Relationship of Weather and Maize Yields in Kenya

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October 2018

Abstract

We explore an unprecedented dataset of almost $6,000$ observations to identify main predictors of climate knowledge, climate risk perception and willingness to pay for climate change mitigation. Among nearly 70 potential explanatory variables we detect the most important ones using multisplit lasso estimator. Importantly, we test significance of individuals' preferences about time, risk and equity. Our study is innovative as these behavioural characteristics were recorded by including experimental methods into a live sample survey. This unique way of data collection combines advantages of survey and experiments. The most important predictors of environmental attitudes are numeracy, cognitive ability, ideological world-view and inequity aversion.

JEL classification: Q54, Q58, D80

Keywords: Climate change, climate knowledge, climate policy, lasso, risk perception, willingness to pay

1 Introduction

Findings:

- OND last year dry spell, max rain very important for Maize, but cumulative precipitation for the same period not so important
- Mar-Sept last year temperature very important for maize yields
- SD temperature last year positive and significant
- dry spell 20 MAM last year important (but not dry spell MAM10)
- interesting. Precipitation 2 months MAM last year very significant and positive
- mean temp last year negative and significant, hill shaped

New findings:

- The yields seem to be more responsive to weather on west than on east

The purpose of this paper is to contribute to better understanding of effects of drought on food security in Kenya and to improve early warning systems. shifting from reactive to proactive approach As a measure of food security we use agricultural maize yields and as measures of drought we use variables created by aggregating daily temperature and precipitation data.

Strong downwards trend in precipitation has 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 also in the areas with decline in total rainfall (Trenberth et al., 2007). Trenberth et al. (2014) argue that as a consequence of global warming, dry areas have strong tendency to get drier while wet areas are getting wetter.

A number of previous studies were focused on estimation of relationship of agricultural yield and measures of precipitation and temperature in Kenya or in other countries in Sub-Saharan Africa. Common measures of precipitation and temperature are 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). Adejuwon (2004) focused on the Sub-Saharan West Africa and he used total rainfall for: *(i)* The first month of the period from sowing to harvesting (June) *(ii)*: The first two months of the period from sowing to harvesting (June and July) and *(iii)*: The first three months of the period from sowing to harvesting (June, July and August). Based on his results, June and July are the most important for crop yield. Other studies are based on seasonal totals or means..(..) Some authors have utilized simulated daily extremes, averages or daily measures of variance (Chipanshi et al. 2003; Abraha and Savage 2006; Schulze et al. 1993). Another measure which appeared to be associated with maize yields in the past literature is wet and dry day counts per months .. The definition of wet and dry days vary across the studies.

describes simulate potential maize yields using generated weather data and generated weather a Erin Lentz, can we cite her paper???

Blignaut: annual averages Chipanschi: daily maximum and minimum temperatures Giannoukopoulos: number of hw days and so... Laux et al.: daily Tmax ¿30C Lobell et al. 2008: Monthly temp and prec. Lobell and Burke 2010: Temp. growing season average, precip:growing season total

(Abraha and Savage 2006; Adejuwon 2004; Ben Mohamed et al. 2002; Blignaut et al. 2009; Chipanshi et al. 2003; Giannakopoulos et al. 2009; Laux et al. 2010; Leemans and Solomon 1993; Lobell et al. 2008; Lobell and Burke 2010; Sagoe 2006; Schulze et al. 1993; Thornton et al. 2009; Tingem et al. 2008, 2009; Walker and Schulze 2008)

Add more studies. Then separate somehow into groups of different topics..

2 Methodology

Prior we started our research, we had to answer the following questions: How do we measure food security? And how do we measure drought? To answer the first questions, the measure which has been used as a proxy for food security in the literature are as follows:

The other important questions which need to be answered before starting our research are: How is drought defined? What are the ways of measuring drought? and How shall we measure drought for the purpose of our study? 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).

Numerous definitions of drought and their role have been reviewed and discussed by Wilhite and Glantz (1985) and Wilhite (2000). They 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 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 (Heim, 2002; Wilhite and Glantz, 1985; Wilhite, 2000).

For an extensive overview of various drought indices see Heim (2002), Monacelli et al. (2005), Svoboda et al. (2016) or Zargar et al. (2011). Keyantash and Dracup (2002)

[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).

quantify, evaluate and compare number of drought indices for meteorological, hydrological and agricultural forms of drought. Based on several criteria they conclude that rainfall deciles and SPI perform the best for meteorological drought.

In the recent period, remote sensing data have been collected and used increasingly to monitor levels of greenness and closely related vegetation conditions. Based on these data, the vegetation condition index (VCI) has been developed for quantifying drought strength and severity (Klisch and Atzberger, 2016).

A description of other drought indices and measures can be found in Appendix 1.

We initially analysed SPEI and VCI indices and we tried to use them as input variables for our analysis. However, there were some serious problems with these measures.....

Therefore we opted for a different approach to gauging drought severity. In particular, we decided to utilize daily precipitation data from...CHIRPS?? with resolution... and daily temperature data from..at resolution..... The frequency of the maize yield data is yearly while we have daily weather data available. Hence, the weather data need to be aggregated in order to obtain a dataset conformable with the yield data. There are many possibilities how to aggregate daily weather data. Based on the literature research in Section 1, we decided to create a set of the following weather aggregates:

We then searched for the best subset of predictors of yield among the variables listed...

The estimation function can be written as (?):

$$\underset{(\beta_0,\beta)\in\mathbb{R}^{(p+1)}}{min} \boldsymbol{R}_\lambda(\beta_0,\beta) = \underset{(\beta_0,\beta)\in\mathbb{R}^{(p+1)}}{min} \left[\frac{1}{2N}\sum_{i=1}^{N}(y_i-\beta_0-x_i^\intercal\beta)^2+\lambda\sum_{j=1}^{p}(|\beta_j|)\right], \qquad (1)$$

In line with common practice, we compute estimator (1) for a series of λ and then we choose a preferred value of λ using cross-validation (**?**).

$$Q_j(\gamma) = min\left\{1, q_\gamma(\{P_j^{(h)}/\gamma; h = 1, ..., H\})\right\}, \tag{2}$$

where and $q_\gamma(\cdot)$ is the (empirical) γ-quantile function. We will further refer to this procedure as a multisplit lasso.

3 Data

All data used in this study except of predicted income and population density, which we use in robustness tests, were collected in the survey conducted by **?**.

In Section **??** we use an alternative measure of income as a robustness test. In particular, this estimated income is obtained from a regression model based on data from Annual Survey of Hours and Earnings (ASHE). More specifically, the predicted income is based on age, gender, occupation, sector and education.

Table 1: *Sex and age distribution*
of the sample and the population

	Sample		UK population[a]	
Age range	**Male**	**Female**	**Male**	**Female**
18 – 24	9.8%	9.4%	6.2%	6.0%
25 – 34	10.0%	10.3%	9.0%	9.1%
35 – 44	7.8%	8.3%	8.6%	8.8%
45 – 54	8.1%	9.4%	9.3%	9.6%
55 – 64	7.4%	8.4%	7.5%	7.8%
65 – 74	4.1%	4.8%	6.2%	6.7%
75 – 80	0.1%	0.1%	2.4%	2.8%

[a] Population data are from the Office of National Statistics, Population Estimates of UK, England and Wales, Scotland and Northern Ireland Mid 2014, Table MYE2.

3.1 Climate variables

Descriptive statistics of our climate variables are summarised in Table 2.

Table 2: ***Dependent variables:*** *Descriptive statistics*

Variable:	**Mean**	**St. dev.**	**Min**	**Max**
Climate change knowledge	3.851	1.266	1	8
Climate change seriousness perception	6.622	2.249	0	10
Climate versus policy effects perception	5.370	2.315	0	10
WTP - gas and electricity tax (£ per year)	123.900	105.459	0	500
WTP - duty on transport fuel (pence per year)	20.530	22.518	0	100

To investigate opinions about seriousness of climate change, the respondents were asked the following question: 'How serious a problem do you think climate change is at this moment?' Using an interactive slider, the respondents answered an integer value between 0 and 10 where min = 0 and max = 10 (as it was noted just below the slider). In a similar way, the respondents were asked if they feel to be more affected by climate change or by climate policy. The wording of the question was: 'Which affects you and your way of life more, climate change or policies to reduce greenhouse gas emissions?' Again, the respondents provided answers on an integer scale from 0 (climate policy) to 10 (climate change) using a slider. Relative frequencies of climate seriousness perception and climate versus policy perception are summarised in Table 3.

Table 3: ***Dependent variables:*** *Relative frequencies (%)*

Variable:	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Climate knowledge	0.0	1.7	11.4	30.4	25.4	20.9	8.6	1.6	0.1	N/A	N/A
Climate seriousness perception	3.3	2.8	5.4	8.1	8.9	27.2	14.0	12.8	8.3	4.1	5.0
Climate vs. policy perception[a]	2.1	1.5	2.5	3.8	4.6	9.8	18.5	21.7	16.7	8.6	10.4

Notes: Total number of observations: 5749

a Higher number means greater concern about climate change, lesser concern about climate policy.

3.2 Behavioural variables

To estimate the social value orientation, respondents played six dictator games with the same questions as in ?. The ring measure of social value orientation which we use in our models is defined as

$$R = \arctan \frac{\sum_{i=1}^{N} P_O - 50N}{\sum_{i=1}^{N} P_S - 50N}, \tag{3}$$

4 Results and discussion

In this section we describe our results and discuss their interpretation.

In the tables which summarise the estimates of lasso below, p-values of some of the explanatory variables are equal to one. These variables were not selected by the lasso in most of the sample splits. They are, however, included in the tables because they represent either a category of a nominal variable whose other category was selected by the lasso or a linear term of a variable whose quadratic term was selected by the lasso.

Table 4: ***Linear mixed effects models:*** *Maize yield and weather*

Fixed effects:	**Scaled**		**Unscaled**[a]	
	Estimate	*p-value*	*Estimate*	*p-value*
Intercept	-0.059	0.646	1.379	$1 \times 10^{-7***}$
Prec. cum. MAM+OND lag 1, east	0.054	0.041^{*}	3×10^{-4}	0.177
Prec. cum. MAM lag 1, west	0.025	0.477	3×10^{-4}	0.197
Temp. avg. Mar.-Sep. lag 1, east	-0.045	0.244	-0.029	0.001^{**}
Temp. avg. Mar.-Sep. lag 1, west	-0.130	0.0001^{***}	-0.027	0.001^{**}
Prec. max OND, east	0.133	0.013^{*}	0.004	$0.085^{\bullet}$
Prec. max OND, west	0.144	0.004^{**}	0.011	$9 \times 10^{-6***}$
Temp. sd. Oc.-Mar. lag 1, east	0.049	0.199	0.075	0.369
Temp. sd. Oc.-Mar. lag 1, west	0.225	4×10^{-12} ***	0.494	7×10^{-12} ***
Random effects:				
Intercept				
Prec. cum. MAM+OND lag 1				
Prec. max OND				
Temp. avg. Mar.-Sep. lag 1				

Notes: 584 observations; $^{\bullet}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

a The variety with unscaled variables fails to converge.

Table 5: ***Mixed effects model:*** *Log of maize yield and weather*

Fixed effects:	*Estimate*	*p-value*
Intercept	0.158	$0.086^{\bullet}$
Prec. cum. MAM+OND lag 1, east	0.066	0.008^{**}
Prec. cum. MAM lag 1, west	-0.006	0.861
Temp. avg. Mar.-Sep. lag 1, east	-0.036	0.292
Temp. avg. Mar.-Sep. lag 1, west	-0.081	0.008^{**}
Prec. max OND, east	0.081	$0.056^{\bullet}$
Prec. max OND, west	0.108	0.009^{**}
Temp. sd. Oc.-Mar. lag 1, east	0.101	0.003^{**}
Temp. sd. Oc.-Mar. lag 1, west	0.142	6×10^{-7} ***
Random effects:		
Intercept		
Prec. cum. MAM+OND lag 1		
Prec. max OND		
Temp. avg. Mar.-Sep. lag 1		

Notes: 584 observations

$^{\bullet}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

4.1 Climate change risk perception

In this section we discuss our estimates of the models which explain individuals' perception of climate change risk. We focus on two measures of climate risk perception, in particular climate change seriousness perception and climate versus policy perception. We present the results of lasso and jackknife OLS with the climate seriousness perception as dependent variable in Table 6. Three predictors were selected, in particular gender, climate knowledge, and degree of agreement with redistribution of income by government. In this case, the effect of being male is negative. This is mostly consistent with results of previous research which typically finds women to take climate risk more seriously than men (**???**). As we can see in Table 6, degree of agreement with income redistribution affects climate change seriousness perception positively as the base category is 'Strongly disagree'. This is in agreement with previous literature as we consider the degree of agreement with income redistribution as an indicator of political and ideological world-view, which was found to be significantly correlated with climate concern by large number of previous studies (e.g. **???**).

We will comment on the significant effects of climate knowledge at the end of Section 4.1.

Table 6: ***Climate change seriousness perception:*** *Multisplit lasso and jackknife OLS*

	Multisplit lasso		Jackknife OLS		
Variable	**Aggregated adj. p-value**		**Aggregated coefficient**	**Aggregated adj. p-value**	
Gender = male	0.0002	***	-0.3658	4.45×10^{-6}	***
Climate knowledge	1.0000		0.1380	1.0000	
Climate knowledge - squared	$< 2.00 \times 10^{-8}$	***	-0.0548	0.0209	*
Redistribution of income: disagree[a]	1.0000		0.1819	1.0000	
Redistribution of income: neutral[a]	1.0000		0.2789	0.8251	
Redistribution of income: agree[a]	$< 2.00 \times 10^{-8}$	***	0.8343	8.58×10^{-8}	***
Redistribution of income: strongly agree[a]	$< 2.00 \times 10^{-8}$	***	1.0828	$< 2.00 \times 10^{-8}$	***
Observations:			5749		

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

For the significant predictors, the signs of the coefficients of the multisplit lasso are the same as those of the jackknife OLS and also size of most of the coefficients is very comparable for these two models.

a Degree of agreement with the following statement: 'Government should redistribute income from the better off to those who are less well off.' The base category is 'Strongly disagree'.

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Appendix 1 Drought indices and measures

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 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.,

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

2010).

Appendix 3 Tables

Table A1: *List of considered (but not selected) predictors in multisplit lasso*

Variable	**Description**
Religion	11 categories including atheist, no religion and prefer not to say
Race	8 categories including prefer not to answer
Length in UK	Question: *How long have you been living in the UK?* Response = 5 categories: All life ,more than 10 years, $5-10$ years, $1-5$ years, less than 1 year
Occupation	14 categories
Sector	18 categories
Operating system	7 categories
Social value orientation	Response = 4 categories: altruist, prosocial, individualist, competitive
Discount rate 0 vs. 5	Annual, %, invest now for five years from now
Discount rate 1 vs. 2	Annual, %, invest a year from now for two years from now
Discount rate 1 vs. 6	Annual, %, invest a year from now for six years from now
Degree of present bias	Continuous, preferences on time
Degree of hyperbolicity	Continuous, preferences on time
Annual discount rate	Continuous, preferences on time
Subsistence income (reserve)	Continuous, **???**
Altruist	Dummy (0/1)
Prosocial	Dummy (0/1)
Individualist	Dummy (0/1)
Competitive	Dummy (0/1)
Egalitarian	Dummy (0/1)
Ineqaverse	Dummy (0/1)
Longitude	Longitude of survey response. Degrees
Latitude	Latitude of survey response. Degrees
Letter	First letter of surname, A=1,B=2,...
Siblings	Number of siblings
Older	Number of older siblings
Children	Number of children
Grandchildren	Number of grandchildren

Note: Variables in this table were not selected by multisplit lasso into any model.

(*continued*)

Table A2: *List of considered (but not selected) predictors in multisplit lasso*

Variable	**Description**
Handedness	0=right, 1=left
Time	Time taken to complete survey, in minutes
Hour	Hour of survey, 24 categories
Day of week	7 categories
Day of the month	Day of survey, $1-31$
Fair share	*Ordinary working people do not get their fair share of the nation's wealth.* Degree of agreement with the statement above, 5 categories
Hard work	Question: *How important is hard work for getting ahead in life?* Response = 5 categories, degree of agreement
Better off parents	Question: *Compared with your parents when they were about your age, are you better or worse in your income and standard of living generally?* Response = 5 categories (degree of agreement) and *Don't know*
Better off children	Q: *Compared with you, do you think that your children, when they reach your age, will be better or worse in their income and standard of living generally?* Answer =5 categories (degree of agreement) and *Don't know*
Always up	Dummy (0/1), Children better off me and me better off parents
Always down	Dummy (0/1), Parents better off me and me better off children
Up then down	Dummy (0/1), Me better off parents and me better off children
Down then up	Dummy (0/1), Parents better off me and children better off me
Financial literacy	3 financial problems, no. of correct answers, **?**
Understands portfolio	Dummy (0/1), 1 = understands
Incoherent dr.	Dummy (0/1), Incoherent answers between investments (0 = coherent)
Primed attitudes	1 = priming questions about time, risk, social were asked, 0 = not
Prime climate	0 = shown picture of polar bear on melting ice (negative), 1 = shown picture of people enjoying beach (positive)
Prime pension	0 = picture of troubled old man, 1 = picture of happy old man
Prime school	0 = picture of unruly kids, 1 = picture of well-behaved kids
Prime NHS	0 = picture NHS in crisis, 1 = picture love NHS
Female × handed	Interaction female and handedness
Female × children	Interaction female and number of children
Age × children	Interaction age and number of children

Note: Variables in this table were not selected by multisplit lasso into any model.

(*continued*)

Table A3: ***Descriptive statistics:*** *Continuous variables*

Variable:	**Mean**	**St. dev.**	**Min**	**Max**
Income - predicted (£ per year)	27729	11719.89	3611	58326
Net assets - total assets minus total debts (£)	152542	223612.90	−400000	2500000
Population (per Km^2, LSOA[a] level)	3336	2975.38	7	25280
Population (per Km^2, LAD[b] level)	3193	3164.75	10	13870
How much is tax gas and electricity (£/yr.)	144.90	111.94	−50	500
How much is duty transport fuel (pence/yr.)	25.18	13.68	0	60
Behavioural variables				
Social value orientation (ring measure)	26.28	15.52	−16.26	83.93
Annual discount rate,%, invest now for a year from now[c]	148.7	181.81	1	500
Risk aversion - estimated median of quadratic utility function	0.33	0.01	0.29	0.38
Risk aversion - estimated median of log utility function	1.81	1.08	0.67	4.33
Risk aversion - estimated median of power utility function	0.42	0.07	0.33	0.57
Risk aversion - estimated mean of power utility function	0.74	0.26	0.33	1.07

Notes: Total number of observations: 8541

a Lower Layer Super Output Area

b Local Authority District

c This variable is called *Discount rate year from now* in the tables with regression estimates