Estimating the impact of seasonal weather conditions and farm-level adaptation practices on yield and production value in smallholder agriculture

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Abstract
Unfavourable seasonal weather conditions are considered a major determinant of low crop yields in rainfed cropping systems across millions of smallholder farms. Improved farm-level management practices are commonly suggested as an effective measure to cope with adverse seasonal conditions. However, in econometric analyses of household survey data, seasonal weather conditions are usually accounted for using meteorological statistics or agro-meteorological indices, while bio-physically modelled water and heat stress indicators are seldom used. Here we show, that estimated impacts of seasonal conditions and improved agricultural practices on crop yield strongly depend on the type of weather indicators used. This is exemplified for maize, sorghum and broad beans, the three largest cropping systems in Ethiopia. We conclude that conventional econometric analyses that utilize only one set of weather indicators without further sensitivity analyses to derive recommendations for the application of specific agricultural management practices may suffer from low validity.

Keywords
Weather conditions; climate change adaptation; smallholder agriculture; climate-smart agriculture.

Introduction

Across Sub-Saharan Africa (SSA), Ethiopia has the largest number of people facing undernourishment (FAOSTAT, 2018), and the third most people living in extreme poverty (World Bank, 2018). The predominant rainfed production systems are sensitive to adverse seasonal weather conditions. In this context, improved farm-level management practices are widely promoted as an efficient means to reduce the negative impacts of unfavorable seasonal weather conditions (Lipper et al., 2014). In this study we compare how strongly different indicators of seasonal weather conditions explain observed yields in smallholder agriculture across Ethiopia. We also assess whether improved farm-level management practices are an effective means to increase yield. As part of the analysis, we investigate whether results change significantly when utilizing (i) different indicators of seasonal weather conditions, and (ii) different time scopes around the core agricultural growing season.

Methods

Data

We utilized panel data on crop management practices and realized production value from the World Bank *Living Standards Measurement Study – Integrated Surveys on Agriculture* (LSMS-ISA) covering the agricultural seasons 2011, 2013, and 2015. The survey is nationally representative for rural households across Ethiopia. The analysis focuses on the three most frequently cultivated crops maize, sorghum, and broad bean.

Precipitation and temperature data are respectively sourced from the *Climate Hazards center Infrared Precipitation with Stations* dataset (CHIRPS; Funk et al. (2015)) and *Climate Hazards center InfraRed Temperature with Stations* dataset (CHIRTS; Verdin et al. (2020)). Both datasets combine information from remotely sensed infrared data, meteorological station data, and climate models. Data on solar radiation and wind speed is used from *AgERA5*, derived from the ERA5 reanalysis (Hersbach et al., 2020). As source of soil data, the *Global High-Resolution Soil Profile Database for Crop Modelling Applications* (Han et al., 2015) is utilized.

Computation of weather indicators
We used gridded weather and soils data of closest proximity to the centerpoint of each enumeration area of the household survey. For each production system reported in the household survey, the Agricultural Production Systems Simulator (APSIM; Keating et al. (2003); McCown et al. (1996)) was used to simulate season-specific water and temperature stress indicators – given the fertilizer quantities as reported by households. Further meteorological indicators and indices were computed directly from meteorological data for the same time frame. The various indicators are shown in Table 1.

Table 1. Indicators of seasonal weather conditions

1) Meteorological indicators	2) Weather indices	3) Bio-physically simulated indicators
Daily precipitation	Standardized Precipitation Index	Growing degree-days
Daily maximum temperature	Standardized Precipitation Evaporation Index	Extreme growing degree-days
	Palmer Drought Severity Index	Extractable soil water
	Weighted Palmer Drought Severity Index	Total plant water uptake
	Palmer Hydrological Drought Index	Actual to potential evapotranspiration ratio
	Palmer Z-index	Plant water supply to water demand ratio

For each indicator displayed in Table 1, we computed the average or cumulative value during the crop-generic growing season or the crop-specific growth period. We tested the sensitivity of our analysis by aggregating weather indicators during two alternative definitions of growing seasons, that are based on Enhanced Vegetation Index (HarvestChoice, 2010) or Normalized Difference Vegetation Index (Whitcraft et al., 2015), as well as three definitions of crop-specific growth periods, that are based on a crop-calendar database (Sacks et al., 2010) or were simulated by the crop-physiological model APSIM.

Econometric analysis
The econometric analysis consists of a linear unobserved effects panel data model of crop management practice and weather condition impacts on (i) crop yield and (ii) production value.

$$Y_{ict} = \alpha_i + \delta\ W_{ict} + \mu\ P_{ict} + \beta\ X_{ict} + \varepsilon_{ict}$$

where:

- Y_{ict} is the natural logarithm of the output variable (crop yield or production value) for farmer i and crop c at time t
- W_{ict} is a vector of weather indicators constituted by systematic subsets of Table 1
- P_{ict} is a vector of crop management practices
- X_{ict} is a vector of further exogenous covariates (including soil conditions, household assets, etc.)
- α_i is the model intercept (including the household-specific, unobserved, time-invariant fixed effect), and ε_{ict} is the idiosyncratic error term

In order to provide a targeted quantification of how strongly unfavourable weather conditions reduce the economic outcomes of smallholder farmers, we employ the above fixed-effects panel data model with output value as the dependent variable. For each set of weather indicators, it is computed how output value changes, if farmers are exposed to weather conditions that are by one standard deviation drier and hotter than the long-term average. Thereby, coefficients of weather indicators that are not significant at a level of 5% are not considered for computations. A 90% winsorization of the data is conducted prior to analysis of results.

Results
From the large number of combinations of weather indicator sets and time periods, we present in the following only those regression models that are characterized by a higher adjusted R-squared statistic: We selected the meteorological, SPEI- and two bio-physical (WS/WD-set or AET/PET-set) weather indicator sets. As time periods, we selected the EVI-derived growing season as well as the crop growth periods simulated by the bio-physical model APSIM (either considering the full crop growth period or its critical stages).
As shown in Table 2, all three weather indicator sets identify that low moisture and high temperatures have significant negative impacts on maize yield. For sorghum, only low levels of moisture are found to have significant impacts to limit yield, while high temperatures in the observed range have no significant negative

impact. For broad bean, the three weather indicator sets provide a more mixed picture: While all indicator sets agree on negative impacts from low moisture levels, the meteorological indicator set finds significant positive impacts from higher daily maximum temperature, while the AET/PET-indicator set finds significant negative impacts from extreme degree days. While overall there is thus largely agreement with regards to the sign of impacts from weather indicators, impact strengths are different.

We further investigate whether improved agricultural management practices have the potential to increase yield in the analysed smallholder systems, and if this evaluation changes based on the utilized weather indicator set. The considered management practices are the application of synthetic and organic fertilizer, the use of improved seed, application of measures for preventing soil erosion, and the application of intercropping. Our analysis finds only very few improved management practices to provide statistically significant yield benefits. Further, findings relevantly diverge based upon which kind of weather indicator set is used as control.

Table 2: Impact of weather conditions and adoption of improved agricultural management practices on crop yield in Ethiopia. Regression table of fixed effects panel data models for different combinations of weather indicators.

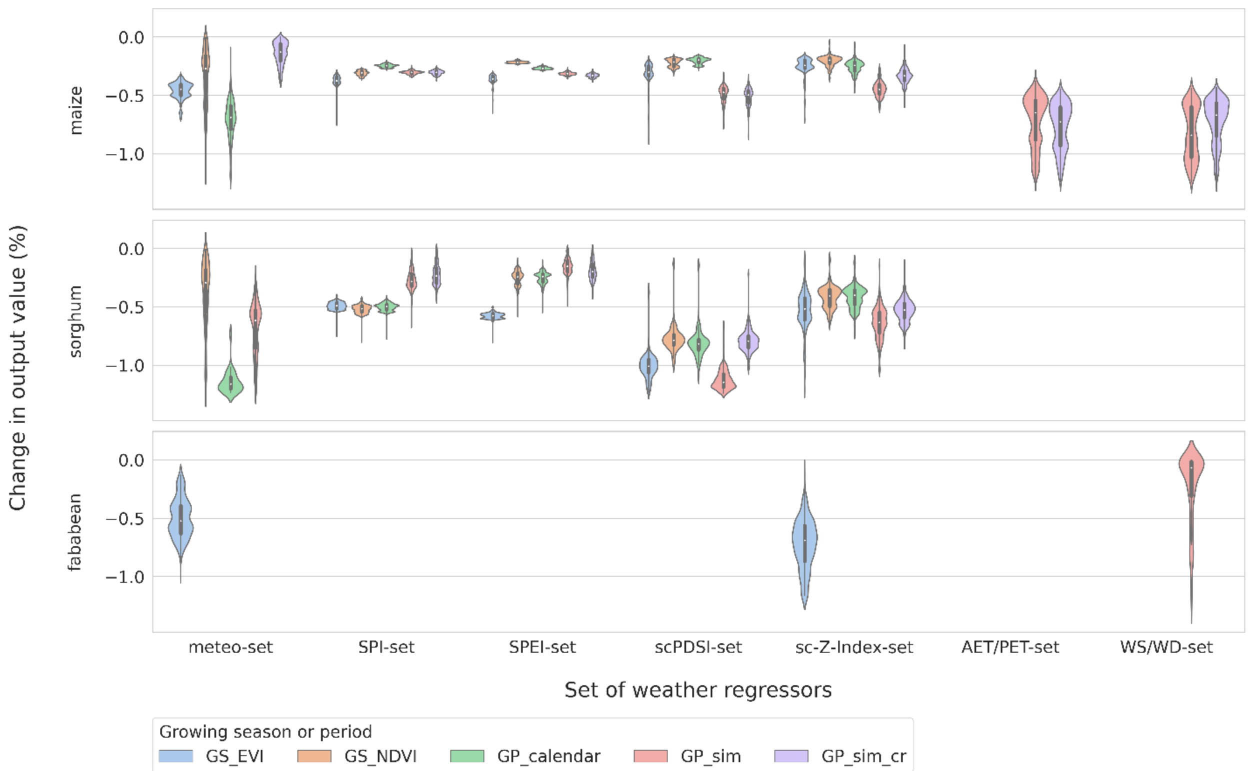
	Crop:	maize			sorghum			broad beans		
	Growing season / period:	GS_EVI	GS_EVI	GP_sim	GP_sim	GS_EVI	GP_sim	GS_EVI	GS_EVI	GP_sim_cr
Regressors:	Weather regressor set:	meteo set	SPEI set	WS/WD set	meteo set	SPEI set	AET/PET set	meteo set	SPEI set	AET/PET set
weather indicators	precipitation	**0.00335*** **		**0.00223*** **	**0.00556***		-0.000549	**0.00714*** **		0.00146
		(0.00125)		(0.000273)	(0.00313)		(0.00124)	(0.00235)		(0.000943)
	standardized anomaly of precipitation	-0.190			-0.308			-0.0563		
	(30 years)	(0.164)			(0.414)			(0.228)		
	Standardized Precipita-tion Evaporation Index		**0.218*** **			**0.654*** **			**0.363** **	
	(SPEI)		(0.0660)			(0.143)			(0.141)	
	Actual to potential evap-otranspiration ratio						**5.664***			**5.949***
	(AET/PET)						(3.155)			(3.419)
	Plant water supply to water demand ratio			**6.060*** **						
	(WS/WD)			(1.860)						
	Maximum temperature (Tmax)	**-0.433*** **	**-0.326** **		0.426	0.449		**0.698** **	0.224	
		(0.144)	(0.141)		(0.410)	(0.338)		(0.307)	(0.311)	
	Growing degree-days (DD)			**-0.0505*** **			0.00131			0.00223
				(0.00656)			(0.00111)			(0.00181)
	Extreme growing degree-days (EDD)			-0.0146			-0.000818			**-0.537***
				(0.0106)			(0.0179)			(0.293)
improved management practices	synthetic fertilizer (quantity)	-1.84e-05	-6.92e-06	-4.78e-05	**-0.0129*** **	-0.00524	**-0.0104** **	-0.00803	-0.0197	-0.00184
		(0.000144)	(0.000136)	(0.000128)	(0.00480)	(0.00451)	(0.00496)	(0.0145)	(0.0131)	(0.0130)
	organic fertilizer (% crop area)	0.284	0.272	0.301	**-0.812***	**-0.709***	**-0.814***	**-0.866***	-0.857	-0.194
		(0.247)	(0.251)	(0.230)	(0.448)	(0.393)	(0.430)	(0.510)	(0.533)	(0.411)
	improved seed (% crop area)	**-0.588** **	**-0.542***	-0.373	**2.530***	0.946	**2.416***	-0.708	-0.319	-1.449
		(0.278)	(0.290)	(0.251)	(1.422)	(0.775)	(1.319)	(1.162)	(1.018)	(0.941)
	erosion prevention (% crop area)	0.127	0.111	0.0522	-0.807	**1.020***	-0.851	0.249	0.223	0.00358
		(0.178)	(0.177)	(0.170)	(0.540)	(0.606)	(0.558)	(0.594)	(0.612)	(0.498)
	intercropping (% crop area)	-0.226	-0.157	-0.213	0.895	1.058	0.860	0.142	0.199	0.377
		(0.204)	(0.197)	(0.180)	(0.908)	(0.892)	(0.914)	(0.494)	(0.517)	(0.438)
	Constant	1.679	-0.259	74.83***	-23.25	-40.38	-4.795	-20.79	-2.885	5.123
		(8.241)	(8.104)	(13.60)	(35.14)	(33.35)	(34.78)	(32.10)	(34.76)	(39.77)
	Observations	1,383	1,383	1,550	468	434	468	236	236	389
	Number of panel-id	925	925	1,050	360	333	360	167	167	283
	household FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
	df_residual	924	924	1049	359	332	359	166	166	282
	df_model	19	18	20	19	18	20	19	18	20
	R-squared-adj	**0.169**	**0.167**	**0.187**	**0.267**	**0.446**	**0.286**	**0.366**	**0.292**	**0.217**
	RMSE	0.842	0.843	0.805	0.735	0.643	0.725	0.655	0.692	0.755
	AIC	3469	3472	3746	1058	866.3	1047	488.1	513.3	904.3
	BIC	3573	3571	3858	1141	943.7	1134	557.4	579.1	987.5
	F	6.077	6.149	7.272	4.030	7.868	3.957	4.574	2.440	3.487
	p	0	0	0	3.31e-08	0	2.88e-08	1.45e-08	0.00133	9.71e-07

Abbreviations of weather regressor sets: (i) meteo set: precipitation, maximum temperature; (ii) SPI-set: Standardized Precipitation Index, maximum temperature; (iii) WS/WD set: precipitation, growing degree days, ratio of plant water supply to water demand, extreme growing degree-days; (iv) AET/PET set: precipitation, growing degree days, ratio of actual to potential evapotranspiration, extreme growing degree-days.
Abbreviations of growing seasons and crop growth periods:
GS_EVI: Enhanced Vegetation Index (EVI) derived agricultural growing season; GP_sim: Bio-physical model (APSIM) simulated crop growing period; GP_sim_cr: Bio-physical model (APSIM) simulated critical crop growth stages.
Further control variables omitted from table for brevity. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 1 identifies how strongly unfavourable weather conditions reduce the economic outcomes of smallholder farmers exposed to weather conditions that are by one standard deviation drier and hotter than the long-term average. For maize, reductions in production value range roughly between 0 - 1.2 percent. The SPI-, SPEI-, scPDSI- and sc-Z-Index regressor sets all compute that reductions in production value from sub-standard seasonal conditions are similar or largely identical across producers. The meteorological and crop/physiological (AET/PET-set, WS/WD-set) indicator sets instead predict that different farmers are very differently impacted by adverse weather conditions. Particularly the AET/PET-set and WS/WD-set predict an approximately bimodal distribution with a larger share of the population being impacted by more intense reductions in production value when facing negative weather events. Across most indicator sets the differences in growing season and crop growth periods used for aggregation only moderately changes the estimated loss in production value.

Partially as a consequence of the lower number of observations for sorghum and fababean, fewer statistically significant relationships were estimated for both crops. The size of losses in production value from moderately negative weather conditions is roughly comparable.

Figure 1: Loss of output value under unfavourable weather conditions in Ethiopia.



Percentage change in output value computed using constant 2010 Purchasing Power Parity (PPP) from exposure to weather conditions that are by one standard deviation drier and hotter than the long-term average. Within each set of weather regressors, only weather indicators with coefficients that are significant at a level of 5 percent were considered. For each location, average and standard deviation of weather conditions are computed during the indicated growing season or crop-growth period for the 30-year time period 1987-2016. Abbreviations as in Table 2.

Conclusion

We compared combinations of weather indicators that are widely used throughout the econometric literature for their ability to explain observed variations in crop yield as well as the effectiveness of improved agricultural management practices to provide yield benefits. While we found largely agreement between the various weather indicator sets with regards to statistical significance and sign of yield impacts from drier and hotter conditions, there is disagreement with regards to the impact strength. More importantly, based on which weather indicator set is used, the evaluation of improved agricultural management practices to provide yield benefits strongly changes. Conventional econometric applications in the field that commonly only make use of one set of weather indicators to derive recommendations on the effectiveness of potential adaptation practices may accordingly suffer from low validity.

References

FAOSTAT (2018). FAOSTAT Food Security Indicators for 2016. (FAO, ed.).

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data* **2**, 150066.

Han, E., Ines, A., and Koo, J. (2015). Global High-Resolution Soil Profile Database for Crop Modeling Applications. (C. U. , M. S. U. and I. F. P. R. I. I. , eds.). Harvard Dataverse.

HarvestChoice (2010). Measuring Growing Seasons. International Food Policy Research Institute (IFPRI) and University of Minnesota, Washington, DC and St. Paul, MN.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society* **146**, 1999-2049.

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I., Hargreaves, J. N. G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J. P., Silburn, M., Wang, E., Brown, S., Bristow, K. L., Asseng, S., Chapman, S., McCown, R. L., Freebairn, D. M., and Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy* **18**, 267-288.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H., Remington, T., Sen, P. T., Sessa, R., Shula, R., Tibu, A., and Torquebiau, E. F. (2014). Climate-smart agriculture for food security. *Nature Climate Change* **4**, 1068-1072.

McCown, R. L., Hammer, G. L., Hargreaves, J. N. G., Holzworth, D. P., and Freebairn, D. M. (1996). APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. *Agricultural Systems* **50**, 255-271.

Sacks, W. J., Deryng, D., Foley, J. A., and Ramankutty, N. (2010). Crop planting dates: an analysis of global patterns. *Global Ecology and Biogeography* **19**, 607-620.

Verdin, A., Funk, C., Peterson, P., Landsfeld, M., Tuholske, C., and Grace, K. (2020). Development and validation of the CHIRTS-daily quasi-global high-resolution daily temperature data set. *Scientific Data* **7**, 303.

Whitcraft, A. K., Becker-Reshef, I., and Justice, C. O. (2015). Agricultural growing season calendars derived from MODIS surface reflectance. *International Journal of Digital Earth* **8**, 173-197.

World Bank (2018). "Poverty and Shared Prosperity 2018: Piecing Together the Poverty Puzzle." World Bank, Washington, DC.