Relationship of Weather and Maize Yields in Kenya

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Abstract

..the full abstract to be written.. This paper contributes to better understanding of effects of drought on food security in Kenya which should lead to improving of early warning systems and food security. Our dataset consists of an yearly panel of 47 counties of Kenya describing the period of 1981-2017.

...Applying the linear mixed effects models, we found that...

Keywords: Drought, Early warning systems, Food security, Food systems, Kenya, Mixed effects models

1 Introduction and literature review

Consequences of droughts and extreme heat waves on agriculture have been well documented (Deschenes and Greenstone, 2007; Bello and Maman, 2015; Lesk et al., 2016; Mehrabi and Ramankutty, 2017; Schwalm et al., 2017). Agricultural drought and soil moister are important factors influencing plant health but they are also essential for land-atmospheric feedback and for temperature variability (Nicolai-Shaw et al., 2017).

Repeated severe droughts have been a major problem in Kenya and in other Sub-Saharan countries (Gitu and Nzuma, 2003; D'Alessandro et al., 2015; Nicholson, 2017). The agricultural sector is the main contributor to the economy of Kenya, hence the effects of droughts can be especially damaging in this country (Mendelsohn et al., 2000). Besides compromising food security, droughts usually lead to severe damage in water supply, electricity and the environment. In 2010-2011, the most devastating drought in decades resulted in food crisis in many East African countries including Kenya (Chen and Georgakakos, 2015). Widespread catastrophic droughts occurred also in 1984-1985, 2005 and 2008 (Hastenrath et al., 2007, 2010, 2011; Chen and Georgakakos, 2015). As a consequence of climate change, the situation is likely to get worse. Dry areas exhibit a strong tendency to get drier while wet areas are getting wetter (Trenberth et al., 2014; Chen and Georgakakos, 2015; Kabubo-Mariara and Kabara, 2015). Strong downwards trend in precipitation has already been observed in the tropics from 10°N to 10°S, especially after 1977 (Trenberth et al., 2007). During the period $1900 - 2005$, the climate has become wetter in many parts of the world (eastern parts of America, northern Europe, northern and central Asia) but it has became much drier in Mediterranean, Sahel, southern Africa and parts of Southern Asia. Furthermore, increased frequency of heavy rain events has been observed in the areas with decline in total rainfall (Trenberth et al., 2007).

Droughts and climate variability do not only affect agriculture but they have widespread consequences on food security in general. Ubilava (2018) has found a connection between commodity prices and phases of the ENSO cycle. Robinson et al. (2010) have used a Computable General Equilibrium (CGE) model for Ethiopia and they have shown that production shocks and resulting price increases have negative effects on farmers' income in drought-prone areas while moderate price increases can be beneficial for farmers in less drought-prone areas. Willenbockel (2011) have focused on sub-Saharan Africa, central America, North Africa and other low-income countries selected by Oxfam and he has concluded that climate change will result in decline in food productivity while food prices will increase. Brown and Kshirsagar (2015) have investigated food prices in 554 local commodity markets in Africa, South Asia and Latin America and they concluded that almost 20% of local market food prices had been affected by weather disturbances.

A large literature has focused on relationship of agricultural production and climate in Sub-Saharan Africa. Increase in temperature has typically been found to affect crop revenue negatively while increase in precipitation has mostly been associated with positive effects in the literature. Bello and Maman (2015) and Ochieng et al. (2016) have found these results by the means of Ricardian analysis. Ochieng et al. (2016) have focused on Kenya while Bello and Maman (2015) have addressed the situation in Niger.

Other studies have investigated the relationship of climate and yields in the context of climate change. Mendelsohn et al. (2000) have developed a simulation model to evaluate impacts of climate change on African agriculture. According to their study, agricultural GDP and climate change exhibit a hill-shaped relationship. Hence, global warming should be beneficial in high latitudes but harmful in low latitudes. The estimated loss of the Africa as a continent ranges from \$25 billion to \$194 billion per year with 2 °C warming (Mendelsohn et al., 2000). Kabubo-Mariara and Karanja (2007) have shown that in

Kenya, higher summer temperatures are harmful while higher winter temperatures are beneficial. Furthermore, fall and summer precipitation is positively correlated with net revenue (Kabubo-Mariara and Karanja, 2007). Kurukulasuriya et al. (2008) and Seo et al. (2008) have investigated the distribution of climate change impacts on agriculture in Africa. They argued that mild scenario would result in income gains for African farmers while more severe scenario is likely to be harmful. Rowhani et al. (2011) have analysed relationship between climate variability and crop production in Tanzania. The authors have shown that by 2050, the climate change will result in significant decrease in crop production and big part of this loss can be attributed to change in intra-seasonal variability of weather. Kabubo-Mariara and Kabara (2015) have estimated effects of climate change on food security in Kenya. They have found that temperature and maize yield exhibit a U-shaped relationship while the relationship of rainfall and maize is hill-shaped. Thus, sufficient precipitation is crucial, but excessive rainfall is harmful for maize yields. Mendelsohn (2008) has reviewed several studies on effects of climate change on agriculture in developing countries. According to the literature review, the tropical and sub-tropical countries are much more sensitive to climate change than temperate agriculture (Mendelsohn, 2008). Knox et al. (2012) conducted a meta-study of papers focused on effects of climate change impacts on crop productivity in Africa and South Asia. The authors concluded that the projected mean change in yield is -8% by the 2050s in both regions. According to a meta-study conducted by Challinor et al. (2014), losses in global production of wheat, maize and rice are expected with 2 °C global warming. However, with adaptation the simulated yields are on average $7 - 12\%$ higher than without adaptation (Challinor et al., 2014).

A number of important studies have focused on responses to drought related disasters or emergency situations. Sandstrom and Juhola (2017) have questioned whether drought is actually a major cause of food insecurity in Ethiopia, Kenya and Somalia. They have analysed causes of the food crisis identified by the humanitarian appeal documents. Majority of these documents have found food availability and food production to be the major causes of food crisis. Sandstrom and Juhola (2017) argue that there is a tendency to explain failure of more complex food systems as 'droughts' and insufficient attention is paid to non-climatic drivers such as food prices or conflicts. According to Sandstrom and Juhola (2017), a large share of humanitarian response budget has been focused on emergency food aid in comparison to the share focused on interventions to build resilience. The authors have suggested to increase the budget share focused on agricultural and livestock production to build resilience. Also other authors have promoted shifting from reactive to proactive approach in disaster risk management (Mechler, 2005; Lavell et al., 2012; Nicholson, 2017). Nicholson (2017) has recommended forecast based financing as it can avoid significant disaster losses. Mechler (2005) has shown that investments into disaster risk reduction had usually been outweighed by avoided losses. Also Lavell et al. (2012) have argued that risk assessment is essential for disaster risk management.

In the light of these arguments, the goal of the present study is to develop a model which will utilize weather data to assess risk of drought and food security. In addition, we want to find out which particular features of climate or weather are the most important factors affecting the yields and food security. Are the average weather conditions the most important or is it the weather variability or length and number of dry spells during the growing season what matters the most? Answering these and other similar questions should help to improve food security and shift the focus from reactive to proactive approach in drought disaster risk management. We focus on Kenya utilizing an yearly panel of 47 counties over the period of $1981 - 2017$.

The main contribution of this study is leveraging the most detailed publicly available weather datasets while accounting for the real life crop calendar and different cropping seasons across the country as practised by Kenyan farmers. Furthermore, we believe that this is the first study which has described an application of linear mixed effects models to estimate effects of precipitation and temperature on crop yields in Kenya. Hence, this is the first time that effects of drought and weather on food security have been estimated taking into account the real crop calendar, spatially-heterogeneous nature of Kenya and allowing for the effects of weather to vary across the country.

2 Methodology

2.1 Measures of food security and drought

Before beginning our research, we had to answer two essential questions: 'How should we measure food security?' and 'How should we measure drought?' Taking into account the aim of this study, previous literature (see Section 1) and data availability, we were considering three main approaches to measuring food security. In particular, we considered health and utility indicators, food prices and agricultural crop yields as measures of food security. Although some health and utility indicators including the Mid Upper Arm Circumference (MUAC) of children under five, the Coping Strategies Index (see Maxwell and Caldwell, 2008) or the NDMA early warning phases are available in the NDMA Early Warning Bulletins, these data are only available since July 2013. The other problem is that the scale of indicators does not seem to be consistent over the counties and time. Furthermore, the values of indicators are often missing and for some months the reports are not present at all.

Using food prices as a measure of food security turned out to be problematic as well. One problem is data availability as the food prices are usually available for market towns but not as county averages. Furthermore, the market data which are available in the publications of Kenya National Bureau of Statistics (KNBS) only cover several years. Another problem is that prices are usually strongly spatially autocorrelated and this could cause the regression estimates to be inconsistent and inefficient unless the model accounts for the spatial autocorrelation structure. Modelling the structure of spatial autocorrelation would require developing and estimation of a complicated model consisting of several structural equations and additional data, which may not be available. Therefore we opted for agricultural crop yields as a measure of food security and we decided to estimate a single reduced form equation with crop yields as the dependent variable. In particular, we focus on maize yields as this crop is the principal staple food in Kenya and it is grown at 90% of farms in Kenya (FAO, 2009).

The other important question to answer before starting our analysis was: 'How is drought defined and which definition and measure of drought is the most suitable for the purpose of this study?' Various definitions of drought and their role have been reviewed by Wilhite and Glantz (1985) and Wilhite (2000). For an extensive overview of drought indices see Heim (2002), Monacelli et al. (2005), Zargar et al. (2011) or Svoboda et al. (2016). Keyantash and Dracup (2002) have quantified, evaluated and compared number of drought indices used for measuring of severity of meteorological, hydrological and agricultural types of drought. For more details about types, measures and indices of drought see Appendix 1.

In the recent period, remote sensing data have been used increasingly to monitor levels of greenness and closely related vegetation conditions (Nicolai-Shaw et al., 2017). Based on these data, various measures (for example the vegetation condition index) have been developed and used for quantifying drought strength and severity (Klisch and Atzberger, 2016).

We have considered the Standardised Precipitation Evapotranspiration Index (SPEI) and the vegetation condition index (VCI) as measures of drought in our analysis. We did not find the county level SPEI to be as good predictor of food security as other precipitation and temperature measures and computing the SPEI for the entire high resolution weather dataset would be inadequately demanding. We did not use the VCI either as we were not confident enough about the reliability of the available data.[1]

After conducting a rigorous literature research on measures of drought previously used in the relevant context, we decided to utilize various aggregates of daily precipitation and temeprature. The frequency of the maize yield data is yearly while the weather data are daily. Hence, the weather data had to be aggregated in order to obtain a dataset conformable with the yield data. There are many possible ways of aggregation. Commonly used measures include monthly averages (or monthly totals in case of precipitation) and their variances or standard deviations (Abraha and Savage 2006; Lobell et al. 2008; Thornton et al. 2009). For example, Adejuwon (2004) has analysed relationship of crop yields and three measures of precipitation in Sub-Saharan West Africa. These include: *(i)* Total rainfall during the first month of the period from sowing to harvesting (June) *(ii)* Total rainfall during the first two months of the period from sowing to harvesting (June and July) and *(iii)* Total rainfall during the first three months of the period from sowing to harvesting (June, July and August). Based on his results, weather during June and July is the most important for crop yield in Sub-Saharan West Africa (Adejuwon, 2004). Other studies have utilised seasonal totals or means (Sagoe 2006; Lobell and Burke 2010) or annual totals or means (Blignaut et al., 2009). Ben Mohamed et al. (2002) have found sea surface temperature anomalies at various locations and amount of rainfall in July, August and September to be significant for millet crops in Niger. The authors have also

[1] The values of the VCI which we obtained from the NDMA were not the same as those available by the University of Natural Resources and Life Sciences Vienna (BOKU). Furthermore, the VCI values did not exactly correspond to the early warning phases although they should according to the National Drought Management Authority (NDMA).

considered the maximum air temperature in the hottest month (April) and the minimum air temperature in the coldest month (January) as possible predictors of crops in Niger, but they did not find them significant. Some studies are based on simulated daily extremes, averages, daily measures of variance (Schulze et al. 1993; Chipanshi et al. 2003; Abraha and Savage 2006) or yearly extremes (Sagoe, 2006). Other measures used to explain variability of maize yield include counts of wet and dry days per a defined period, usually a month or a season (Ben Mohamed et al. 2002; Abraha and Savage 2006; Sagoe 2006; Giannakopoulos et al. 2009) or length of rainy season (Leemans and Solomon 1993; Ben Mohamed et al. 2002). Definitions of wet and dry days and rainy season vary. For example, Ben Mohamed et al. (2002) have assumed that rainy season begins when the amount of rainfall in three consecutive days reaches at least 25 mm and no dry spell of more than seven days occurs in the following thirty days. According to this study, the end of the rainy season is defined as that rainy day after which rain recorded during 20 days is less than 5 mm.

An important group of studies focused on relationship of yield and climate in Sub-Saharan Africa has been focused on degree days (Schulze et al. 1993; Tingem et al. 2008; Walker and Schulze 2008; Tingem et al. 2009) or on the number of days with temperature above certain level or within a defined range (Giannakopoulos et al. 2009; Laux et al. 2010).

Based on the literature research above and complexity of deriving the measures, we short-listed the following aggregates of the weather data:

- **Precipitation:**
  - Cumulative precipitation and its square
  - Cumulative precipitation during the first two months of season
  - Additionally, I will test significance of the cumulative precipitation during the first month of each season - Guigma has just provided the aggregated variables

- Coefficient of variation
- Maximum length of dry spell in number of days
- Number of dry spells lasting for at least four days
- Number of dry spells lasting for at least ten days
- Number of dry spells lasting for at least twenty days
- Maximum daily precipitation
- Additional indicators of floods:
  - One of the Climate Extreme Indices described at `https://www.climdex.org/indices.html` is the sum of precipitation amount on the days where precipitation is above 99th percentile of precip. of the whole period (i.e. 1981-2017 in our case). The 99th percentile is calculated based on the sample of wet days, that is the days where precipitation is above or equal to 1 mm (index no. 26)
  - Guigma has just sent me this measure and its varieties with thresholds 95th percentile and 90th percentile instead of the 99th percentile

- **Temperature**
  - Seasonal average (of daily average) and its square
  - Average maximum daily temperature
  - Standard deviation
  - Cumulative degree days $10 - 30°C$
  - Number of heatwave days $> 35°C$

Description of how the weather data were aggregated temporally - seasons

2.2 Linear mixed models

Kenya consists of 47 counties with semi-autonomous county governments (Barasa et al., 2017). As a result of the high degree of county-level autonomy, the policies and regulations often differ across the counties, hence the effects of weather on crop yield are likely to be different across the counties. Therefore, following the standard methodology, we estimated a battery of linear mixed effects models (also known as mixed models) commonly used to analyse longitudinal data (Bates et al., 2000). Mixed models are suitable for analysis of panel data as they account for the panel structure of the dataset. These types of models include both fixed effects parameters and random effects. Fixed effects are analogous to parameters in a classical linear regression model and value of each effect is assumed to be fixed over all counties (Bates, 2010). On the other hand, random effects are unobserved random variables. There are at least three benefits of treating a set of parameters as a random sample from some distribution. *(i)* Extrapolation of inference to a wider population *(ii)* improved accounting for system uncertainty and *(iii)* efficiency of estimation (Kery, 2010b,a).

Formally, a linear mixed model can be described by the distribution of two vectors of random variables: the response $\mathscr{Y}$ and the vector of random effects $\mathscr{B}$. The distribution of $\mathscr{B}$ is multivariate normal and the conditional distribution of $\mathscr{Y}$ given $\mathscr{B} = \mathbf{b}$ is multivariate normal of a form (Bates, 2010; Kery, 2010b):

$$(\mathscr{Y}|\mathscr{B} = \mathbf{b}) \quad \sim \quad N(\mathbf{X}\beta + \mathbf{Z}\mathbf{b}, \sigma^2\mathbf{I}), \tag{1}$$

where $\mathbf{X}$ is an $n \times p$ model matrix of fixed effects, β is a p-dimensional fixed-effects parameter, $\mathbf{Z}$ is an $n \times q$ model matrix for the q-dimensional vector of random-effects variable $\mathscr{B}$ evaluated at $\mathbf{b}$ and σ a scale factor. The distribution of $\mathscr{B}$ can be written as:

$$\mathscr{B} \sim N(0, \mathbf{\Sigma}), \tag{2}$$

where $\mathbf{\Sigma}$ is a $q \times q$ positive semi-definite variance-covariance matrix.

- Add a description of residual and other diagnostic tests (AIC, VIF, autocorrelation)
- Describe the procedure that I have done to find the preferred way of modelling the correlation structure in errors (ARMA errors)

2.3 Data

- Source of data
- Verbal description of the data, resolution, period, frequency
- Plot(s)/barplots of yield, precip. and temp.
- Maybe a table of descriptive statistics or ref. to a table in the Appendix
- Description how the weather data were aggregated spatially over counties

3 Results and discussion

- Tables of estimates of two models:
  1. The base model which only includes seasonal precipitation and average seasonal temperature
  2. The preferred specification which includes the significant weather variables (see the preliminary results in Table 1)

– For all counties

– For Arid and semi-araid (ASAL) counties

– For non-ASAL counties

Table 1: ***Mixed effects model:*** *Log of maize yield and weather, ARMA(1,1) errors*

	All counties		*ASAL*		*non-ASAL*	
Fixed effects:	*exp*(β)	F-value[a]	*exp*(β)	F-value[a]	*exp*(β)	F-value[a]
Intercept	1.296***	19.916	1.276*	5.230	1.410**	10.061
Prec. total	1.081*	5.402	1.006	0.022	1.278***	19.386
Prec. total sq.	0.973*	4.289	1.004	0.051	0.880***	23.747
Prec. c. of var.	0.924•	3.277	0.969	0.246	0.909	2.231
Dry spell -length	0.935*	4.810	0.833**	6.969	0.988	0.163
Dry spells $\geq$ 4 d.	0.939*	4.826	0.855**	8.065	0.989	0.096
Temp. - average	0.819***	12.127	0.808*	5.376	0.878	1.580
Temp. std. dev.	1.043•	3.125	1.039	0.558	1.059 *	5.640
Random effects:						
Intercept						
Number of observations:	1300	698	602			

Notes: Standard errors in brackets, 1256 observations

• $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a Marginal (type III) sum of squares. The F-statistics correspond to the sum of squares attributable to each fixed effect.

- Verbal description and interpretation of the results
- Estimates of future impacts and comparison of forecast accuracy of the base and preferred model
  - The idea is to choose two points in time from within our period of data and imagine that we are in the earlier of the two time points. Now we want to make a prediction of yields for the later point in time. We will make two predictions: one using the base model and the other based on the preferred specification and we will compare their prediction accuracy. Here, we assume that predictions of the weather measures are available (the explanatory variables of our models). We can use real weather data instead of the forecast. This will demonstrate why it is important to not only forecast totals/means but also other characteristics (measures) of weather/climate.
  - Accompany with a graph(s), possibly barplot(s)
- Estimate a variant of the model which separates the effects of the seasons for ASAL counties (OND and MAM separately). If interesting show a table and discuss.
- Show a variant of the model without the outliers. This could be presented either by a table in this section, a table in the Appendix or a table in a footnote.
- If time, I can also estimate similar models for different important crops in Kenya (e.g. wheat, rice, sorghum or millet)
- Possibly estimate simple regressions with the same explanatory variables as the preferred mixed effects specification. This would give us an approximation of R^2 which could be used to compare our models.

- Annemie has advised me that for a more precise approximation of R^2 we can estimate a simple regression of yields on the random intercepts (county level dummy variables) and then subtract the R^2 of this model from the R^2 of the simple regression with the explanatory variables of the preferred mixed models (the model described in the bullet point above). This would give us a percentage of yield variability explained by the weather measures not including the variability explained by the random intercepts.

4 Conclusion

- There are many weather/climate characteristics (measures) which are important for yield, not only seasonal totals (averages)
- Current weather and climate forecasts (in the context of disaster management) are mostly focused on totals in precipitation (and average temperature?)
- There is a strong movement to shift the focus from forecasting merely weather/climate to forecast of weather/climate and its impacts

  → **We can stress the importance of focusing the forecast on the climate characteristics (or measures) which we find significant in our models**

- Caveats
  - Yield data: Is the collection method consistent over time and space?
  - Livestock not explicitly taken into account
  - Cropping calendar is likely to differ across the country
  - Some more??

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Appendix 1 Drought: definitions, measures and indices

According to the international meteorological community, drought can be defined in several ways. In particular, drought is a *'prolonged absence or marked deficiency of precipitation'*, a *'deficiency of precipitation that results in water shortage for some activity or for some group'* or a *'period of abnormally dry weather sufficiently prolonged for the lack of precipitation to cause a serious hydrological imbalance'* (Heim, 2002; Trenberth et al., 2007). American Meteorological Society (1997) has defined three types of droughts: *(i)* 'Agricultural drought' which is defined in terms of moister deficits in upper layer of soil up to about one meter depth *(ii)* 'meteorological drought' which refers to prolonged deficit of precipitation and *(iii)* 'hydrological drought' which relates to low streamflow, lake and levels of groundwater. The American Meteorological Society (1997) policy statement was later replaced by another statement (American Meteorological Society, 2013) which besides the three types of drought above, covers also the 'socioeconomic drought' which associates the supply and demand of some economic good with elements of meteorological, agricultural and hydrological drought (Heim 2002; Trenberth et al. 2007).

Wilhite and Glantz (1985) and Wilhite (2000) have distinguished two main categories of definitions of drought: *(i)* conceptual and *(ii)* operational. Conceptual definitions are dictionary types, usually defining boundaries of the concept of drought[2]. Operational definitions are essential for an effective early warning system. An example of operational definition of agricultural drought can be obtaining the rate of soil water depletion based on precipitation and evapotranspiration rates and expressing these relationships in terms of drought effects on plant behaviour (Wilhite, 2000).

In order to compare severity of drought across different time periods or geographical

[2] An example of conceptual definition of drought is an 'extended period - a season, a year, or several years of deficient rainfall relative to the statistical multi-year mean for a region' Schneider and Hare (1996).

locations a numerical measure turns out to be necessary. However, as a result of a large disagreement about a definition of drought, there is no single universal drought index. Instead of that a number of measures of drought has been developed (Wilhite and Glantz, 1985; Wilhite, 2000; Heim, 2002).

Examples of early measures of drought are Wilhite and Glantz (1985), Munger (1916), Blumenstock (1942) or McQuigg (1954). Munger (1916) suggested to use length of period without 24-h precipitation of 1.27 mm. Wilhite and Glantz (1985) is based on a measure of precipitation over a given time period. Blumenstock (1942) proposed to measure severity of drought as a length of drought in days where the end of a drought is defined by occurrence of 2.54 mm of precipitation in 48 hours. McQuigg (1954) developed the Antecedent Precipitation Index (API) which is based on amount and timing of precipitation and it was used for forecasting of floods. Hence, the API is a reverse drought index.

The study of Palmer (1965) was a significant milestone in the history of quantification of drought severity. Palmer (1965) developed the Palmer Drought Severity Index (PDSI) using a complex water balance model. The PDSI is based on a hydrological accounting system, which incorporate antecedent precipitation, moisture supply and moisture demand (Heim, 2002; Palmer, 1965). As the PDSI suffers from several weaknesses (for details see e.g. Heim 2002), other indices were developed in the following decades. These include the standardized precipitation index (SPI) developed by McKee et al. (1993) and the standardized precipitation evapotranspiration index (SPEI) developed by Vicente-Serrano et al. (2010). The SPI specifies observed precipitation as a standardised departure from a chosen probability distribution which models the precipitation data. Values of SPI can be viewed as a multiple of standard deviations by which the observed amount of rainfall deviates from the long-term mean (John Keyantash and National Center for Atmospheric Research Staff (Eds.), 2016).[3] The SPEI is similar to SPI, but unlike SPI, the SPEI includes

[3] Can be created for various periods of 1-36 months, usually using monthly data.

the role of evapotranspiration (which captures increased temperature). It is based on water balance, therefore it can be compared to the self-calibrated PDSI (Vicente-Serrano et al., 2010).

Appendix 3 Tables