Background Paper: Annex Chapter 2—Adapting to Climate Change in Sub-Saharan Africa

This Annex provides details on the data and econometric results underlying the discussion in the chapter.

2.1. NIGHTLIGHT REGRESSION

2.1.1. Data

High-resolution grid-level data are used from several sources, which include:

- Temperature and precipitation: Harris and others (2014), CRU TS v. 4.03, provide 1901-2018 global land data for multiple variables on a $0.5° \times 0.5°$ grid on monthly frequency. For the analysis used in this chapter, temperature and precipitation are averaged at the state level, weighted by the area of each grid within state boundaries.

- Nightlights: National Oceanic and Atmospheric Administration (NOAA) provides average monthly composite of nightlights starting in May 2012 on a $15'' \times 15''$ grid. This chapter uses nightlights data between 2013 and 2018 from the Visible Infrared Imaging Radiometer Suite (VIIRS) monthly composites of average radiance images. Nightlights are summed up to the state level as a proxy for economic activity.

- Forest change: Hanson and others (2013) and the project's update (maintained by the University of Maryland) quantify forest change between 2000 and 2018 based on Earth observation satellite data with a spatial resolution of 30 meters.

- Water surface change: Pekel and others (2016) provide global surface water occurrence and intensity change based on three million Landsat satellite images at 30-meter resolution.

2.1.2. Econometric Model

To analyze the impact of temperature and precipitation on economic activity at the state level, the following regression is estimated:

$$\Delta z_{i,t} = \beta_1 z_{i,t-1} + \beta_2 c_{i,t} + \mu_i + \alpha_t + \epsilon_{i,t},$$

where $z_{i,t}$ is the logarithm of nightlights in state i in time t; $\Delta z_{i,t} = z_{i,t} - z_{i,t-1}$ is the growth rate of nightlights; $c_{i,t}$ is the climate variable of interest measured in deviations from its past 30-year average for the same month; μ_i and α_t are state and time fixed effects, respectively; and $\epsilon_{i,t}$ is the error term. Temperature is measured in Celsius degree; and precipitation is measured in 10 millimeters. The above equation is estimated for the period between 2013 and 2018 using the ordinary least squares method, with standard errors clustered at the state level. β_2 measures the impact of temperature or precipitation deviations from historical average on local economic growth.

2.1.3. Results

Annex Table 2.1 shows that the impact of temperature deviation has a statistically significant impact on economic growth. A 1°C deviation is associated with about 2 percentage points reduction in monthly growth of nightlights for the world on average. The effect is larger for sub-Saharan Africa (4.2 percentage points), and even larger for the Sahel region (6.4 percentage points). Interestingly, the result for sub-Saharan Africa is almost entirely driven by Western Africa. Annex Table 2.2 shows that precipitation deviation has a similar impact on different regions of the world.

Annex Table 2.1: Sub-Saharan Africa: Impact of Temperature on Nightlights at State Level

	Dependent variable: Nightlight growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	World	SSA	Sahel	EMEDEV	Eastern Africa	Southern Africa	Western Africa	Central Africa
Nightlights (lagged)	-0.771***	-0.786***	-0.827***	-0.743***	-0.817***	-0.755***	-0.774***	-0.805***
	(0.007)	(0.010)	(0.025)	(0.007)	(0.016)	(0.033)	(0.017)	(0.022)
Temperature deviation	-0.019***	-0.042***	-0.064**	-0.026***	-0.006	0.028	-0.052**	-0.030
	(0.002)	(0.012)	(0.031)	(0.002)	(0.049)	(0.046)	(0.026)	(0.051)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,475	21,125	2,953	80,309	8,665	1,599	8,178	4,138
R-squared	0.482	0.590	0.690	0.478	0.787	0.764	0.759	0.712
No of states	2223	473	64	1704	216	36	161	99

Source: IMF staff estimates.

Annex Table 2.2: Sub-Saharan Africa: Impact of Precipitation on Nightlights at State Level

	Dependent variable: Nightlight growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	World	SSA	Sahel	EMEDEV	Eastern Africa	Southern Africa	Western Africa	Central Africa
Nightlights (lagged)	-0.772***	-0.786***	-0.824***	-0.746***	-0.816***	-0.752***	-0.774***	-0.805***
	(0.007)	(0.010)	(0.025)	(0.007)	(0.016)	(0.032)	(0.017)	(0.022)
Precipitation deviation	-0.006***	-0.008***	-0.012**	-0.008***	-0.002	-0.010	-0.008***	-0.005
	(0.001)	(0.001)	(0.006)	(0.001)	(0.002)	(0.006)	(0.003)	(0.004)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,475	21,125	2,953	80,309	8,665	1,599	8,178	4,138
R-squared	0.482	0.591	0.689	0.479	0.787	0.764	0.759	0.712
No of states	2223	473	64	1704	216	36	161	99

Source: IMF staff estimates.
Note: The impact of temperature and precipitation deviations on economic activity is temporary, lasting for one or two months depending on the number of lags introduced in the regression. There is some evidence that precipitation deviations have a larger and longer impact during crops' growing seasons. EMEDEV=emerging market and developing economies. Standard errors in parenthesis.

2.2. COUNTRY-LEVEL PANEL REGRESSION

Two analyses are proposed. The first assesses the impacts of disasters on per capita growth (impact analysis). The second considers the policies that can help improve the resilience to disasters (policy response analysis).

2.2.1. Data

The models are based on a 181-country panel from 1960 to 2018. To correct for short-term disturbances and avoid noisy growth results, the initial yearly data are aggregated into 5-year windows with the new values being the averages over the windows. (The final dataset has 12 five-year periods.) The intensity proxy captures the proportion of disruptive disasters in the 5-year period, while the event proxy captures the average effects of the disasters (through the average ratio of deaths to population).

Annex Table 2.3: Description of Variables

Variable	Description (source)
Variables used for the impact analysis (growth model)	
Intensity drought	Proportion of disruptive droughts (EM-DAT)
Intensity flood	Proportion of disruptive floods (EM-DAT)
Intensity epidemic	Proportion of disruptive epidemics (EM-DAT)
Intensity storm	Proportion of disruptive storms (EM-DAT)
Effect drought-storm	Ratio deaths-population on the account of droughts-storms (EM-DAT)
Log of per capita GDP	Real per capita GDP, PPP (WEO)
Education	Gross rate of enrollment in the secondary (WDI)
Investment	Gross fixed capital formation, percent of GDP (WEO)
Government consumption	Percentage of per capita GDP government consumption (PWT)
Inflation	Consumer Prices, period average, percent change (WEO)
Trade openness	Ratio (Import+Export)-GDP (WEO)
Change in terms of trade	Change, ratio price export-price import (PWT)
Variables used for the policy response analysis	
Telecommunication	Mobile cellular subscriptions per 100 people (WDI)
Financial depth	Domestic credit to private sector, percent of GDP (WDI)
Education	Gross rate of enrollment in the secondary (WDI)
Health	Life expectancy at birth (WDI)
Agri. Machinery	Agricultural machinery, total tractors (WDI)
Electricity	Access to electricity, percent of population (WDI)
Other variables used for the policy response analysis (no significant effect detected, data issues)	
Irrigation	Agricultural irrigated land, percent of total agricultural land (WDI)
Sanitation	People using safely managed sanitation services, percent of population (WDI)
Quality of fiscal policy	CPIA quality of budgetary and financial management, 1=low to 6=high (WDI)
Roads	Quality of roads, 1=low to 7=high (WDI)

For the impact analysis, the control variables are selected following Loayza and others (2012). This is to reduce multicollinearity and reverse causality that would arise when the disaster proxies are included in the model. Therefore, we use a “sparse” growth model. On the other hand, the policy response analysis relies on a large set of controls, with no prior restriction. Annex Table 2.3 is a description of the main control variables.

2.2.2. Econometric Results

The following panel model is estimated for the impact analysis:

$$\overline{Gr}_{i,p} = \mathrm{a}\overline{Log(GDP_{i,p})} + b_1\overline{Intens}_{i,p}^{j} + b_2\overline{Freq}_{i,p}^{j} + B_3\bar{X}_{i,p} + c_p + d_i + \varepsilon_{i,p}\ ,$$

where

- p is the 5-year period, going from $t_{p1}$to t_{p5}
- $\overline{Gr}_{i,p} = \frac{1}{5}\sum_{t=t_{p1}}^{t_{p5}} Gr_{i,t+1}$, with $Gr_{i,t+1}$ the per capita growth of country *i* in year *t+1;*
- $\overline{Intens}_{i,p}^{j} = \frac{1}{N_j}\sum_{t=t_{p1}}^{t_{p5}} Intens_{i,t}^{j}$, with $Intens_{i,t}^{j}$ the intensity indicator associated with disasters of type *j* in country *i* during year *t*, and N_j the number of disasters in the 5-year period;
- $Intens_{i,t}^{j}$ is a dummy variable that takes the value 1 if, in country *i* and during year *t*, the disasters of type *j* weigh on over 0.01 percent of the population, where the ratio of (death + 0.3*affected) to population is used;
- $\overline{Freq}_{i,p}^{j} = \frac{1}{5}\sum_{t=t_{p1}}^{t_{p5}} \frac{Death_{i,t}^{j}}{Pop_{i,t}}$, with $Death_{i,t}^{j}$ the death toll associated with disasters of type *j* in country *i* during year *t*, and $Pop_{i,t}$ the population of country *i* in year *t;*
- $\overline{Log(GDP_{i,p})}$ and $\bar{X}_{i,p}$ are the log GDP and the additional control variables (5-year averages), c_p is the time fixed effects, and d_i is the country fixed effects.

The results (Annex Table 2.4) are presented for the Emerging Markets and Developing Economies (EMDEs) and for Sub-Saharan Africa (SSA).

The policy response analysis identifies policy areas that help reduce the negative impact of weather-related disasters on growth. The following model is considered:

$$\overline{Gr}_{i,p} = \mathrm{a}\overline{Gr}_{i,p-1} + b_1\overline{Dis}_{i,p}^{j} + b_2\overline{Dis}_{i,p}^{j} * z_{i,p} + b_3 z_{i,p} + c_p + d_i + \varepsilon_{i,p}\ ,$$

where *p* is the 5-year period, $z_{i,p}$ is a policy variable and $\overline{Dis}_{i,p}^{j}$ is either the intensity or the frequency proxy defined earlier. The policy variables are analyzed one by one; with b_1 negative, the policy variable is interpreted to improve resilience if b_2 is significant and positive. Annex Table 2.5 reports the changes in sub-Saharan Africa’s per capita growth if its average conditions improve to the levels of emerging markets and developing economies.

Annex Table 2.4: Selected Economies: Estimation of Growth Models with Disaster Indicators

	EMDEs				SSA			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Log of per capita GDP	-2.09**	-2.03***	-2.52**	-1.06	-2.37	-1.57	-1.51	6.72
	(0.98)	(0.65)	(0.99)	(1.16)	(1.43)	(1.37)	(1.07)	(3.94)
Intensity drought	-2.66***				-7.81***			
	(0.74)				(2.16)			
Frequency drought	-0.34***				-0.41***			
	(0.05)				(0.04)			
Intensity flood		-1.31***				-1.49**		
		(0.44)				(0.54)		
Frequency flood		-0.06**				-0.18**		
		(0.03)				(0.08)		
Intensity epidemic			-0.20				-0.53	
			(0.33)				(0.41)	
Frequency epidemic			-0.00				-0.01	
			(0.13)				(0.16)	
Intensity storm				-0.38				0.32
				(0.47)				(1.00)
Frequency storm				-0.19**				-12.26
				(0.08)				(11.27)
Education	-0.07**	-0.07***	-0.05*	-0.07***	-0.05	-0.07*	-0.06	-0.16
	(0.03)	(0.02)	(0.03)	(0.02)	(0.06)	(0.04)	(0.05)	(0.16)
Investment	0.03***	0.09***	0.07***	0.02	0.03***	0.05*	0.05**	0.09
	(0.01)	(0.02)	(0.02)	(0.04)	(0.01)	(0.02)	(0.02)	(0.06)
Government consumption	-0.01	0.02	0.05**	-0.02	-0.01	0.06*	0.05**	0.08
	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)	(0.06)
Inflation	0.00***	-0.00**	-0.00***	-0.01***	0.00	-0.00***	-0.00***	0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)
Trade openess	0.36	0.05	0.15	-0.29	0.63	1.74	4.52**	-1.52
	(0.38)	(0.64)	(1.06)	(0.70)	(1.27)	(1.42)	(1.87)	(4.76)
Change in terms of trade	0.00	-0.02	0.03	0.09*	-0.11	0.07	0.06*	-0.03
	(0.07)	(0.06)	(0.05)	(0.06)	(0.09)	(0.06)	(0.04)	(0.36)
Intercept	21.37***	20.31***	20.61**	14.34	26.85***	12.29	7.99	-46.39
	(7.53)	(5.23)	(7.98)	(10.14)	(9.38)	(9.11)	(8.79)	(27.15)
Country fixed effect (y/n)	y	y	y	y	y	y	y	y
Year fixed effect (y/n)	y	y	y	y	y	y	y	y
Clustered standard deviation (country level)	y	y	y	y	y	y	y	y
Number of observations	211	513	312	325	113	163	158	67

Source: IMF staff estimates.
Note: Dependent variable is per capita GDP growth in the following year. Robust standard errors in parenthesis.

2.3. HOUSEHOLD SURVEYS ON FOOD SECURITY

2.3.1. Data

The data used in this section comes from nationally representative household surveys in Ethiopia, Malawi, Mali, Niger, and Tanzania, collected in collaboration with the World Bank Living Standards Measurement Study (LSMS). As part of these surveys, households are asked about shocks they experienced in the last one to five years and the coping strategies they adopted.[4] For the purposes of our analysis, we focus only on the shocks that are likely to occur more frequently as a result of increased climate variability, rising temperatures and sea levels.

Annex Table 2.5: Selected Economies: Policy Response Analysis

	Intensity			Frequency		
	Drought	Flood	Storm	Drought	Flood	Storm
Telecommunication	-	0.006	-	-	-	-
Access to finance	0.029	0.018	-	0.013	-	-
Education	-	-	0.076	-	0.030	-
Health	-	0.084	0.081	0.006	0.017	0.006
Mechanization	-	0.005	-	-	0.046	-
Electricity	0.430	-	-	-	-	-

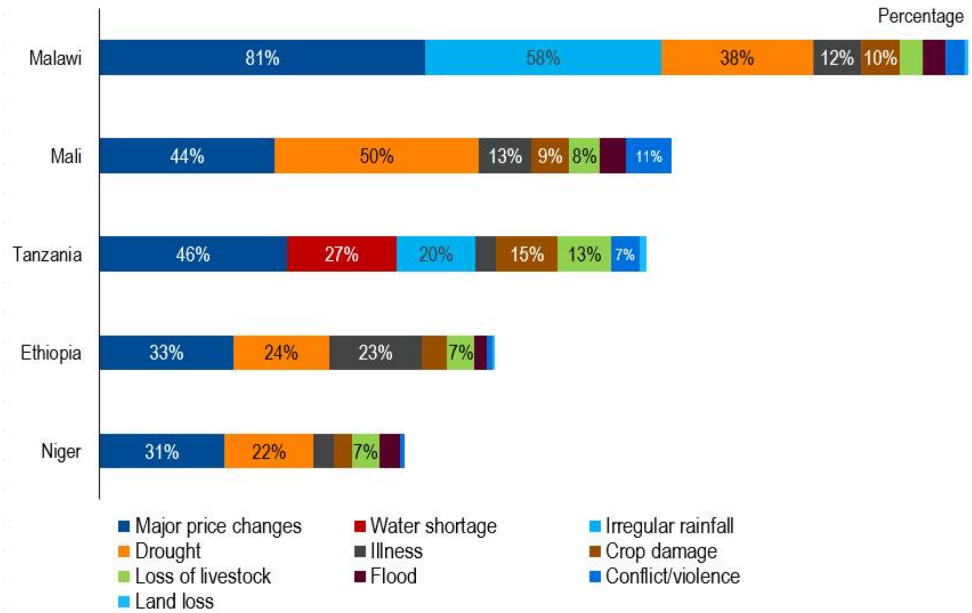
Source: IMF staff estimates.
Note: The blank areas indicate statistically non-significant effects

Annex Figure 2.1 displays the percentage of households that report each type of shock by country. As households can report more up to three shocks, the percentages do not add up to 100 percent. The chart shows that households in Malawi reported the most shocks overall, followed by Mali, Tanzania, Ethiopia and Niger. In all countries, major price changes (increases in food or input prices or decreases in crop output prices) affected over 30 percent of households, whereas droughts, water shortages and irregular rainfall also affected a large number of households. Severe illness, crop damage, and loss of livestock are other frequently experienced shocks, followed by flood and conflict or violence. Land loss and fire affected a small percentage of households.[9]

[4] The time frame differs by country. In Ethiopia, Malawi and Niger, households are asked only about shocks experienced in the last 12 months; in Mali, households are asked about shocks experienced in the last 3 years; and in Tanzania, households are asked about shocks experienced in the last 5 years.

[9] Land loss was not asked about in Niger and Mali, while fire was asked about only in Ethiopia.

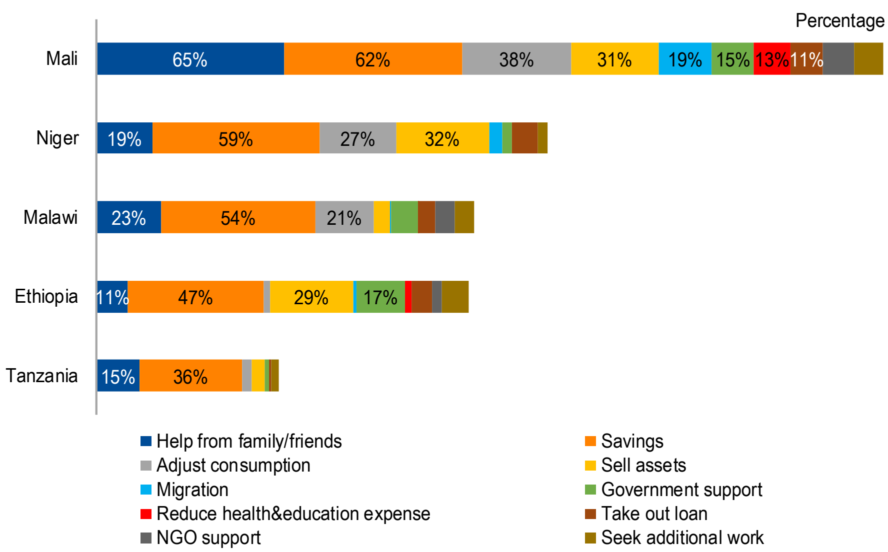
Annex Figure 2.1: Selected Countries: Prevalence of Shocks by Country



Source: IMF staff estimates.

Annex Figure 2.2 reports the major coping strategies reported by households in response to shocks. By far the most common coping strategy is to draw on savings, while many households also report relying on friends and family for support, selling assets, and adjusting their consumption. In Ethiopia and Mali, 17 percent and 15 percent of households, respectively, report receiving help from the government. Other coping strategies reported are migration, reducing health and education expenditure, taking out a loan, seeking additional work, and non-governmental organization (NGO) support.

Annex Figure 2.2: Selected Countries: Household's Coping Strategies in Response to Shocks



Source: IMF staff estimates.

2.3.2. Econometric Results

To assess the impact of climate-related shocks on household welfare, we run the following regression, in which we define a household as having been subject to a shock if it reports experiencing *any* one of the shocks listed in Annex Figure 2.1:[10]

$$Food\ security_{hh,c} = \beta_{0,c} + \beta_{1,c}shock_{hh,c} + \beta_2 controls_{hh,c} + \mu_{hh,c}$$

Here, hh stands for household, c for country, and $\mu_{hh,c}$ is the error term. Food security is a dummy variable that takes the value of 1 for households who report that they have not recently been worried about having enough to eat. We control for a household wealth index as well as dummies for major regions and living in a rural area.[11] The model is estimated as a linear probability model using ordinary least squares.

Shocks are associated with a 5 to 20 percent higher incidence of food insecurity across the five countries, with the estimated impact stronger for more recently experienced shocks (Ethiopia, Malawi and Niger). As expected, higher wealth positively predicts food security, with a one standard deviation increase in the household wealth index increasing the probability of a household to report food security by 5 to 15 percent (Annex Table 2.6). This suggests that richer households have significantly higher buffers, which make them less likely to be pushed into food insecurity by climate-related shocks.

Annex Table 2.6: Selected Economies: The Effect of Shocks on Food Security

	Dependent variable: Food security				
	(1)	(2)	(3)	(4)	(5)
	Ethiopia	Malawi	Mali	Niger	Tanzania
Shock	-0.229***	-0.185***	-0.110***	-0.168***	-0.059***
	(-0.011)	(-0.023)	(-0.016)	(-0.016)	(-0.017)
Household wealth index	0.102***	0.152***	0.049***	0.137***	0.090***
	(-0.006)	(-0.004)	(-0.007)	(-0.008)	(-0.023)
Constant	0.870***	0.531***	0.762***	0.614***	0.700***
	(-0.013)	(-0.028)	(-0.019)	(-0.02)	(-0.018)
Region and rural dummies	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.152	0.204	0.163	0.239	0.075
Number of observations	4954	12447	3813	3617	3352

Sources: LSMS surveys; and IMF staff calculations.
Note: Robust standard errors in parenthesis.***,** and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

[10] A household who reports more than one shock is treated the same here as a household who reports only one shock. Both are assigned a value of 1 for the shock variable.

[11] The household wealth index is constructed via principal component analysis of durable goods a household owns and converted into a standardized index with mean 0 and standard deviation 1.

To investigate which factors help households alleviate the impact of shocks on food security, we next limit the sample to households who report having experienced a shock and run the following regression:

$$Food\ security_{hh,c} = \beta_{0,c} + \beta_{1,c} X_{hh,c} + \beta_{2,c} controls_{hh,c} + \mu_{hh,c} \qquad if\ shock = 1$$

$X_{hh,c}$ contains access to banking, mobile communication devices, robust housing, improved sanitary facilities, and literacy of the head of household, as available in each survey. Controls again include the household wealth index, region fixed effects and a rural dummy.[12] Annex Table 2.7 reports the results from estimation via ordinary least squares by country.

Although not all variables are significant across the five surveys, the results broadly support an important role of access to finance, mobile communication, robust housing, improved sanitation and literacy in helping build buffers against food insecurity among households facing climate-related shocks. As in the full sample, higher household wealth positively predicts food security, which confirms that richer households are less likely to report food insecurity even when they are hit by a shock.

Annex Table 2.7: The Role of Coping Strategies in Securing Food Security

	Dependent variable: Food security conditional on experiencing a shock				
	(1)	(2)	(3)	(4)	(5)
	Ethiopia	Malawi	Mali	Niger	Tanzania
Household wealth index	0.070***	0.115***	0.031***	0.164***	0.056*
	(-0.011)	(-0.006)	(-0.01)	(-0.021)	(-0.03)
Bank account	0.082***	0.006	0.072***		0.074**
	(-0.022)	(-0.01)	(-0.025)		(-0.037)
Mobile phone	0.138***	0.036***	0.015	0.060***	0.064**
	(-0.021)	(-0.009)	(-0.025)	(-0.008)	(-0.03)
Robust housing	0.130***	0.191***	0.078**	0.061	0.105***
	(-0.014)	(-0.006)	(-0.011)	(-0.018)	(-0.013)
Improved sanitation	0.054***	0.061***	0.065***	0.027	-0.001
	(-0.019)	(-0.022)	(-0.02)	(-0.042)	(-0.026)
Literacy	0.048**	0.049***	0.02	-0.005	0.068***
	(-0.021)	(-0.009)	(-0.019)	(-0.024)	(-0.026)
Constant	0.370***	0.150***	0.520***	0.326***	0.421***
	(-0.031)	(-0.021)	(-0.038)	(-0.04)	(-0.045)
Region and rural dummies	YES	YES	YES	YES	YES
adj_R-squared	0.136	0.206	0.17	0.26	0.09
N	2836	12043	2847	1828	2157

Sources: LSMS surveys; and IMF staff calculations.
Note: Robust standard errors in parenthesis. ***,** and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively

[12] Bank account, mobile phone, improved sanitation and literacy are all defined as dummy variables and take either a value of 1 or 0. Improved sanitation refers to enhanced pit latrines or flush toilets. Robust housing is defined as a variable ranging from 0 to 1 with 1 indicating the most robust housing possible (i.e. housing made of robust materials such as brick and cement. It is constructed as the sum of dummies for having robust walls, robust flooring, and a robust roof divided by three.

2.4. HOUSEHOLD SURVEYS ON CROP YIELDS

2.4.1. Data

The dataset is comprised of nationally representative household surveys from Ethiopia, Rwanda, and Uganda, collected in collaboration with the World Bank Living Standards Measurement Study (LSMS). We assess the extent to which weather adversely affects crop yields and family consumption. We also assess the degree to which farmers attempt to protect their lands from crop damage through erosion mitigation methods, access to investment finance, and agricultural inputs.[13]

Annex Table 2.8 shows that crop damage associated with changing weather patterns is extensive. The surveys for Ethiopia and Rwanda show that almost 40 percent of farmers have been affected by crop damage during the agricultural season associated with the survey. Moreover, 70 percent of the farmers attribute the crop damage to climate change with an additional 10-20 percent associating crop damage with erosion and crop disease.

Annex Table 2.8. Selected Economies: Type of Crop Damage

	Rwanda 2017	Ethiopia 2017
Percent of households reporting crop	38	38
Of which (in percent of households reporting crop damage)		
Change of climate (too much/little rain)	72.2	66
Landslide	6	
Erosion/insects/crop disease	10.2	21.8
Destructive rains/hail	5.5	5.2
Loss of soil fertility	6.1	2.7
Other		4.3

Sources: LSMS surveys; and IMF staff calculations.
Note: ***, ** and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

2.4.2. Econometric Results

Annex Table 2.9 provides econometric results on the determinants of crop yields using ordinary least squares. Alternative non-linear estimation methods such as the Heckman missing variable estimator yield similar results. The results indicate that the use of inputs is important for raising crop yields. Both the use of insecticide and improved seeds are significant determinants in both Ethiopia and Rwanda while fertilizer is also important in Ethiopia and irrigation plays a major role in improving crop yields in Rwanda.

[13] The Ethiopia data comes from the 2015/16 Socioeconomic Survey, the Rwanda source is the 2016/17 EICV4 survey and the Uganda data uses the 2015/16 National Panel Survey

Annex Table 2.9. Selected Economies: Determinants of Crop Yields

	(1)	(2)
	Ethiopia	Rwanda
Fertilizer	0.728***	-0.148
	(-0.083)	(-0.093)
Insecticide	0.863***	0.387***
	(-0.231)	(-0.044)
Improved seeds	1.225***	0.06
	(-0.132)	(-0.041)
Irrigation	1.246***	-0.068
	(-0.241)	(-0.085)
Protection against erosion	0.525***	-0.541
	(-0.109)	(-0.04)
Access to finance	-0.092	0.091***
	(-0.094)	(-0.047)
R-squared	0.088	0.344
Number of observations	8368	7338

Sources: LSMS surveys; IMF staff calculations.
Note: Crop yield in log kilograms per hectare. Control variables (not reported above) include age, gender, plot ownership, soil quality, elevation, slope, the use of plot (partial versus whole), log surface area of plot and farm, type of settlement (urban versus rural), literacy, educational level, household size, primary occupation, and the ownership of non-agricultural enterprises. Robust standard errors in parenthesis. ***, ** and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

REFERENCES

Hansen, M., P. Potapov, R. Moore, M. Hancher, S. Turubanova, A. Tyukavina, D. Thau, S. Stehman, S. Goetz, T. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. Justice, J. Townshend. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." *Science*. 342 (6160): 850–853.

Harris, I., P. Jones, T. Osborn, and D. Lister. 2014. "Updated High-Resolution Grids of Monthly Climatic Observations – The CRU TS3.10 Dataset." *International Journal of Climatology*. 34 (3): 623–642.

Loayza, M., E. Olaberria, J. Rigolini, and L. Christiaensen. 2012. "Natural Disasters and Growth: Going Beyond the Averages." *World Development*. 40 (7): 1317–1336.

Pekel, J., A. Cottam, N. Gorelick, and A. Belward. 2016. "High-Resolution Mapping of Global Surface Water and Its Long-Term Changes." *Nature*. 540 (7633): 418–422.