

Maize, Cassava, and Sweet Potato Yield on Monthly Climate in Malawi

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Abstract

Climate change and climate variability in Malawi have negatively affected the production of maize, a staple food crop. This has adversely affected food security. On the other hand, there have been increases in growing area, production, yield, consumption, and commercialization of both cassava and sweet potato. Factors behind these increases include the adaptive capacity of these crops in relation to climate change and variability, structural adjustment programs, population growth and urbanization, new farming technologies, and economic development. Cassava and sweet potato are seen to have the potential to contribute to food security and alleviate poverty among rural communities.

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This study used a simple generic growth index model called GROWEST to model observed yields of maize, cassava, and sweet potato across Malawi between 2001 and 2012. The method can be viewed as a hybrid approach between complex process-based crop models and typical statistical models. For each food crop, the GROWEST model was able to provide a robust correlation between observed yields and spatially interpolated monthly climate. The model parameters, which included optimum growing temperatures and growing seasons, were well determined and agreed with known values. This indicated that these models could be used with reasonable confidence to project the impacts of climate change on crop yield. These projections could help assess the future of food security in Malawi under the changing climate and assist in planning for this future.

Keywords

Climate change · Food security · Maize · Cassava · Sweet potato · Crop yield modelling

Introduction

Process-based simulation models and statistical models are commonly used to assess the impact of climate variability and climate change on food crop yields (Lobell and Asseng 2017). The former typically have complex plant and environmental data requirements, while the latter can have large uncertainties in fitted parameters that make application to climate change assessment difficult (Schlenker and Lobell 2010; Ray et al. 2019). This paper examines a hybrid approach that statistically calibrates a simple generic plant growth model, called GROWEST, using spatially distributed yield and monthly climate data. The model parameters are robustly determined and hence able to provide baseline models suitable for assessing the potential yields of maize, cassava, and sweet potato in relation to projected climate change. The GROWEST plant growth index model was originally developed by Fitzpatrick and Nix (1970) and Nix (1981) and has been implemented by Hutchinson et al. (2002). It has been used to develop a global agroclimatic classification that has identified agroclimatic classes for Australia (Hutchinson et al. 2005) that have been used to support a wide variety of ecosystem assessments.

The model is applied to annual yield data for the eight Agricultural Development Divisions (ADDs) across Malawi and corresponding spatially distributed monthly climate data. Spatial climate data were available from 1981 to 2012. The maize analyses were restricted to the years 2006–2012 after the introduction of the Farm Input Subsidy Program (FISP) in 2005/06 which had a significant impact on maize yields. Reliable annual yield data were available for cassava for the period 2001–2011 and for sweet potato for the period 2006–2012. The yield model is based on regressing the logarithms of the observed crop yields on average weekly growth indices of the GROWEST model, with the average taken over the respective growing season for each crop. Three key parameters of the GROWEST model, the

optimum growth temperature and the starting and finishing weeks of the growth season, are tuned to the observed yield data for each crop. The regressions take into account variations in site and management conditions across different ADDs and are extended to take into account systematic increases in yields over time due to plant breeding programs, improvements in growing practice, and carbon dioxide fertilization. Robustly calibrated models are obtained for local, composite, and hybrid maize varieties and for cassava and sweet potato.

Maize, Cassava, and Sweet Potato Growth

As noted by Kawaye and Hutchinson (2018), maize is a staple food crop in Malawi that is grown under both irrigation and rainfed farming systems. However, rainfed farming dominates as it covers about 99% of Malawi's agriculture, mainly on smallholder farms. Kawaye and Hutchinson (2018) further noted that rainfed maize is normally planted between November and December (the start of the rainy season). It grows rapidly during the high rainfall months of January and February and matures by early April. It is harvested in late April or early May. Maize yields in Malawi range from less than 1000 kg to over 4000 kg per hectare, depending on various factors including climate, location, seed variety, fertilizer use, labor, and policy-related factors including access to credit, input and output markets and extension services.

Cassava (*Manihot esculenta* Crantz) is a perennial woody shrub with an edible starchy tuberous root (Mathieu-Colas et al. 2009). Cassava grows under diverse ecological and agronomical conditions. It favors a warm moist climate with mean temperature of 24–30 °C (Nassar 2004; Mkumbira 2002). It can tolerate temperatures from 16 °C to 38 °C (Cock 1984). It does not favor excess soil moisture nor high salt concentrations nor pH above 8 (Nassar 2004; Mkumbira 2002). Cassava is normally planted early in the wet season, usually around mid-November. As a perennial crop, cassava has no definite lifetime or maturation period. After full development of the canopy, root growth slowly decreases and finally stops. This is the maturation point of cassava when maximum or near maximum yield is obtained. Cassava is harvested when the returns for production and utilization are maximized. Thus harvesting can be delayed to well after when the tubers have matured. The optimum time to harvest is 9–12 months (Mathias and Kabambe 2015) depending on various ecological factors such as rainfall, temperature, and soil fertility (Mathieu-Colas et al. 2009; Benesi 2005).

Sweet potato (*Ipomoea batatas* Lam) is an annual crop (Mathieu-Colas et al. 2009). It is widely grown in tropical, subtropical, and temperate areas between 40°N and 32°S. It grows best with air temperatures between 20 °C and 25 °C, and growth is restricted below 15 °C (Ramirez 1992). It can be cultivated across a wide variety of soil types and prefers lightly acid or neutral soils with a pH between 5.5 and 6.5 (Ramirez 1992). Sweet potato is commonly grown as an intercrop with maize and planted early in the calendar year (FAO 2005). It can also be planted toward the end of the wet season in late April and grown on residual soil moisture. Like cassava, the

growth period of sweet potato depends on various ecological factors, but it generally takes 4–5 months to mature (Mathieu-Colas et al. 2009).

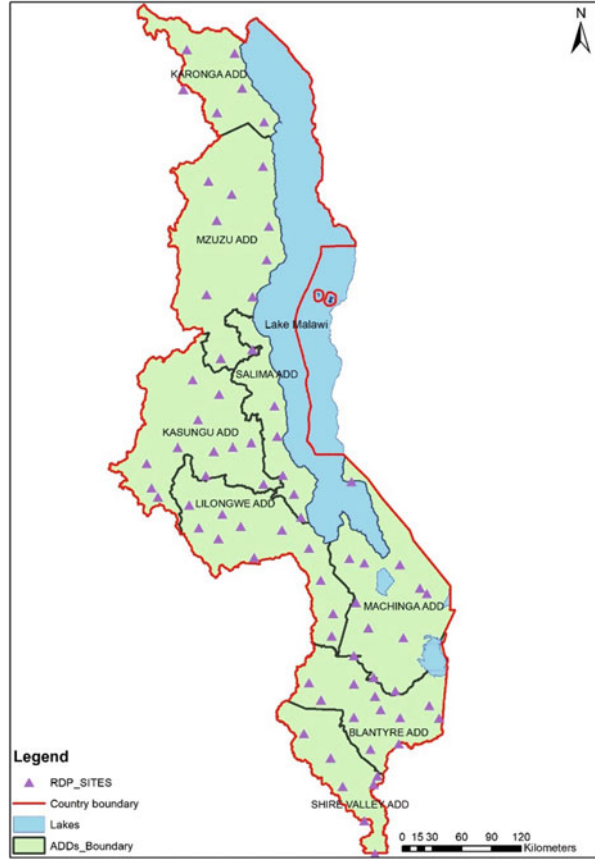
Methodology

This study modelled the dependence of observed maize, cassava, and sweet potato yields on spatially distributed monthly climate to provide a basis for assessing the impact of projected climate change. The models were constructed by performing multilinear regressions of the logarithms of the observed yields on accumulated outputs from the GROWEST growth index model. The GROWEST model generates a generic, process-based, growth index that depends on weekly or monthly climate with a minimal number of parameters. The growth index varies between 0 (climate totally limiting for growth) and 1 (climate optimal for growth). It is normally assumed to be proportional to the rate of relative increase in plant biomass over time. The growth index is calculated as the product of three separate indices that incorporate the impact of temperature, solar radiation, and modelled soil moisture. The simplicity of the model, and its underlying process basis, makes it well suited to deriving robust calibrations of yield response to climate using yield data limited in quantity or quality. The modelling approach can be seen as a hybrid between complex crop simulation models and statistical analysis of growing season weather variables (Lobell et al. 2011). The critical parameters of the GROWEST model are able to be determined by maximizing the alignment of the GROWEST outputs with the observed crop yields using standard multilinear regression. These regression analyses are extended to take account of observed systematic increases in crop yields over time due to crop breeding programs, improvements in crop management, and possible carbon dioxide fertilization.

GROWEST Analysis

The models were calibrated on yield data for each ADD over the periods for which both climate and reliable yield data were available, namely, 2006–2012 for the three main varieties of maize, 2001–2011 for cassava, and 2006–2012 for sweet potato. The GROWEST model was applied to monthly climate across all eight ADDs using interpolated monthly climate values at 74 points that approximately equi-sampled the cropping areas across the eight ADDs of Malawi as shown in Fig. 1. The interpolated climate values were obtained using thin plate smoothing splines as provided by the ANUSPLIN Version 4.4 package (Hutchinson and Xu 2013). The output growth indices (GIs) were averaged across each ADD to match the average yields reported for each ADD. The GROWEST model runs on a weekly time step but can be applied to monthly climate data by interpolating monthly data to weekly data “on the fly.” It can provide weekly or monthly outputs. Weekly GROWEST outputs were used to obtain finer-scale demarcations of the fitted growing seasons.

Fig. 1 Seventy-four sites sampling crop growing areas across the eight Agricultural Development Divisions (ADDs) of Malawi



A robust regression model was used to determine critical GROWEST parameters for all five crop varieties. Since the GROWEST model describes a relative growth rate, it is natural to formulate the regression model in terms of the natural logarithm of the observed yields. The log formulation has been used in other yield studies (Lobell et al. 2011) and appears to offer a natural separation between site and climatic effects on observed crop yields. A similar approach, but not applying the log transformation, was described by Kawaye and Hutchinson (2018). The regression model for the observed yields Z_{ij} for year Y_i and ADD_j ($j = 1, \dots, 8$) was defined by:

$$\log(Z_{ij}) = a_j + b G_{ij} + c Y_i + \varepsilon_{ij}$$

where G_{ij} denotes the accumulated growth index for year Y_i and ADD_j and ε_{ij} denotes a zero-mean random error. The model parameters a_j and b were initially fitted by least squares regression while setting $c = 0$. Three additional critical

GROWEST parameters were optimized during this initial fitting of the model. These parameters were the optimum temperature of the temperature index, used in calculating the weekly growth index, and the first and last weeks of the fitted growing season, used to define the growing season period. The soil water balance parameters of the GROWEST model were set to default values with the soil water holding capacity set to 150 mm and the soil drying rate set to that of a clay loam soil. The soil water balance is an important component of the growth index, but it is not very sensitive to departures from these default parameter values.

For the three maize varieties, parameter c was fitted by refitting all parameters using least squares regression. For cassava and sweet potato, parameter c was fitted by least squares regression on year of the residuals of the data from the initial model. This removed instabilities when all parameters were fitted directly to the cassava and sweet potato data.

The model is robust with just ten parameters. It has a constant dependence of \log (yield) on the climate-based accumulated growth index but has a site varying intercept to allow for different site and management conditions across different ADDs. The linear dependence on year via parameter c allows for underlying improvements in yield due to crop breeding programs, improvements in crop management, and possible carbon dioxide fertilization.

As in Kawaye and Hutchinson (2018), the GROWEST parameters were optimized by automating GROWEST runs and initial regressions using FORTRAN code and standard LINPACK numerical analysis software (Dongarra et al. 1979). Comprehensive analyses of the fitted models were computed using the standard regression package within Excel software. These analyses permitted the identification and removal of a small number of yield data outliers with large standardized residuals. These were associated with anomalies and accounting errors evident in the supporting yield data.

Once outliers were removed and GROWEST optimizations were complete, final comprehensive statistical analyses were computed, making due allowance for the three degrees of freedom associated with estimating the three GROWEST parameters. Standard errors of the fitted GROWEST parameters for the initial regressions were calculated from the diagonal elements of the inverse of the associated Hessian matrix. The Hessian matrix was estimated by calculating second-order finite differences of the residual sums of squares of the model with respect to the three fitted GROWEST parameters.

The final fitted models were applied to the associated growing areas for each ADD and each year. These outputs were aggregated across all ADDs to obtain modelled national yield and production for all crops analyzed. These values were compared with the tabulated national yield and production values to assess the performance of the models at the national scale.

With a view to assessing the potential impacts of climate change, the domains of the fitted temperature indices for each crop were compared with the distributions of the weekly temperatures that occurred across the ADDs over the fitted growing seasons.

Results

Trends in Production and Yield of Maize, Cassava, and Sweet Potato

Three main varieties of maize are cultivated in Malawi. These are (i) local (traditional) varieties, (ii) composite varieties, and (iii) hybrid varieties. There are major differences between the yield potentials of these varieties (Giertz et al. 2015; Pauw et al. 2010; Denning et al. 2009; JICAF 2008; Heisey and Smale 1995; Ngwira and Sibale 1986). Local varieties have the lowest yield. They are not subject to yield improvement programs, and harvested seed is recycled from year to year. Composite varieties have higher yields and are often more drought tolerant. They are subject to yield improvement programs but seed can be recycled. Hybrid varieties are the highest yielding and most expensive. They are subject to strictly controlled yield improvement programs, and harvested seed cannot be recycled.

Figure 2 compares growing areas and yields of these three maize varieties from 1984 to 2015. There has only been significant composite maize production since the late 1990s. There has been a steady increase in the area devoted to composite and hybrid varieties and a simultaneous reduction in local maize growing area. This shift has been encouraged by increasing climate stress, such as increasing temperatures, and poor access to farm inputs for local maize production. There is significant year-to-year variation in maize yields, with composite and hybrid yields particularly low from 2001 to 2005. This could be attributed in part to poor climate including low rainfall. The generally higher yields of composite and hybrid maize after 2005 coincide with the introduction of the Farm Input Subsidy Program (FISP). Kawaye and Hutchinson (2018) have presented evidence that FISP has made a significant improvement in composite and hybrid yields since 2006. The analysis of maize yields presented below is therefore restricted to the post FISP years.

Figure 3 shows that cassava and sweet potato production has been generally increasing. There was an abrupt increase in cassava yield in the year 2000 followed by a steady increase, while sweet potato yield has been steadily increasing since the mid-1990s. The abrupt increases in yields in earlier years suggest there have been major improvements in crop-growing practice, and perhaps recording practice, during the 1990s. The steady increase in yields since 2000 reflects increased policy and institutional support, such as the introduction of higher yielding varieties, and improved management practices to diversify the food security basket. The general increase in area under cultivation cassava and sweet potato since 2005 indicates that more farmers have been planting these crops on new land or on land withdrawn from or shared with maize. As noted above, this is due to an increasing reliance on cassava and sweet potato for food security, especially in maize deficit (drought) years.

There was a sharp drop in both yield and production for all crops (maize, cassava, and sweet potato) in the drought year of 2005. For the other years, major variations in production are largely explained by major variations in growing areas as shown in Figs. 2 and 3. On the other hand, minor year-to-year variations in yield are likely to be attributable to year-to-year climatic variations. The differing year-to-year

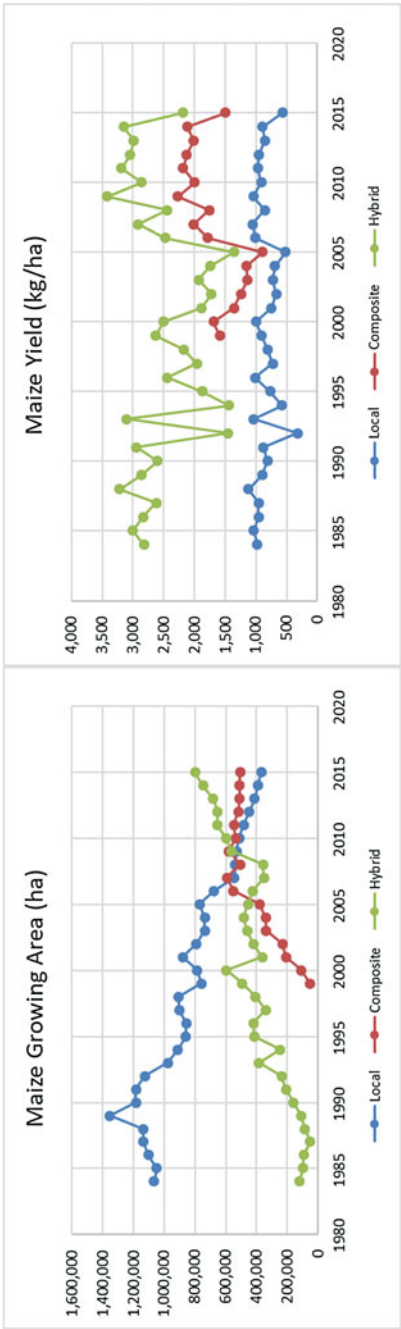


Fig. 2 Growing areas and total yield for local, composite, and hybrid maize from 1984 to 2015

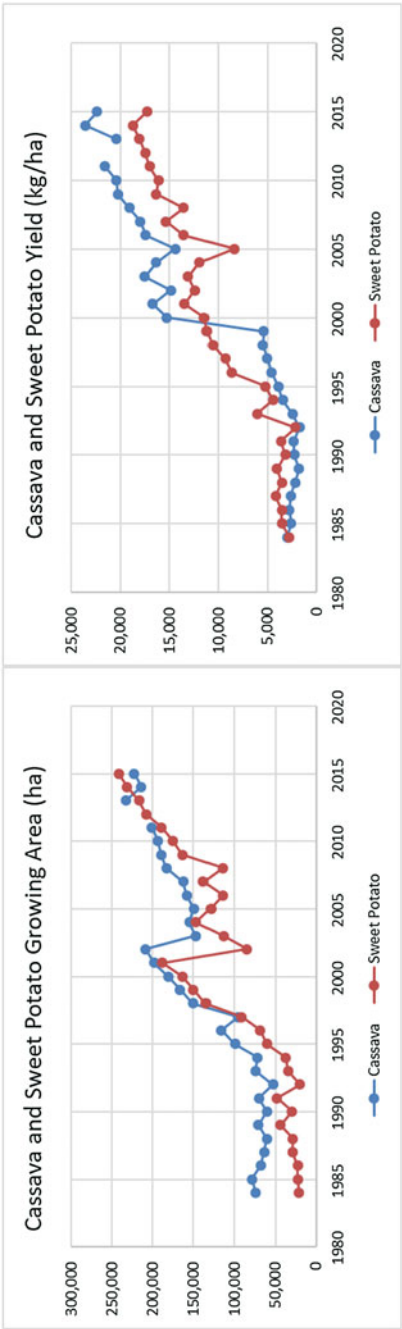


Fig. 3 Growing areas and total yield of cassava and sweet potato from 1984 to 2015

variations in yield and climate by ADD enable the calibration of the yield responses to monthly climate using the models described here.

GROWEST Analyses

For each crop the model was initially fitted to the available yield data values with the optimum GROWEST temperature set to a commonly accepted value for each crop. The automated model fitting code was used to adjust the growing season to minimize the standard error of the fitted model. A small number of large standardized residuals for each model were found to correspond to anomalous growing areas or yields for particular RDPs making up the ADD yield data. These large outliers were removed from the analysis, and the three key GROWEST parameters, the optimum growing temperature and the beginning and end of the growing season, were finally optimized by minimizing the residual sum of squares of the fitted model. There were two outliers for each of the three maize analyses, none for the cassava analysis and four for the sweet potato analysis. The values of the three key GROWEST parameters were found to be quite critical to the overall performance of the model. This is in keeping with the finding of Wang et al. (2017) who similarly found that the shape and location of the temperature response function in process-based crop models are critical to their performance. The fitted GROWEST parameters are listed in Table 1.

The fitted starting weeks for the three maize varieties were remarkably similar. Allowing for a period of around 2 weeks from sowing to emergence when the maize plants begin to interact with the atmosphere, the fitted starting weeks corresponded to planting in early December when the wet season is underway. Composite and hybrid maize had fitted growing seasons lasting 13 and 12 weeks, while local maize had a somewhat longer fitted growing season of 15 weeks. These values are all in reasonable agreement with standard management practice. There is systematic variation in the fitted optimum growing temperatures. The fitted temperature for local maize is consistent with documented optimum temperatures of around 26 °C

Table 1 Optimized GROWEST parameters and mean yield for each crop. Standard errors for each parameter value are provided in parentheses. Weeks are numbered sequentially 1–52 for each year

Crop	Number of data points	Optimum growing temperature (°C)	First week of growing season	Last week of growing season	Mean crop yield (kg/ha)
Local maize	54	24.5 (0.9)	52 (1.0)	15 (1.7)	928
Composite maize	54	28.9 (0.4)	52 (0.8)	13 (1.3)	1,981
Hybrid maize	54	30.2 (0.6)	51 (1.4)	12 (1.5)	2,883
Cassava	88	27.3 (0.6)	47 (2.0)	26 (2.9)	17,984
Sweet potato	52	23.4 (0.7)	7 (2.9)	22 (2.0)	15,920

Table 2 Critical parameter estimates and the percent of yearly variance accounted for the fitted models for all five crops. Standard errors of the fitted parameter values are provided in parentheses

Crop	Number of data points	Model standard error	Parameter b	Parameter c	Percent yearly variance accounted for (%)
Local maize	54	0.141	2.79 (0.55)	0.000 (0.009)	38
Composite maize	54	0.141	3.33 (0.71)	0.013 (0.010)	36
Hybrid maize	54	0.150	2.61 (0.69)	0.032 (0.011)	34
Cassava	88	0.132	2.16 (0.34)	0.025 (0.004)	54
Sweet potato	52	0.070	0.85 (0.17)	0.016 (0.005)	47

for maize root growth and grain filling (Sánchez et al. 2014). The fitted temperature for composite maize is consistent with documented optimum temperatures of around 28 °C to 30 °C for maize growth from sowing to anthesis. The slightly higher fitted temperature for hybrid maize is consistent with documented optimum temperatures of around 31 °C for whole plant maize growth. The fitted parameter values indicate that hybrid and composite maize are better adapted to higher temperatures and have shorter growing seasons than the traditional local maize varieties. These are both accepted aims of maize breeding programs.

The fitted growing season for cassava corresponded to planting cassava in mid-November and effective growth terminating by around the end of June. This agrees with the usual growing practice for cassava reported above, with planting time somewhat variable from year to year depending on the arrival of rain and harvesting time variable according to a range of conditions. The latter is consistent with the larger standard error for the finishing week. The fitted optimum growing temperature for cassava is in good agreement with accepted values (Nassar 2004; Mkumbira 2002; Cock 1984).

The fitted growing season for sweet potato corresponded to planting sweet potato in early February and effective growth terminating by around the beginning of June. This is consistent with sweet potato being mainly grown as an intercrop with maize and planted after the maize crop is in place. The fitted optimum growing temperature for sweet potato is also in good agreement with accepted values (Ramirez 1992).

Statistics and key model parameter estimates for each crop are provided in Table 2. All of the model fits were highly statistically significant well beyond the 0.001% level. The performance of the model, with a single coefficient of the accumulated growth index and a different model intercept for each ADD, is remarkably consistent across all crops. Allowing the coefficient of the accumulated growth index to vary from ADD to ADD gave unstable behavior and did not improve the standard error of any model. This confirmed that the relative dependence of crop yield on climate via the accumulated growth index was effectively constant across all sites, justifying the use of a single parameter b across all ADDs.

The standard errors of the fitted models are generally no more than 15%, and the fitted values of parameter b are mostly between 2 and 3 with relatively small standard errors of around 20%. The percent of yearly variation in crop yields explained by the model, after removing variation between sites, ranged from 34% for hybrid maize to 54% for cassava. These values are consistent with the finding of Ray et al. (2015) that climate variation explains around a third or more of crop yield variability.

The smaller value of parameter b for sweet potato suggests that the model has been less successful in calibrating the full impact of climate on tuber growth. This may have been contributed to by the relatively short data record available for sweet potato and the larger number of apparent accounting errors in the yield data. The variation in planting dates between the traditional early planting date in February and the less common late planting date at the end of the wet season may have also contributed to the less strong fitted dependence on climate via parameter b . On the other hand, the small model standard error suggests that sweet potato yields may be more stable in relation to climatic variability than cassava. Analysis of yield data over a larger number of years would help to resolve this question.

The underlying rates of increase in crop yields are well determined for all crops. The fitted rate of zero for local maize is consistent with no breeding program in place for local maize. The marginally statistically significant rate of increase for composite maize of 1.3% per year is consistent with the modest breeding program in place for composite maize, and the statistically significant rate for hybrid maize of 3.2% per year is consistent with the strong breeding program in place for hybrid maize. The fitted rates of increase of around 2% per year for sweet potato and cassava are consistent with breeding programs being in place for both crops.

Plots of the log (yield) data values versus modelled values are shown in Fig. 4. Individual plots (not shown) of the fitted model, as a function of accumulated GI for each ADD, show considerable scatter of the observed yield data about the fitted model, but the constant slope b of the fitted line across all ADDs is estimated with reasonable precision, as described above. Likely contributors to the scatter about the fitted model include changes in management practice from year to year, including variations in planting dates, inaccuracies in recording crop yields, and possible misalignments between the locations of the sites sampling climate across the ADDs and the main locations of crop growth. The monthly time scale of the supporting climate data is likely to have made only a small contribution to the scatter about the fitted model given that the largest departures from the fitted model are in every case attributable to clear accounting errors in particular resource development districts (RDDs) within each ADD rather than systematic climate-related anomalies across all RDDs in any ADD.

The smallest observed and modelled values in the plot for cassava are for the drought year 2005 in Shire Valley ADD. The drought was severe in the other southern Machinga and Blantyre ADDs but particularly severe for the Shire Valley ADD (FAO 2005). The plots in Fig. 4 show that the model is able to recognize most drought conditions with reasonable accuracy but somewhat overestimates cassava yield during particularly severe droughts.

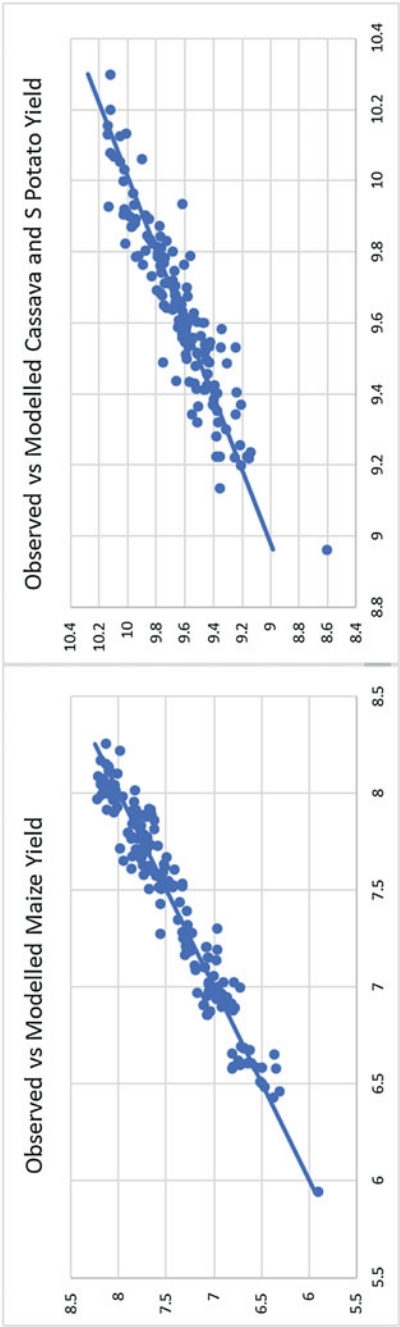


Fig. 4 Log (ADD yield) versus log (modelled ADD yield) for maize, cassava, and sweet potato

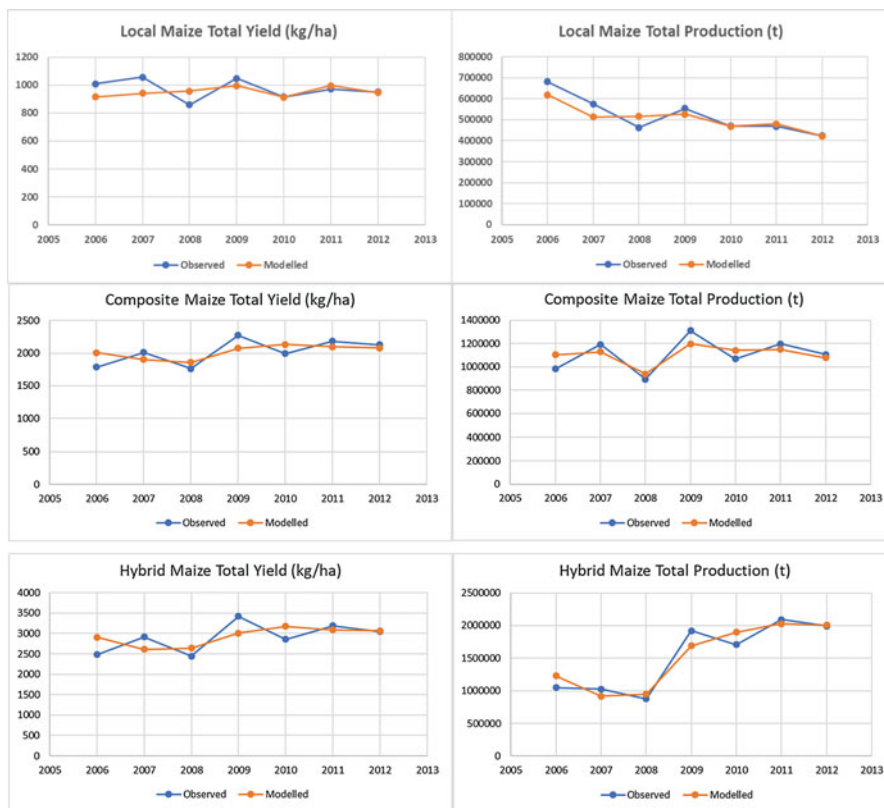


Fig. 5 Modelled and actual total yield and production for all three maize varieties

The models were finally assessed by their ability to explain the total yield and production across Malawi. The observed and modelled yield data were aggregated across all ADDs and plotted in Figs. 5 and 6. The spatially aggregated models provide accurate explanations of the observed values with average percentage differences from the actual annual values around 7% for the three maize varieties and less than 5% for cassava and sweet potato. The larger departures in these plots generally correspond with known accounting errors in the supporting yield data.

The fitted temperature index curves and the corresponding relative histogram of weekly temperatures observed over the fitted growing season for the 74 sites representing the eight ADDs across Malawi are plotted for local maize, hybrid maize, cassava, and sweet potato in Fig. 7. The plots show that the apparent temperature constraints on local maize and sweet potato are well matched to the observed weekly temperatures across Malawi, while the optimum temperatures of hybrid maize and cassava are somewhat larger than the mode of the observed weekly average temperatures. This suggests that projected future increases in temperature of around 2 °C would have minimal impact on local maize yield, perhaps slightly

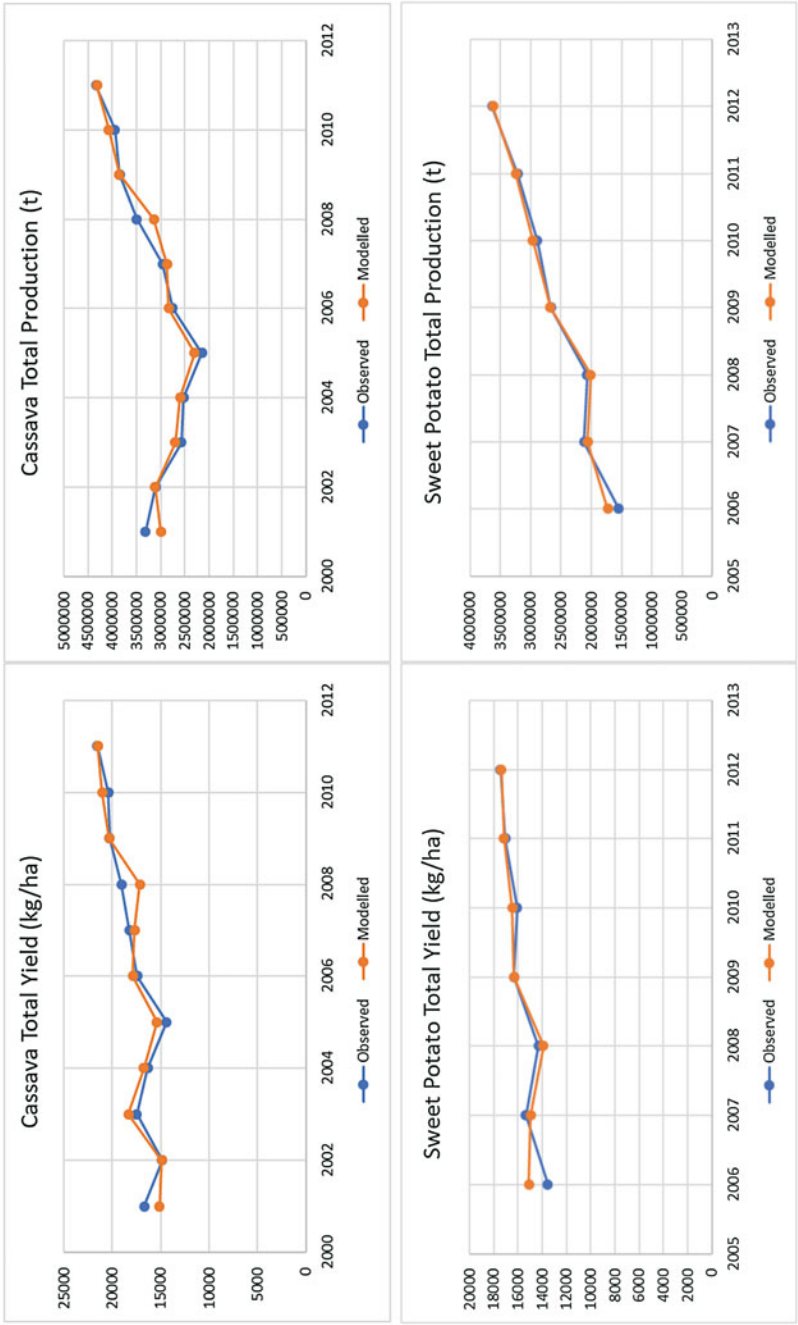


Fig. 6 Modelled and actual total yield and production for cassava and sweet potato

reduce sweet potato yield and moderately enhance yields of higher temperature adapted hybrid maize and cassava. Possible changes in soil moisture regimes also need to be taken into account to obtain a more complete estimate of the likely impact of projected future climate. Soil moisture status is particularly important in the grain filling stage of maize (Li et al. 2018).

Discussion

The fitted regressions on accumulated GI have provided reasonably accurate models of observed maize, cassava, and sweet potato yields for each ADD and are more accurate when aggregated to the national level. The model formulation is robust and able to fit well-determined trends on accumulated growth index, despite the uncertainty associated with the supporting data, including some imprecision in the location of actual crop growing areas and year-to-year variations in planting times and growing practice. Schlenker and Lobell (2010) have noted the particular difficulties in modelling cassava that this model has appeared to overcome.

The fitted growing seasons agree well with known practice. The fitted optimum temperatures also agree with generally accepted values for all five crops, with hybrid maize better adapted to higher temperatures than traditional local maize varieties. This close agreement with known values provides strong support for the adequacy of the fitted models in calibrating the climate dependencies of maize, cassava, and sweet potato yields. The formulation of the regression model has permitted an effective separation between site-specific effects (such as soil fertility and particular crop management practices) and climatic effects on relative plant growth. The site-specific effects are accounted for by a separate intercept for each ADD in the regression model, while the relative climatic effects appear to operate independently of different site conditions and can be effectively calibrated by a single factor across all ADDs. Allowing this factor to vary across the ADDs did not improve the fit of the model for any crop. The model formulation is similar to that employed by Lobell et al. (2011) but uses a specifically tuned nonlinear plant growth index instead of various growing season weather variables. The effectiveness of this modelling approach reflects the finding of Wang et al. (2017) that the form of the temperature response function is quite critical in the accuracy of crop simulation models. The functional form of the temperature indexes plotted in Fig. 7 is similar to the preferred functional forms described by Wang et al. (2017).

The single parameter for the climatic effects was an important factor in the robustness of the regression growth models. On the other hand, allowing a separate site-specific intercept for each ADD was an important factor in incorporating different conditions modifying yields across the different ADDs. The resulting robust statistical model could reliably detect data outliers, as confirmed by inspection of the supporting data for the contributing RDPs. The robustness of the spatial analyses of the supporting monthly climate data has also contributed to the robustness of the fitted growth models. The net result has been well-determined

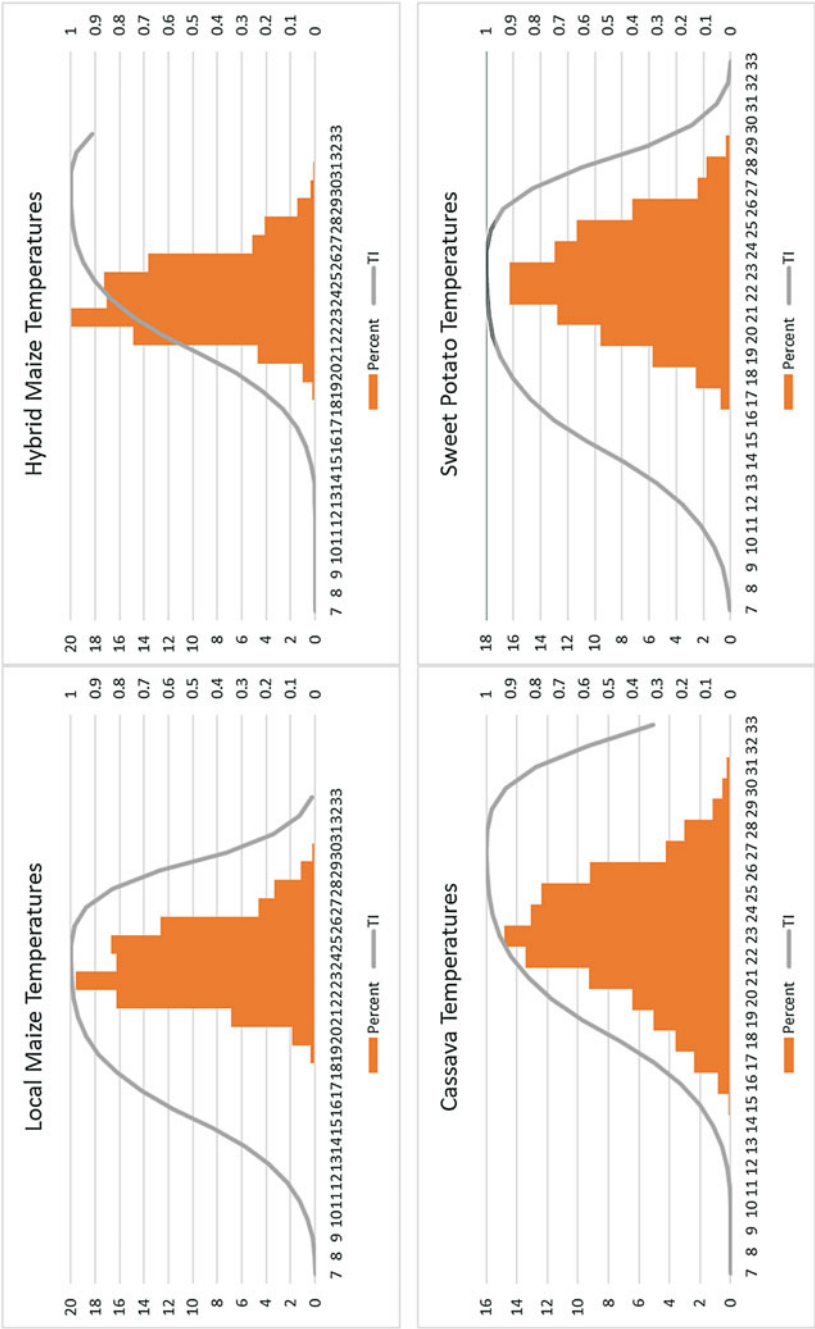


Fig. 7 Fitted temperature index curves (line) and observed monthly average temperatures (relative histogram) over the fitted growing season for local maize, hybrid maize, cassava, and sweet potato

coefficients calibrating the dependence of the three maize varieties and cassava and sweet potato yields on monthly climate via appropriately accumulated GI.

The models have simultaneously calibrated significant underlying increasing trends in yield over time that can be ascribed to improvements in plant breeding, crop management, and carbon dioxide fertilization. The fitted underlying trends of around 2% increase in yield per year for cassava and sweet potato may have been augmented by carbon dioxide fertilization. For such tubers there is around a 15% increase in tuber yield per 100 parts per million increase in atmospheric carbon dioxide concentration (Kimball 1983; Miglietta et al. 1998). In view of the prevailing rate of an increase in carbon dioxide concentration of two parts per million per year, this would give rise to an increase in tuber yield of around 0.3% per year over the analysis period. This is similar to the standard error of the fitted annual percentage increases in crop yield, making it difficult to discriminate from other increases in crop yield. It is not clear whether the fitted underlying percentage increases in crop yields will be maintained indefinitely. The impacts of improved production and reporting methods are likely to plateau in the future. However, ongoing improvements due to plant breeding and carbon dioxide fertilization are likely to continue, and the fitted trends of around 2% per year are remarkably consistent with the documented increase in world average cereal yields over the 50 years from 1961 to 2009 (Prohens 2011). It is unlikely that conventional crop breeding methods are able to maintain this rate of progress into the future, but Prohens (2011) argues that recent progress in molecular biology and genetic engineering offers great promise to further increase crop yields. Thus the fitted models should be able to be used, with appropriate qualifications, in assessing the impact of projected climate change.

Conclusion

This study analyzed the impact of monthly climate on the observed yields of maize, cassava, and sweet potato across the eight ADD crop production regions of Malawi via a robust yield regression model that can be viewed as a hybrid approach between complex process-based models and statistical modelling using selected weather variables. It offers progress toward the eventual dissolution of the differences between these approaches as suggested by Lobell and Asseng (2017). A particular strength of the GROWEST model used here is its incorporation of a process-based temperature response function that could be readily tuned to maximize model performance. This reflects the finding of Wang et al. (2017) that appropriate parameterization of the temperature response function is critical to crop model performance. The tuning of the period of the effective growing season was similarly critical. An additional important contribution to the accuracy and robustness of the regressed GROWEST models is their effective separation of site-specific and climatic effects. This aspect is shared by the statistical modelling approach described by Lobell et al. (2011). Finally, the calibration of the model in terms of monthly, instead of daily, climate data offers robustness in delivering spatially distributed

climate data from limited point sources and in generating projected future climate data. Projecting daily precipitation data in particular is problematic with many approaches simply adjusting positive daily rainfall amounts but leaving daily rainfall occurrence structure unchanged. Such changes in daily precipitation structure can be subsumed within simple changes in monthly precipitation totals, although at the expense of losing some precision in the timing of precipitation within the month.

The main limitation of the modelling approach described here, and many others, is an assumption that management practice does not change significantly from year to year. This can be violated in periods of extreme drought or flooding when planting dates can be significantly delayed or disrupted. This assumption could also be violated in future scenarios when there could be a systematic shift in planting times in response to systematic changes in seasonal climate. Changes in planting density due to changes in intercropping practice are also possible. There is also an assumption that a fixed temperature response function applies over the entire growing season. The differing temperature optima over different stages of maize growth cited by Sánchez et al. (2014) suggest that the model could be usefully elaborated to reflect this, although at the expense of fitting additional model parameters. Despite these limitations, the GROWEST plant growth index model applied to spatially distributed monthly climate data has provided robust correlations between modelled and actual yields for all five crops examined. These correlations have yielded process-based parameter values that agree with known values, and the dependence on accumulated growth index has been fitted with enough precision for the models to be able to be used with reasonable confidence in projecting the impacts of climate change on future yields. The comparisons of the fitted temperature index curves with observed monthly average temperatures in Fig. 7 show that projected increases in temperature are likely to have minimal impact on local maize and sweet potato yield while yields of high temperature adapted hybrid maize and cassava are likely to be enhanced. Such projections need to be coordinated with projected changes in soil moisture levels.

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