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The Effects of weather on maize yields: New evidence from Kenya

Monika Novackova, Pedram Rowhani, Martin Todd and Dominic Kniveton

Department of Geography, University of Sussex, Falmer, UK

E-mail: monika.novac@gmail.com

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

.. to be written later..

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

2. Methods

...a case study looking at Kenya...

2.1. Data

In this study, we analyzed the relationship between maize yields and climate. Our dataset consists of an yearly panel of 47 counties of Kenya describing the period of 1981 – 2017. We acquired the county level yearly yield data from the Famine Early

Warning Systems Network (FEWS NET). As for the weather data, we utilized 0.25° resolution precipitation and temperature gridded datasets. The precipitation data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) while the temperature data are available at the website of the Berkeley Earth. We calculated spatial averages of the gridded data over the counties resulting in a single value for each county and each point in time. The frequency of precipitation and temperature data was daily, therefore, further aggregation was needed to obtain yearly values corresponding to the yearly frequency of the yield data. Hence, each weather characteristic was further aggregated over years resulting in a county-level panel conformable with the yield data.

There are two predominant rainfall regimes in Kenya. The arid and semi-arid (ASAL) counties exhibit mostly bi-modal precipitation patterns with long rains lasting from March to May and short rains occurring between October and December. In the non-ASAL counties, the single rainy season usually starts in March and lasts until August. Following the precipitation patterns and closely related planting and harvesting calendar, we computed yearly values of various weather characteristics as follows: For the ASAL counties, we used daily data covering October, November and December of the previous year and March, April, May of the current year and for the non-ASAL counties we used daily data covering March to August of the current year.

Following the procedure described above, we calculated a number of previously used characteristics of precipitation and temperature including indicators of floods. Only some of them were found significant in our models. The significant measures include: Total seasonal precipitation and its squared values, average seasonal temperature, coefficient of variation of seasonal precipitation, standard deviation of average seasonal temperature ‡, maximum length of dry spell in number of days and the number of

‡ In case of temperature, we used standard deviation rather than coefficient of variation because

dry spell lasting for four days or more (a dry day has been defined as a day when precipitation didn't exceed 1mm). We did not include squared values of the average seasonal temperature as it was not significant.

2.2. Statistical approach

Kenya consists of 47 counties with semi-autonomous county governments (Barasa, Manyara, Molyneux & Tsofa 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, Pinheiro, Pinheiro & Bates 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

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

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

temperature is measured on an interval scale and the coefficient of variation does not have any meaning for this type of data.

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.

To find the most suitable set of predictors, we adapted a step-down model building approach using the Satterthwaite's method to determine the p-values of the individual t-tests (Kuznetsova, Brockhoff & Christensen 2017). To be more specific, we started with a model which included the complete set of our weather measures in both fixed effects and random effects. In the following steps, we were sequentially removing the insignificant variables until we were left with a model with only significant predictors in fixed and random effects. For both fixed and random effects we considered the level of significance $\alpha = 0.05$.

According to the conditional Lagrange multiplier (LM) test developed by Baltagi & Li (1991) and Baltagi & Li (1995), the errors exhibited a within group autcorrelation structure in our models (the p-value of the LM test was 9.48×10^{-14}). To further investigate the autocorrelation structure of the errors, we estimated a number of models (with the subset of predictors chosen as described above) with ARMA(p,q) error structure. In particular, we estimated all variants of our model with ARMA(p,q) errors such that $p \leq 2$ and $q \leq 2$. Comparing the AIC criteria and using the corresponding likelihood ratio statistics, we found that the most appropriate error correlation structure was ARMA(1,1). The value of the AIC criterion of the model with ARMA(1,1) error structure was 2122.2 while the AIC was 2129.2 for the model with ARMA(1,0) errors. The p-value of the likelihood ratio test of the comparison of the model with ARMA(1,1) errors and the model with ARMA(1,0) errors was smaller than 1×10^{-4}, hence the ARMA(1,1) error structure turned out to be a better fit. The AIC criteria and the likelihood ratio tests of all the models with ARMA(p,q) errors are summarised in table 2 in the appendix.

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

	All counties		*ASAL*		*non-ASAL*	
Fixed effects:	**Estimate**	**F-value[a]**	**Estimate**	**F-value[a]**	**Estimate**	**F-value[a]**
Intercept	0.259***	19.916	0.243*	5.230	0.344**	10.061
Prec. total	0.078*	5.402	0.006	0.022	0.246***	19.386
Prec. total sq.	−0.028*	4.289	0.004	0.051	−0.128***	23.747
Prec. c. of var.	−0.079•	3.277	−0.031	0.246	−0.095	2.231
Dry spell -length	−0.067*	4.810	−0.183**	6.969	−0.012	0.163
Dry spells $\geq$ 4 d.	−0.063*	4.826	−0.157**	8.065	−0.011	0.096
Temp. - average	−0.199***	12.127	−0.213*	5.376	−0.130	1.580
Temp. std. dev.	0.042•	3.125	0.038	0.558	0.057 *	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. Discussing goodness of fit using various criteria such as AIC or alternatives to R^2.
- relative importance of the individual variables and its measures
- show VIF
- If we get the yield data for the period from 2015 onwards: Out of sample predictions and comparison with the real data

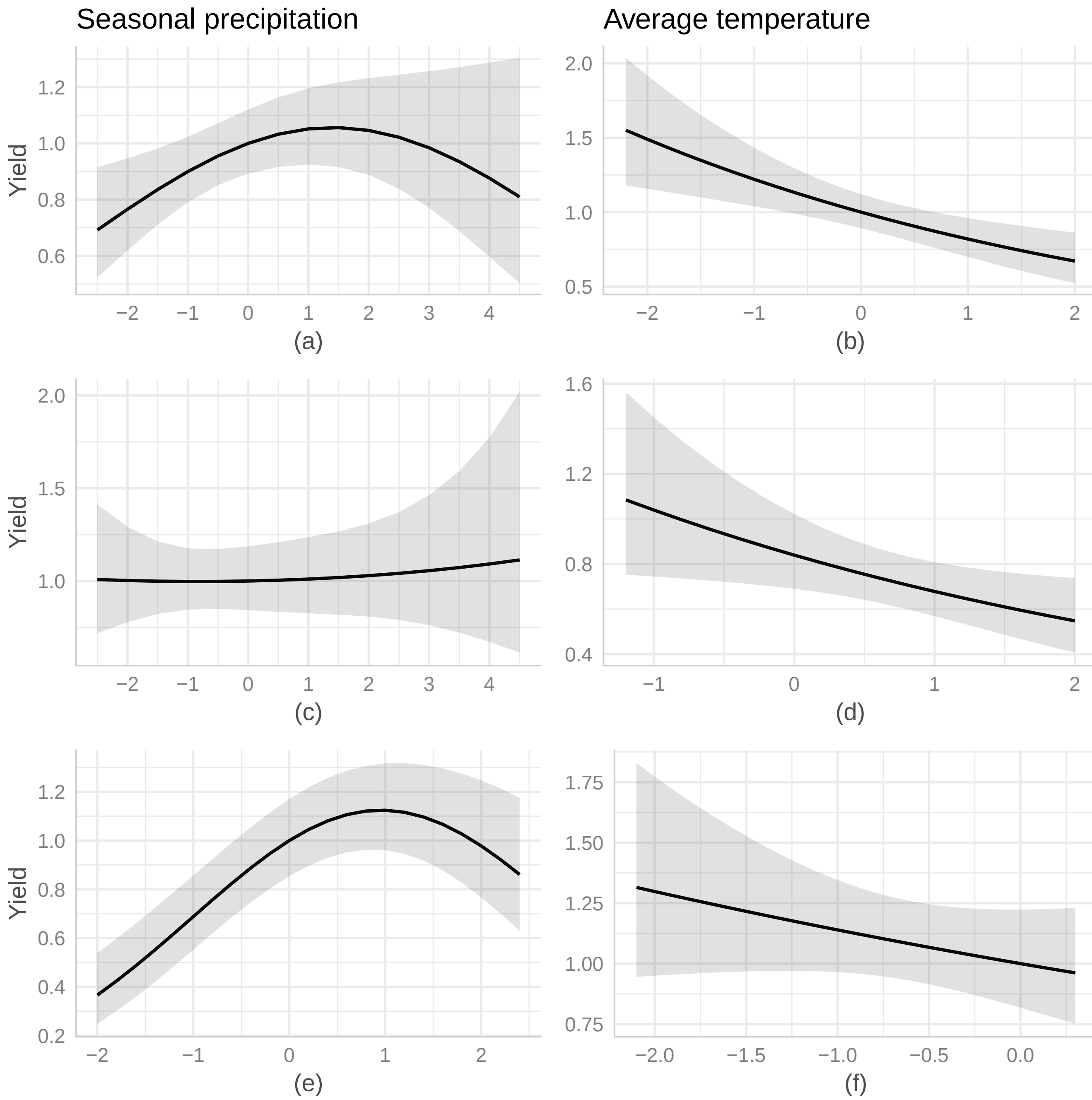

Figure 1. Predicted multiplicative marginal effects of seasonal precipitation (left column) and average seasonal temperature (right column) on maize yields. The first row (a, b) represents the model for all counties, the second row (c, d) is based on the subsample of arid and semi-arid counties (ASAL) and the third row (e, f) represents the model for the non-ASAL counties. Precipitation and temperature (x-axis) are in multiples of their standard deviations. The effects are multiplicative as the models are in log-linear form.

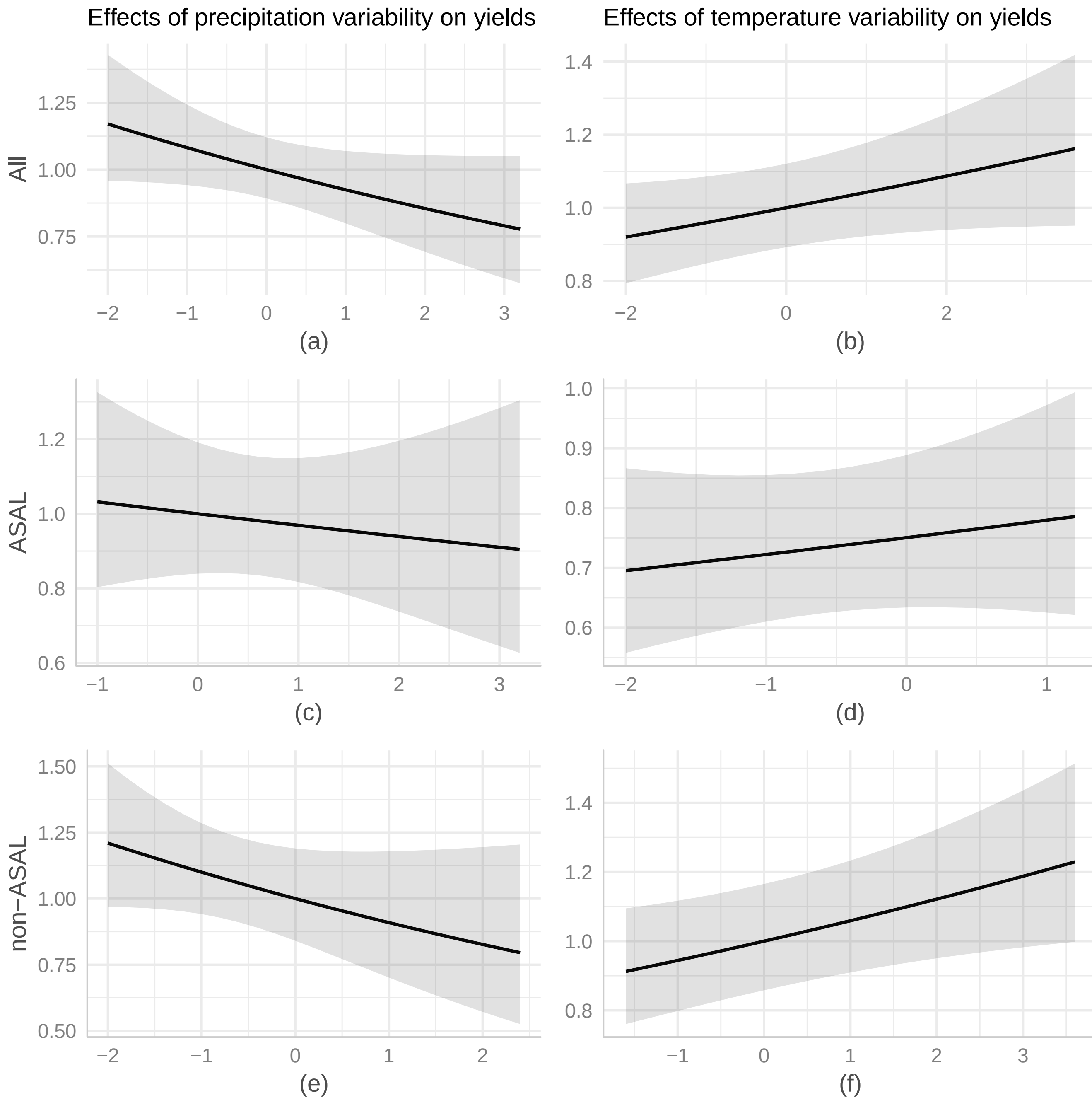

Figure 2. Predicted multiplicative marginal effects of coefficient of variation (CV) of precipitation (left column) and standard deviation (SD) of temperature (right column) on maize yields. The first row (a, b) represents the model for all counties, the second row (c, d) is based on the subsample of arid and semi-arid counties (ASAL) and the third row (e, f) represents the model for the non-ASAL counties. CV of precipitation and SD of temperature (x-axis) are in multiples of their standard deviations. The effects are multiplicative as the models are in log-linear form.

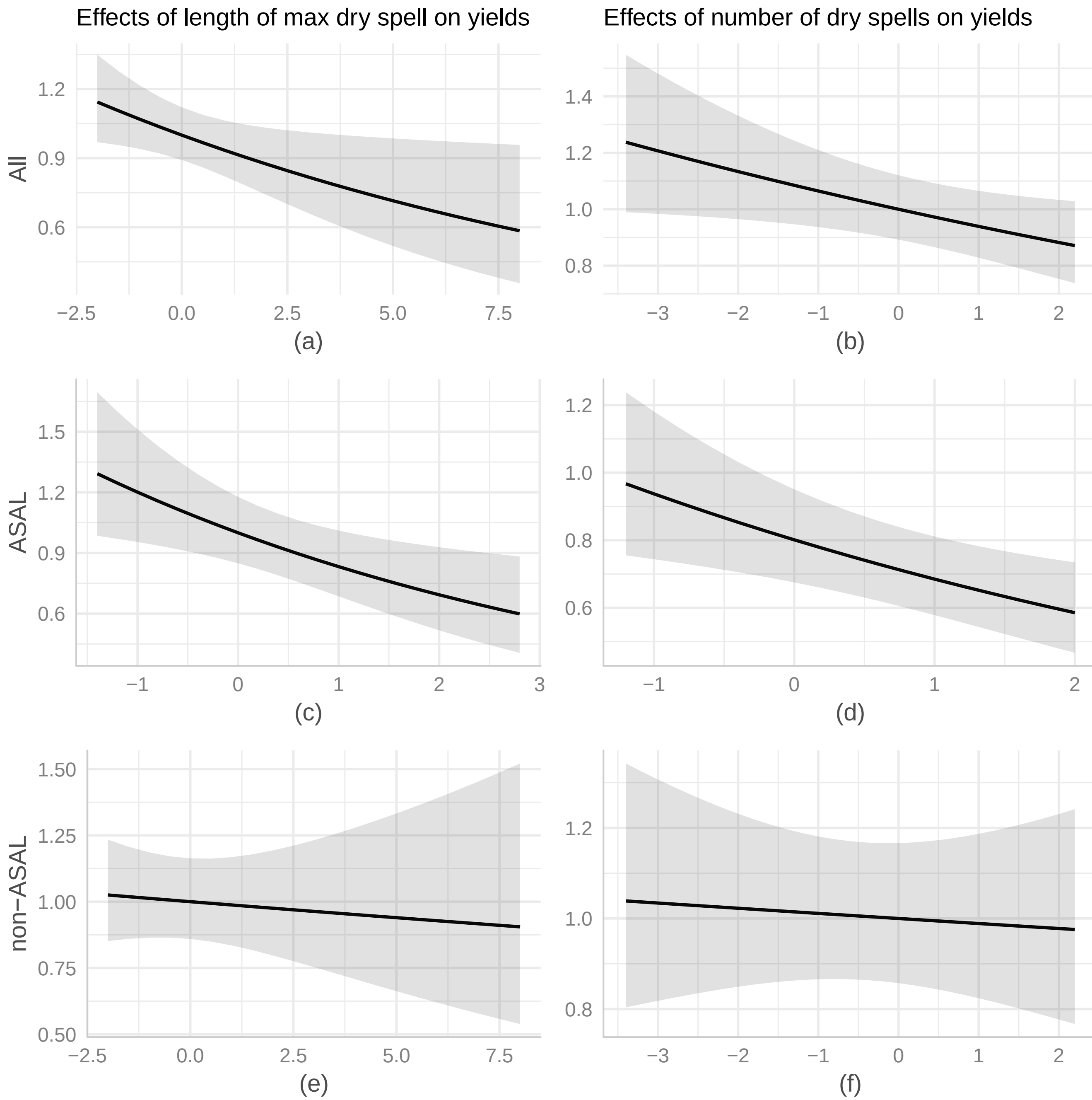

Figure 3. Predicted multiplicative marginal effects of length of maximum dry spell in days (left column) and number of dry spells lasting for four days or more (right column) on maize yields. The first row (a, b) represents the model for all counties, the second row (c, d) is based on the subsample of arid and semi-arid counties (ASAL) and the third row (e, f) represents the model for the non-ASAL counties. Maximum length of dry spell and number of dry spells (x-axis) are in multiples of their standard deviations. The effects are multiplicative as the models are in log-linear form.

Appendix

should be at the end of the main text but before list of references

Table 1. List of arid and semi-arid (ASAL) and non-ASAL counties

ASAL:	Baringo, Embu, Garissa, Isiolo, Kajiado, Kilifi Kitui, Kwale, Laikipia, Lamu, Makueni, Mandera, Marsabit, Meru, Mombasa, Narok, Nyeri, Samburu, Taita-Taveta, Tana River, Tharaka Nithi, Turkana, Wajir, West Pokot
non-ASAL:	Bomet, Bungoma, Busia, Elgeyo Marakwet, Homa Bay, Kakamega, Kericho Kiambu, Kirinyaga, Kisii, Kisumu, Machakos, Migori, Murang'a, Nakuru, Nyamira, Nyandarua, Siaya, Trans Nzoia, Uasin Gishu, Vihiga

Table 2. Comparison of models with different error autcorrelation structure

		Likelihood ratio vs. ARMA(1,1)[a]	
Error autocorrelation structure	**AIC**	**Statistic**	**p-value**
None	2205.1	86.94	$< 1 \times 10^{-4}$
ARMA(1,0)	2129.2	9.01	0.0027
ARMA(0,1)	2144.9	24.72	$< 1 \times 10^{-4}$
ARMA(1,1)	2122.2	− − −	− − −
ARMA(2,1)	2124.0	0.14	0.7066
ARMA(1,2)	2124.2	0.01	0.9143
ARMA(2,2)	2125.8	0.31	0.8545

[a] Likelihood ratio test of comparison with the ARMA(1,1) error structure model. ARMA(1,1) error structure seems to be the most suitable as all lower-order correlation structure models are rejected against ARMA(1,1) while ARMA(1,1) is not rejected against the higher order structures.

Possibly include a table of all values which I get from the lme or lme4 models summary in R, that is. correlation of the fixed effects etcetera

Maybe also a table with standard errors here

Table 3. ***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.

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