Agricultural and Forest Meteorology 151 (2011) 449–460

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Climate variability and crop production in Tanzania

Pedram Rowhani[a,*], David B. Lobell[b], Marc Linderman[c], Navin Ramankutty[a]

[a] Department of Geography, McGill University, 805 Sherbrooke Street West, Montreal, QC H3A, Canada
[b] Department of Environmental Earth System Science, Stanford University, CA, USA
[c] Department of Geography, University of Iowa, Iowa City, IA, USA

ARTICLE INFO

Article history:
Received 17 June 2010
Received in revised form 8 December 2010
Accepted 12 December 2010

Keywords:
Food security
Climate variability
Tanzania

ABSTRACT

Improved understanding of the influence of climate on agricultural production is needed to cope with expected changes in temperature and precipitation, and an increasing number of undernourished people in food insecure regions. Many studies have shown the importance of seasonal climatic means in explaining crop yields. However, climate variability is expected to increase in some regions and have significant consequences on food production beyond the impacts of changes in climatic means. Here, we examined the relationship between seasonal climate and crop yields in Tanzania, focusing on maize, sorghum and rice. The impacts of both seasonal means and variability on yields were measured at the subnational scale using various statistical methods and climate data. The results indicate that both intra- and interseasonal changes in temperature and precipitation influence cereal yields in Tanzania. Seasonal temperature increases have the most important impact on yields. This study shows that in Tanzania, by 2050, projected seasonal temperature increases by 2 °C reduce average maize, sorghum, and rice yields by 13%, 8.8%, and 7.6% respectively. Potential changes in seasonal total precipitation as well as intra-seasonal temperature and precipitation variability may also impact crop yields by 2050, albeit to a lesser extent. A 20% increase in intra-seasonal precipitation variability reduces agricultural yields by 4.2%, 7.2%, and 7.6% respectively for maize, sorghum, and rice. Using our preferred model, we show that we underestimate the climatic impacts by 2050 on crop yields in Tanzania by 3.6%, 8.9%, and 28.6% for maize, sorghum and rice respectively if we focus only on climatic means and ignore climate variability. This study highlights that, in addition to shifts in growing season means, changes in intra-seasonal variability of weather may be important for future yields in Tanzania. Additionally, we argue for a need to invest in improving the climate records in these regions to enhance our understanding of these relationships.

1. Introduction

The well-being of large populations around the world depends on access, stability and availability of food (Schmidhuber and Tubiello, 2007). This is especially true in the developing world with predominant small land holders and subsistence farmers for whom the on-farm agriculture and off-farm agricultural labor provides the main source of food and income (Ito and Kurosaki, 2009). Besides a series of non-climate related factors, the vulnerability of these smallholder and subsistence farmers is greatly influenced by changes in climate (Morton, 2007). Changes in climate have already decreased crop yields in several regions and, for example, are estimated to have reduced global maize production by 12 Mt a year between 1981 and 2002 (Lobell and Field, 2007).

It has been suggested that a larger percentage of the African population will enter poverty as short-term changes in climate will increase the stress on food production (Ahmed et al., 2009a). Sub-Saharan Africa (SSA) relies heavily on weather-sensitive agriculture (Stige et al., 2006). Moreover, hunger and poverty prevail in SSA and it is crucial to prioritize investments and policy in this region in order to prevent the destructive impacts of future changes in climate on food production (Lobell et al., 2008; Schlenker and Lobell, 2010).

So far, most studies have focused on measuring the impacts of changes in climatic means on crop yields (Lobell and Field, 2007; Kucharik and Serbin, 2008; Lobell and Burke, 2008; Lobell et al., 2008; Tao et al., 2008). However, in addition to changes in climate means, climate variability is expected to increase in some regions in the future, including the frequency and intensity of extreme events (IPCC, 2007b). Some have proposed that changes in extremes will have a more adverse impact on crop production than changes in mean climate alone (Porter and Semenov, 2005; Morton, 2007; Tubiello et al., 2007). In 2003, unusually high temperatures during the summer reduced food production (and killed over 50,000 people), with cereal and fruit harvests dropping drastically in Europe, especially in Italy and France where maize produc-

* Corresponding author. Tel.: +1 514 627 4217.
E-mail address: pedram.rowhani-ardekani@mcgill.ca (P. Rowhani).

0168-1923/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.agrformet.2010.12.002

tion fell by more than 30% (Ciais et al., 2005; Battisti and Naylor, 2009).

However, little is known about the effects of current, observed extreme events (Easterling et al., 2000) on crop yields. In the past, some simulation studies investigated the impacts of projected changes in the frequency and severity of extreme climate events during the growing season on agricultural production (Rosenzweig et al., 2002; IPCC, 2007a). Other crop simulation models have shown the negative impacts of climate variability on crop growth, especially if it happens at specific crop development stages (Semenov and Porter, 1995). Extreme daily temperatures above a certain threshold may have damaging consequences on crop yields (Wheeler et al., 2000; Challinor et al., 2005; Porter and Semenov, 2005; Schlenker and Lobell, 2010; Welch et al., 2010). Recently, Cabas et al. (2009) used statistical models to highlight the importance of intra-seasonal changes in temperature and precipitation on crop production in southwestern Ontario, Canada. They showed that, although precipitation and temperature variability might have a negative impact on average yields, net crop yields will be higher in the future due to a lengthening of the growing season.

The main impetus of this empirical study was to estimate the impacts of climate variability on crop yields in East Africa. More specifically, we analyzed the impacts of intra- and inter-seasonal fluctuation in temperature and precipitation on yields of maize, sorghum, and rice in Tanzania. For this purpose, climate and crop data at the subnational level from 1992 to 2005 were used in a mixed model statistical approach to examine overall trends and the differences between regions within the country.

2. Tanzania

On the Indian Ocean, the United Republic of Tanzania possesses a complex landscape, formed by the western and eastern branches of the East African Rift, resulting in substantial spatial variability in climate within the nation. The country's climate varies from tropical at the coast to temperate in the highlands. There are two predominant precipitation regimes in Tanzania with an average annual rainfall of 600–800 mm. In the northern parts, one finds a bi-modal precipitation regime with the long rains generally occurring between March and May and the short rains experienced from October to December. The rest of the country generally experiences rain from December to May (ICID, 2010).

Several studies (Nicholson, 2001; Stige et al., 2006; Giannini et al., 2008) confirm the influence of large-scale climatic events such as the El Nino-Southern Oscillation (ENSO) or the North Atlantic Oscillation on Tanzanian climate. But the western part of Tanzania seems to be in the transition region between the areas of strong ENSO impact with above average rainfall over East Africa and below average rainfall over southern Africa during an El Nino event. In Tanzania, temperatures are predicted to rise 2–4 °C by 2100, warming more during the dry season and in the interior regions of the country (Hulme et al., 2001; Paavola, 2008). The interior regions are also expected to experience a reduction in precipitation up to 20%, prolonging the dry season and increasing the risk of drought, whereas in Eastern Tanzania and the regions around Lake Victoria rainfall is expected to increase by up to 50% during this time period increasing the frequency and severity of floods (Hulme et al., 2001; Paavola, 2008).

Administratively, Tanzania is divided into 26 regions. In this study, the islands Pemba and Zanzibar were not considered and, for conformity reasons, we grouped Dar es Salaam with its surrounding Pwani region and grouped the Arusha and Manyara regions (Arusha was officially split in two in 2002). In the end, our study considered 19 administrative units (Fig. 1). The country achieved its independence in 1962 and was ruled until the mid-1980s under

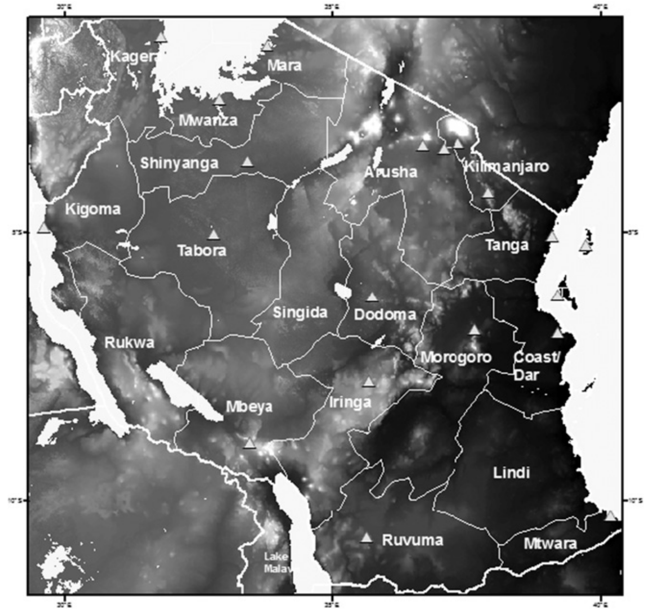

Fig. 1. Tanzania's 19 regions used in this study and a Digital Elevation Model (DEM) showing the complex topographical landscape. The spatial distribution of the 20 climate stations are also represented (triangle).

a communist, one-party dictatorship. Since 1985, liberalization efforts and democratic reforms helped increase the nation's GDP and food production, and improved road infrastructure (Putterman, 1995). However, due to deficiencies in policy and implementation, Tanzanian agriculture witnessed only a very modest growth in the early 1990s, with maize yields averaging 1.4 tons per hectare (Putterman, 1995). Today, Tanzania relies strongly on its agricultural production as it represents around 46% of its GDP. In the past 20 years, ~38% of total land surface was used for agricultural activities. In Tanzania agriculture is dominated by smallholder farmers and is the main work sector in the country. However, people active in the agricultural sector also represent the vast majority of the 12.5 million people living below the national poverty line (Ahmed et al., 2009b).

In Tanzania, only 15% of the total potential arable land (representing 6.3 Mha) is being used for crop production, with 1.5 Mha used only for maize. Not only is Tanzanian agriculture underdeveloped, it is also mostly rain-fed and low in intensity using very little chemical inputs. For maize, synthetic fertilizers were used only on 10% of cultivated land and represented 125 kg per fertilized cultivated hectare, around 60% less than in the USA (310 kg/ha) (FAO, 2007). Moreover, the irrigation infrastructure is not well developed, using mainly traditional surface irrigation methods. With the sharp increase in population and degradation of the infrastructure dating from colonial times, the irrigation schemes have become inefficient (ICID, 2010).

3. Methodology

3.1. Crop data

In Tanzania, maize production is the most important agricultural activity and is considered as the main economic driver (Thurlow and Wobst, 2003). Other major cereals planted in Tanzania are rice, sorghum, millet, and wheat. In this study, we analyzed the relationship between crop yields and climate for three cereals which are widely planted across Tanzania: maize, rice and sorghum. Data on harvested area (ha) and production (tons) for these three cereals were acquired from the Tanzanian Ministry of Agriculture as

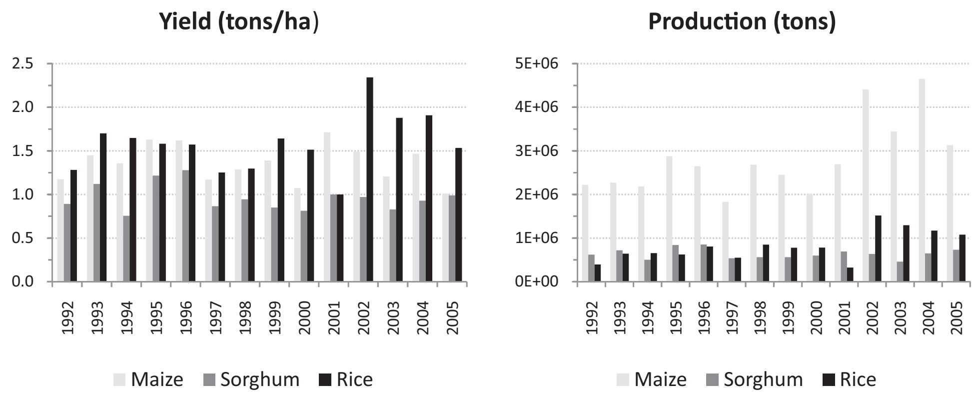

Fig. 2. The temporal trends of cereal yield and production over the 1992–2005 period in Tanzania.

well as from the Agro-MAPS dataset (Monfreda et al., 2008). The data covers the 19 regions of continental Tanzania and represent the period from 1992 to 2005. These data were then converted to yields (tons/ha). Obvious outliers related to poor data quality and typographical errors were removed.

3.2. Cereal cultivation from 1992 to 2005

Of the three crops used in this study, maize is by far the most produced cereal in Tanzania, with a spike in production and harvested area in 2002. Prior to this year, maize production averaged around 2.5 Mt, but rose to ~4 Mt after 2002. Over the studied time period, maize yields fluctuate around an average of 1.3 tons/ha (Fig. 2). For Sorghum, production and harvested area remained relatively constant during the 1992–2005 period, with more variability shown during the earlier part of this period. Rice yields were rather constant until 2002 when yields more than doubled in 1 year. In 2005, yields in rice reached 1.7 tons/ha, a value similar to the yields before 2002. The shift in agricultural production around the year 2002 may be the result of a switch in the method of collecting/estimating agricultural production which was introduced for the agricultural census that was carried out in 2002/3 in Tanzania (James Thurlow, personal communication).

As expected (Bisanda et al., 1998), the regions of Iringa and Mbeya in the southern highlands were the highest producing maize region in Tanzania (Fig. 3). These two regions account for a quarter of the national maize production, producing on average more than 700,000 tons each year. Other important maize producing regions are, in order of production, Shinyanga, Rukwa, and Arusha. The maize-deficit regions are Coast/Dar es Salaam, Mtwara, and Lindi, all three along the coast. The highest and lowest yields in maize are usually found in the highest and lowest producing regions (Fig. 3), except for Arusha and Shinyanga where yields of 1.24 tons/ha and 1.07 tons/ha respectively, are in the middle and lower end in Tanzania.

Sorghum is mostly produced in the dryer central regions of Singida and Dodoma, as well as in Mwanza and Shinyanga around Lake Victoria. These regions generated over 43% of the national sorghum production during the studied time period, around 350,000 tons each year. On the opposite end, the regions of Kilimanjaro, Ruvuma, and Tanga produced the lowest amount of sorghum in 1992–2005. Having the highest average yield in sorghum over the 1992–2005 period (1.26 tons/ha), Ruvuma produced on average only 4400 tons/year. Rice was mostly produced in Mbeya, Morogoro, and Mwanza (>48% of national production) whereas Dodoma, Kagera, and Mara were rice-deficit regions. The region with the highest yield in rice (Kilimanjaro with 3.6 tons/ha) produced only 24,000 tons, representing less than 3% of the national rice production.

3.3. Climate data

Many studies have relied on temperature and precipitation datasets, which were obtained by spatially interpolating data from various climate stations, such as the global gridded datasets from the Climate Research Unit (CRU; Lobell and Field, 2007; Lobell et al., 2008; Schlenker and Lobell, 2010). However, the density of gauge observations used to develop these products is very low in certain regions of the world. This is true for Tanzania, where CRU only uses three climate stations across the country (Dar es Salaam, Songea, and Tabora). As a consequence, the data developed over large areas using a limited number of stations will be unreliable as some local climatic heterogeneity will be averaged out (Fig. 4). We therefore acquired climate data from the Tanzanian Meteorological Agency. Monthly values of precipitation and mean temperature were available from 20 different stations from 1991 to 2008 uniformly covering the country (Fig. 1). Including a Digital Elevation Model, thin plate smoothing splines were used to extract gridded precipitation and mean temperature maps using ANUSPLIN v4.2 (Hutchinson, 1995). In order to relate the climate data to the regional agricultural production, spatial averages of monthly total precipitation (P) and monthly mean temperature (T) over each of the 19 regions were calculated. In a comparison effort, monthly climate data from the CRU TS 3.0 (Mitchell and Jones, 2005) dataset were processed using a similar approach.

Following the rainfall patterns and the specific planting and harvesting calendar for maize, rice, and sorghum in Tanzania, seasonal mean temperature and mean monthly precipitation were computed for the January-June period for each year. Planting usually happens after the first rains, between December and February. The three cereals studied here are harvested at the end of the rainy season, in June or July (USDA, 2003). Furthermore, both seasonal precipitation and temperature anomalies relative to the 1992–2005 average were used instead of the seasonal means to reduce skewness in our statistical models.

This study is mainly focused on the impacts of climate variability on crop yields. Climate variability is a broad concept and rarely defined clearly. Indeed, climate varies at various time scales, from daily (Semenov and Porter, 1995), intra- (Cabas et al., 2009; Rowhani et al., accepted for publication) and inter-seasonal (Rosenzweig et al., 2002; Lobell et al., 2008) to decadal scales. Multi-annual wet or dry periods impact food production (De Waal, 1997; Mitchell, 2008). Here, we are analyzing the impact of intra- and inter-seasonal climatic variability on crop yields. Thus, apart from measuring the seasonal climate means, variables capturing intra-seasonal variability in temperature and rainfall were also included in the analysis. This variability was measured by the seasonal coefficient of variation (CV) calculated as the seasonal ratio of the standard deviation to the mean of each climate variable (CV_T and CV_P).

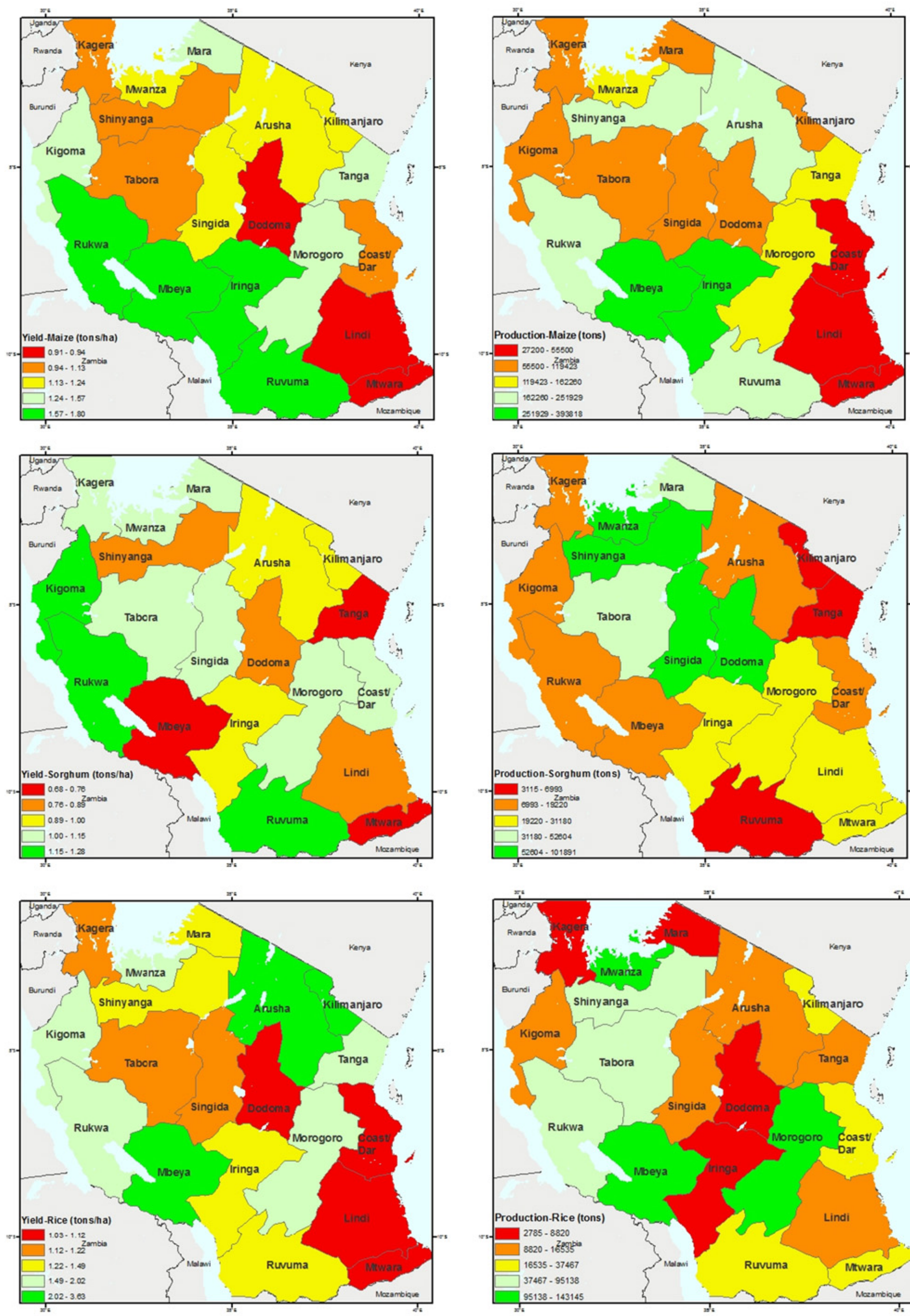

Fig. 3. The spatial distribution of the average yield and production of maize, sorghum and rice over the 1992–2005 time period.

3.4. Precipitation and temperature from 1992 to 2005

Some disparities were evident between the CRU dataset and the spatially interpolated station data (Figs. 4 and 5). While precipitation is mostly overestimated in the CRU (Fig. 5c), national mean temperature from January to June is most often underestimated (Fig. 5d), when compared to the spatially interpolated station data. The CRU uses records from 3 climate stations in Tanzania to develop their gridded dataset. We gathered climate data from 20 stations across the country and spatially interpolate those using thin-plate splines. The CRU applied the same interpolation method as we did to develop their gridded dataset (New et al., 1999). With more observational data, we are able to better detect the spatio-temporal variations in precipitation and temperature. The results given here are based on our gridded climate dataset.

The central part of the country receives on average around 70–90 mm of precipitation each month between January and June (Fig. 6a). This region is surrounded by a high precipitation zone where the average monthly rainfall exceeds 100 mm, with a maximum of 129 mm in the Great Lakes region of Kagera. The temporal profiles show a peak in precipitation around the turn of century for most regions (temporal profiles are not shown here). This may be due to important warm ENSO events (bringing more rain to East Africa) during the last decade of the 20th century followed by a 2-year La Nina period which decreases precipitation in this region. Precipitation variability during the growing season, as measured by

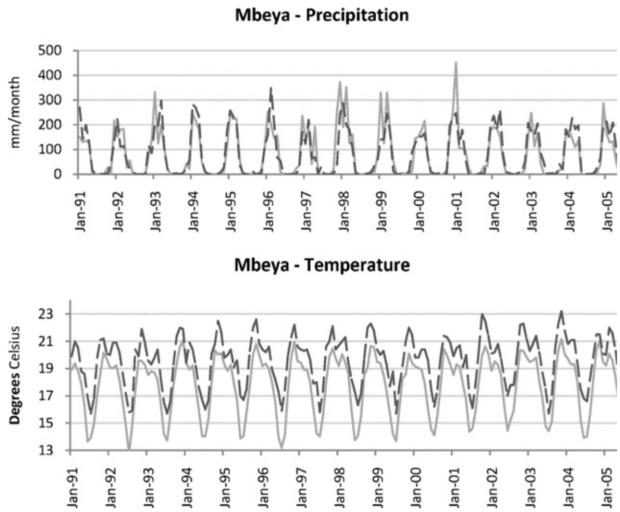

Fig. 4. Comparison between CRU TS 3.0 data and observed precipitation and temperature in Mbeya. The CRU profile represents the 0.5° pixel covering the climate station in the region of Mbeya.

the coefficient of variation, is highest in the southern regions, while the least variable regions are along the coast and in northwestern Tanzania.

The coastal regions are warmest during the January–June time period with average temperature above 23 °C (Fig. 6b). The cooler regions are along the mountain ranges along the eastern and western branches of the Great Rift Valley. During the growing season, the average temperatures in the plateau region of Tanzania, which is in between these two branches, vary between 22 °C and 23 °C. In general, the temporal profiles also reveal a steady increase in temperatures during the past 20 years, with certain regions experiencing a more pronounced increase than others (data not shown). Temperatures between January and June are more stable in the plateau region and more variable in the mountainous regions along the Eastern branch of the East African Rift.

3.5. Statistics

In order to determine the effects of climate on agricultural yields, and to exploit the cross-sectional and temporal attributes of our dataset, we developed linear mixed models for each of the three crops (maize, rice, and sorghum). This method is appropriate for longitudinal data (Pinheiro and Bates, 2000; Zuur et al., 2009) where observations within a group are often more similar than would be predicted on a pooled-data basis. In this case, a simple linear regression ignores grouping effects and violates the assumption of independence of observations. A first-order autoregressive (AR1) serial correlation structure was included in the models to capture temporal trends related to non-climatic factors and other technological progress. The full model included a fixed part comprised of P and T (and their interaction term), CV_T and CV_P (and their interaction term), as well as P^2, and random intercepts. The squared temperature values were not used as it was clear from scatterplots that the relationship between yield and temperature is linear:

$$y_{ij} = \beta_0 + \beta_1 T_{i,j} + \beta_2 P_{i,j} + \beta_2 P^2_{i,j} + \beta_4 \mathrm{CW}_{T-i,j} + \beta_5 \mathrm{CV}_{p-i,j} + a_i + \varepsilon_{ij}$$

where y is yield, i represents the regions and j the observations within a region, β_{0-5} represent model parameters, a_i represents the random intercept term, and ε is an error term.

Analogous measures to the widely used R^2 in linear regressions have been developed for mixed models but are not widely used. Here, goodness of fit was rather based on likelihood ratio test using Akaike's Information Criterion (AIC) and/or Bayesian Information Criterion (BIC). A backward model selection was performed on the

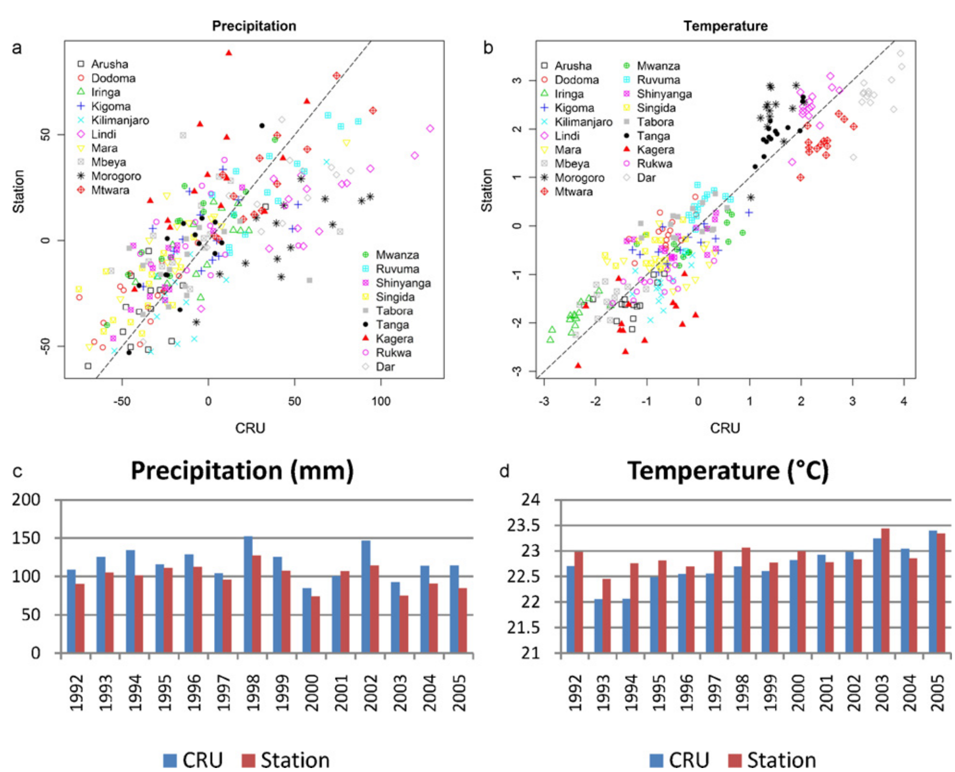

Fig. 5. Comparison between CRU TS 3.0 data and observed precipitation and temperature anomalies. Both variables were averaged over each region for the 1992–2005 period. The scatterplots between the climate anomalies (a and b) and annual national averages of precipitation (c) and temperatures (d) are shown. For the precipitation anomaly (a), the R^2 = 0.53 and the RMSE = 26.66. The R^2 between the CRU and observed temperature anomaly (b) equal 0.84 (RMSE = 0.61). The dashed line shows the 1:1 line.

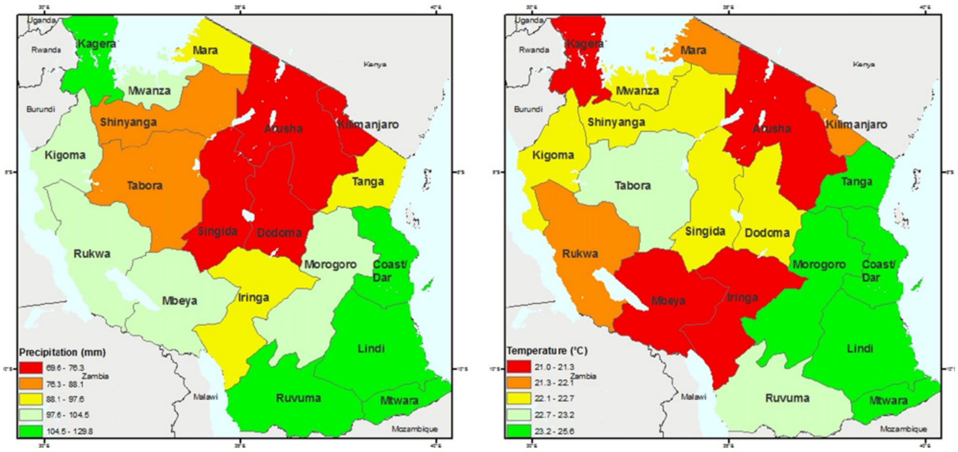

Fig. 6. The spatial distribution of average precipitation (a) and temperature (b) over the 1992–2005 period. These figures are based on our gridded dataset based on records from 20 stations across Tanzania.

fixed terms following Zuur et al. (2009). Models with random slopes (using all potential independent variables) were also tested but never resulted in a better fit. We evaluated issues of heterogeneity and assessed the two distributional assumptions for mixed effect models (Pinheiro and Bates, 2000), i.e. the within-group errors are independent and normally distributed and they are independent of the random effects, and the random effects are normally distributed and are independent for different groups.

For comparison, the coefficients resulting from the mixed models were compared to those obtained from simple linear regression models that included the different regions as a dummy variable to account for fixed effects. Furthermore, a time variable (Year from 1992) was also used in these linear models to capture yield changes related to non-climatic factors and other technological development:

$$y_j = \beta_0 + \beta_1 T_j + \beta_2 P_j + \beta_2 P_j^2 + \beta_4 CV_{T-j} + \beta_5 CV_{p-j} + \beta_6 \mathrm{Region}_j + \beta_7 Year_j + \varepsilon_j.$$

These linear models were developed using stepwise model selection based on the AIC. In order to compare climate data effects on yield estimates, both sets of models, the mixed and linear models, were also developed using climate data extracted from the CRU dataset.

Finally, we analyzed the climatic impacts on crop yields in Tanzania in the year 2050 based on the historical relationships. For this purpose, data from 22 Global Circulation Model (GCM) experiments (Meehl et al., 2007) from the Phase 3 Coupled Model Intercomparison Project (CMIP3) were used at the national level (Ahmed et al., 2009b). We were not able to account for any potential shifts in the growing season as each GCM presents different seasonal shifts. Thus, growing season averages (January-June) of precipitation and temperature were measured over the 1992–2005 period and compared to the January–June averages over the 2040–2059 period, under the SRES A2 emissions scenario. This is one of the most fossil fuel intensive scenarios, with greenhouse gas emissions rising monotonically. Both intra-seasonal variability metrics, CV_T and CV_P, were also compared between these two time periods.

All the statistical analyses here were also performed over the 1992–2001 time period, as a consequence of the shift in the agricultural dataset. However, the results did not change significantly to alter our general conclusions, and thus, only the results from the 1992 to 2005 period are presented here.

4. Results and discussions

4.1. Model results for maize

Changes in climate between and within seasons have a significant impact on crop yields in Tanzania (Fig. 7). The results from the mixed model analysis using the spatially interpolated station data (Table 1) show a significant relationship between yields in maize and seasonal mean precipitation, with an increase in precipitation favoring yields. Furthermore, maize yields seem to level off over 120 mm of monthly precipitation during the growing season (as shown by the significant squared precipitation variable). Variability in precipitation within the growing season has a negative impact on yields, i.e. an increase in intra-seasonal precipitation variability by 0.1 in CV_P reduces yields by 0.036 ± 0.018 tons/ha. The results of the mixed models also show that there is a small variability in the intercepts between the regions. The variance of the intercept term between plots was 0.06 while the within region variance, measured by the error variance, was approximately 0.15. Our model also shows a small, positive lag-1 serial autocorrelation term of 0.11.

Using CRU data, the mixed models indicate similar results for most of the coefficients (Table 1). The exception lies in the intra-seasonal climate variability metrics where the CRU data shows a positive relationship between CV_T and CV_P, and maize yields. These results seem counterintuitive as increased temperature and precipitation variability are anticipated to reduce crop yields. The stepwise linear regressions using the station data (Table 2) show very similar results to the mixed models. These models show an additional non-significant and negative relationship between intra-seasonal variability in temperature and maize yields, as well as a stronger relationship between seasonal temperatures and yields. Around 40% of the variance is explained by these variables. The same linear models using CRU data (Table 2) present a positive estimate for CV_T and a weaker relationship between precipitation and maize yields. These models show an R^2 of 0.32.

4.2. Model results for sorghum

The model relating sorghum yields to climatic variables extracted from the station data is very similar to the one characterizing maize yields (Table 3). However, precipitation has only a linear, yet still positive relationship with yields in sorghum. Increases in temperature and intra-seasonal variability in precipitation have a negative impact on sorghum yields in Tanzania.

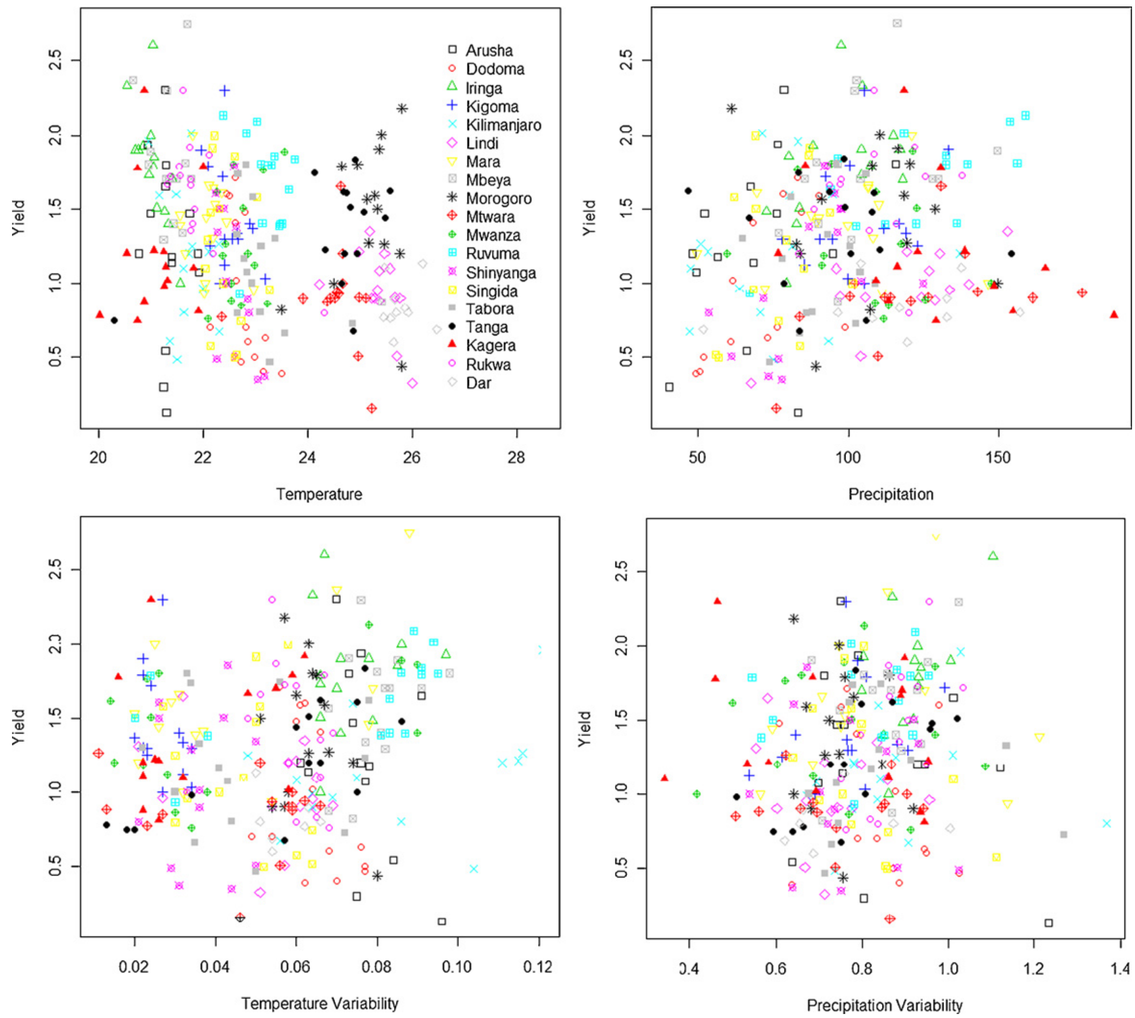

Fig. 7. Scatterplots showing the relationships between maize yields and the various climate factors used in this study. Temperature is measured in mean seasonal °C and precipitation is shown in mean mm/month whereas maize yields are represented in tons/ha. Climate variability is measured using the coefficient of variation over the growing season.

Variability between and within the regions is low and there is some serial autocorrelation with a positive lag-1 value of 0.30.

The mixed models using CRU data present similar results (Table 3). However, the final selected model includes also intra-seasonal variability in temperature and P^2, both with a negative coefficient. Using linear regression models (Table 4), the negative relationship between sorghum yields and mean seasonal temperatures is stronger (estimate of −0.16 compared to −0.06). The stepwise model selection procedure based on the AIC also kept the interaction term between precipitation and temperature (a measure of soil moisture) in the final model. This term is however non significant. There are two major differences between the linear models using CRU and station data (Table 4). Mean seasonal temperature is not significant in the CRU model and P^2 is negatively associated to sorghum yields, just like the CRU mixed model results. Another disparity is that the negative trend over the 1992–2005 period is marginally significant when CRU data is used.

Table 1
Results of the mixed model analysis relating maize yields to climate variables. Two separate climate datasets were used; spatially interpolated observed climate data from 20 stations in Tanzania and gridded climate data from the climatic research unit (CRU).

Maize	Station			CRU		
	Estimate	Std. error	*p*-Value	Estimate	Std. error	*p*-Value
Intercept	1.640	0.161	<0.0001	0.834	0.198	<0.0001
Precipitation	0.005	0.001	0.0001	0.003	0.001	0.0040
Temperature	−0.126	0.035	0.0004	−0.116	0.030	0.0001
CV_P	−0.361	0.179	0.0459	0.292	0.197	0.1385
CV_T				5.131	2.393	0.033
Precipitation^2	-8.65×10^{-05}	2.57×10^{-05}	0.0009	-3.40×10^{-05}	1.41×10^{-05}	0.0172
Between region variability (σ_b^2)	0.06			0.03		
Within region variability (σ^2)	0.15			0.17		
Correlation between observations from same region	0.27			0.15		
AR1 parameter estimate (φ)	0.11			0.09		

Table 2
Results from the stepwise multiple linear regressions relating maize yields to climate variables. Two separate climate datasets were used; spatially interpolated observed climate data from 20 stations in Tanzania and gridded climate data from the climatic research unit (CRU). Coefficient estimates for the significant dummy variable representing the 19 regions are not shown.

Maize	Station			CRU		
	Estimate	Std. error	*p*-Value	Estimate	Std. error	*p*-Value
Intercept	1.671	0.258	<0.0001	1.048	0.204	<0.0001
Precipitation	0.004	0.001	0.0016	0.002	0.001	0.0310
Temperature	−0.205	0.076	0.0072			
Precipitation^2	-8.5×10^{-05}	2.7×10^{-05}	0.0016	-2.2×10^{-05}	1.5×10^{-05}	0.1305
CV_P	−0.475	0.193	0.0143	0.374	0.207	0.0721
CV_T	−2.529	1.605	0.1164			
Year-1992	0.013	0.006	0.0381			
Adjusted R^2	0.395			0.3244		

Table 3
Results of the mixed model analysis relating sorghum yields to climate variables. Two separate climate datasets were used; spatially interpolated observed climate data from 20 stations in Tanzania and gridded climate data from the climatic research unit (CRU).

Sorghum	Station			CRU		
	Estimate	Std. error	*p*-Value	Estimate	Std. error	*p*-Value
Intercept	1.326	0.108	<0.0001	1.457	0.149	<0.0001
Precipitation	0.003	0.001	0.0011	0.003	0.001	0.0002
Precipitation^2				-2.0×10^{-05}	9.510^{-06}	0.1103
Temperature	−0.060	0.025	0.018	−0.050	0.025	0.0442
CV_T				−3.069	1.788	0.0873
CV_P	−0.431	0.122	0.0005	−0.374	0.137	0.0069
Between region variability (σ_b^2)	0.02			0.02		
Within region variability (σ^2)	0.09			0.09		
Correlation between observations from same region	0.21			0.19		
AR1 parameter estimate (φ)	0.29			0.27		

4.3. Model results for rice

For rice, our mixed model results show that climate variability over the growing season is an important factor for yields in Tanzania (Table 5). It has to be noted that some observations showing very high yields were removed as outliers from this analysis (9 observations) as these probably indicate important irrigation efforts. Increased precipitation variability between the months of January and June has a negative impact on yields whereas, surprisingly, increasing temperature variability over the same period seems to improve yields. Moreover, our model indicates that higher temperatures reduce yields. There is still some variability within and between regions due to unobserved factors.

Compared to the model using station data, the results from the mixed model using CRU climate data (Table 5) present the same important positive association between intra-seasonal temperature variability and rice yields. However, this model also indicates an effect of precipitation and P^2. Furthermore, precipitation variability over the January–June season does not appear to have an effect on rice yields when CRU data is used.

The stepwise simple linear regressions show comparable results for rice (Table 6). One major difference compared to the mixed model is that mean seasonal temperatures are not related to rice yields, whether we use CRU or station climate data. Dissimilarities between the linear models using different climate data are analogous to the ones found using mixed models.

4.4. Future impacts in 2050

To examine the relative importance of the coefficients derived above, we estimated the yield impacts of changes in each climate variable as predicted by the 22 GCMs analyzed in Ahmed et al. (2009b). The average seasonal temperature in these models rise between 1 °C and 2 °C by 2050 (with an average increase of 1.4 °C), whereas, the changes in January-June total precipitation range between −15.8% and +21.5% compared to the 1992–2005 average, with a mean of +5%. The 22 GCM's also show a −39% to +13% change in intra-seasonal temperature variability in 2050 (with a mean of −14%), as measured by the CV_T. Finally, the intra-seasonal precip-

Table 4
Results from the stepwise multiple linear regressions relating sorghum yields to climate variables. Two separate climate datasets were used; spatially interpolated observed climate data from 20 stations in Tanzania and gridded climate data from the climatic research unit (CRU). Coefficient estimates for the significant dummy variable representing the 19 regions are not shown.

Sorghum	Station			CRU		
	Estimate	Std. error	*p*-Value	Estimate	Std. error	*p*-Value
Intercept	1.207	0.167	<0.0001	1.353	0.159	<0.0001
Precipitation	0.002	0.001	0.0137	0.003	0.001	0.0006
Temperature	−0.081	0.054	0.1317			
Precipitation^2				-1.5×10^{-05}	1.1×10^{-05}	0.1484
CV_P	−0.424	0.140	0.0027	−0.305	0.155	0.0501
Year-1992				−0.009	0.005	0.0655
Precip.:Temp.	8.2×10^{-04}	5.510^{-04}	0.1404			
Adjusted R^2	0.3343			0.3217		

Table 5
Results of the mixed model analysis relating rice yields to climate variables. Two separate climate datasets were used; spatially interpolated observed climate data from 20 stations in Tanzania and gridded climate data from the climatic research unit (CRU).

Rice	Station			CRU		
	Estimate	Std. error	*p*-Value	Estimate	Std. error	*p*-Value
Intercept	1.639	0.227	<0.0001	1.190	0.222	<0.0001
Precipitation				0.003	0.001	0.0293
Precipitation^2				-3.7×10^{-05}	2.0E−05	0.0618
Temperature	−0.129	0.048	0.0074	−0.098	0.054	0.0723
CV_T	8.612	2.128	0.0001	7.415	3.734	0.0483
CV_P	−0.757	0.267	0.0051			
Between region variability (σ_b^2)	0.07			0.12		
Within region variability (σ^2)	0.38			0.38		
Correlation between observations from same region	0.15			0.24		
AR1 parameter estimate (φ)	0.31			0.27		

Table 6
Results from the stepwise multiple linear regressions relating rice yields to climate variables. Two separate climate datasets were used; spatially interpolated observed climate data from 20 stations in Tanzania and gridded climate data from the climatic research unit (CRU). Coefficient estimates for the dummy variable representing the 19 regions are not shown.

Rice	Station			CRU		
	Estimate	Std. error	*p*-Value	Estimate	Std. error	*p*-Value
Intercept	2.119	0.331	<0.0001	2.003	0.192	<0.0001
Precipitation				0.004	0.002	0.0060
Precipitation^2				-3.3×10^{-05}	2.1×10^{-05}	0.1184
CV_P	−0.704	0.287	0.0149			
CV_T	3.780	2.593	0.1463			
Year-1992	0.032	0.009	0.0005	0.034	0.009	0.0002
Adjusted R^2	0.3709			0.3735		

itation variability (CV_P) in 2050 changes between −11% and +20% as compared to the current values (+2.1% on average).

For simplicity, we consider changes of 20% in precipitation, 2 °C in temperature, and 20% in CV_P and CV_T. Fig. 8 presents the climatic impacts of each change on cereal yields in 2050. Our analysis shows little variation in the results depending on the statistical method chosen whereas choice of climate data appears to have significant impact on the model results for CV_P. Depending on the dataset, the relationship between intra-seasonal precipitation variability and maize yields is positive or negative. Assuming the weather station data is more reliable, the results of the mixed model show that an increase of 2 °C in temperature relative to the 1992–2005 growing season average will reduce maize, sorghum, and rice yields by 18.6 ± 5.2%, 12.6 ± 5.3%, and 16.3 ± 6.0% respectively. By contrast, an increase in precipitation has a positive impact on maize and sorghum, where an increase of 20% in average monthly growing season precipitation (equivalent to around 20 mm) increases yields by 6.7 ± 1.7% and 5.7 ± 1.7% respectively. An increase in the coefficient of variation of precipitation by 20% (equivalent to an increase of 0.16 compared to the historical CV_P) during the same time period reduces yields by 4.2 ± 2.1%, 7.2 ± 2.0%, and 7.6 ± 2.7% respectively for maize, sorghum, and rice. Temperature variability during the growing season, as measured by the coefficient of variation, was only significant for rice (using station data in a mixed

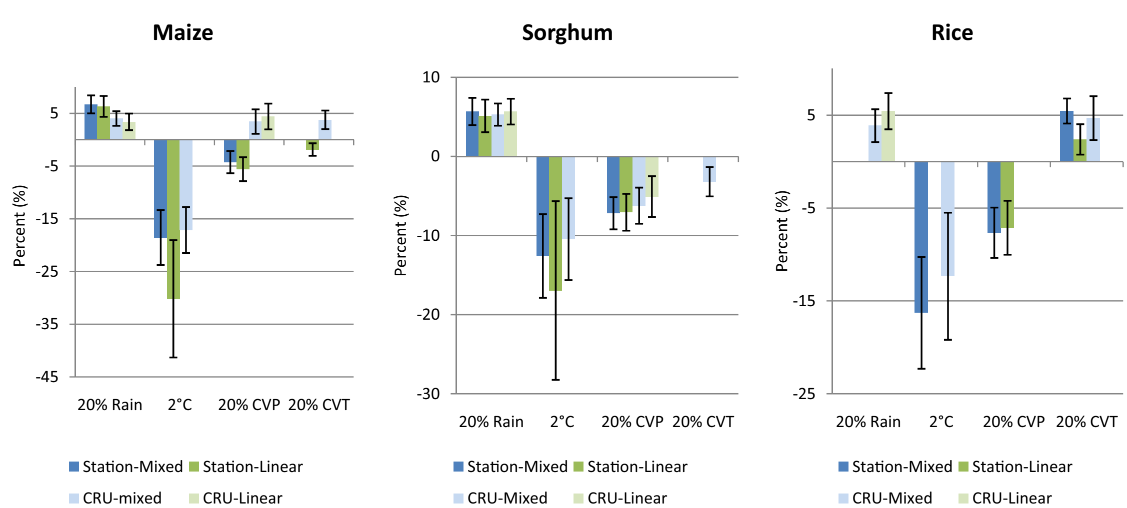

Fig. 8. The percent impact on cereal yields of an increase by 20% in precipitation (equivalent to 20 mm), 2 °C in temperature, and 20% in the coefficient of variation of precipitation (CVP; equivalent to an increase of 0.16 in CV_P) and temperature (CVT; equivalent to an increase of 0.01 in CV_T). Results from the mixed and linear models are shown for both climatic datasets, i.e. the spatially interpolated station data and the gridded CRU TS 3.0 (available at http://www.badc.nerc.ac.uk). Only variables which were included in the final model are shown. The bars represent the standard errors.

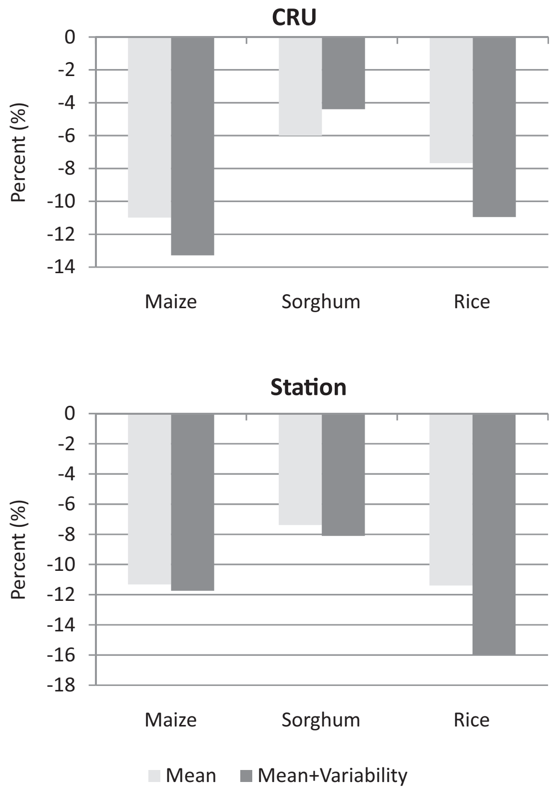

Fig. 9. Comparing the total percent impact on cereal yields. The total impact on yields due to changes in climatic means (light) is compared to the total impact due to the combined effects of climatic means and variability (as measured by the coefficient of variation; in dark). Temperature and precipitation means were measured over the January–June period whereas temperature and precipitation variability is measure by the coefficient of variation over the same time period. Results from both climate datasets (CRU and observed station data) are shown.

model). An increase of 20% in CV_T (equivalent to an increase of 0.01 compared to the historical CV_T) has an unexpected positive impact on rice yield, increasing yields by $5.4 \pm 1.3\%$. Using CRU data, the models show that an increase by 0.01 in CV_T increases maize yields by $3.7 \pm 1.8\%$ and decreases sorghum yields by $3.2 \pm 1.9\%$.

If we assume no changes in planting and harvest dates, the expected changes in seasonal temperatures seem to have the largest impacts on agricultural yields in 2050. However, the results here show that changes in seasonal precipitation as well as in intra-seasonal variability in temperature and precipitation may also have a significant impact on cereal production in Tanzania.

Additionally, we also compared the combined impacts of changes in climatic means on crop yields to those when both means and variability are accounted for (Fig. 9) using the average modeled climate change for the year 2050 (i.e., increase of 1.4 °C and 5% in precipitation as well as a decrease in temperature variability by 14% and an increase in precipitation variability by 2.1%). Whether we use CRU data or detailed station data, we almost always underestimate the impacts on crop yields when we only concentrate on changes in climatic means. The exception concerns sorghum when we use CRU data, which shows a reduced impact on yields when both means and variability are taken into account. Using station data, the models underestimate the climatic impacts on crop yields by 3.6%, 8.9%, and 28.6% for maize, sorghum and rice respectively, when focusing only on means. The differences are even more pronounced when CRU data is used (underestimation of 17.3% and 29.9% for maize and rice, and overestimation of 36.8% for sorghum).

5. Conclusions

Our empirical study is among the first to document the effects of intra-seasonal climate on crop yields (Cabas et al., 2009). Many studies focused on the non-linear effects of temperature on crop production (Wheeler et al., 2000; Challinor et al., 2005; Porter and Semenov, 2005; Schlenker and Roberts, 2009). However, in water-limited regions, moisture availability is key to crop development, enhancing the role of precipitation variability. In Tanzania, both inter- and intra-seasonal changes in precipitation and temperature are associated with changes in maize, sorghum, and rice yields. Similar to previous studies (Lobell and Field, 2007; Cabas et al., 2009), this analysis shows that cereal yields increase with more seasonal precipitation and decrease with higher temperatures. However, we also show that increased precipitation variability during the growing season reduces yields for maize, rice, and sorghum.

Some of our results are also counter-intuitive. Believing that increased exposure to extremes would lead to crop damages, we anticipated increased temperature and precipitation variability to reduce crop yields (Semenov and Porter, 1995; Wheeler et al., 2000; Cabas et al., 2009). However, certain complex mechanisms influencing the climate variability (as measured by the coefficient of variation) may lead to better yields. Beside threshold effects (Porter and Semenov, 2005; Schlenker and Roberts, 2009), changes in phenology and in timing in temperature and in precipitation can improve crop yields (Challinor et al., 2009; Welch et al., 2010). To analyze these mechanisms in detail, higher temporal resolution climatic data are needed.

In certain regions in Tanzania, a shortening of the rainy season and more frequent dry spells have already reduced yields (Lema and Majule, 2009) forcing the Tanzanian farmer to adapt their practices (Paavola, 2008). These climate-related changes in agricultural productivity may increase food insecurity (Rowhani et al., accepted for publication) and poverty (Ahmed et al., 2009a), especially in regions with low-input and rainfed agricultural systems.

Methodologically speaking, this study showed that yield responses to climate were rather consistent throughout the country. When dealing with a longitudinal dataset, mixed model analysis is the preferred statistical method to highlight within-country heterogeneities related to a variety of factor such as soils, technology, management, and political and economical initiatives. However, there do not seem to be large regional differences in these factors and the results from the linear regression models were comparable to the mixed model coefficients. This suggests that our conclusions are robust to the use of different statistical methods.

Furthermore, statistical methods for analyzing yield trends have been criticized in the past (Gifford et al., 1998; Godden et al., 1998). Indeed, these models are subject to a number of deficiencies (Lobell et al., 2008). However, using subnational yield and climate data over the growing season and by taking into account the technological and area trends we are able to reduce the uncertainties related to methodological aspects. Additionally, this study also relies on two sets of climatic data as well as two statistical methods to measure the robustness of our results.

A key factor in any model is the quality of the input data. The results of our study show that intra-seasonal precipitation variability has either a positive or negative relationship with maize yields, depending on the climatic data used. This highlights the importance of climate data – different data can yield different results. Most global scale climate datasets are developed using observational records from climate stations. In certain regions of the world, the density of climate stations used is very poor. Indeed, the global gridded climate data from CRU uses only 3 stations over Tanzania. With a total area of around 1 Mkm^2 and a complex terrain, more observational data is required to capture the detailed spatio-temporal variations in climate within this country. Unfortunately, such data is seldom available over many regions of the world. Most large scale analyses in these regions have to rely on CRU (Lobell et al., 2008) or other modeled datasets (Schlenker and Lobell, 2010). These studies provide critical insight on the impacts of climate change on food production. However, in order to improve our understanding of these relationships, we need to invest in improving the climate records in these regions to enable better analysis.

Ranking 151st in the Human Development Index (0.53, 151st), Tanzania will face greater challenges in the future if agricultural production is reduced due to climate change. However, investments in management practices and improved governmental policies can certainly balance some adverse effects of climate change (Funk et al., 2008). Increased availability and utilization of organic and mineral fertilizers along with improved cultivars are likely required for African farmers to match the gains seen in other regions (Sánchez, 2010). Nevertheless, it is clear that crop yield and food security are intimately linked to both intra-annual variability and interannual trends. Thus, simultaneous considerations of technological improvements and the development of the overall availability and predictability of water resources are likely required to see sustainable improvements in agriculture given projected climate trends and variability.

Acknowledgements

Pedram Rowhani gratefully acknowledges the support of the World Bank's Trust Fund for Environmentally and Socially Sustainable Development. This work was also partly supported by an EPA grant subcontracted from Purdue University to Navin Ramankutty. We also would like to thank Sébastien Breau (McGill University) for his useful statistical explanations and support.

References

Ahmed, S.A., Diffenbaugh, N.S., Hertel, T.W., 2009a. Climate volatility deepens poverty vulnerability in developing countries. Environ. Res. Lett. 4, 034004.

Ahmed, S.A., Diffenbaugh, N.S., Hertel, T.W., Lobell, D.B., Ramankutty, N., Rios, A.R., Rowhani, P., 2009b. Climate Volatility and Poverty Vulnerability in Tanzania. Policy Research Working Paper 5117. World Bank, Washington, DC.

Battisti, D.S., Naylor, R.L., 2009. Historical warnings of future food insecurity with unprecedented seasonal heat. Science 323, 240–244.

Bisanda, S., Mwangi, W., Verkuijl, H., Moshi, A., Anandajayasekeram, P., 1998. Adoption of Maize Production Technologies in the Southern Highlands of Tanzania. CIMMYT, Mexico, DF.

Cabas, J., Weersink, A., Olale, E., 2009. Crop yield response to economic, site and climatic variables. Clim. Change 101, 599–616.

Challinor, A., Ewert, F., Arnold, S., Simelton, E., Fraser, E., 2009. Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. J. Exp. Bot. 60, 2775.

Challinor, A., Wheeler, T., Craufurd, P., Slingo, J., 2005. Simulation of the impact of high temperature stress on annual crop yields. Agric. For. Meteorol. 135, 180–189.

Ciais, P., Reichstein, M., Viovy, N., Granier, A., Ogee, J., Allard, V., Aubinet, M., Buchmann, N., Bernhofer, C., Carrara, A., 2005. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature 437, 529–533.

De Waal, A., 1997. Famine Crimes: Politics & the Disaster Relief Industry in Africa. Indiana University Press.

Easterling, D.R., Meehl, G.A., Parmesan, C., Changnon, S.A., Karl, T.R., Mearns, L.O., 2000. Climate extremes: observations, modeling, and impacts. Science 289, 2068–2074.

FAO, 2007. FertiStat [Online], Available at: http://www.fao.org/ag/agl/fertistat/index_en.htm.

Funk, C., Dettinger, M.D., Michaelsen, J.C., Verdin, J.P., Brown, M.E., Barlow, M., Hoell, A., 2008. Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development. Proc. Natl. Acad. Sci. U.S.A. 105, 11081–11086.

Giannini, A., Biasutti, M., Held, I.M., Sobel, A.H., 2008. A global perspective on African climate. Clim. Change 90, 359–383.

Gifford, R., Angus, J., Barrett, D., Passioura, J., Rawson, H., Richards, R., Stapper, M., Wood, J., 1998. Climate change and Australian wheat yield. Nature 391, 448–449.

Godden, D., Batterham, R., Drynan, R., 1998. Climate change and Australian wheat yield. Nature 391, 447–448.

Hulme, M., Doherty, R., Ngara, T., New, M., Lister, D., 2001. African climate change: 1900–2100. Clim. Res. 17, 145–168.

Hutchinson, M.F., 1995. Interpolating mean rainfall using thin plate smoothing splines. Int. J. Geogr. Inf. Sci. 9, 385–403.

ICID, 2010. Tanzania country profile [Online], Available at: http://www.icid.org.

IPCC, 2007a. Climate change 2007: impacts, adaptation and vulnerability. In: Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J., Hanson, C.E. (Eds.), Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom/New York, NY.

IPCC, 2007b. Climate change 2007: the physical science basis. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller, H.L. (Eds.), Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom/New York, NY.

Ito, T., Kurosaki, T., 2009. Weather risk, wages in kind, and the off-farm labor supply of agricultural households in a developing country. Am. J. Agric. Econ. 91, 697–710.

Kucharik, C., Serbin, S., 2008. Impacts of recent climate change on Wisconsin corn and soybean yield trends. Environ. Res. Lett. 3, 034003.

Lema, M.A., Majule, A.E., 2009. Impacts of climate change, variability and adaptation strategies on agriculture in semi arid areas of Tanzania: the case of Manyoni District in Singida Region, Tanzania. J. Environ. Sci. Technol. 3, 206–218.

Lobell, D.B., Burke, M.B., 2008. Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. Environ. Res. Lett. 3, 034007.

Lobell, D.B., Burke, M.B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P., Naylor, R.L., 2008. Prioritizing climate change adaptation needs for food security in 2030. Science 319, 607–610.

Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2, 014002.

Meehl, G., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J., Stouffer, R., Taylor, K., 2007. The WCRP CMIP3 multimodel dataset. Bull. Am. Meteorol. Soc. 88, 1383–1394.

Mitchell, D., 2008. A Note on Rising Food Prices. Policy Research Paper 4682. World Bank, Washington, DC.

Mitchell, T.D., Jones, P.D., 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. Int. J. Climatol. 25, 693–712.

Monfreda, C., Ramankutty, N., Foley, J.A., 2008. Farming the planet. 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochem. Cycles 22, GB1022, doi:10.1029/2007GB002947.

Morton, J.F., 2007. The impact of climate change on smallholder and subsistence agriculture. Proc. Natl. Acad. Sci. U.S.A. 104, 19680–19685.

New, M., Hulme, M., Jones, P., 1999. Representing twentieth-century space-time climate variability. I. Development of a 1961–90 mean monthly terrestrial climatology. J. Clim., 12.

Nicholson, S.E., 2001. Climatic and environmental change in Africa during the last two centuries. Clim. Res. 17, 123–144.

Paavola, J., 2008. Livelihoods, vulnerability and adaptation to climate change in Morogoro, Tanzania. Environ. Sci. Policy 11, 642–654.

Pinheiro, J.C., Bates, D.M., 2000. Mixed Effects Models in S and S-Plus. Springer, New York.

Porter, J.R., Semenov, M.A., 2005. Crop responses to climatic variation. Philos. Trans. R. Soc. Lond. Ser. B: Biol. Sci. 360, 2021–2035.

Putterman, L., 1995. Economic reform and smallholder agriculture in Tanzania: a discussion of recent market liberalization, road rehabilitation, and technology dissemination efforts. World Dev. 23, 311–326.

Rosenzweig, C., Tubiello, F., Goldberg, R., Mills, E., Bloomfield, J., 2002. Increased crop damage in the US from excess precipitation under climate change. Global Environ. Change 12, 197–202.

Rowhani, P., Degomme, O., Guha-Sapir, D., Lambin, E., 2011. Malnutrition and conflict in East Africa: the impacts of resource variability on human security. Clim. Change., in press.

Sánchez, P., 2010. Tripling crop yields in tropical Africa. Nat. Geosci. 3, 299–300.

Schlenker, W., Lobell, D.B., 2010. Robust negative impacts of climate change on African agriculture. Environ. Res. Lett. 5, 014010.

Schlenker, W., Roberts, M., 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proc. Natl. Acad. Sci. U.S.A. 106, 15594.

Schmidhuber, J., Tubiello, F.N., 2007. Global food security under climate change. Proc. Natl. Acad. Sci. U.S.A. 104, 19703–19708.

Semenov, M., Porter, J.R., 1995. Climatic variability and the modelling of crop yields. Agric. For. Meteorol. 73, 265–283.

Stige, L.C., Stave, J., Chan, K.-S., Ciannelli, L., Pettorelli, N., Glantz, M., Herren, H.R., Stenseth, N.C., 2006. The effect of climate variation on agro-pastoral production in Africa. Proc. Natl. Acad. Sci. U.S.A. 103, 3049–3053.

Tao, F., Yokozawa, M., Liu, J., Zhang, Z., 2008. Climate–crop yield relationships at provincial scales in China and the impacts of recent climate trends. Clim. Res. 38, 83–94.

Thurlow, J., Wobst, P., 2003. Poverty-focused social accounting matrices for Tanzania. IFPRI Discussion Paper No. 112. International Food Policy Research Institute, Washington, DC.

Tubiello, F.N., Soussana, J.-F., Howden, S.M., 2007. Crop and pasture response to climate change. Proc. Natl. Acad. Sci. U.S.A. 104, 19686–19690.
USDA, 2003. Crop calendar of Tanzania [Online]: Foreign Agricultural Service, Available at: http://www.fas.usda.gov/.
Welch, J.R., Vincent, J.R., Auffhammer, M., Moya, P.F., Dobermann, A., Dawe, D., 2010. Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. Proc. Natl. Acad. Sci. U.S.A..
Wheeler, T., Craufurd, P., Ellis, R., Porter, J., Vara Prasad, P., 2000. Temperature variability and the yield of annual crops. Agric. Ecosyst. Environ. 82, 159–167.
Zuur, A.F., Ieno, E.N., Walker, N., Saveliev, A.A., Smith, G.M., 2009. Mixed Effects Models and Extensions in Ecology with R (Statistics for Biology and Health). Springer.