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A DATA REVOLUTION FOR AGRICULTURAL PRODUCTION STATISTICS IN SUB-SAHARAN AFRICA

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Abstract

We argue that vastly improved agricultural production forecasts and estimates in SSA fit within an emerging view of information as a key input into the development process. We assess the current quality and timeliness of agricultural production data, finding both quality and timeliness to be inadequate. These inadequacies persist despite substantial benefits of improved agricultural production projections and estimates, notably benefits to market participants, not least farmers. New technologies such as satellite remote sensing provide scope to vastly improve agricultural production estimation methods at substantially lower cost than traditional farm surveys. Research efforts in this area are required to identify the most robust and effective applications of new technologies to agricultural statistics. Consideration of institutional challenges and frameworks is also necessary to benefit from these technologies. We conclude that accurate and timely agricultural production projections and estimates are possible at lower cost than at any time in recent history. And, these relatively small investments in improving SSA agricultural production data systems have the potential to deliver real progress towards attaining key Sustainable Development Goals.

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1 Introduction

In 2013, the United Nations published a report developed by a panel of eminent persons led by Homi Kharas on the post-2015 development agenda (United Nations 2013). The Millennium Development Goals (MDGs) had established targets to be attained by 2015, and it was an apt time to evaluate the MDG process and to consider what should succeed it. Across the full sweep of the MDGs, the panel highlighted the combination of an inspirational vision, concrete and time-bound goals and targets, and the data systems required for adequate monitoring as "the great strength of the MDGs" (United Nations 2013, p. 23). By concentrating attention on achieving eight overarching goals, the MDGs also effectively concentrated attention on the 48 indicators chosen to monitor progress towards those goals and the data systems necessary to produce the indicators.

This focus on data and data systems happened essentially as a by-product of the MDG process. The MDGs themselves contain no specific mention of efforts to improve data and data systems. The Kharas report, in contrast, explicitly calls for nothing short of a data revolution (United Nations 2013). While recognizing the progress realized in data and data systems during the pursuit of the MDGs, the Kharas report emphasized both the very large data shortcomings that remained in place and the massive potential that new technologies provided to improve, indeed revolutionize, data systems at low cost.

This call for a data revolution struck a chord. A second UN report detailed modes for mobilizing the data revolution for sustainable development (United Nations 2014); and, the UN data revolution merits its own web site (undatarevolution.org). The idea of a data revolution is also receiving ongoing academic support. For example, in a comprehensive assessment of living standards in Sub-Saharan Africa (SSA), Arndt, McKay, and Tarp (2016) highlight data and data systems as key inputs for achieving development and sustainability objectives. In an assessment of SSA development from a historical perspective, McMillan (2016) points to deficiencies in public information systems as a potential major explanatory factor for the relatively slow long-term economic growth of SSA relative to other regions of the globe. Kiregyera (2015) discusses the emerging data revolution in Africa in a recent book.

Improvements in agricultural data quality are particularly needed in SSA where the agricultural sector maintains a large share of gross domestic product and is even more important in terms of employment, and where continental average input use and yield growth rates are drastically lower than in other parts of the developing world over recent decades (World Bank 2007). In this article, we argue that it is plausibly the case that low quality and untimely agricultural production data impede agricultural development in SSA. This is so because poor market information leads to market inefficiencies, and, hence, reduced sector wide productivity. Additionally, new technologies can be used to vastly improve agricultural production forecasts and estimates in SSA at relatively low-cost relative to traditional methods and using these technologies to obtain better data will be essential for advancing SSA agricultural development in the years ahead.

The remainder of this article is structured as follows. Section 2 assesses the current quality and timeliness of agricultural production data, finding both quality and timeliness to be inadequate. Section 3 highlights four primary benefits of improved agricultural production projections and estimates. Emphasis is given to timeliness, and the information needs of market participants. Section 4 discusses the possibilities brought about by new technologies to vastly improve agricultural production statistics at low cost compared to traditional farm surveys. A final section calls for research efforts in this area with the goal of identifying the most robust and effective applications of new technologies to agricultural statistics in the context of varying capacity of statistical agencies across countries. It also discusses some institutional challenges and frameworks necessary to benefit from these technologies. We conclude that accurate and timely agricultural production projections and estimates are clearly possible at low cost. And, these relatively small investments in improving SSA agricultural production data systems have the potential to deliver progress towards attaining key Sustainable Development Goals.

2 Existing data systems for agricultural production projection and estimation

There has been a great deal of criticism of African data systems in general, driven in part by Jerven (2013). And, some criticism is merited. Figure 1 provides an example of discrepancies in agricultural production estimates across sources as well as issues of missing data. The figure illustrates recent trends in maize production levels for Mozambique from two sources of data—the Statistical Yearbook, which is official data, and the production series one obtains by downloading the data from FAOStat. The visual impressions derived from the two series are completely different. With the Statistical Yearbook, maize production is clearly stagnating. With the FAOStat data, maize production is increasing smartly to 2011. It then falls calamitously in 2012, before recovering very mildly in 2013 and 2014.

A few points merit highlighting. First, even though the visual impressions given by the series are very different, seven of the ten points appearing from the Statistical Yearbook series are shared with the FAOStat series. Second, the Statistical Yearbook series has obvious problems in that, for four of the years in the series, the data are missing. Finally, the most salient aspect of the FAOStat series, the production collapse of 2012, is very unlikely to have, in fact, occurred. The corresponding effects in terms of food prices and food imports do not corroborate the outcome.

This final point is worth elaborating. Kiregyera et al. (2007) evaluate two sources for maize production data in Mozambique. They find that the source used for all the data points in the Statistical Yearbook series is likely to be more reliable. The FAOStat series appears to have reverted to the alternative (less reliable) source for the years 2009, 2010, and 2011, where data are missing, as well as (and less explicably) 2007 and 2008. The 'production collapse' of 2012 appears to be simply a matter of reverting to the official (more reliable) data source.

Based on comprehensive evaluations of trends in living conditions compiled in Arndt, McKay and Tarp (2016), two general guidelines in using African data are developed. These two guidelines apply directly to the maize production case considered here. First, there are real problems in African statistical systems. Simply downloading data from web sites maintained by international organizations can be deeply misleading. Second, while problems exist, there is information content in African data, particularly if one is aware of the history, context, and methods employed. Triangulation of outcomes across data sources is also helpful in accurately interpreting the data.

Or, returning to Mozambique, the more likely story is one of stagnation of maize production levels.[2]

Problems with agricultural production data are by no means confined to Mozambique. Nigeria has not implemented an agricultural census since the 1970s (Onyeri 2011), and the most recently publicly available national Nigerian production estimates are for 2012. In their review of agricultural statistical agency capacity in Mali, Mozambique, Rwanda, and Zimbabwe, Kelly and Donovan (2008) found that although the institutional arrangement of official agricultural statistics agencies for these countries appears to be sufficient to make it plausible that they could implement high quality data gathering methods, they all had crucial deficiencies in personnel capacity and funding needed to do so. While progressing compared to the nascent, non-existent, or purely administrative systems that were prevalent in the 1980s, they point to "major problems regarding sampling and measurement in some cases." (p. v). They also point out that "inaccurate crop forecasts have led to government policies to ban exports or limit imports, creating crises in the markets with either too much or too little product available."

These case studies of five SSA countries do not mean that all countries have poor quality data systems, but they provide enough examples to inspire further investigation into the breadth and depth of the issues across all SSA countries. Alternatively stated, a more comprehensive review of the current state of agricultural statistics systems would be valuable. Nevertheless, the available evidence indicates that there is little reason to believe that agricultural statistics systems have advanced dramatically in recent years. The broad characterization is one of production estimates that are very rarely timely, sometimes non-existent, frequently inaccurate, and at best intermittently trusted. This lack of timely and reliable information has opportunity costs, to which we now turn.

3 Benefits of timely and reliable agricultural production projections and estimations

As noted, timely and reliable information on agricultural production volumes is not available in most African countries (Jerven 2013; Arndt, McKay and Tarp 2016; Kelly and Donovan 2008). This lack of information is costly for at least four reasons.

First, in countries characterized by widespread food insecurity, accurate production forecasts facilitate the management of relief programs designed to avoid massive negative impacts on human welfare due to production shortfalls. While large negative production shocks are mostly noticed and responded to, sometimes even major nationwide production shocks are missed (Kiregyera et al. 2008). And, as noted above, misinformation has led to inappropriate trade policies (Kelly and Donovan 2008).

Second, reliable and timely agricultural production data is critical to the ability to design, implement and adjust public policies aimed at improved agricultural productivity and resilience. The Comprehensive Africa Agriculture Development Programme (CAADP), via the Maputo Declaration, as well as more recent comprehensive reviews, such as Fischer, Byerlee, and Edmeades (2014), highlight the importance of investments (often public) into the agricultural

[2] It is also possible that neither data source adequately reflects true levels and trends.

sectors of developing countries. However, the CAADP target for public investment in agriculture is unfulfilled in most countries (Benin 2016). While difficult to quantify, ministries of finance are understandably reluctant to allocate funds to agricultural programs when basic production information is so unreliable (Blandford 2007). In this way, countries can become locked in a vicious cycle of limited reliability of production data, limited data usage by policymakers, and under-investment in the sector more broadly (including in developing statistical capacity). Low data analysis capacity can further undermine incentives to collect high quality data.

For those countries that have allocated significant resources to agriculture, weak production information represents a prominent barrier to evaluation and learning. To give just one example, Malawi's very large fertilizer input subsidy programme was widely perceived as a potential model across the continent (Jayne and Rashid 2013). Yet, the lack of faith in national production and area statistics for major crops in Malawi has substantially complicated the task of program evaluation and improvement (Arndt, Pauw, and Thurlow 2016) and compromised the ability of other countries to draw lessons from the Malawian experience.

Third, timely and reliable data on agricultural production may improve accountability in low income countries, where large shares of the population are employed in agriculture and need information on agricultural productivity levels and trends to understand whether governments are promoting their economic interests. Fundamentally, a transparent regime is one that provides the public with accurate information about itself and about the country as a whole (Hollyer, Rosendorff, and Vreeland 2011). The public can then use this information as a tool in forming attitudes about how well the government is doing in promoting economic development and other goals.

Precisely because information on agricultural productivity could be so valuable to the public in making these judgments, governments can face countervailing political incentives. On the one hand, such economic indicators can improve the quality of policymaking by telling agencies whether their goals are being achieved, as noted above. Improved policies and policymaking processes should presumably raise the public's evaluation of government performance. On the other hand, collecting such data raises the risk that the data will point to negative signals about the government's policies. Concerns about showing development progress to the public and to donors can lead public statistics offices to systematically overestimate economic statistics (Sandefur and Glassman 2015). Nonetheless, wide public availability of reliable economic indicators is fundamental to accountability.

Fourth, timely and reliable agricultural statistics are critical to ensuring well-functioning agricultural markets. Government statistics are known to move agricultural market prices *in developed countries*. The seminal work of Hayami and Peterson (1972) concluded that even conservative estimates of private sector benefits (i.e., ignoring all benefits generated by the public sector through, for example, improved public policy formation) of more accurate production forecasts in the United States indicate very high benefit-cost ratios (on the order of 50 or more). Baur and Orazem (1994) examined the price effects of government orange production forecasts in the United States and found that 'significant price movements occur in response to announced production' (p. 681). The value of production information to global markets was recently confirmed by Adjemian (2012) who found that U.S. Department of Agriculture (USDA) announcements of world agricultural supply and demand estimates (WASDE) for major crops are rapidly incorporated into futures markets prices. Usefully, the effect WASDE is amplified in periods characterized by low stocks, when price spikes are much more likely (Wright 2011).

We will dwell on this fourth point. Even in developed country settings and despite very substantial pecuniary benefits, market participants are not omnisciently capable of efficiently pricing in the information content of official agricultural production data prior to its announcement.[3] Throughout the developing world, market prices are meant to provide the appropriate signals to market participants across the value chain from producers to consumers. If sophisticated developed country markets require public information for efficient functioning, it is difficult to see how markets in developing countries can appropriately price commodities when the relevant quantities are so poorly known.

Reliable production forecasts and estimates are particularly important for the trajectory of agricultural prices through time. In many low-income countries, prices for staple commodities routinely pass from single (at post-harvest) to double (in the pre-harvest hungry season), particularly in more distant markets. Gilbert, Christiansen, and Kaminski (2016) find that "excess seasonality is observed in virtually all the [African] maize and rice markets studied" and conclude that seasonality requires greater policy attention if the Sustainable Development Goal for Hunger is to be met. The near complete absence of timely and reliable production forecasts and information almost surely contributes substantially to seasonal price volatility (Hayami and Peterson 1972). For small farmers, many of whom sell mainly at post-harvest lows and then are often obliged to purchase back at pre-harvest highs, the welfare implications are substantial (Barrett 1996; Stephens and Barrett 2011).

Despite these observations, the role of timely and reliable agricultural production projections and estimates in contributing to efficient market functioning is often forgotten in the African context. For example, in answering the question 'what are the dominant agricultural data needs?', Kelly and Donovan (2008) focus exclusively on the needs of government and donors (the first two of the four reasons for producing timely and reliable statistics discussed) with respect to projection and estimation of production volumes. Specifically, they focus on: government and donor identification and response to potential food production shortfalls; implementation of Poverty Reduction Strategy Papers (PRSPs); meeting the Millennium Development Goals; CAADP/NEPAD budget commitments; decentralization of budgetary authority and concomitant needs of local governments for disaggregated statistics; and a host of research issues. There is no discussion on the need for production statistics for efficient market functioning.[4]

[3] In developed country contexts such as the United States, companies, such as Tellus Labs, are now announcing on their web sites that their estimates "consistently predicted USDA's 2016 corn and soybean yield projections ahead of all publicly available in-season forecasts" and that their "crystal ball for corn crop yields will revolutionize commodity trading" (telluslabs.com accessed on April 14, 2017).

[4] The role of market information systems, which broadcast prices and estimates of quantities traded in key markets, is recognized and emphasized by Kelly and Donovan (2008).

This contrasts with, for example, the given fundamental rationale for the National Agricultural Statistics Service of the USDA (USDA/NASS). USDA publishes a history of agricultural statistics (USDA 2017) that reads:

> "USDA itself was established by Abraham Lincoln in 1862. He called it 'the people's department,' and its first crop report appeared in July 1863. NASS traces its roots all the way back to 1863, when USDA established a Division of Statistics.
>
> During the Civil War [1861-65], USDA collected and distributed crop and livestock statistics to help farmers assess the value of the goods they produced. At that time, commodity buyers usually had more current and detailed market information than did farmers, a circumstance that often-prevented farmers from getting a fair price for their goods. Producers in today's marketplace would be similarly handicapped were it not for the information provided by NASS."

Once again, a more rigorous assessment of the current African statistical situation and its implications would be useful; nevertheless, it is hard to avoid the impression that, in many African contexts, systems for agricultural production data, are largely conceived of as serving the needs of governments, donors, and researchers. The needs of private sector market participants (including farmers) are given short shrift. In this environment of information scarcity on production volumes in critical post-harvest periods, it is highly likely that large market participants, who can effectively generate informal production estimates through their extended networks, maintain a significant advantage over small and medium sized market participants, particularly with respect to inter-temporal price arbitrage. Framing the provision of agricultural statistics as a public service to smallholder farmers, as opposed to one catering to government and donor bureaucrats as well as researchers, may also increase the government's incentives to collect and disseminate them.

Producing timely and reliable agricultural production estimates is not a panacea. And, the rigorous research necessary to estimate the benefits of such information has not been conducted. Nevertheless, the general paucity of information is almost surely problematic, perhaps strongly so. At a minimum, it leaves on the table potentially very important gains. This role of information as an important input into the development process is one part of the call for a data revolution. The second part focuses on our greatly expanded abilities to produce and disseminate information. The next section turns to this aspect.

4 New opportunities

4.1 On the ground data collection

To understand the scale and scope of the new opportunities for efficiently and effectively gathering and disseminating timely and reliable agricultural statistics at low cost, it is helpful to consider what has been done in the past. The experience of Morocco in the late 1980s and early 1990s is illustrative. In the mid-1980s, Morocco operated one of the most tightly state controlled agricultural sectors in the world (Bouanani and Tyner 1991). As part of a relatively standard structural adjustment program, the agricultural sector was targeted for broad based liberalization

(Arndt and Tyner 2003). Reliable agricultural production statistics were viewed as a key public good for efficient functioning of agricultural markets.

To this end, major public investments were undertaken to establish a closed segment area frame system for estimating production of all crops with economic significance (see Davies 2009 for a description of area frame estimation). This effort involved purchase of a mini-mainframe computer that was so large it would not have fit in a standard university office, shipment of the computer to Morocco, installation in a specially air-conditioned room in the basement of the Ministry of Agriculture in order to diffuse the heat generated by the machine, chartering of airplanes to fly the country for the purposes of aerial photography of land use, digitization of the photographs, and purchase of satellite navigation devices for the purposes of locating precise areas on the ground.

Since the early 1990s, Morocco has, on the main, produced credible crop statistics on a timely basis, alongside credible and timely output forecasts, for more than two and a half decades. A relatively recent review of agricultural statistics for Mediterranean countries concluded that the area frame samples used by the Moroccan Statistics Division of the Ministry of Agriculture and Maritime Fisheries “are robust and in accordance with international standards” (Serghini-Idrissi and Lucchesi, 2013, p. 21).

Today, the heavy expense items purchased to initiate the Moroccan production statistics effort--the mini-mainframe computer with its associated designated room and air conditioning system, the aerial photography, the photography digitization, and the satellite navigation devices—are either many orders of magnitude cheaper or free. Very high-resolution photography combined with machine learning algorithms hold out good potential for at least partially substituting for crop cuttings, simplifying the most complicated step in a closed segment area frame approach. In short, the costs of mounting standard closed segment area frame sampling techniques have arguably never been lower in real terms.

Overall, our ability to execute standard closed segment area frame estimations, the method of choice in diverse regions including Morocco and the United States, has never been greater. This method is straightforward and robust. There is every reason to believe that it would function well in the Africa context. These observations alone should be sufficient to catalyze a reinvigorated effort to collect statistics that takes advantage of these new technologies.

The recent initiatives in Pakistan to complement existing comprehensive farm surveys with more limited surveys in bridge years between implementation of the comprehensive surveys are instructive for understanding how new technologies can provide high-quality estimates at substantially lower cost. GSARS (2015) describes how Pakistan Agricultural Information System, which has been operating as a complement institution to the Ministry of Food, Agriculture, and Livestock (MINFAL), has been able to obtain production estimates that are within 7 percent of the survey estimates for single crop areas and 10 percent in mixed crop areas. The relatively small deviations for the mixed crop areas are encouraging for application of similar methods in SSA countries, since mixed cropping patterns are common in many areas on the continent. The Pakistan Agricultural Information System achieved these results with a staff of 18 people and a budget of $300,000, relative to the 3,500-person staff and $7 million budget of the MINFAL for implementation of the comprehensive farm survey (GSARS 2015). These cost savings arise because remote sensing technologies, such as satellite data combined with geographic information system (GIS) data, can replace the need to do extensive area and yield surveys on the ground as described above. Additionally, the data from the Pakistan Agricultural Information System are made available months in advance of those from the official farm surveys (Ahmad et al. 2014).

Ongoing trials in SSA using unmanned aerial vehicles (UAV) are forging a new frontier for agricultural data collection and planning. For example, agricultural planners in Nigeria are using UAV imagery to inform rice paddy design, irrigation and drainage systems to take advantage of inherent terrain characteristics (ICT update, 2016). Researchers in Tanzania are using spectral imaging collected from UAV's to monitor sweet potato production in order to identify plants that are water stressed, nutritionally deficient, or suffering from pests (International Potato Center, 2014).

Thus, remote sensing technologies (including satellite and UAV technology), as well as other sensors such as low-cost biomass, rainfall and weather station sensors may pave the road for substantial cost savings in data collection compared to traditional farm surveys in SSA. In addition, mobile phone technology, data upload capacity, and data security continues to improve and, in most cases, provides for more efficient database management than earlier data collection and entry systems housed on large data servers.

It is important to note, however, the current state of the art for use of satellite remote sensing data in agricultural area or yield estimation will require investments in base estimates, training, and computer hardware and software (which may require relatively large upfront costs). Investments in human capacity to analyze and manage new data collection systems would be important to the overall success and sustainability of the program. Many SSA countries are already providing advanced courses on remote sensing and data management. These curricula could be updated and extended to provide the necessary skills for agricultural data collection and management systems. Additionally, occasional comprehensive surveys, such as an agricultural census which the FAO recommends implementing every decade (FAO 2015), would need to be done, but the variable costs would be much lower in years in non-comprehensive survey years.

4.2 Satellite remote sensing

At the same time, the technologies that appear to have strong potential for facilitating crop data collections 'on the ground' are being paired with rapidly improving satellite-based remote sensing capabilities. On March 7 2017, the European Space Agency (ESA) launched satellite Sentinel-2B as part of Copernicus, a program meant to serve as "Europe's eyes on Earth." Sentinel-2B joins Sentinel-2A and a host of other satellites already in orbit, notably those deployed by National Aeronautical and Space Administration (NASA), that are designed to monitor environmental states, fluxes, and properties at high spatio-temporal granularity in all regions of the globe. Both ESA, through Copernicus, and NASA, through its Applied Sciences Program, specifically aim to improve food security. Satellites, such as Sentinel-2B, are currently closely monitoring growing conditions in regions such as sub-Saharan Africa, and these data are freely available (Lobell 2013). These data, in addition to ground-truth data (via localized ground sensors (rainfall, temperature, biomass, etc.) and crop area and production data collection provide the key components to agricultural production and yield estimates.

Satellites are essentially overhead sensors. They can monitor and record information that is reflected from the earth's surface. However, this information, in and of itself, is not particularly useful. It must be interpreted. This requires some form of modeling to convert what the satellite can observe, such as spectral reflectance measurements, into a meaningful measure of conditions on the ground, such as soil moisture or vegetation density. Models can go one step further, describing the complex physical processes that underlie crop growth, transpiration, and senescence in order to provide high-resolution (national to sub-national) estimates and/or forecasts of crop production and yields. For example, Figure 2 presents estimates of maize production in the year 2000 at approximately 2500 km^2 resolution for six crop production models driven by satellite data and more. These six models were designed to predict global risks to agricultural production under climate change [*Rosenzweig et al.*, 2014].

When historical crop production data are available, models can alternatively be based on statistical regression [*Challinor et al.*, 2014]. Whether "process-based" or "statistical," these models provide a robust basis for evidence-driven agricultural decision-making. Model forecasts can be used to evaluate and compare proposed management, policy, and investment alternatives; predict year-to-year risks to food security due to droughts, floods, and pests; or predict long-term risks and market shifts due to, e.g., climate change and land use change. IFPRI's IMPACT model, for example, couples a crop production model to models of the global climate system, water systems, and economic systems in order to inform long-term agricultural planning from regional to global scales [Rosegrant et al., 2008].

At the plot or field scale, modeling is often a straightforward process because the data required for model development are comparatively easy to collect. At continental to global scales, first-order ("broad brush") estimates based on satellite data, agricultural census data, and other 'on-the-ground' data collection similarly suffice to address many questions of interest (e.g., "Will climate change have a net negative impact on global food security?") [Challinor et al., 2014; Rosenzweig et al., 2017]. The greatest challenge in crop modeling is often not the field-scale or global-scale assessment of crop production, but reliable estimation of crop production at regional and national scales in order to inform policy development, investment planning, and agricultural management [Challinor et al., 2014; Dale et al., 2017].

Despite major advances in data and crop model design, the accuracy of crop models at regional and national scales remains limited. For example, each of the models presented in Figure 2 paints a dramatically different picture of maize production levels in Africa in 2000 even though all models were driven by climate data from the same global climate model [Rosenzweig et al., 2014]. These differences generally stem from differences in both other data inputs and model formulation. Importantly, GEPIC and EPIC (Figure 2) differ only with respect to model inputs, revealing that a single crop model can generate dramatically different results under two equally justifiable sets of assumptions about (for example) management practices and soil properties [Rosenzweig et al., 2014].

A lack of reliable observational data is a principal factor underlying the dispersion in model results shown in Figure 2. Observational data serve as the ultimate test of model performance and the best means of improving model design. The best way to choose between alternative models is to select the one that more accurately predicts actual historical yields. However, a collection of models should be regarded as "equally reliable" if their performance fall within observational uncertainty. An equally beneficial evaluation is to eliminate model solutions that are outside an acceptable range of observed behavior (e.g. yield or production). Inter-model evaluations to historical data serve to provide more reliable scenario analyses, trustworthy forecasts and, ultimately, a more informed basis for decision-making. Sensitivity and uncertainty analysis can be used to reveal the model parameters that are highly uncertain and/or have a controlling influence on model outputs; these findings then guide future data collection efforts and allow an iterative approach to model design that leads to incremental improvements in model performance [Morgan et al., 1990].

Crop model quality is a strong function of the quality of data used for model development and parameter selection; the data limitations introduced above can therefore severely limit the accuracy and usefulness of crop models for the developing world. In fact, high-quality, high-resolution data is arguably of even greater value for models of developing nations than it is for developed nations. Agricultural practices in developing regions are more spatially and temporally heterogeneous because most production occurs on smallholder farms characterized by diverse farming practices and widespread intercropping and sequential cropping [Waha et al., 2013]. Developing regions are also characterized by large gaps between actual and potential yields [Mueller et al., 2012; van Ittersum et al., 2016]; model performance in this case becomes highly dependent on the ability of the model to capture the many biophysical constraints on crop growth and their complex and non-linear relationships with one another.

In sum, the lack of reliable information on agricultural production, discussed in section 2, is itself forming a powerful brake on efforts to advance statistics, policy development, and management through agricultural models. Especially, the inability to systematically ground-truth data-driven crop models has given rise to a situation where competing models generate markedly different results. This inability to compare model results with facts on the ground strongly impedes an iterative process of forecast and estimation improvement.

5 Summary and conclusions

Official agricultural production forecasts and estimates are, in a large number of SSA countries, late, of poor quality, and sometimes non-existent, even for key staple crops. This dearth of timely and reliable information on production volumes is costly. It impedes response to food crises. It hampers public policy formulation. It retards nascent democratic processes by depriving voters of information on basic performance in a crucial sector. Finally, it leads to inefficient agricultural market functioning as knowledge of supply is critical to proper price formation.

Ongoing technological developments are generating substantial opportunities for producing timely and reliable agricultural production statistics at relatively low cost. This is true both from the ground up and from space down.

An important topic for future research is how exactly to grasp these opportunities. Efforts on the ground are almost certain to be a key component of setting in place a data revolution for agricultural statistics in SSA. Without adequate efforts on the ground, Africa's ability to profit from the wealth of satellite remote sensed data will be unnecessarily hamstrung. A coordinated effort, where satellite data inform the design and implementation of closed segment area frame samples and the results from these area frames permit the application of a spectrum of model/computational methods to estimate and predict crop yields and production, seems the most promising.

The specter of a data revolution in agricultural statistics also has implications for institutions. Ongoing technological developments are shifting the nature of the task of estimating agricultural production from a mainly logistical operation to a principally analytical challenge. An institutional approach that is well suited to a more analytically demanding and less logistically demanding set of tasks would also appear to be desirable. Hence, both technical and institutional aspects of fomenting a data revolution need to be in focus.

To close, we believe that vastly improved agricultural production forecasts and estimates are attainable at relatively low cost. While not a panacea, improved production information has high potential to contribute to improved living standards for literally hundreds of millions of Africans through improved food security response, better economic and agricultural policy formulation, enhanced transparency and accountability in a key sector, and improved functioning of agricultural markets. Better estimates of the benefits of improved agricultural production forecasts and estimates remains a topic for future research; nevertheless, the available information points to extraordinarily high benefit to cost ratios from fomenting a data revolution in agricultural production statistics for sub-Saharan Africa.

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7 Figures

Figure 1a: Maize production estimates for Mozambique: Statistical Yearbook.

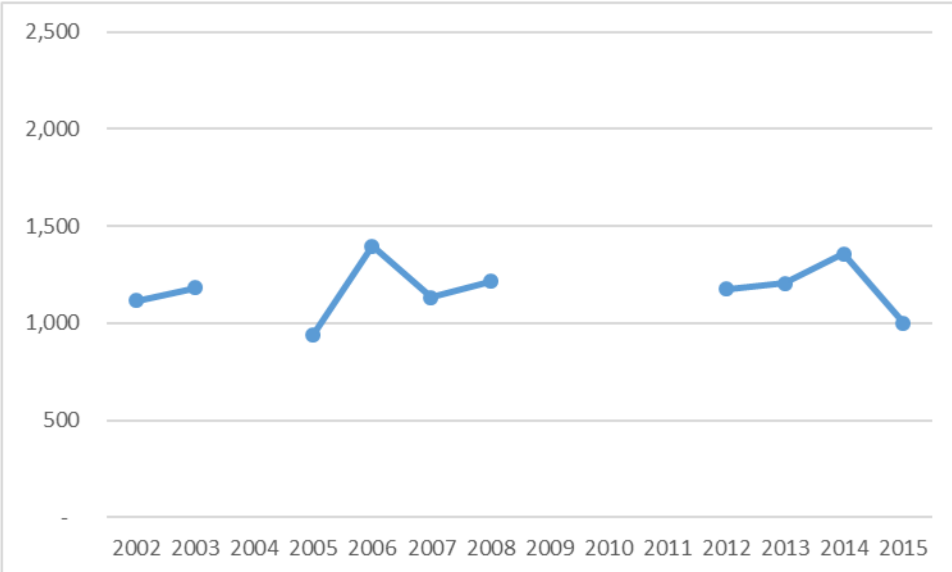

Figure 1b: Maize production estimates for Mozambique: FAOStat.

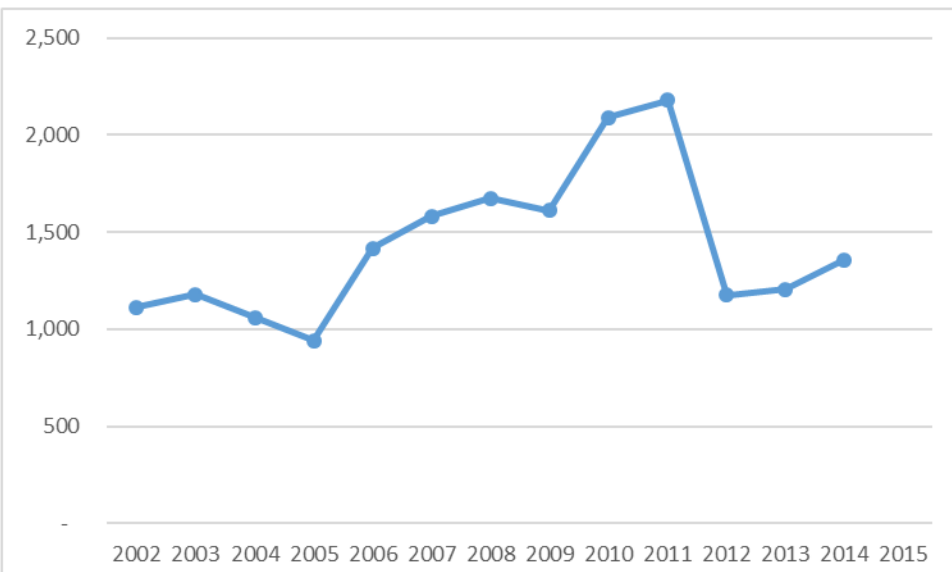

Figure 2. Year 2000 maize yields (t/ha) predicted by six global process-based crop models from the Agricultural Model Intercomparison and Improvement Project (AgMIP) [*Rosenzweig et al.*, 2014]. Data are available at esg.pik-potsdam.de/search/isimip-ft/