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# The Effects of weather on maize yield: New evidence from Kenya

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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 analysed the relationship between maize yields and climate. Our dataset consisted 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). Regarding the weather data, we exploited 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 to get 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 the 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. These measures are listed in table 2 in the appendix. The measures which we found significant were: Total seasonal precipitation and its squared values, average seasonal temperature, coefficient of variation (CV) of seasonal precipitation, CV of average seasonal temperature (converted into Kelvin because the Celsius scale is interval and CV does not have any meaning for data measured on an interval scale), maximum length of dry spell measured as number of consecutive dry days and the number of dry spells lasting for four days or more (for the purpose of this study we defined a dry day as a day when precipitation didn't exceed 1 mm). We did not include squared values of the average seasonal temperature in our preferred model as it was not significant and most of the past literature has not supported the evidence of the non-linear relationship between yield and average temperature.

### *2.2. Statistical approach*

Kenya consists of 47 counties with semi-autonomous county governments. 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 (Kery 2010b, Kery 2010a).

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

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

where $\mathbf{X}$ is an $n \times p$ model matrix of fixed effects, $\beta$ is a $p$-dimensional fixed-effects parameter, $\mathbf{Z}$ is an $n \times q$ model matrix for the $q$-dimensional vector of random-effects variables $\mathscr{B}$ evaluated at $\mathbf{b}$ and $\sigma$ is 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.

It was apparent from the histogram of the maize yield that the distribution of the yield data was closer to a log-normal than to a normal distribution. Therefore, we opted for a log-linear functional form of our models as is a common practice in the agricultural economics. Furthermore, we scaled all predictors by subtracting their mean and dividing them by their standard deviation to avoid convergence problems during estimation procedures.

To find the most suitable set of fixed effects, we adapted a stepwise selection procedure which minimized the Akaike's Information Criterion (AIC). The first step of the procedure was the estimation of the model with the complete set of our weather measures in the fixed effects and with the random intercepts. After this, we performed a search through the subsets of the fixed effects minimizing the AIC and allowing for steps in both 'backward' and 'forward' directions (that is removing and adding the predictors). We decided not to include number of heatwave days and average maximum daily temperature although including them as fixed effects would slightly improve the AIC. The reasons for not including them were their strong correlation with average seasonal temperature (the correlation coefficient was 0.981 in the case of maximum daily temperature and 0.517 for the number of heatwave days with the p-values smaller than $1 \times 10^{-6}$ in both cases), high variance inflation factor (VIF) of the maximum temperature (5.397) and the lack of significance of their individual t-tests (the p-values were 0.121 for the maximum daily temperature and 0.075 for the number of heatwave days). Furthermore, including heatwave days and maximum daily temperature would only lead to a small change in the AIC from 2080.877 to 2076.439 (these values differ from the AIC presented in table 3 in the appendix because the final estimates reported in table 3 were obtained using the restricted maximum likelihood (REML) whereas the models were re-estimated using the ML method for the comparison‡). In addition, the coefficients of both heatwave days and maximum daily temperature were positive, which is opposite to what we expected. Hence, we concluded that the decrease in the AIC and the positive signs are likely to be results of the high correlation with average temperature and we did not include them in our preferred specification.

After we found a set of significant fixed effects, we applied a series of likelihood ratio tests to test for the significance of random slopes. No subset of the random slopes improved the fit; therefore, besides the fixed effects, our final model only includes the random intercepts.§

To verify our results, we adapted an alternative step-down model building approach using the Satterthwaites method to determine the p-values of the individual t-tests (Kuznetsova, Brockhoff & Christensen 2017). We started with a model which included the complete set of our weather measures in both fixed effects and random effects. In

‡ REML is generally the preferred estimation method for the mixed effects models as the ML estimates of the variance component are biased, however, the REML criterion is not meaningful for comparison of the models with different fixed effects. Therefore, we re-estimated the models by ML for the purpose of comparison (Zuur, Ieno, Walker, Saveiliev & Smith 2009).

§ Although adding the random slope of CV of temperature improved the AIC from 2122.226 to 2122.110, we decided to not to include this variable in the random effects. The reason for not including the random slope is that the difference in AIC was negligible and the F-test of the comparison of the two models was insignificant favouring the simpler model (p-value= 0.128).

the first part of the procedure, insignificant random effects were removed one by one. In each iteration, the insignificant variable with the highest p-value was removed. This was repeated until only significant random effects remained. After this, we applied an analogous procedure to the fixed effects until we were left only with significant variables. As recommended in literature, we considered the level of significance $\alpha = 0.1$ for the random effects and $\alpha = 0.05$ for the fixed effects (Kuznetsova et al. 2017). This method led us to the same results as those obtained with our primary AIC-based method described above.

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 $1.1 \times 10^{-13}$). 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 an 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 the 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 0.003, 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 3 in the appendix.

## 3. Results

Besides our main model estimated for all counties of Kenya, we estimated the same specification for two subsamples of the Kenyan counties. In particular, we estimated the model for the subsample of the ASAL counties and for the subsample of the non-ASAL counties separately to compare the effects of various weather characteristics across the two areas with significantly different climate. The estimates of all three models are summarised in table 1. The first two columns represent the model for all counties, the third and fourth columns include estimates for the subsample of the ASAL counties and the last two columns describe the estimates based on the subsample of the non-ASAL counties. All predictors were standardised, therefore the estimates and the corresponding p-values can be interpreted as measures of relative importance. As an additional measure of relative importance we included F-values of the type *III* analysis of variance (ANOVA) in table 1. The type *III* ANOVA is conducted using the marginal rather than the sequential sum of squares. That is, for each variable, the F-test is a test of significance of that part of explained sum of squares which can be contributed to the particular explanatory variable. In other worlds, the F-value is a test statistic of comparison of the preferred model (with all the variables in table 1 in our case) and the model without the explanatory variable in question but including all other predictors. The main advantage of the type *III* ANOVA is that the test statistic does not depend on the order in which the effects are entered in the model.

The preferred specification has a log-linear functional form, therefore the estimates in table 1 are not directly interpretable as marginal effects and the coefficients are multiplicative. The predicted marginal effects of all coefficients are depicted in figures 1 in this section and in figures 1 and 2 in the appendix. The units of all predictors in all three figures are multiples of their standard deviations since the predictors were standardised. For the values of the marginal effects smaller than one, the effect on yield is negative while marginal effects higher than one can be interpreted as a positive effect. If, for example, a marginal effect of an explanatory variable $x$ being equal to its standard deviation is 1.1, one should interpret this as follows: if $x$ is equal to its standard deviation, the dependent variable (in our case maize yield) is 1.1 times higher than it would be if the explanatory variable $x$ was equal to its mean (which is zero in figure 1 in this section and in figures 1 and 2 in the appendix as the predictors were standardised).

The exponents of the estimates (which can be interpreted as the additive marginal effects on yield) can be found in table 4 in the appendix.

In the following few paragraphs, we will discuss the estimates based on the sample of all counties and after that we will focus on the estimates based on the two subsamples.

**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*** | 19.908 | 0.241* | 5.084 | 0.342** | 9.891 |
| Prec. total | 0.078* | 5.358 | 0.007 | 0.028 | 0.244*** | 19.140 |
| Prec. total sq. | −0.028* | 4.263 | 0.003 | 0.037 | −0.127*** | 23.384 |
| Prec. c. of var. | −0.079• | 3.278 | −0.031 | 0.237 | −0.097 | 2.326 |
| Dry spell -length[b] | −0.067* | 4.800 | −0.181** | 6.841 | −0.012 | 0.164 |
| Dry spells ≥ 4 d. | −0.063* | 4.848 | −0.156** | 8.032 | −0.011 | 0.087 |
| Temp. - average | −0.199*** | 12.010 | −0.214* | 5.409 | −0.128 | 1.525 |
| Temp. c. of var. | 0.042• | 2.961 | 0.032 | 0.355 | 0.058* | 5.372 |
| **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.
b In number of days.

The estimates of the model of the whole sample are summarised in the first two columns of table 1. Consistently with our assumptions, seasonal precipitation and average temperature have significant effects on yield. As we expected, the effect of temperature is negative. The linear term of precipitation is positive while the squared term of precipitation is negative and as we can see in figure 1(a), the plot of the marginal effect of precipitation is hill-shaped. That is, the effect of precipitation is negative and increasing if the amount of precipitation is below its mean and the marginal effect increases with the amount of precipitation until it reaches 1.403 times its standard deviation. At this point, the effect starts to decrease with increasing precipitation and it becomes negative again once the amount of precipitation reaches 2.805 times its standard deviation. Therefore, too much rain is harmful for agricultural yield as well as not enough rain. This is intuitive mainly because extreme rainfall can cause flooding which is damaging for yield.

Other fixed effects which we found significant include CV of temperature and precipitation and length and number of dry spells (see the first column of table 1). As it is apparent from figures 1(a)-(b) and 2(a)-(b) in the appendix, the relationship of maize yield and each of these variables is linear. In accordance with our expectation, the yield decreases with increasing CV of precipitation. However, the yield seems to increase with increasing variability of temperature which is counter-intuitive......*reasoning...*

As we can see in figures 2(a) and 2(b) in the appendix, yield declines with increasing number of dry spells and with increasing length of maximum dry spell linearly. This is in accordance with our expectations.

According to the magnitude of the standardised regression coefficients and F-values in the first two columns of table 1, the most important variable is average seasonal temperature which appears to be much more important than the remaining predictors. The second most important variable is total seasonal precipitation. The value of the F-statistic corresponding to temperature is 12.010 while the F-statistic of the linear term of cumulative precipitation is equal to 5.358 and the F-statistic of its quadratic term is 4.263. Similarly, according to the Satterthwaite's p-values, average temperature is the most important predictor as the corresponding Satterthwaite's p-value is equal to $6 \times 10^{-4}$ which is much lower than the p-values of the other explanatory variables.

We will now discuss and compare the results of the models estimated for the subsample of the ASAL counties (the third and fourth columns of table 1) and the model estimated for the subsample of the non-ASAL counties (the fifth and sixth columns of table 1). Interestingly, different predictors were found significant for each of the two subsamples. Regarding the subsample of the ASAL counties, the only significant fixed effects are average seasonal temperature and length and number of dry spells. According to our expectation, all three variables have a negative sign. On the other hand, the variables which were found significant for the subsample of the non-ASAL counties are seasonal precipitation (positive) and its square (negative) and CV of temperature (positive). According to the F-statistics, the most important explanatory variables for the ASAL counties are number of dry spells and length of the longest dry spell with values of the F-statistics equal to 8.032 and 6.841, respectively. The F-statistic of the average temperature is 5.409 and the F-statistics of the remaining predictors are lower than one. However, according to the magnitude of the standardised regression coefficients, the average temperature is the most important as its coefficient is equal to $-0.214$ while it is equal to $-0.156$ and $-0.181$ for the number of dry spells and the length of maximum dry spell, respectively.

With regard to the subsample of the non-ASAL counties, the most important explanatory variables based on the F-statistic are precipitation and its squared term. The F-statistic of the squared values of precipitation is 23.384 and the F-value of the linear term of precipitation is 19.140. The variable with the third highest value of the F-statistic is CV of temperature and the corresponding F-statistic is equal to 5.372. Hence, the difference in importance of the precipitation and CV of temperature is relatively large. The standardised regression coefficient of squared precipitation is equal to $-0.127$, the coefficient of the linear term of precipitation is 0.244 and the standardised regression coefficient of CV of temperature is 0.058. In terms of the magnitude of the coefficients, the average temperature is also relatively important as the value of its coefficient is $-0.128$. However, average temperature is insignificant according to the Satterthwaite's p-value and also the value of its F-statistic is relatively low (1.528).

To sum up, temperature is much more important for the ASAL counties than for the non-ASAL counties where temperature is isignificant. On the other hand, precipitation is not significant for the ASAL counties while it is strongly significant for the non-ASAL counties. This is illustrated in figures 1(c)-(f) in this section. The plot of the marginal effect of precipitation is almost flat for the ASAL counties (figure 1(c) in this section) while it is hill-shaped and steep for the non-ASAL counties (figure 1(e) in this section) similarly as in the case of the whole sample. As one can see in figures 1(d) and 1(f) in this section, the marginal effect of temperature is linear and decreasing for the both subsamples . Marginal effects of the remaining predictors are depicted in figures 1(c)-(f) and 2(c)-(f) in the appendix.

The AIC is an important criterion for comparison of competing models, however it does not provide any information about the absolute goodness of fit. In order to assess the absolute goodness of fit of a model, a different measure is needed. For a simple linear regression, the coeffiecient of determination $R^2$ or its adjusted version is typically used for this purpose. Nevertheless, obtaining the $R^2$ or the adjusted $R^2$ is not straightforward for linear mixed models or for models estimated by the maximum likelihood in general. In this study, we used the coefficient of determination of generalized linear mixed-effects models introduced by (Nakagawa & Schielzeth 2013). For each of our samples (all counties, ASAL and non-ASAL), we present two versions of the statistic in table 2. These include marginal $R^2$ which can be interpreted as the variance explained by the fixed effects and the conditional $R^2$ which can be interpreted as the variance explained by both fixed effects and random effects. In our case, the only random effects are the

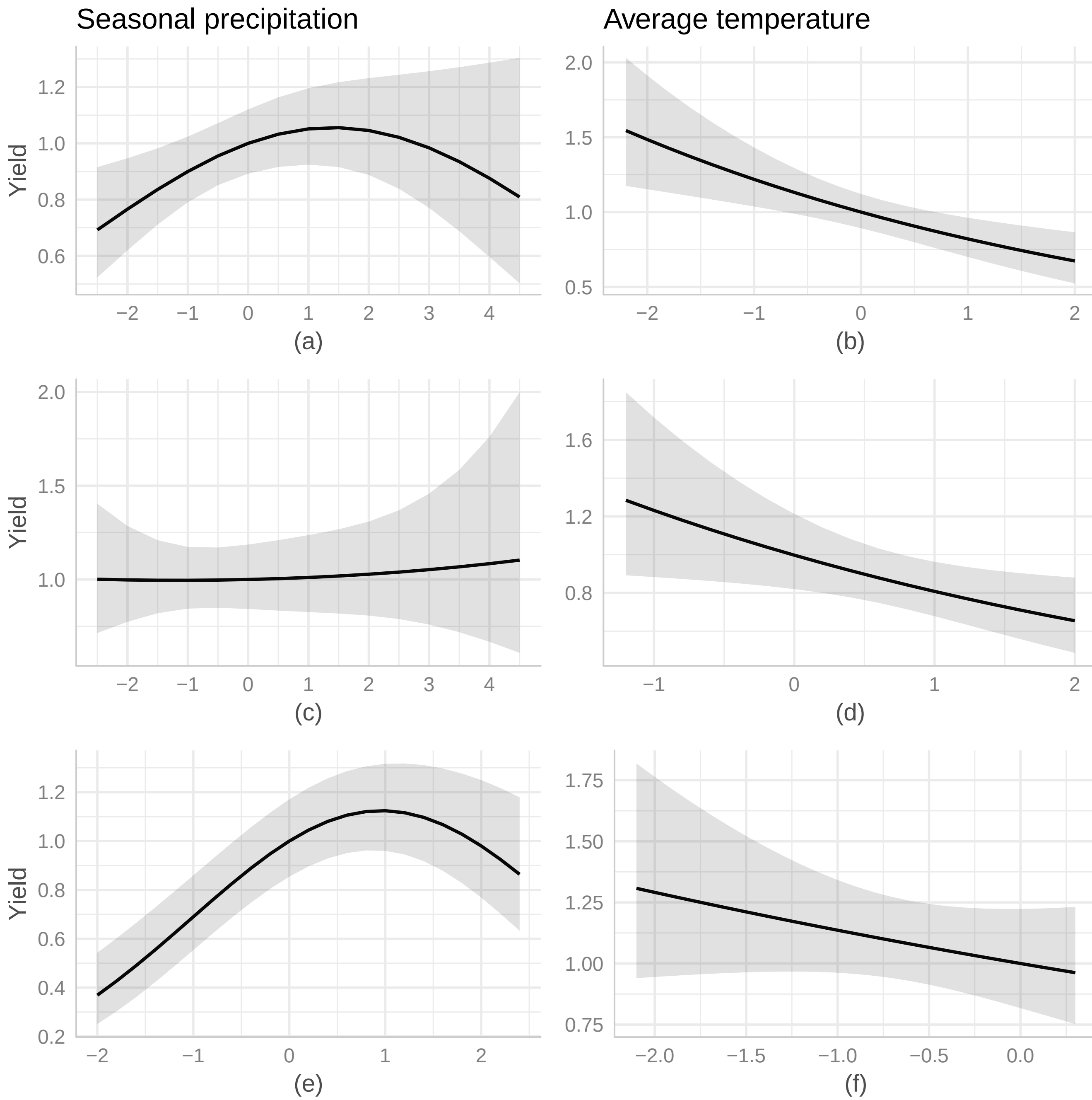


**Figure 1.** Predicted multiplicative marginal effects of seasonal precipitation (left column) and average seasonal temperature (right column) on maize yield assuming that all other variables are fixed at their means (which is zero, as the predictors were standardised). The first row (a, b) represents 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 as the models were standardised. The effects are multiplicative as the models are in the log-linear form.

intercepts, hence the difference between the two variants is the variance explained by the random intercepts. As is apparent from table 2, the fixed effects explain about 30% of the variance in case of the model for all counties, about 13% of the variance in the model based on the ASAL counties and about 15% of the variance in the model based on the non-ASAL counties.

**Table 2.** Coefficient of determination $R^2$ for mixed models

| **Sample:** | Marginal[a] | Conditional[b] |
|---|---|---|
| All counties | 0.300 | 0.526 |
| ASAL | 0.134 | 0.353 |
| non-ASAL | 0.153 | 0.436 |

*Notes:* The coefficient of determination from generalised linear mixed-effects models. The statistic is based on (Nakagawa & Schielzeth 2013).

a The marginal $R^2$ is interpreted as the variance explained by the fixed effects

b The conditional $R^2$ is explained by both fixed affects and random effects (in our case by fixed effects and random intercepts)

Following a standard practise, we calculated the variance inflation factors (VIF) of the explanatory variables to test for presence of multicollinearity. With only two exceptions, the VIF is below 2 for all predictors in our final models. For CV of precipitation, the value of VIF is 2.172 in the model of all counties, 2.147 in the model for the subsample of the ASAL counties and it is equal to 2.182 in the model based on the subsample of the non-ASAL counties. These values are well below the threshold of problematic multicollinearity. The other exception is the linear term of seasonal precipitation as its VIF is 2.407 in the model for the non-ASAL counties, probably due to presence of the squared term of precipitation. However, 2.407 is below the threshold of the problematic multicollinearity and the VIF of precipitation is below 2 in the other two models. Therefore, we can conclude that the models do not suffer from presence of multicollinearity.

**Table 3.** Cross validation: Mean absolute prediction error scaled by IQR

| Sample: | All covariates | Only seasonal | Naive forecast |
|---|---|---|---|
| All counties | 0.3811 | 0.3889 | 0.4277 |
| ASAL | 0.5300 | 0.5342 | 0.5835 |
| non-ASAL | 0.2845 | 0.3858 | 0.4510 |

*Notes:* The coefficient of determination from generalised linear mixed-effects models. The statistic is based on (Nakagawa & Schielzeth 2013).

a The marginal $R^2$ is interpreted as the variance explained by the fixed effects
b The conditional $R^2$ is explained by both fixed affects and random effects (in our case by fixed effects and random intercepts)

**Table 4.** Cross validation: Mean absolute prediction error

| Sample: | All covariates | Only seasonal | Naive forecast |
|---|---|---|---|
| All counties | 0.3599 | 0.3673 | 0.4040 |
| ASAL | 0.134 | 0.353 | |
| non-ASAL | 0.153 | 0.436 | |

*Notes:* The coefficient of determination from generalised linear mixed-effects models. The statistic is based on (Nakagawa & Schielzeth 2013).

a The marginal $R^2$ is interpreted as the variance explained by the fixed effects
b The conditional $R^2$ is explained by both fixed affects and random effects (in our case by fixed effects and random intercepts)

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

## 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.** Precipitation and temperature measures considered

- Total precipitation over the rainy season
- Coefficient of variation of the precipitation during the rainy season
- Maximum length of dry spell during the rainy season (in number of days)
- Number of dry spells during the rainy season: a dry spell defined as 4 consecutive days without rain or more[a]
- Number of dry spells during the rainy season: a dry spell defined as 10 consecutive days without rain or more[a]
- Number of dry spells during the rainy season: a dry spell defined as 20 consecutive days without rain or more[a]
- Average temperature during the rainy season
- Standard deviation of temperature during the rainy season
- Cumulative degree days during the rainy season (excluding the days when maximum temperature above 30°C or below 10°C
- Number of heatwave days during the rainy season when max. temperature > 35°C
- Maximum daily precipitation - to control for possible floods
- Sum of precipitation amount on days where precipitation is above $90^{th}$ percentile of precip. of the whole period[b]
- Sum of precipitation amount on days where precipitation is above $95^{th}$ percentile of precip. of the whole period[c]
- Sum of precipitation amount on days where precipitation is above $99^{th}$ percentile of precip. of the whole period[d]
- Number of days where precipitation is above $90^{th}$ percentile of precip. of the whole period[b]
- Number of days where precipitation is above $95^{th}$ percentile of precip. of the whole period[c]
- Number of days where precipitation is above $99^{th}$ percentile of precip. of the whole period[d]

[a] Threshold for a dry day was considered 1mm.
[b] $90^{th}$ percentile was calculated for the subsample of wet days, that is the days where precipitation is above or equal to 1mm.
[c] $95^{th}$ percentile was calculated for the subsample of wet days, that is the days where precipitation is above or equal to 1mm.
[d] $99^{th}$ percentile was calculated for the subsample of wet days, that is the days where precipitation is above or equal to 1mm.

**Table 3.** Comparison of models with different error autcorrelation structure

| | | Likelihood ratio vs. ARMA(1,1)[a] | |
|---|---|---|---|
| **Error autocorrelation structure** | **AIC** | **Statistic** | **p-value** |
| *None* | 2205.4 | 87.17 | $< 1 \times 10^{-4}$ |
| ARMA(1,0) | 2129.2 | 8.99 | 0.0027 |
| ARMA(0,1) | 2145.0 | 24.73 | $< 1 \times 10^{-4}$ |
| ARMA(1,1) | 2122.2 | $---$ | $---$ |
| ARMA(2,1) | 2124.1 | 0.15 | 0.6990 |
| ARMA(1,2) | 2124.2 | 0.01 | 0.9181 |
| ARMA(2,2) | 2125.9 | 0.31 | 0.8549 |

[a] Likelihood ratio test of a comparison of the model in each row against 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 any of the higher order structures.

**Table 4.** **Mixed effects model:** exponents of the coefficient estimates Log of maize yield and weather, ARMA(1,1) errors

| **Fixed effects:** | ***All counties*** | ***ASAL*** | ***non-ASAL*** |
|---|---|---|---|
| Intercept | $1.296^{***}$ | $1.272^{*}$ | $1.408^{**}$ |
| Prec. total | $1.081^{*}$ | 1.007 | $1.277^{***}$ |
| Prec. total sq. | $0.973^{*}$ | 1.003 | $0.881^{***}$ |
| Prec. c. of var. | $0.924^{\bullet}$ | 0.970 | 0.907 |
| Dry spell -length | $0.935^{*}$ | $0.834^{**}$ | 0.988 |
| Dry spells $\geq$ 4 d. | $0.939^{*}$ | $0.855^{**}$ | 0.989 |
| Temp. - average | $0.820^{***}$ | $0.808^{*}$ | 0.880 |
| Temp. c. of var. | $1.043^{\bullet}$ | 1.032 | 1.060 $*$ |
| **Random effects:** | | | |
| Intercept | | | |
| *Number of observations:* | 1300 | 698 | 602 |

*Notes:* Standard errors in brackets; $^{\bullet}$ $p < 0.1$; $^{*}$ $p < 0.05$; $^{**}$ $p < 0.01$; $^{***}$ $p < 0.001$

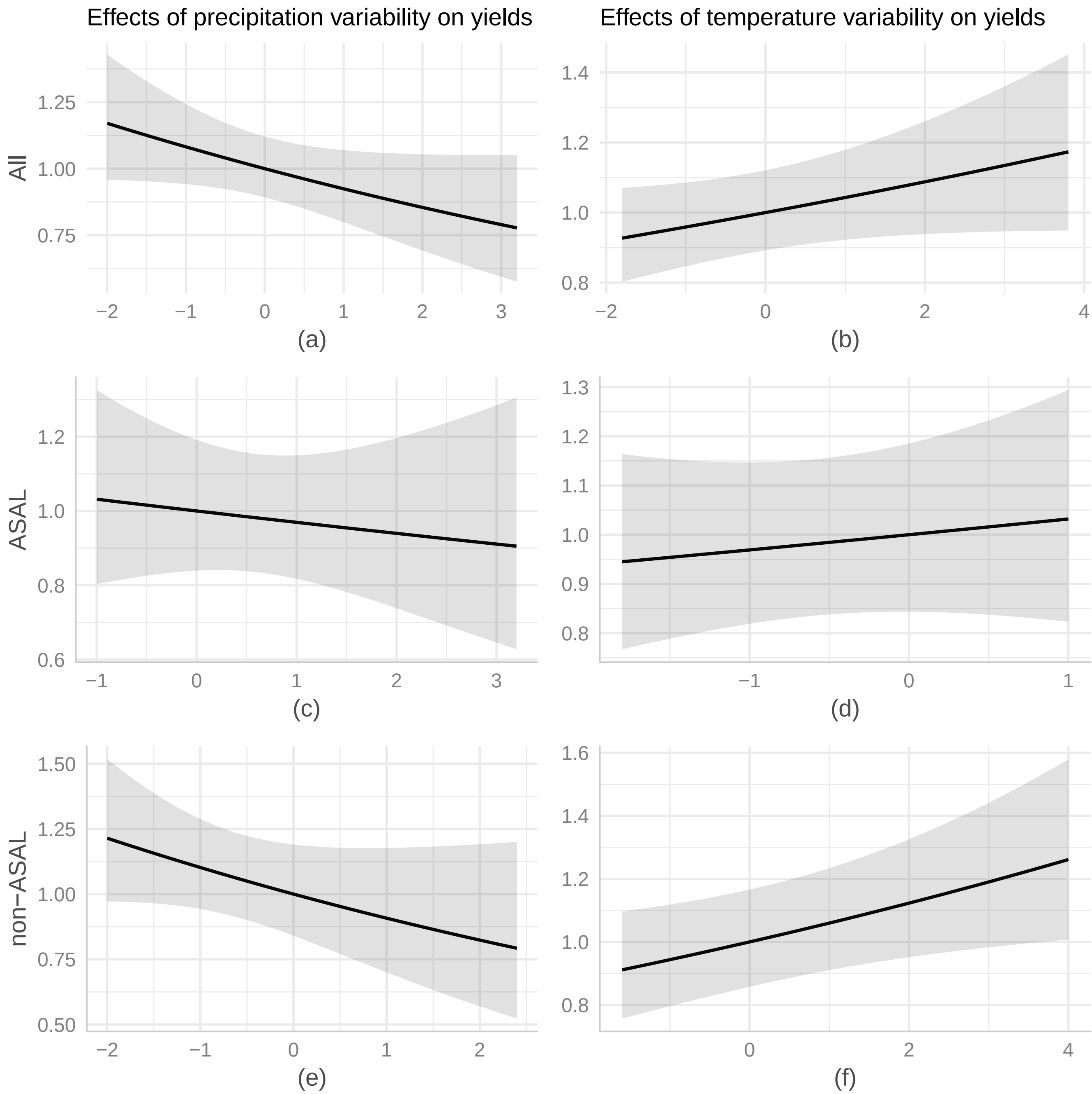


**Figure 1.** Predicted multiplicative marginal effects of coefficient of variation (CV) of precipitation (left column) and CV of temperature (right column) on maize yield assuming that all other variables are fixed at their means (which is zero, as the predictors were standardised). The first row (a, 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 temperature (x-axis) are in multiples of their standard deviations as the models were standardised. The effects are multiplicative because the models are in the log-linear form.

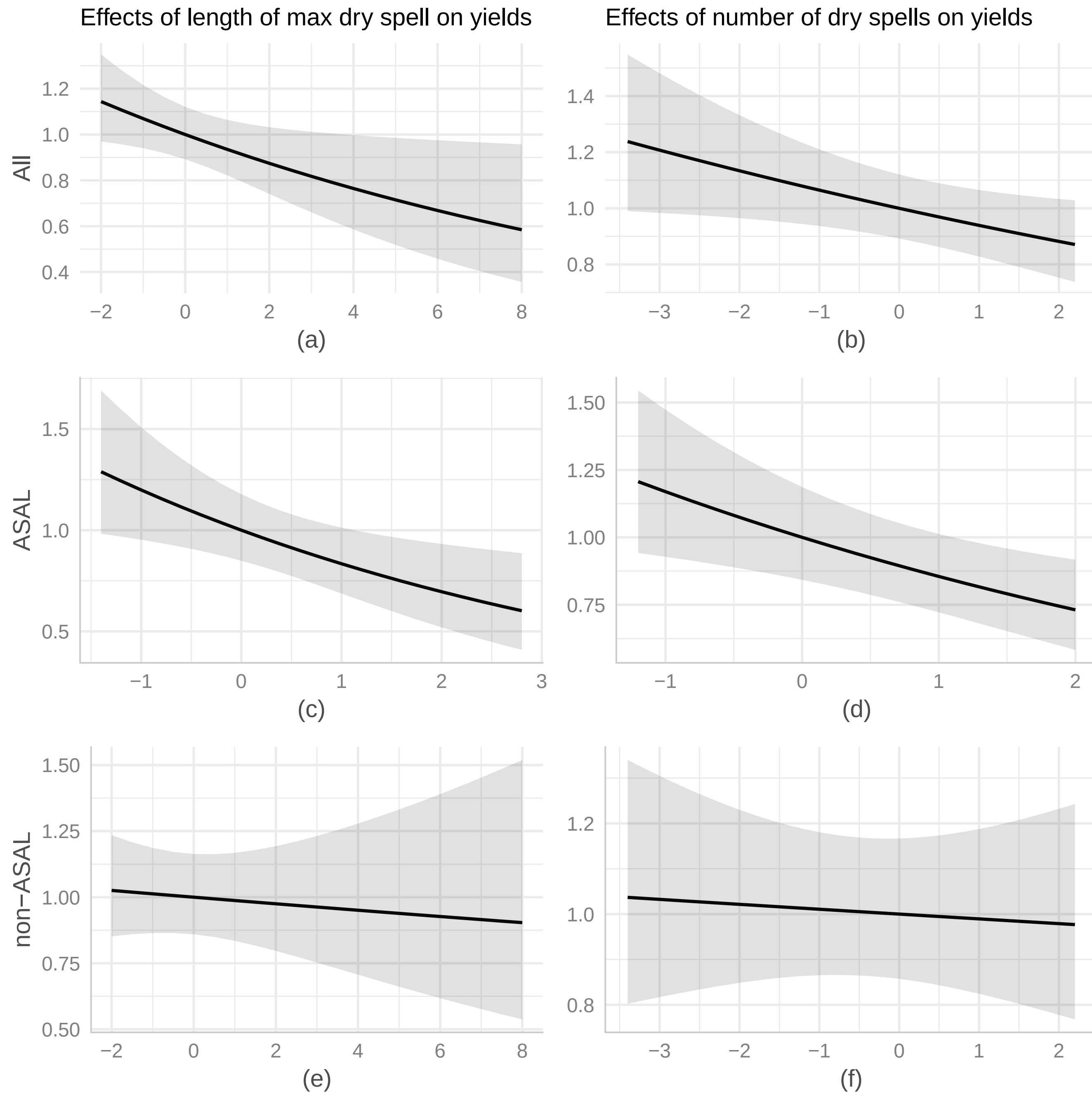


**Figure 2.** Predicted multiplicative marginal effects of length of maximum dry spell in days (left column) and number of dry spells lasting for four days or more (right column) on maize yield assuming that all other variables are fixed at their means (which is zero, as the predictors were standardised). 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 as the models were standardised. The effects are multiplicative because the models are in the log-linear form.

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