The Effects of Weather on Maize Yields: New Evidence from Kenya

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- The title is provisional, we will decide about the final title when most of the paper will be written

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

Paragraph 1

– Extreme weather causes disasters → early warning systems have been developed

Paragraph 2

– What weather forecasts (measures) have been used in EWS? *ref. litrature*

∗ Mostly seasonal precip. totals and temperature averages

Paragraph 3

– Identify difference between hazard and disaster

∗ Not every hazard turns into disaster

∗ For a hazard to become a disaster it needs to have **impact**

∗ Here, we identify the key metrics which have impact on yield

Paragraph 4

– Crop yield versus climate forecasting

Paragraph 5

– Aim of the paper

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 $1981 - 2017$.

2 Methodology

- *case study looking at Kenya...*

2.1 Data

- Source of the climate data University of Natural Resources and Life Sciences Vienna (BOKU) and Berkeley Earth

- Source of the yield data (Kenya MoA)

2.2 Statistical approach

- *We used commonly used measures of weather/drought (Only mention the significant weather measures/variables)*

- Describe the temporal aggregation of the weather variables, seasons

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:

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

where $\boldsymbol{\Sigma}$ 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 applied to find the preferred combination of fixed effects and random effects

- Describe the procedure that I have applied to find the preferred way of modelling the correlation structure in errors (ARMA errors)

3 Results

- Tables of estimates of 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*

Fixed effects:	All counties		ASAL		non-ASAL	
	$exp(\beta)$	**F-value**[a]	$exp(\beta)$	**F-value**[a]	$exp(\beta)$	**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;   • $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

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

- 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.

- If we get the yield data for the period from 2015 onwards: Out of sample predictions and comparison with the real data

4 Discussion

- 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

$\rightarrow$ **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??

If time

- 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 (which only includes precipitation and temperature) 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.

- I can also estimate similar models for different important crops in Kenya (e.g. wheat, rice, sorghum or millet)

References

American Meteorological Society. Meteorological drought Policy statement. Technical report, 1997.

American Meteorological Society. Drought - An Information Statement of the American Meteorological Society. Technical report, 2013.

Barasa, E., Manyara, A., Molyneux, S., and Tsofa, B. 2017. "Recentralization within decentralization: County hospital autonomy under devolution in Kenya". *PLOS ONE*, pages 114–124.

Bates, D. M. 2010. lme4: Mixed-effects modeling with R.

Bates, J., Pinheiro, J., Pinheiro, J., and Bates, D. 2000. *Mixed-Effects Models in S and S-PLUS*. Statistics and Computing. Springer New York. ISBN 9780387989570.

Berkeley Earth.
(accessed October, 2018) http://berkeleyearth.org/data/.

Blumenstock, G. 1942. *Drought in the United States analyzed by means of the theory of probability*. US Department of Agriculture.

Heim, R. R. 2002. "A Review of Twentieth-Century Drought Indices Used in the United States". *Bulletin of the American Meteorological Society*, 83(8):1149–1165.

John Keyantash and National Center for Atmospheric Research Staff (Eds.). 2016. The Climate Data Guide: Standardized Precipitation Index (SPI). Retrieved from `https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-index-spi`. Last modified 02 Mar 2016.

Kery, M. Chapter 12 - Linear Mixed-Effects Model. In Kry, M., editor, *Introduction to WinBUGS for Ecologists*, pages 151 – 166. Academic Press, Boston, 2010a. ISBN 978-0-12-378605-0. doi: https://doi.org/10.1016/B978-0-12-378605-0.00012-0. URL `http://www.sciencedirect.com/science/article/pii/B9780123786050000120`.

Kery, M. Chapter 9 - Normal One-Way ANOVA. In Kry, M., editor, *Introduction to WinBUGS for Ecologists*, pages 115 – 127. Academic Press, Boston, 2010b.

McKee, T. B., Doesken, N. J., Kleist, J., et al. The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, volume 17, pages 179–183. American Meteorological Society Boston, MA, 1993.

McQuigg, J. 1954. "A simple index of drought conditions". *Weatherwise*, 7(3):64–67.

Munger, T. T. 1916. "GRAPHIC METHOD OF REPRESENTING AND COMPARING DROUGHT INTENSITIES". *Monthly Weather Review*, 44(11):642–643.

Palmer, W. C. 1965. *Meteorological drought*, volume 30. US Department of Commerce, Weather Bureau Washington, DC.

Schneider, S. H. and Hare, F. K. 1996. *Encyclopedia of climate and weather*, volume 678. Oxford University Press New York.

Trenberth, K. E., Jones, P. D., et al. 2007. *IPCC, 2007: Summary for Policymakers. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S. and D. Qin, M. Manning and Z. Chen and M. Marquis and K.B. Averyt and M.Tignor and H.L. Miller (eds.)].* Cambridge University Press.

University of Natural Resources and Life Sciences Vienna.
(accessed October, 2018). http://ivfl-info.boku.ac.at/index.php/homepage?view=featured.

Vicente-Serrano, S. M., Beguera, S., and Lpez-Moreno, J. I. 2010. "A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index". *Journal of Climate*, 23(7):1696–1718.

Wilhite, D. A. 2000. "Drought as a natural hazard: concepts and definitions".

Wilhite, D. A. and Glantz, M. H. 1985. "Understanding: the drought phenomenon: the role of definitions". *Water international*, 10(3):111–120.

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[1]. 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

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[1]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).[2] The SPEI is similar to SPI, but unlike SPI, the SPEI includes

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[2]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