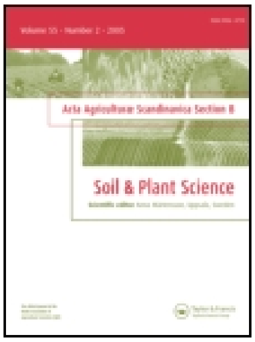

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ORIGINAL ARTICLE

Modeling potential rain-fed maize productivity and yield gaps in the Wami River sub-basin, Tanzania

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The cause for low maize yields in rain-fed production systems is usually associated with water stress due to perceived suboptimal seasonal precipitation. A modeling study using Agricultural Model Intercomparison and Improvement Project modeling framework was conducted to determine the magnitude of rain-fed potential yield and yield gap of maize in the Wami River sub-basin, Tanzania. Primary and secondary data on soils, weather, management, and crop yields and cultivars were used. Data matrix search technique was used to calibrate CERES-Maize Crop System model against reported yield for each of 168 farms involved in this study. Then the individual farms' simulated yields, actual reported yields, and the resultant yield gaps were aggregated into ward-level averages. Model calibration was robust as there was a very close agreement between reported and simulated yield (R^2 = 0.9). Actual yields reported from farm survey ranged from 50 kg ha^{-1} to 3600 kg ha^{-1} with an average of 860 kg ha^{-1}. Simulated rain-fed potential yield was between 2073 kg ha^{-1} and 5443 kg ha^{-1} and a mean of 4033 kg ha^{-1}. It is apparent therefore that there exists a wide maize yield gap of 79% with current management under rain-fed conditions. This suggests that there is a large scope of improving maize yields under rain-fed conditions. Narrowing the yield gaps would require an intensive soil fertility improvement in the study area.

Keywords: AgMIP framework; CERES-Maize; crop modeling; rain-fed agriculture; yield

Introduction

Maize (*Zea mays* L.) is the most important staple grain in Tanzania, grown on 45% of total cultivated area and accounting for up to 65% of total cereal production (United Republic of Tanzania 2012). Generally, maize production has been increasing by 76,600 metric tons per annum while grain yield has been increasing at a rate of 0.02 tons ha^{-1} per annum for over 50 years (FAOSTAT 2014). This suggests that maize production is from more expanded cropland rather than improved productivity. Low productivity is being reflected by surge in maize grain imports (FAOSTAT 2014). To reverse this trend for increased maize production, more maize should come from existing cropland through improved productivity. Expanding more cropland would not be sustainable since it would interfere with protected areas such as forests and other fragile ecosystems. Improving crop productivity by closing the yield gap is seemingly a justified option.

Maize production in Tanzania depends to a large extent on rainfall, up to 98% of total production. As a result, actual yield and productivity to that effect is very low, estimated to around 1.2 tons ha^{-1} (FAOSTAT 2014). However, the causes of low yield for maize are so far not explicit. For example, average seasonal precipitation within the Wami River sub-basin range from 400 mm to 600 mm (IUCN 2010), which is apparently sufficient for maize production. Low maize yields therefore point out to some other issues that are perhaps yet to be addressed by farmers on one the hand and policy on the other

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hand. Understanding the underlying causes of low maize yields and subsequent formulation of options to address these causes, a close investigation of the potential yield, actual yield, and resulting yield gap is important (Lobell et al. 2009). The importance of knowing the crop potential yield and yield in a given area is that: it enables projection of the future crop yields; it is an indicator of the possibility of future yield expansion; and it facilitates the knowledge and understanding of the biophysical constraints hindering attainment of maximum crop yields (Lobell et al. 2009). Crop yield gap studies have been conducted elsewhere and have helped to improve various crops productivities after growers had put the advice given to work, e.g., in the Netherlands (van Ittersum et al. 2013) and Australia (Passioura and Angus 2010; Hochman et al. 2012). This kind of analysis has not been done in the Tanzanian context so as to understand the potential maize productivity, yield gap, and biophysical constraints that limit higher maize yields.

Dynamic crop models are appropriate tools for yield gap assessment (van Ittersum et al. 2013; van Wart et al. 2013). However, most studies which use crop models suffer fundamental shortfalls. First, interpolation adds more uncertainty into crop models for specific region since the weather or soil data may or may not be representative of the local conditions. Second, large spatial scale study may not represent the current management of a cropping system, which varies significantly even within an agro-ecological zone. And third, based on the understanding that actual yields differ from one location to another, the use of single actual yield to estimate the yield gap for a country or a region aggravates the uncertainty already caused by weather and soil data. For example, actual yield data in developing countries are normally estimates by FAOSTAT which itself has some transparency issues (van Ittersum et al. 2013).

The aim of this work was to evaluate the scope of maize productivity for individual farms under rain-fed conditions in the Wami River sub-basin, Tanzania, and in particular: (1) to determine the parameters which are responsible for yield variability among small-scale farms across Wami River sub-basin, (2) to simulate the potential yield for small-scale farms across the sub-basin, and (3) to estimate the magnitude of rain-fed maize yield gaps under rain-fed conditions in the sub-basin.

Materials and methods

This study underpins an Agricultural Model Intercomparison and Improvement Project (AgMIP) protocols (Rosenzweig et al. 2013) with new computing tools for improved crop modeling studies in efficiently characterizing agricultural systems. The rationale for adopting the AgMIP protocol is based on: its capacity to handle multiple site-year model inputs and simulations using its data overlay for multi-model export (DOME) tools and QuadUI translation software; its capacity to include assumptions or expert knowledge which is not normally captured in regional surveys, yield trials, or even experiments; and its ability to produce model output for multiple site-years via AgMIP crop model output tool. (See AgMIP handbook of methods and procedures (Version 5) at www.agmip.org).

Study area description

Wami River sub-basin is located between 5°–7°S and 36°–39°E, covering an area of 43,000 square kilometers (Figure 1; IUCN 2010) with an altitudinal gradient of approximately 2260 m.

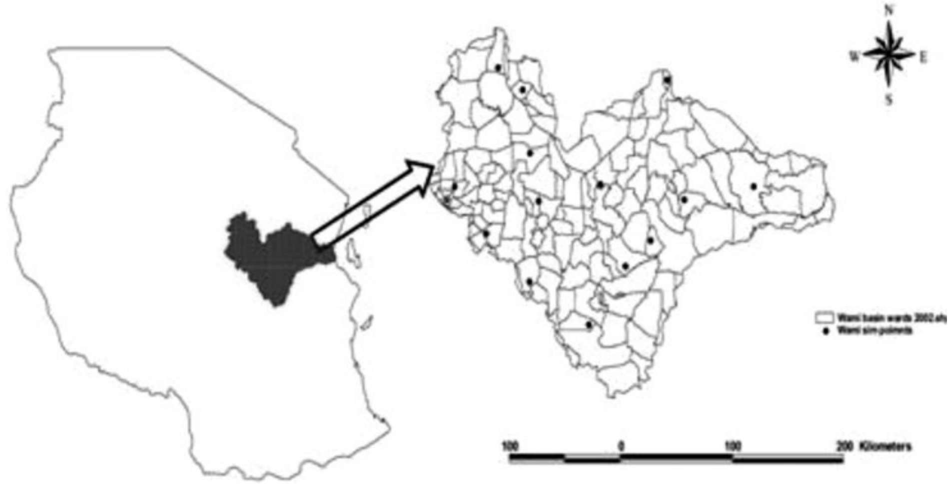

Figure 1. Wami River sub-basin.

Wami River sub-basin receives annual rainfall between 550–700 mm in the highlands near Dodoma and 900–1000 mm in the lowlands near Dakawa and at the river estuary with dry periods from July to October and wet periods from November to December (*vuli*) and from March to June (*masika*; IUCN 2010). The annual mean temperature is approximately 26°C, coolest month being August with average temperature of 18°C and hottest month is February with average of 32°C. The study area has variable soil types, major reference groups (FAO-UNESCO classification; FAO 2006) being *Cambisols*, *Fluvisols*, *Luvisols*, *Ferralsols*, and *Nitisols*.

Model input data

Historical weather data

A total of 15 weather stations were identified in the study area, of which 6 stations had a 30-year measured daily weather data. The remaining 9 stations had synthetic, 30-year daily weather data. Weather parameters included minimum and maximum temperature, solar radiation, and rainfall.

Modern era-retrospective analysis for research and analysis (MERRA; Rienecker et al. 2011) was used to create new, synthetic weather stations and to fill in missing values in weather stations with observed data. The MERRA products are generated using version 5.2.0 of the Goddard Earth Observing System – data assimilation system with the model and analysis each at 1/2 x 2/3 latitude and longitude degrees resolution, respectively.

Soil data

Within the study area, a total of 20 soil profiles, 8 soil profiles were excavated in the course of this study and 12 were obtained from the harmonized soil database (Leenaars 2013). Soil hydrological properties for each layer in each soil profile were estimated using soil water properties calculator (Saxton & Rawls 2009). Input variables were soil texture (sand, silt, and clay) and organic matter, whereas the outputs were the drained lower limit (SLLL; mm mm^{-1}), drained upper limit, (SLDUL; mm mm^{-1}), saturation (SLSAT), and available water for respective soil layer.

Management and actual yields information

A comprehensive household panel survey database (National Bureau of Statistics 2012) was used to identify a total of 168 farm fields within the study area whose maize yields for the 2009/2010 growing season were recorded. Apart from maize yields, such information as amount of organic or inorganic fertilizers, previous crop and irrigation were extracted from the database for each farm. However, such information as planting dates, maturity or harvesting dates, planting density, and the type of maize cultivars used per farm were not reported in the survey database; thus, supplemental information was obtained from the key informants' interview across the study area. Information on the indicative normal planting dates, type of cultivars, plant population, and indicative yields was recorded from key informants' interview at eight locations across the study area. This information and other assumptions were used to create model input files.

Modeling protocol

CERES-Maize model description

CERES-Maize (CERES, Crop–Environment–Resource–Synthesis) module (Jones & Kiniry 1986) within the Decision Support System for Agrotechnology Transfer (DSSAT; v. 4.5; Hoogenboom et al. 2010) uses simplified functions to predict the growth of maize crop as influenced by major factors that affect yield. These factors include genetics, climate (daily minimum and maximum temperatures, solar radiation, and precipitation) soils, and management (Hunt & Boote 1998). The rationale for using this crop system model is that, amongst an array of dynamic crop models, CERES-Maize has been used in a wide range of environments. CERES-Maize model, like other models of the DSSAT suite, requires minimum data sets (Hunt & Boote 1998), some of which can easily be estimated or obtained from field measurements or observations or informed assumptions from expert knowledge. Moreover, CERES-Maize model has been fitted with cultivar-specific parameters for four locally adapted maize cultivars (Mourice et al. 2014). CERES-Maize model has the ability to simulate the effects of nitrogen, soil water deficit, and low or high temperature on the photosynthesis and pathways of carbohydrate movement in plants (Rosenzweig & Iglesias 1998). Under nonoptimal conditions of low or high temperature, water, or nitrogen stress, the actual daily biomass production is normally constrained by a reduction factor which varies from zero to one, where one means no limitations while zero means maximum limitations (Ritchie et al. 1998).

CERES-Maize model calibration

Objective spatial parameterization approach of the CERES-Maize model by Irmak et al. (2001) was adopted to solve for spatially variable model input variables/parameters that minimize error between simulated and reported yield from survey. This approach was adopted in this study because specific values for critical model input variables/parameters were not available or would have been difficult to measure at a desirable precision across the study area to sufficiently account for yield variability. Thus, in this approach, a range of critical inputs at a regular step sizes were used to create a large data matrix of simulated yields. Although this approach is recommended for small, homogeneous areas (Sadler et al. 2002), it is nonetheless useful for large and heterogeneous areas. Moreover, it is efficient in terms of computer time in situations where there are many simulation points (fields), many model inputs with small step sizes, and thus large solution space (Irmak et al. 2001). Model input variables/parameters whose values were not known for each field include planting dates, planting density, soil initial inorganic nitrogen (NO_3–N), and initial water content. A solution space matrix of 11,160 data values per field (Table 1) was searched through to find the input variable/parameter combination which minimized the objective function (root mean square error – RMSE; Equation 1):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2} \quad (1)$$

where $\hat{Y}$ is the simulated yield and Y is the reported yield, i is the ith variable/parameter combination, and n is the number of combinations.

Table 1. Optimization parameters/input variables.

Variable/ parameter	Unit	Step size	Range searched	Total values
Planting date	Day	1	30	31
Plant population	Plants/m^2	0.5	1.1–4.9	8
Initial NO_3–N	ppm	0.5	0.01–2.0	5
Initial water	% water	10	10–80	9
Solution space				11,160

Model inputs and simulation

According to AgMIP modeling framework, three model input files were created:

(1) survey import file which includes the farm code, weather stations used, soil profile for each farm, planting dates, plant population, nitrogen fertilizer applied, organic manures, and reported actual yields, where each row represents individual farm;

(2) field overlay file – an Excel file in which such information as initial conditions (soil water and mineral Nitrogen content) and all unknown management assumptions (e.g. soil fertility factor (SLPF), soil organic carbon, and root distribution); and

(3) the seasonal overlay file – also an Excel file which specifies the span of years for which simulations are sought, atmospheric CO_2 concentrations and automatic planting events for each year.

Maize cultivar *Situka* was used in this study due to its popularity within the study area for its high yield, early maturity, and drought tolerance. Moreover, it featured more than other cultivars during key informants' interviews. Furthermore, its cultivar-specific coefficients (Table 2) have been determined and fitted into the DSSAT cropping system model. The three files were individually zipped, loaded into QuadUI translation tool to create the DSSAT model-ready files. From the DSSAT folder that is created afterward, simulation was initiated by executing the *RUN45.BAT* file.

Model assumptions

In the model, planting was automatically invoked when a total of 25 mm of rain or more was received within five consecutive days. This minimized the possibility of false start of growing season and also allowed for variation of start of rains from year to year among the farms. Since the crop residues from

Table 2. Cultivar-specific parameters for *Situka* maize cultivar.

	P1	P2	P5	G2	G3	PHINT
Cultivar	(°C day)	(day)	(°C day)	(# grains/ear)	(mg/day)	(°C day)
Situka	199.5	0.5	672	673	10.03	42.8

P1, thermal time in degree day (°C day); thermal time from seedling emergence to the end of the juvenile phase;
P2, extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours);
P5, thermal time from silking to physiological maturity;
G2, maximum possible number of kernels per plant;
G3, Kernel filling rate during the linear grain filling stage and under optimum growth conditions;
PHINT, phyllochron interval; an interval in thermal time between successive leaf tip appearances.
Source: Mourice et al. 2014.

the previous harvest could not be measured for each farm, a minimum of 500 kg ha^{-1} was assumed to be the initial surface residues from previous crop, which was assumed to be maize for all fields. This value was based on the fact that normally most residues are used as animal feeds during the dry season, or some residues are blown away in the course of time between harvesting and next season's planting. For a few fields which reported the use of inorganic fertilizers in the panel survey, two rounds of application were assumed: the first being 14 days after sowing (DAS; 33% of total amount) and the second round application at 45 DAS (remaining 67% of the total). As regards to other crop growth limitations which could not be explicitly addressed by the available data, e.g., insect pests, weeds, or crop diseases, an SLPF of 1.0 was assumed across for all farms. Start and end of simulation were set to, respectively, 30 days and 200 days before and after sowing.

Simulation of rain-fed potential yield

The three zipped DOME files were translated using QuadUI software (version 1.2.1 Beta11) to create DSSAT input files. To allow DSSAT to simulate rain-fed potential yield, an external simulation control file (DSCSM045.CTR) was edited to switch off nitrogen, phosphorus, potassium, and diseases limitations. Then the command line in the RUN45. BAT file was modified so that it calls an external control file, so as to override internal simulation controls specified in regular FILEX of the DSSAT system.

Rain-fed yield gap

Rain-fed maize yield gap was calculated as the difference between rain-fed potential yield and the actual yield reported from the survey for each farm.

Thereafter, the farms' actual yield, potential yield, and yield gap were up scaled to give respective average values on per ward basis.

Results and discussion

Model calibration

The simulated and observed or reported yields from farm survey are presented in Figure 2. There was good agreement between simulated and reported yields (R^2 = 0.91). Unlike in trial and error approach to model calibration, a variant of database search method proposed by Irmak et al. (2001) shows good convergence between simulated and reported yields. Since calibration was based on an individual farm/field, the results suggest that assumptions made per each field and combination of model variables or parameters per field were plausible for most fields. However, the limitation to this procedure in this study is that one season (2009/2010) grain yield data was the only variable available to adjust the model.

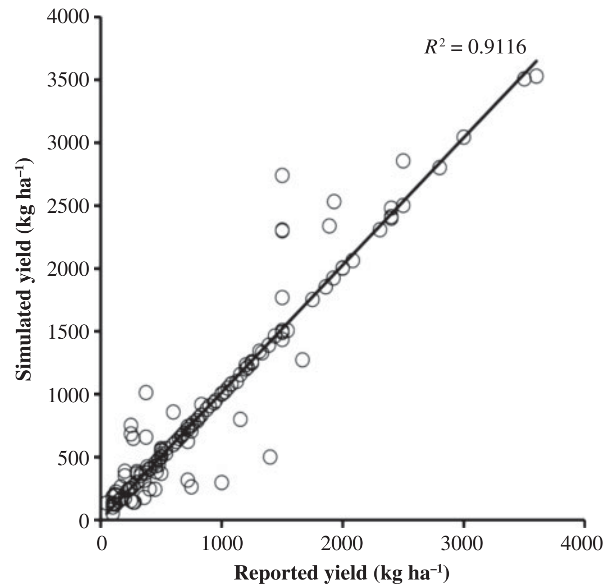

Figure 2. Comparison of simulated and reported maize yields.

Rain-fed potential yield

Rain-fed potential yield in the study area varied significantly from one farm to another, ranging from 1515 kg ha^{-1} to 5477 kg ha^{-1} with a mean value of 3287 ± 154 kg ha^{-1} (at 95% confidence level). The probability of farms exceeding rain-fed potential of 3000 kg ha^{-1} was 52%, whereas that of exceeding 5500 kg ha^{-1} was as low as 0.3% (Figure 3). Up to 36% of all fields had potential yield ranging between 4000 kg ha^{-1} and 5000 kg ha^{-1}. When potential yield was aggregated on per ward basis, average rain-fed

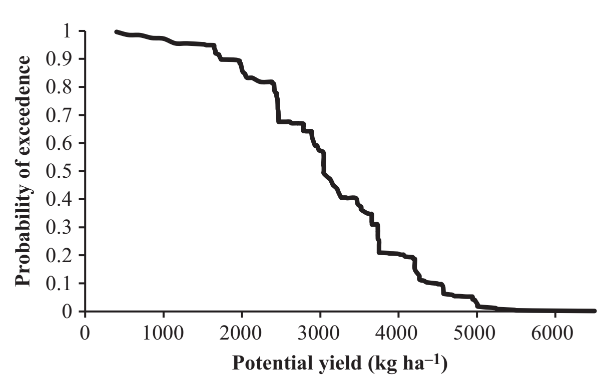

Figure 3. Cumulative distribution function for the simulated rain-fed potential yield in the Wami River sub-basin.

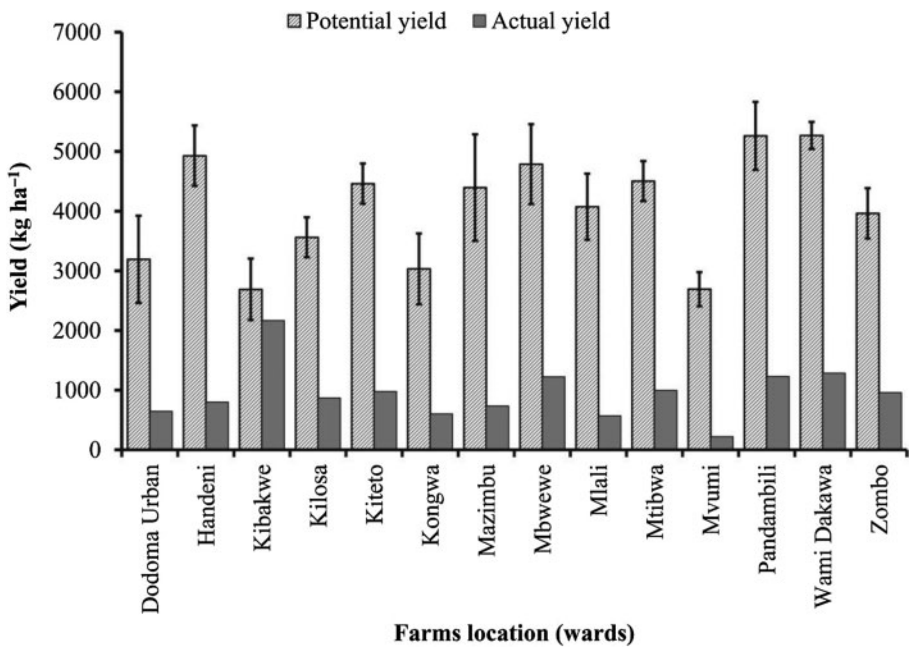

Figure 4. Actual and rain-fed potential yields.

potential yield was high in Handeni, Pandambili, and Wami wards. Farms in Kibakwe and Mvumi wards indicate the least rain-fed potential yield for maize (Figure 4).

Rain-fed potential yield was not correlated to the number of days to crop maturity. Potential yield for fields in Kiteto area (1450 m above sea level) with 103 simulated mean days to maturity did not differ from those in Kibakwe (1100 m above sea level) with 81 simulated mean days to maturity.

The concept of rain-fed potential yield reflects the yield which would be expected if soil water was the only limiting factor. However, the spatial rain-fed yield variation may indicate varied rainfall amounts and distribution across the growing seasons as well as soil physical properties which determine available soil water dynamics, which also vary from one field to another.

There was no correlation between the rain-fed maize yield potential and the long-term seasonal average precipitation, suggesting the potential yield is affected by other biophysical variables (e.g. soil hydrological properties) and/or management, besides total seasonal rainfall. The lack of the association between rain-fed potential yield and mean seasonal rainfall may be attributed to the narrow range of the latter among the weather stations involved in this study. The coefficient of variation for the long-term average rainfall among the stations was 18% while that of rain-fed potential yield was 30%. Lack of correlation between seasonal precipitation and rain-fed potential yield may perhaps be attributed to seasonal rain characteristics. Ifabiyi and Omoyosoye (2011) reported that maize yields were correlated with number of rainy days, rather than the annual rainfall in Kwara State, Nigeria. Conversely, Bhatia et al. (2008) reported a positive, curvilinear association between soybean rain-fed potential yields and long-term seasonal rains. IFDC (2012) conducted a nationwide simulation study (using DSSAT v4.5) to determine maize potential yield for estimating fertilizer requirement. On average, the simulated rain-fed maize potential yield in the study area was estimated at 4.2 tons ha^{-1} with a range between 2.5 tons ha^{-1} and 7.0 tons ha^{-1} (IFDC 2012). Apparently, the IFDC study estimates are higher than those obtained in this study. The disparity may be due to the differences in levels model calibration, the input data used, and the number of points over which model simulation was conducted.

Actual yields

The distribution of actual farmers' yields reported from field survey is presented in Figure 5. On per farm basis, the actual yield ranged from 50 kg ha^{-1} to 3600 kg ha^{-1} with an average of 860 kg ha^{-1}. Actual yield variability within the study area indicates diverse environment (in soil and rainfall) as well as management (cultivars, planting dates, fertilizer application, and plant population) under which maize production is undertaken. Actual yields were high for farms in which inorganic fertilizer use was reported. Although soil organic matter affects soil available water (Saxton & Rawls 2006), the latter was not associated with actual yields. There was also

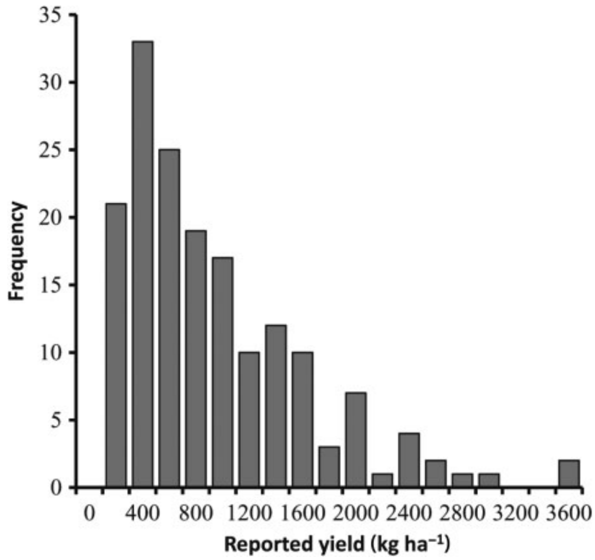

Figure 5. Actual yields reported from panel survey.

weak association between actual yield and total soil available water (R^2 = 32%). When farms were aggregated on per ward basis, average actual yield exceeded 1000 kg ha^{-1} in Pandambili, Mbwewe, Wami, and Kibakwe wards. Farms around Mvumi ward reported the lowest actual yields, averaging 220 kg ha^{-1} (Figure 5). Low rain-fed potential yields around Mvumi ward may be due to low seasonal precipitation or inherent low soil fertility due to degradation. Mvumi area is in semiarid central Tanzania with soils highly vulnerable to erosion (Dejene et al. 1997). Normally, farmers in areas with degraded soils and dry environment would adapt to low-input production strategy to avoid risks, hence low productivity.

Rain-fed yield gap

Mean yield gap ranged from 10% to 88%, indicating a wide gap between potential and actual yield under rain-fed conditions. Farms in Dodoma urban and Kiteto exhibited a scenario where production could be as high as potential yield (0% yield gap) or total crop failure (100% yield gap (Figure 6). Yield gaps for farms in Kibakwe exhibited unusual behavior, with some having actual yield higher than the simulated potential yield under rain-fed conditions.

Wide yield gaps suggest that there is a large scope of improving maize yields under rain-fed conditions (Lobell et al. 2009; van Ittersum et al. 2013). All locations except Kibakwe have higher potential to increase maize productivity due to the wider yield gaps under rain-fed conditions. The reason for low potential yields in Kibakwe ward could probably be poor rainfall distribution along growing season. Ifabiyi and Omoyosoye (2011) pointed out that yield is related to the number of rainy days in a season rather than total seasonal rains. Moreover, Kibakwe, like many parts of semiarid central Tanzania, is characterized by degraded soils (Dejene et al. 1997). Therefore, it is likely that the soils in the area are not responsive to nitrogen fertilizer application (Tittonell & Giller 2013), the reason for low potential for yield improvement, even under adequate nitrogen fertilization as defined in the crop system model.

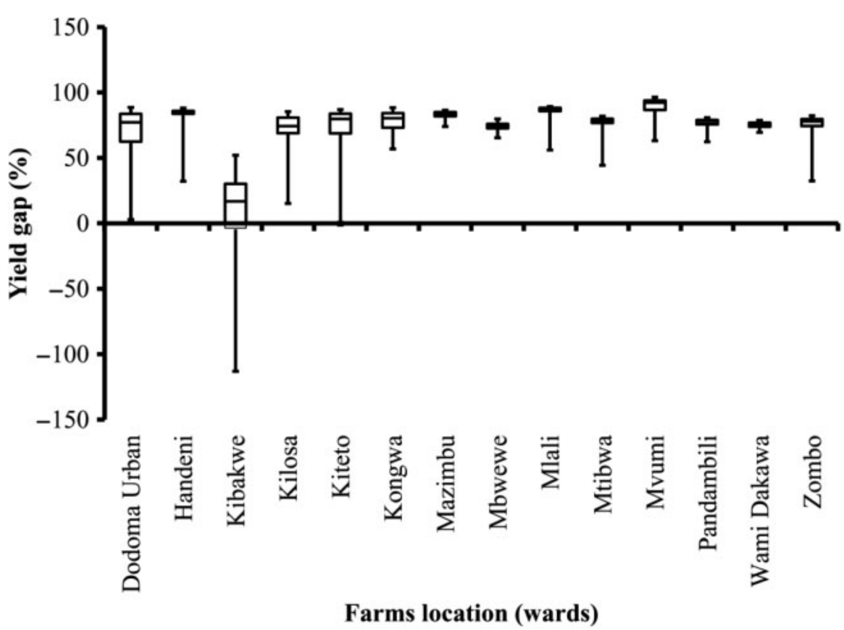

Figure 6. Box and whisker plot indicating maize yield gap aggregated for 168 farms under rain-fed conditions.

In Africa, small-scale crop production is characterized by nutrient mining as a result of insufficient input of inorganic fertilizer and organic matter (Stoorvogel et al. 1993, Sanchez et al. 1997). Therefore, poor soil fertility is the major limitation to bridging crop yield gap (Tittonell & Giller 2013). This study indicates that if nitrogen was not limiting, current actual yields would be comparable to potential yields. In view of high costs of nitrogen fertilizers, losses through volatilization, denitrification and leaching and fixation, integrated soil fertility management (ISFM; Place et al. 2003; Nezomba et al. 2014) may be appropriate in maize productivity intensification in the study area.

Although perfection in growing conditions as indicated in crop model may not be possible under real-life situation (Lobell et al. 2009), the exploitable yield gap in the study area may be lower than indicated. Because attaining potential yield is not economically effective since after maximum farm yield is attained, the yield tends to increase at a decreasing rate for every incremental input (Koning et al. 2008). Therefore, in addressing the maize yield gaps, economically effective measures which would result in optimum productivity while maintaining a good profit margin may be recommended. To achieve this goal, further studies to investigate input combination which would result into optimum yields and low yield gaps under rain-fed conditions are still required.

Model calibration approach for spatially variable fields was robust, and model assumptions were reasonably plausible. AgMIP modeling framework and tools used for the assessment of rain-fed potential yield were highly efficient in terms of populating model inputs and fixing the model assumptions. Given that model inputs were not physically measured in the field, AgMIP protocol is robust and flexible in allowing incorporation of local knowledge into modeling. There have been no documented stand-alone yield gap studies in Tanzania against which this study could be compared. However, the findings in this study show there is large scope for intensification of maize production, since current yield gap is 79%. Its implication is that using current cultivars and improvement in farm practices, especially ISFM which permits enhanced soil quality, maize yields would be improved fourfold from current productivity. This study gives the new direction for policy focus in implementing sustained intensification approach. All locations have high potential for improving maize productivity except Mvumi and Kibakwe, since the soils were not responsive to nonlimiting nitrogen fertilization as indicated by simulated potential yields.

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