfer of advanced technologies, such as precision agriculture, improved varieties and integrated soil fertility management to Tanzanian maize farmers. However, studies that analysed the technology gap at the firm and national level have pointed out that successful technology transfer is a long-run, difficult and far from automatic process (Nelson & Pack 1999; Fagerberg & Verspagen 2002). It involves a process of technological learning, which requires a certain capacity to 'absorb' existing technologies, including a national agricultural innovation system, human capital and infrastructure (Cohen & Levinthal 1990; Bell & Pavitt 1992), which are often lacking in developing countries. From a short-run perspective, it would be more effective to implement policies that target the other three yield gap components, including: (1) expanding extension services and facilitate learning from best practice farmers to close the technical efficiency yield gap; (2) providing credit and insurance to close the allocative yield gap; and (3) improve infrastructure and expand input dealer networks to close the economic yield gap.

The framework to decompose the total yield gap is data intensive and therefore might be sensitive to data errors and assumptions that underlie the yield gap estimation. The analysis can be improved by collecting additional information on feasible input and output combinations by means of surveys and interviews with farmers and experts. Finally, another promising avenue for further research is the investigation of prime factors that explain the technical efficiency, allocative, economic and technology yield gaps. Although, conceptually the individual yield gap components can be linked with broader determinants (e.g. infrastructure, transaction cost and extension services), it would be interesting to empirically relate these determinants with the different yield gap components to establish their order and magnitude.

Acknowledgements

We are grateful to the following persons for input and comments: Ezra Berkhout, Lenny van Bussel, Katrien Descheemaeker, Kees Duijvendijk, Gideon Kruseman, Johan Leenaars, Marloes van Loon, Jeff Powell, Joao Vasco Silva and Participants of the 2nd Global Food Security Conference at Cornell University. We also thank the World Bank for making available an additional GPS dataset. Finally, we would like to express our gratitude to two referees, who provided comments. This work was supported by ESRC/DFID as part of the IMAGINE project (ES/L012294/1), the International Maize and Wheat Improvement Center (CIMMYT) through the CGIAR research program on MAIZE and Wageningen University & Research.

References

Ackello-Ogutu, C., Paris, Q. & Williams, W.A., 1985. Testing a von Liebig Crop Response Function against Polynomial Specifications. *American Journal of Agricultural Economics*, 67(4), pp.873–880.

Affholder, F. et al., 2013. The yield gap of major food crops in family agriculture in the tropics: Assessment and analysis through field surveys and modelling. *Field Crops Research*, 143, pp.106–118.

Aigner, D., Lovell, C.A.K. & Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), pp.21–37.

Alexandratos, N. & Bruinsma, J., 2012. *World agriculture towards 2030/2050: the 2012 revision*, ESA Working paper Rome, FAO. Available at: http://environmentportal.in/files/file/World%20agriculture%20towards%202030.pdf [Accessed April 16, 2013].

Asseng, S. et al., 2013. Uncertainty in simulating wheat yields under climate change. *Nature Climate Change*, 3(9), pp.827–832.

Battese, G.E., 1997. A Note on the Estimation of Cobb-Douglas Production Functions When Some Explanatory Variables Have Zero Values. *Journal of Agricultural Economics*, 48(1–3), pp.250–252.

Beddow, J.M. et al., 2015. *Rethinking yield gaps*, University of Minnesota, Department of Applied Economics. Available at: https://ideas.repec.org/p/ags/umaesp/201093.html [Accessed June 28, 2016].

Bell, M. & Pavitt, K., 1992. Accumulating Technological Capability in Developing Countries. *The World Bank Economic Review*, 6(suppl 1), pp.257–281.

Berck, P. & Helfand, G., 1990. Reconciling the von Liebig and Differentiable Crop Production Functions. *American Journal of Agricultural Economics*, 72(4), pp.985–996.

Bravo-Ureta, B.E. et al., 2007. Technical efficiency in farming: a meta-regression analysis. *Journal of Productivity Analysis*, 27(1), pp.57–72.

Burke, W.J., 2012. *Maize production in zambia and regional marketing: Input productivity and output price transmission*. PhD Dissertation. Michigan State University.

van Bussel, L.G.J. et al., 2015. From field to atlas: Upscaling of location-specific yield gap estimates. *Field Crops Research*, 177, pp.98–108.

Coelli, T.J. et al., 2005. *An Introduction to Efficiency and Productivity Analysis, 2nd Edition,* Springer.

Cohen, W.M. & Levinthal, D.A., 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1), pp.128–152.

De Bie, C.A.J.M., 2000. *Comparative performance analysis of agro-ecosystems*,

De Datta, S.K., 1981. *Principles and practices of rice production*, New York: John Wiley & Sons.

Dillon, B. & Barrett, C.B., 2014. *Agricultural Factor Markets in Sub-Saharan Africa : An Updated View with Formal Tests for Market Failure*, Washington, DC: World Bank Group.

Eastwood, R., Lipton, M. & Newell, A., 2010. Chapter 65 Farm Size. In B.-H. of A. Economics, ed. Elsevier, pp. 3323–3397. Available at: http://www.sciencedirect.com/science/article/pii/S1574007209040651 [Accessed January 6, 2016].

Evans, L.T. & Fisher, R.A., 1999. Yield potential: Its definition, measurement, and significance. *Crop Science*, 39(6), pp.1544–1551.

Fagerberg, J., 1994. Technology and International Differences in Growth Rates. *Journal of Economic Literature*, 32(3), pp.1147–1175.

Fagerberg, J. & Verspagen, B., 2002. Technology-gaps, innovation-diffusion and transformation: an evolutionary interpretation. *Research Policy*, 31(8–9), pp.1291–1304.

FAO, 2004. *Rice and narrowing the yield gap*, Rome, Italy.

Färe, R. et al., 1994. Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries. *The American Economic Review*, 84(1), pp.66–83.

Fischer, R.A., 2015. Definitions and determination of crop yield, yield gaps, and of rates of change. *Field Crops Research*, 182, pp.9–18.

Fischer, T., Byerlee, D. & Edmeades, G., 2014. *Crop yields and global food security: Will yield increase continue to feed the world?*, Canberra: Australian Centre for International Agricultural Research.

Foley, J.A. et al., 2011. Solutions for a cultivated planet. *Nature*, 478(7369), pp.337–342.

Grassini, P. et al., 2015. How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. *Field Crops Research*, 177, pp.49–63.

Hall, A.J. et al., 2013. Gaps between farmer and attainable yields across rainfed sunflower growing regions of Argentina. *Field Crops Research*, 143, pp.119–129.

Hengl, T. et al., 2015. Mapping Soil Properties of Africa at 250 m Resolution: Random Forests Significantly Improve Current Predictions. *PLoS ONE*, 10(6), p.e0125814.

Hoang, V.-N., 2013. Analysis of productive performance of crop production systems: An integrated analytical framework. *Agricultural Systems*, 116, pp.16–24.

van Ittersum, M.K. et al., 2013. Yield gap analysis with local to global relevance—A review. *Field Crops Research*, 143, pp.4–17.

van Ittersum, M.K. & Rabbinge, R., 1997. Concepts in production ecology for analysis and quantification of agricultural input-output combinations. *Field Crops Research*, 52(3), pp.197–208.

Jauregui, M.A. & Sain, G.E., 1992. *Continous economic analysis in crop response to fertilizer in on-farm research*, Mexico, D.F.: CIMMYT.

Kaswende, J.S. & Akulumuka, V.C., 1997. Maize yield responses to plant density and nitrogen fertilization in low and mid-altitude environments in Tanzania. In 5. Proceedings of the Eastern and Southern Africa Regional Maize Conference, Arusha (Tanzania), 3-7 Jun 1996.

CIMMYT. Available at: http://agris.fao.org/agris-search/search.do?recordID=QY1998000115 [Accessed May 21, 2015].

Kelly, V., Adesina, A.A. & Gordon, A., 2003. Expanding access to agricultural inputs in Africa: a review of recent market development experience. *Food Policy*, 28(4), pp.379–404.

Kennedy, P.E., 1981. Estimation with correctly interpreted dummy variables in semilogarithmic equations. *American Economic Review*, 71(4), p.801.

de Koeijer, T.. et al., 1999. A conceptual model for analysing input–output coefficients in arable farming systems: from diagnosis towards design. *Agricultural Systems*, 61(1), pp.33–44.

Latruffe, L., Fogarasi, J. & Desjeux, Y., 2012. Efficiency, productivity and technology comparison for farms in Central and Western Europe: The case of field crop and dairy farming in Hungary and France. *Economic Systems*, 36(2), pp.264–278.

Liverpool-Tasie, L.S.O., 2016. Is fertiliser use inconsistent with expected profit maximization in sub-Saharan Africa? ‘Evidence from Nigeria’. *Journal of Agricultural Economics*, p.n/a-n/a.

Lobell, D.B., Cassman, K.G. & Field, C.B., 2009. Crop Yield Gaps: Their Importance, Magnitudes, and Causes. *Annual Review of Environment and Resources*, 34(1), pp.179–204.

Marenya, P.P. & Barrett, C.B., 2009. State-conditional Fertilizer Yield Response on Western Kenyan Farms. *American Journal of Agricultural Economics*, 91(4), pp.991–1006.

Meeusen, W. & Broeck, J. van D., 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, 18(2), pp.435–444.

Mekonnen, D.K. et al., 2015. Innovation systems and technical efficiency in developing-country agriculture. *Agricultural Economics*, p.n/a-n/a.

Morris, M. et al., 2007. *Fertilizer Use in African Agriculture : Lessons Learned and Good Practice Guidelines*, The World Bank. Available at: https://ideas.repec.org/b/wbk/wbpubs/6650.html [Accessed July 11, 2016].

Mourice, S.K. et al., 2015. Modeling potential rain-fed maize productivity and yield gaps in the Wami River sub-basin, Tanzania. *Acta Agriculturae Scandinavica, Section B—Soil & Plant Science*, 65(2), pp.132–140.

Mowo, J.G. et al., 1993. *Review of fertilizer recommendations in Tanzania: Part 1*, Tanga, Tanzania: Ministry of Agriculture.

Msuya, E.E., Hisano, S. & Nariu, T., 2008. Explaining Productivity Variation among Smallholder Maize Farmers in Tanzania. Available at: https://mpra.ub.uni-muenchen.de/14626/ [Accessed July 14, 2016].

Mueller, N.D. et al., 2012. Closing yield gaps through nutrient and water management. *Nature*, 490(7419), pp.254–257.

Nelson, R.R. & Pack, H., 1999. The Asian Miracle and Modern Growth Theory. *The Economic Journal*, 109(457), pp.416–436.

Ogundari, K., 2014. The Paradigm of Agricultural Efficiency and its Implication on Food Security in Africa: What Does Meta-analysis Reveal? *World Development*, 64, pp.690–702.

Paris, Q., 1992. The von Liebig Hypothesis. *American Journal of Agricultural Economics*, 74(4), pp.1019–1028.

Reynolds, T.W. et al., 2015. *How Common Crop Yield Measures Misrepresent Productivity among Smallholder Farmers*, International Association of Agricultural Economists. Available at: http://econpapers.repec.org/paper/agsiaae15/212485.htm [Accessed July 12, 2016].

Sadoulet, E. & De Janvry, A., 1995. *Quantitative development policy analysis*, Johns Hopkins University Press Baltimore. Available at: http://caoye.lzu.edu.cn/upload/news/N20141106111536.pdf [Accessed February 5, 2015].

Sadras, V.O. et al., 2015. *Yield gap analysis of field crops: Methods and case studies*, Rome: FAO.

Sheahan, M., Black, R. & Jayne, T.S., 2013. Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. *Food Policy*, 41, pp.39–52.

Sherlund, S.M., Barrett, C.B. & Adesina, A.A., 2002. Smallholder technical efficiency controlling for environmental production conditions. *Journal of Development Economics*, 69(1), pp.85–101.

Silva, J.V. et al., 2016. Explaining rice yields and yield gaps in Central Luzon, Philippines: An application of stochastic frontier analysis and crop modelling. *European Journal of Agronomy*. Available at: http://www.sciencedirect.com/science/article/pii/S1161030116301307 [Accessed August 12, 2016].

Stiglitz, J.E., 1989. Markets, Market Failures, and Development. *The American Economic Review*, 79(2), pp.197–203.

Sumberg, J., 2012. Mind the (yield) gap(s). *Food Security*, 4(4), pp.509–518.

Theriault, V. & Serra, R., 2014. Institutional Environment and Technical Efficiency: A Stochastic Frontier Analysis of Cotton Producers in West Africa. *Journal of Agricultural Economics*, 65(2), pp.383–405.

Tittonell, P. & Giller, K.E., 2013. When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. *Field Crops Research*, 143, pp.76–90.

de Wit, C.T., 1992. Resource use efficiency in agriculture. *Agricultural Systems*, 40(1–3), pp.125–151.

Wooldridge, J.M., 2010. *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

World Bank, 2014. *Tanzania Public Expenditure Review: National Agricultural Input Voucher Scheme*, Washington D.C.

World Bank, 2015. World Development Indicators. Available at: http://databank.worldbank.org/data/views/variableSelection/selectvariables.aspx?source=world-development-indicators [Accessed January 28, 2015].

Xu, Z. et al., 2009. Factors influencing the profitability of fertilizer use on maize in Zambia. *Agricultural Economics*, 40(4), pp.437–446.

You, L. et al., 2014. Spatial Production Allocation Model (SPAM) 2005 v2.0. Available at: http://mapspam.info [Accessed October 1, 2015].

8 Appendix A: Data

The main data for our analysis are taken from the 2010-11 and 2012-13 waves of the Tanzania Living Standards measurement Study Integrated Surveys in Agriculture (LSMS-ISA). We only include plot information that pertains to the main long season because of the variation between the bi-modal systems in the North of Tanzania and the uni-model systems in the rest of the country. We exclude any plots that are located on Zanzibar because of the different climatological and economic environment. Between the two survey years, a number of households split into two or more households. As we are predominantly interested in plot level information, we assumed that the part of the household that stayed in the same location could be linked with the household in the first year. To account for measurement error and outliers, we limit the sample to plots that fulfil a number of criteria that in our view reflect realistic characteristics of smallholder plots in Tanzania. First, we exclude several plots that use more than 1,000 kg of nitrogen per ha. Second, we remove plots that have an area of less than 0.05 ha for which GPS measurements are less accurate and more than 10 ha, which we do not consider small scale farmers. Finally, we remove a small number of plots that have a yield of more than 16 tons per ha, which is the highest potential yield in Tanzania according to the GYGA. The final dataset is an unbalanced sample of 1,163 farm households in 2010 and 1,394 households in 2012 that operate 1,671 and 1,966 plots, respectively.

For the yield gap analysis the definition and determination of yield are crucial. Yield can be defined in several ways (Reynolds et al., 2015). Here, we define yield as total harvested quantity divided by harvested area, which is the same definition as used by FAOSTAT and GYGA. Total quantity harvested is directly provided by the LSMS-ISA, while harvested area is estimated. The LSMS-ISA includes information on plot size and harvested area provided by the farmer as well as GPS measured plot size. Research comparing GPS-measured and self-reported plot size shows that the latter measures area with a systematic error (Carletto et al., 2015). It is therefore likely that self-reported harvested area is also biased. As it seems easier for the farmer to determine relative measures (e.g. the share of the plot that is planted), we calculate harvested area as the product of GPS-measured plot size times the ratio of self-reported harvested area to self-reported plot size. GPS data are only available for around seventy five percent of the plots. To remedy this issue, the World Bank has developed a multiple imputation procedure to impute missing values (Palacios-Lopez and Djima, 2014), which we also adopt.

For the majority of maize growing farmers, the LSMS-ISA records the production and value received by the farmer for total maize crop. We used this information to derive median maize prices for all districts in Tanzania. To remove the effect of outliers, we winsored all data at three times the median value. We only used the district median if there were more than five observations. If not, we averaged at the region level, then at the zonal level and finally at the country level. Regarding fertilizer, farmers were asked which types of fertilizer they used (e.g. UREA, CAN and DAP), how much they used and the total value paid for the different fertilizers. Following Sheahan et al. (2013) we used the chemical composition of fertilizer to estimate the price of Nitrogen and used the same procedure as for maize prices to calculate average prices for each of the districts. As some farmers received the fertilizer subsidies as part of the NAIVS, the average fertilizer prices are a mix of market and subsidised prices. All prices as well as asset value were inflated to 2013 levels using the consumer price index from the World Development Indicators.

The LSMS-ISA provides the geo-coordinates for all of the enumeration areas. These codes are used to link a number of geo-spatial variables from additional sources, some of which are provided with the LSMS-ISA datasets. In our analysis we use information on Agro-Ecological Zones prepared by

IFPRI/Harvest Choice. Due to the limited number of observations in some AEZ zones, we aggregated them into three zones. We used the geo-coordinates to link information from AfSIS (http://www.isric.org/data/afsoilgrids250m) and GYGA (www.yieldgap.org). For confidentiality reasons the household cluster coordinates are presented to the public with a random offset, which potentially introduces a bias if the linked variables if they are presented at high resolution. To mitigate this use we aggregated the AfFIS soil data from 250m to the 5 degree spatial resolution before linking. The GYGA resolution is much larger and therefore does not cause problems.

Table 1 presents descriptive statistics for the main variables that were used to estimate the stochastic frontier model and Table 2 presents additional information on yield, nitrogen use and prices at the zonal level.

Table 4: Descriptive statistics of main variables, pooled sample

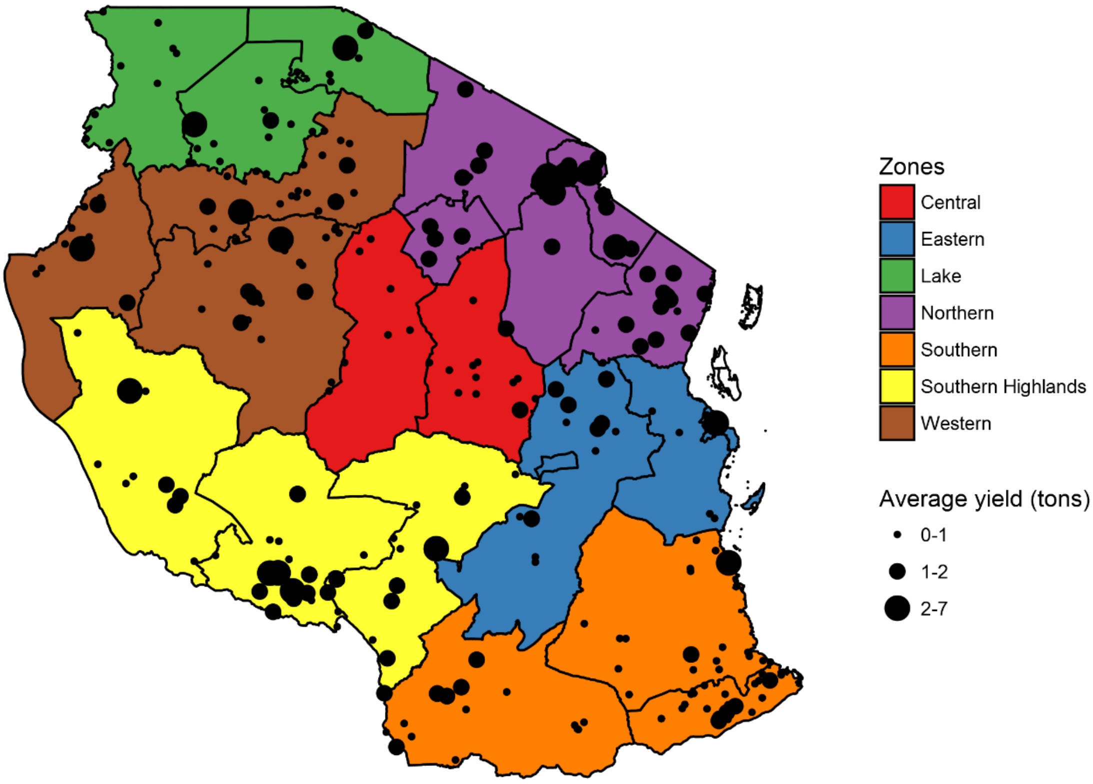
Statistic	Description	Mean	St. Dev.
Yield	Maize yield on plot (kg/ha)	1,111	1,355
Growth defining factors			
Hybrid seeds	Hybrid seed used on plot (= 1)	0.17	0.37
Slope	Slope (%)	5.90	6.38
AEZ	Agro-Ecological Zone: 1 = Semi-arid, 2 = Tropic-warm/ sub-humid, 3 = Tropic-cool/sub-humid		
Growth limiting factors			
Yes Nitrogen	Fertilizer applied on plot (= 1)	0.18	0.38
N	Nitrogen content of applied fertilizers (kg/ha)	13.42	50.88
Manure	Manure applied on plot (= 1)	0.16	0.37
Rain	Total rainfall in wettest quarter (mm)	525	201
Irrigation	Irrigation on plot (= 1)	0.02	0.13
Soil	Soil type: 1 = sandy, 2 = loam, 3 = clay, 4 = other		
SOC	soil organic carbon stock over 200 cm soil layer (kg/m2)	9.96	4.79
pH	pH of the soil over 200 cm soil layer: $1 = \text{pH} < 5.5$, $2 = 5.5 \leq \text{pH} \leq 7$, $3 = \text{pH} > 7$		
Growth reducing factors			
Pesticides	Pesticides applied on plot (= 1)	0.10	0.30
Farm factors			
Assets	Value of total assets (1000 Ts/ha, 2012 prices)	1,642	7.409
Labour	Total days worked on plot	375	646
Area	GPS measured size of plot (ha)	0.65	0.88
Control factors			
Pure maize plot	Only maize grown on plot (= 1)	0.39	0.49
Year	Survey year (2010 = 1)	0.46	0.50

Table 5: Maize yield, nitrogen and prices per zone

Zone	Number of plots	Actual yield (kg/ha)[a]	Share of plots that apply nitrogen (%)	Nitrogen (kg/ha)[b]	Price of nitrogen (Ts/kg)[c]	Price of maize (Ts/kg)[c]
Northern	558	1,087	10	100	2,374	331
Lake	265	563	2	7	2,622	335
Western	572	502	12	74	3,057	306
Central	281	612	6	31	2,488	248
Eastern	231	697	2	19	2,759	400
Southern Highlands	896	886	39	75	2,619	262
Southern	834	654	19	73	2,689	287
Total	3637	712	18	74	2,650	312

Note: [a] Weighted by area, [b] Conditional on fertilizer use, [c] Constant 2012 prices.

Figure 5: Zones in Tanzania and actual maize yield



Source: Actual yield by enumeration area from the World Bank LSMS-ISA surveys. To reduce the impact of outliers, enumeration areas that contain information for only one plot are not depicted.

9 Appendix B: Stochastic frontier analysis and correlated random effects estimation

The stochastic frontier production function model (Aigner et al., 1977; Meeusen and Broeck, 1977) is specified as follows for our study:

$$y_i = x_i\beta + v_i - u_i \tag{12}$$

where, y_i is the logarithm of actual yield (y_a) for maize plot i, x_i is a vector containing growth defining, growth limiting and growth reducing factors and a set of control variables, β is a vector of parameters, v_i is a symmetric random error and u_i is non-negative random variable with a truncated normal distribution that measures technical inefficiency. The error terms v_i and u_i will be influenced by unobserved household and plot-specific effects, such as farmers' management skills and soil quality, which are correlated with some of the explanatory variables, such as fertilizer application. Simply pooling the data for the two survey years will result in coefficients that are biased (Hausman and Taylor, 1981). To control for time-invariant unobserved heterogeneity, we apply the correlated random effects (CRE) estimator (Wooldridge, 2010), which is also referred to as the Mundlak-Chamberlain device, following the work of Mundlak (1978) and Chamberlain (1984). CRE is the standard approach in recent and similar micro-econometric studies that use panel data to control for time-invariant heterogeneity (e.g. Mason and Ricker-Gilbert, 2013; Mason and Smale, 2013; Sheahan et al., 2013). It can be used on unbalanced samples and be combined with stochastic frontier analysis (Farsi et al., 2005; Abdulai and Tietje, 2007). The CRE estimator allows for correlation between the time invariant unobserved household specific omitted variable and the explanatory variables. The technique is implemented by modelling the distribution of the omitted variable, conditional on the means of the strictly exogenous variables:

$$c_i = \vartheta + \overline{x_k}\delta + a_i \tag{13}$$

$$E(a_i|c_i x_i) = 0 \tag{14}$$

where c_i is the unobserved household specific omitted variable and $\overline{x_k}$ is a vector of average values of the explanatory variables x_k at the household level i. It is assumed that after controlling for c_i the remaining heterogeneity is uncorrelated with all the explanatory variables. The CRE approach is implemented by including the average values for each input x_k, for each household in the model. This is done for each survey year in the panel. Subsequently all data are pooled and the stochastic frontier model is estimated.

The CRE estimator only captures omitted household level characteristics because the LSMS-ISA only tracks households over time, not plots. Omitted plot level characteristics may therefore still bias the estimation. Since we include a large number of variables that capture soil quality and other plot characteristics (i.e. SOC, pH and soil type), we assume that unobserved heterogeneity at the plot level is sufficiently controlled for. All estimations are done with the FRONTIER package in R (Coelli and Henningsen, 2013).

Table 3 presents the results for the pooled and CRE models. Although roughly the same variables are significant in both models, the coefficients differ somewhat. In particular, the CRE model presents lower coefficients for yield response to nitrogen. The use of the pooled model would have resulted in upward biased estimations of the economic optimal yield level and biased yield gap estimations.

Table 6: Pooled and CRE models

	Pooled			**CRE**		
	Coef.	Std. error		Coef.	Std. error	
Constant	3.50	0.19	***	3.58	0.23	***
Growth defining factors						
Hybrid seeds	0.22	0.04	***	0.04	0.07	
Slope	0.001	0.003		0.0002	0.003	
Tropic-warm/sub-humid	-0.24	0.05	***	-0.21	-0.05	***
Tropic-cool/sub-humid	-0.04	0.05		-0.05	-0.05	
Growth limiting factors						
No nitrogen	0.86	0.13	***	0.72	0.19	***
Nitrogen	0.29	0.03	***	0.21	0.05	***
Manure	0.03	0.04		-0.03	-0.07	
Rainfall	-0.0005	0.0001	***	-0.0004	-0.0001	***
Irrigation	0.30	0.11	**	-0.08	-0.21	
Loam	0.38	0.04	***	0.15	0.07	**
Clay	0.36	0.05	***	0.12	0.08	
Other soil	0.82	0.11	***	0.33	0.16	*
SOC stock	0.01	0.004	**	0.01	0.004	**
pH 5.5-7	0.35	0.06	***	0.32	0.06	***
pH >7	0.19	0.09	**	0.17	0.09	*
Growth reducing factors						
Pesticides	-0.02	0.05		0.06	0.08	
Farm factors						
ln(assets)	0.07	0.01	***	0.07	0.01	***
ln(labour)	0.36	0.02	***	0.45	0.02	***
ln(area)	0.07	0.01	***	-0.08	-0.03	**
Control factors						
Pure maize plot	0.26	0.03	***	0.05	0.05	
Year	0.21	0.03	***	0.23	0.03	***
Mean no nitrogen				0.10	0.26	
Mean ln(N)				0.10	0.06	
Mean ln(labour)				-0.13	-0.03	***
Mean ln(area)				0.02	0.03	
Mean loam				0.26	0.08	**
Mean clay				0.28	0.11	**
Mean other soil				0.48	0.22	**
Mean irrigation				0.41	0.25	
Mean hybrid seeds				0.23	0.08	**
Mean manure				0.07	0.08	
Mean pesticides				-0.12	-0.10	
Mean pure maize crop				0.30	0.06	***
σ^2	1.62	0.07	***	1.61	0.07	***
γ	0.78	0.02	***	0.79	0.02	***
Log-likelihood	-4,378			-4,699		
Likelihood ratio statistic	130***			137***		
Observations	3,637			3,637		

Note: coefficients for dummy variables have been transformed following Kennedy (1981) to measure impact in percentages; * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

10 Appendix C: Procedure to estimate yield levels

The following procedure is used to estimate the various yield gap levels:

1. Actual farm yield is taken from the LSMS-ISA.
2. Stochastic frontier analysis is used to estimate the frontier yield response curve and technically efficient yield.
3. The frontier yield response function is combined with the maize and fertilizer price information to calculate economic optimal nitrogen and economic yield. If optimal nitrogen is larger than 120 kg N/ha, the amount we use to calculate feasible yield, it is capped at 120 kg N/ha.
4. Feasible yield is calculated using the frontier yield response function and assuming 120 kg N/ha fertilizer, a 50% increase in capital and labour use, 100% application of pesticides and hybrid seeds.
5. Water-limited potential yield is taken from the GYGA.
6. All yield levels are compared with the water-limited potential yield as we assume that this is the absolute maximum and capped to this level if necessary.

11 Appendix D: Yield levels and absolute yield gap results per zone

Table 7: Yield levels per zone

Zone	Actual yield (kg/ha)	Technically efficient yield (kg/ha)	Economic yield (kg/ha)	Feasible yield (kg/ha)	Potential yield kg/ha)
Northern	1,087	1,642	3,823	5,150	6,948
Lake	563	1,397	3,650	5,141	7,474
Western	502	1,130	2,397	3,456	4,496
Central	612	1,288	2,433	2,961	3,253
Eastern	697	1,259	3,177	4,734	8,313
Southern Highlands	886	1,447	2,635	4,117	7,670
Southern	654	1,143	2,109	3,642	8,913
Total	712	1,303	2,683	3,967	6,600

Note: Average for 2010 and 2012. Plot size used as weights. Difference between Technically efficient yield and actual yield is not equal to $TEYg_l$ in Table 5 because the stochastic frontier function also includes an error term (*e*). $TEYG_l$ only measures the inefficiency (*u*)

Table 8: Absolute yield gaps per zone (kg/ha)

Zone	$TEYg_l$	AYg_l	EYg_l	TYg_l	Yg_l
Northern	787	2,181	1,327	1,798	6,092
Lake	822	2,253	1,491	2,333	6,899
Western	639	1,267	1,059	1,040	4,005
Central	715	1,145	528	292	2,680
Eastern	661	1,917	1,557	3,579	7,714
Southern Highlands	703	1,188	1,482	3,554	6,926
Southern	584	966	1,533	5,271	8,354
Total	680	1,380	1,284	2,633	5,976

Note: Average for 2010 and 2012. Plot size used as weights.

12 References

Abdulai, A., Tietje, H., 2007. Estimating technical efficiency under unobserved heterogeneity with stochastic frontier models: application to northern German dairy farms. Eur. Rev. Agric. Econ. 34, 393–416. doi:10.1093/erae/jbm023

Aigner, D., Lovell, C.A.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econom. 6, 21–37. doi:10.1016/0304-4076(77)90052-5

Carletto, C., Gourlay, S., Winters, P., 2015. From Guesstimates to GPStimates: Land Area Measurement and Implications for Agricultural Analysis. J. Afr. Econ. 24, 593–628.

Chamberlain, G., 1984. Chapter 22 Panel data, in: Econometrics, B.-H. of (Ed.), . Elsevier, pp. 1247–1318.

Coelli, T., Henningsen, A., 2013. Frontier: stochastic frontier analysis. R package version 1.1.

Farsi, M., Filippini, M., Kuenzle, M., 2005. Unobserved heterogeneity in stochastic cost frontier models: an application to Swiss nursing homes. Appl. Econ. 37, 2127–2141. doi:10.1080/00036840500293201

Hausman, J.A., Taylor, W.E., 1981. Panel Data and Unobservable Individual Effects. Econometrica 49, 1377–1398. doi:10.2307/1911406

Kennedy, P.E., 1981. Estimation with correctly interpreted dummy variables in semilogarithmic equations. Am. Econ. Rev. 71, 801.

Mason, N.M., Ricker-Gilbert, J., 2013. Disrupting Demand for Commercial Seed: Input Subsidies in Malawi and Zambia. World Dev. 45, 75–91. doi:10.1016/j.worlddev.2012.11.006

Mason, N.M., Smale, M., 2013. Impacts of subsidized hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia. Agric. Econ. 44, 659–670. doi:10.1111/agec.12080

Meeusen, W., Broeck, J. van D., 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. Int. Econ. Rev. 18, 435–444. doi:10.2307/2525757

Mundlak, Y., 1978. On the Pooling of Time Series and Cross Section Data. Econometrica 46, 69–85. doi:10.2307/1913646

Palacios-Lopez, A., Djima, I.Y., 2014. Land Areas in the LSMS-ISA country datasets: An Application of Multiple Imputation (MI) methods.

Reynolds, T.W., Anderson, C.L., Slakie, E., Gugerty, M.K., 2015. How Common Crop Yield Measures Misrepresent Productivity among Smallholder Farmers (2015 Conference, August 9-14, 2015, Milan, Italy No. 212485). International Association of Agricultural Economists.

Sheahan, M., Black, R., Jayne, T.S., 2013. Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. Food Policy 41, 39–52. doi:10.1016/j.foodpol.2013.04.008

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press.