# Climate, Conflict and Growth in Africa Reverse Causality and Predictive Power

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# Introduction

- Many studies review the links between climate and conflict (Burke et al., 2015), and their economic effects (Koubi, 2017; Carleton & Hsiang, 2016; Dell et al., 2014).
- Most studies focus on identification and partial (local) effects
- This paper focuses on the bigger picture and attempts to address two often neglected questions:
  - 1 **Relevance**: What proportion of conflict and economic activity can be predicted with climate variables?
  - 2 Equilibrium Effects: How strong are the channels Economy → Conflict and Conflict → Economy?
- Regional focus on Africa: continent most prone to conflict driven by agricultural or economic factors.

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# Predicting Economic Activity and Conflict

 $\rightarrow$  ML on a rich set of climate moments to predict conflict and economic activity, using Random Forests (Breiman, 2001).

# Data

- Panel data for 42 countries in Sub-Saharan Africa over 1971-2007, combined from 6 studies examining the links between climatic events, the economy and intergroup conflict: Miguel & Satyanath (2011) (M&S), Hendrix & Salehyan (2012) (H&S), Buhaug et al. (2015) (BBST), Koubi et al. (2012) (KOB), Bergholt & Lujala (2012) (B&L), Landis (2014) (LAN) and Couttenier & Soubeyran (2014)
- 0.5° gridded geospatial data from the PRIO grid and UDCP/ACLED conflict data for years 1980-2016.

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# **Cross-Country Panel**

Data

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## Table: DATA COVERAGE: 42 SSA COUNTRIES, 1971-2007

Country	Years	Ν	Country	Years	Ν	Country	Years	Ν
Angola	1975 - 2007	33	Gabon	1971 - 2007	37	Niger	1971 - 2007	37
Benin	1971 - 2007	37	Gambia	1971 - 2007	37	Nigeria	1971 - 2007	37
Botswana	1971 - 2007	37	Ghana	1971 - 2007	37	Rwanda	1971 - 2007	37
Burkina Faso	1971 - 2007	37	Guinea	1971 - 2007	37	Senegal	1971 - 2007	37
Burundi	1971 - 2007	37	Guinea-Bissau	1974 - 2007	34	Sierra Leone	1971 - 2007	37
Cameroon	1971 - 2007	37	Kenya	1971 - 2007	37	Somalia	1971 - 2007	37
Central African R	1971 - 2007	37	Lesotho	1971 - 2007	37	South Africa	1971 - 2007	37
Chad	1971 - 2007	37	Liberia	1971 - 2007	37	Sudan	1971 - 2007	37
Congo	1971 - 2007	37	Madagascar	1971 - 2007	37	Swaziland	1971 - 2007	37
Cote d'Ivoire	1971 - 2007	37	Malawi	1971 - 2007	37	Tanzania	1971 - 2007	37
Democratic Republ	1971 - 2007	37	Mali	1971 - 2007	37	Togo	1971 - 2007	37
Djibouti	1977 - 2007	31	Mauritania	1971 - 2007	37	Uganda	1971 - 2007	37
Equatorial Guinea	1971 - 2007	37	Mozambique	1975 - 2007	33	Zambia	1971 - 2007	37
Ethiopia	1991 - 2007	17	Namibia	1991 - 2007	17	Zimbabwe	1971 - 2007	37

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### Table: PREDICTED DEPENDENT VARIABLES

Variables	Ν	Mean	SD	Min	Max	Skew	Kurt
PWT version 6.3 - GDP per capita PPP	1,497	2,290	2,361	154	23,444	3.38	20.6
PWT version 6.3 - GDP per capita growth PPP	1,497	0.91	9.29	-62.4	123	2.93	38.7
WDI - GDP per capita growth	1,393	0.96	8.40	-50.2	142	4.52	74.8
B&L - Conflict year (25+ battle deaths in current year)	1,497	0.20	0.40	0	1	1.51	3.29
LAN - UCDP Non-State Conflict	834	0.32	0.96	0	8	4.06	22.3
B&L - Onset (>25 death) after >2 years of peace	1,497	0.043	0.20	0	1	4.52	21.4
KOB - Civil Conflict Onset (>25 deaths) after >9 years of p.	1,317	0.029	0.17	0	1	5.63	32.7
KOB - Conflict onset (>1000 deaths) after >9 years of peace	1,317	0.012	0.11	0	1	8.91	80.3
BBST - PRIO battle deaths best estimate	1,497	577	2,834	0	36,250	8.63	91.3

### Table: PAIRWISE CORRELATIONS OF DEPENDENT VARIABLES

# Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<ol> <li>GDP per capita PPP, PWT version 6.3</li> </ol>	1								
(2) GDP per capita growth PPP, PWT version 6.3	.11	1							
(3) WDI - GDP per capita growth	.15	.77	1						
(4) B&L - Conflict year (25+ battle deaths in current year)	09	10	10	1					
(5) BBST - PRIO battle deaths best estimate	08	08	10	.40	1				
(6) B&L - Onset (>25 death) after >2 years of peace	04	03	02	.42	.01	1			
(7) KOB - Civil Conflict Onset (>25 deaths) after >9 years of p.	04	04	03	.29	.02	.65	1		
(8) KOB - Conflict onset (>1000 deaths) after >9 years of peace	04	02	05	.18	.02	.43	.64	1	
(9) LAN - UCDP Non-State Conflict	13	06	03	.21	.10	.02	.01	03	1

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## Table: CLIMATE VARIABLES, N = 1497, KMO = 0.63

# Variables	Mean	SD	Min	Max	Skew	Kurt
(1) KOB - Precipitation dev from 30-year moving avg, GPCC	-47.1	152	-944	994	-0.33	7.15
(2) KOB - Temperature dev from 30-year moving avg, GPCC	0.22	0.50	-1.43	3.15	0.42	5.38
(3) C&S - Palmer Drought Severity Index	-0.49	1.11	-4.65	3.40	0.13	3.34
(4) B&L - Dummy = 1 if drought year	0.050	0.22	0	1	4.12	18.0
(5) LAN - El Nino Year dummy	0.21	0.41	0	1	1.39	2.94
(6) B&L - Large climate related disaster 1[>10,000 affected]	0.12	0.32	0	1	2.34	6.50
(7) B&L - Affected by floods (% of pop), time weights	0.0017	0.016	0	0.33	14.5	239
(8) B&L - Affected by storms (% of pop), time weights	0.00052	0.0091	0	0.31	29.1	948
(9) B&L - Population share affected by earthquakes	4.7e-06	0.00013	0	0.0043	31.2	1,024
(10) B&L - Population share affected by volcanoes	3.1e-06	0.000078	0	0.0023	27.0	745
(11) BBST - Mean temperature (°C), UDel data	24.2	3.37	10.2	29.4	-1.46	6.26
(12) BBST - Mean temperature growth (%), UDel data	0.077	1.94	-9.73	8.82	-0.021	4.74
(13) BBST - Mean precipitation (1000mm), UDel data	0.93	0.49	0.11	2.45	0.56	3.06
(14) BBST - Mean precipitation growth (%), UDel data	1.68	19.1	-52.6	167	1.49	10.3
(15) BBST - Mean temperature in 1961-90	23.9	3.30	11.4	28.2	-1.43	6.07
(16) BBST - Mean precipitation in 1961-90	0.96	0.51	0.15	2.24	0.55	3.02
(17) BBST - Temperature dev as std dev from 1961-90 mean	0.50	1.04	-2.71	3.53	0.049	2.76
(18) BBST - Precipitation dev as std dev from 1961-90 mean	-0.23	0.95	-4.76	4.16	0.27	4.14
(19) LAN - NCAR/NCEP Yearly Temperature Mean	23.6	3.10	14.4	28.3	-0.96	3.31
(20) LAN - Temperature Shock	0.089	0.29	-0.84	1.79	0.88	5.69
(21) LAN - Standard Deviation of Temperature Mean	1.88	1.08	0.61	4.37	0.75	2.33
(22) LAN - Standard Deviation Precipitation Mean	2.18	0.99	0.62	5.00	0.73	3.49

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# **Empirical Challenges**

- The Unconfoundedness Assumption when using cross-sectional climate variation (Burke et al., 2015) → Data reject fixed effects, thus no data transformation.
- 2. The Frequency-Identification Tradeoff (Hsiang, 2016)

$$E[Y_{i\tau+\Delta\tau}|C,\mathbf{x}_{i\tau+\Delta\tau}] = E[Y_{i\tau}|C,\mathbf{x}_{i\tau}]$$
(1)

 $\rightarrow$  Controlling for observable characteristics  $\mathbf{x}_{i\tau}$  in period  $\tau$ and  $\tau + \Delta \tau$  and conditioning on a fixed climate *C*, the outcome of interest *Y* is the same in  $\tau$  and  $\tau + \Delta \tau$ , such that the effect of climate change on *Y* can be identified as

$$\hat{\beta}_{\Delta C} = E[Y_{i\tau+\Delta\tau}|C_{\tau+\Delta\tau}, \mathbf{x}_{i\tau+\Delta\tau}] - E[Y_{i\tau}|C, \mathbf{x}_{i\tau}].$$
(2)

The Frequency-Identification Tradeoff states that (1) only holds if  $\Delta \tau$  is small i.e. if society has no time to 'adapt'.

**Empirical Challenges** 

Data

 African societies have likely become more resilient against climate in the last 30 years: changes in the composition of income from strongly agricultural economies to more industry and service oriented economies, supported by anecdotal empirical evidence such as the near collapse of the strong inverse relationship between rainfall and growth studied by Miguel et al. (2004) and others in the early 2000's, along with greater macroeconomic stability and financial deepening (see also KWP 2229 for a recent study).

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• An imperfect examination of the time series homogeneity assumption (Eq. 1) underlying the *Frequency-Identification Tradeoff* is to study the correlation of climate moments with growth and conflict over time.

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## **Cross-Country Results**

### Figure: PWT Version 6.3 GDP per capita

% Variance Explained = 91.67 | N. Trees = 1000 | N. Vars at each split = 13



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### Figure: PWT Version 6.3 GDP per capita Growth

% Variance Explained = 5.14 | N. Trees = 1000 | N. Vars at each split = 2



BBST - Precip dev as std dev from 1961-90 mean BBST - Mean precipitation in 1961-90 KOB - Precip dev from 30-year moving avg, GPCC LAN - Standard Deviation of Temperature Mean BBST - Temp dev as std dev from 1961-90 mean LAN - NCAR/NCEP Yearly Temperature Mean BBST - Mean temperature in 1961-90 BBST - Mean precipitation growth (%), UDel data BBST - Mean temperature (°C), UDel data BBST - Mean temperature growth (%), UDel data LAN - Standard Deviation Precipitation Mean LAN - Temperature Shock C&S - Palmer Drought Severity Index KOB - Temp dev from 30-year moving avg. GPCC B&L - Large clim. rel. disaster 1[ >10,000 affected] I AN - El Nino Year B&L - Population share affected by volcanoes B&L - Affected by storms (% of pop), time weights B&L - Dummy = 1 if drought year B&L - Affected by floods (% of pop), time weights B&L - Population share affected by earthquakes

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### Figure: WDI GDP per capita Growth

% Variance Explained = 6.92 | N. Trees = 1000 | N. Vars at each split = 2



BBST - Mean precipitation (1000mm), UDel data LAN - Standard Deviation Precipitation Mean LAN - NCAR/NCEP Yearly Temperature Mean BBST - Mean precipitation growth (%), UDel data BBST - Mean precipitation in 1961-90 BBST - Mean temperature (°C), UDel data BBST - Precip dev as std dev from 1961-90 mean BBST - Mean temperature in 1961-90 BBST - Temp dev as std dev from 1961-90 mean I AN - Temperature Shock BBST - Mean temperature growth (%), UDel data C&S - Palmer Drought Severity Index LAN - Standard Deviation of Temperature Mean KOB - Temp dev from 30-year moving avg, GPCC KOB - Precip dev from 30-year moving avg. GPCC I AN - El Nino Year B&L - Dummy = 1 if drought year B&L - Large clim, rel, disaster 1[ >10,000 affected] B&L - Affected by storms (% of pop), time weights B&L - Population share affected by earthquakes B&L - Affected by floods (% of pop), time weights B&L - Population share affected by volcanoes

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### Figure: Conflict Incidence (Conflict Year)

Accuracy = 89.37% [False Pos.: 79/195 (40.51%), False Neg.: 41/934 (4.39%)] | N. Trees = 1000 | N. Vars/Split = 15



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#### Figure: Non-State Conflict Onset

Accuracy = 91.24% [False Pos.: 36/88 (40.91%), False Neg.: 17/517 (3.29%)] | N. Trees = 1000 | N. Vars/Split = 22



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#### Figure: ACLED Battle Death Best Estimate

% Variance Explained = 11.38 | N. Trees = 1000 | N. Vars at each split = 3



LAN - Standard Deviation of Temperature Mean BBST - Mean precipitation in 1961-90 BBST - Mean temperature (°C), UDel data LAN - NCAR/NCEP Yearly Temperature Mean BBST - Mean precipitation (1000mm), UDel data BBST - Mean temperature in 1961-90 LAN - Standard Deviation Precipitation Mean BBST - Mean precipitation growth (%), UDel data BBST - Temp dev as std dev from 1961-90 mean KOB - Temp dev from 30-year moving avg, GPCC C&S - Palmer Drought Severity Index LAN - Temperature Shock BBST - Precip dev as std dev from 1961-90 mean BBST - Mean temperature growth (%), UDel data B&L - Large clim, rel, disaster 1[ >10.000 affected] I AN - FI Nino Year KOB - Precip dev from 30-year moving avg, GPCC B&L - Affected by storms (% of pop), time weights B&L - Population share affected by earthquakes B&L - Affected by floods (% of pop), time weights B&L - Population share affected by volcanoes B&L - Dummy = 1 if drought year

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# **Cross Country Results**

- Climate variables predict about 5-7% of the cross-country variation in GDP per capita growth rates, and 90-92% of variation in GDP per capita levels<sup>1</sup>.
- The most important variables are mean precipitation and deviations from mean precipitation, closely followed by temperature moments.
- Climate variables predict about 60% of conflict incidence and non-state conflict onset, with a small false negative rate of around 4%.
- The standard deviation of year-to-year levels of precipitation is the most important variable<sup>2</sup>.

<sup>&</sup>lt;sup>1</sup>With doubly demeaned data, the variance explained drops to 0 for growth rates and 3% for GDP levels.

 $<sup>^2</sup>$ Using double demeaned climate predictors, the algorithm still rightly predicts 27% of conflict incidences and 8% of non-state conflict onsets (sensitivity). The false negative rate (specificity) drops to 1% in both cases yielding still an overall predictive accuracy of around 85% in both cases.

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## **Gridded Prediction**

### Table: SPATIAL DEPENDENT VARIABLES

Variables	N	Mean	SD	Min	Max	Skew	Kurt
Conflict incidence, UCDP-GED	147,858	0.029	0.167	0	1	5.629	32.689
# Conflict events, UCDP-GED	141,864	0.111	1.486	0	126	36.699	1,880
Conflict onset, UCDP-GED	146, 169	0.016	0.125	0	1	7.763	61.265
Conflict incidence, ACLED 1997-2010	82,125	0.042	0.201	0	1	4.563	21.821
Gross Cell Product per Capita, PPP\$ USD	38,539	0.144	0.671	0	21.260	15.241	329.502
Gross Cell Product per Capita, PPP\$ USD growth	27,671	20.530	25.799	-68.692	482.863	3.025	38.414
Nightlights calibrated, mean	214,748	0.040	0.034	0	0.957	8.508	129.119
Nightlights calibrated, mean, growth	196,747	45.975	770.171	-69.562	75,803	49.104	3,243
Nightlights, standard deviation	222,206	0.721	2.173	0	26.118	5.164	35.942

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## Table: Correlation Matrix of Spatial Dependent Variables

(				/					
# Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Conflict incidence, UCDP-GED	1	1							
(2) # Conflict events, OCDP-GED (2) Conflict exect LICDP CED	.425	472	1						
(4) Conflict incidence, ACLED 1997-2010	.405	.472	.291	1					
(5) Gross Cell Product per Capita, PPP\$ USD	.061	.127	.038	.058	1				
(6) Gross Cell Product per Capita, PPP\$ USD growth	019	018	002	016	.010	1			
(7) Nightlights calibrated, mean	.078	.101	.045	.107	.669	005	1		
(8) Nightlights calibrated, mean, growth	002	001	001	.001	055	392	033	1	
<ol><li>Nightlights, standard deviation</li></ol>	.090	.097	.056	.136	.531	015	.749	011	1

### (*Pairwise Correlations*)

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# Table: Spatial Climate Variables, N = 544,716, cells = 10,260, years = 64

# Variables	Mean	SD	Min	Max	Skew	Kurt
droughtyr_speibase	0.054	0.065	0	0.833	1.654	8.259
droughtstart_speibase	-0.041	1.040	-5.877	7.314	0.185	2.617
droughtend_speibase	-0.083	1.032	-5.564	4.369	0.088	2.642
temp	24.108	4.011	7.509	40.224	-0.405	3.088
<li>(1) g_temp</li>	0.124	3.090	-50.844	131.561	1.014	40.515
(2) temp_30MA	23.879	3.905	10.223	38.893	-0.427	3.003
(3) temp_30SD	0.611	0.388	0	7.478	5.085	44.200
(4) temp_30MA_dev	0.229	0.774	-9.254	15.627	0.205	13.286
(5) temp_30SD_dev	0.331	0.344	0	12.618	4.207	42.048
prec_gpcc	158.703	156.722	0	1,478.142	1.018	3.736
<ol><li>g_prec_gpcc</li></ol>	67.314	4,447	-100	1,937,000	293.348	103,272
(2) prec_gpcc_30MA	161.360	156.061	0.056	1,067.414	0.938	3.365
(3) prec_gpcc_30SD	29.411	22.164	0.004	225.304	0.974	4.815
(4) prec_gpcc_30MA_dev	-2.657	36.657	-486.116	634.246	0.117	10.293
(5) prec_gpcc_30SD_dev	15.531	17.427	0	454.228	2.539	17.745

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# **Gridded Results**

# Figure: Conflict Incidence UDCP



Accuracy = 97.22% [False Pos.: 4040/4264 (94.75%), False Neg.: 66/143509 (0.05%)] | N. Trees = 1000 | N. Vars/Split = 5

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### Figure: Conflict Onset UDCP

Accuracy = 98.42% [False Pos.: 2301/2310 (99.61%), False Neg.: 10/143775 (0.01%)] | N. Trees = 1000 | N. Vars/Split = 5



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# Figure: Gross Cell Product per Capita, PPP\$ growth (5-year, 1995, 2000, 2005)



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### Figure: Nightlights Calibrated Mean, Growth

% Variance Explained = 4.5 | N. Trees = 1000 | N. Vars at each split = 5



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### Figure: Nightlights Calibrated Mean

% Variance Explained = 52.3 | N. Trees = 1000 | N. Vars at each split = 5



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# **Gridded Results**

- Climate predicts conflict incidence at the cell-level with a sensitivity of 5.25%, a specificity of 99.95%, and an overall accuracy of 97.22%.
- The best predictors are 30-year MA's of temperature and precipitation, followed by moving SD's and levels of the same variables.
- For conflict onset the sensitivity drops to 0.4%, with a specificity of 99.99%. The feature importance ranking is similar as for incidence i.e. long-term averages are more important than deviations/shocks.
- RF predicted almost 70% of the variation of GCP growth in Africa, with long-term measures of precipitation the most important variables, followed by temperature shocks.
- For nightlights growth the explained variation drops to 4.5%, but nightlights levels can be predicted with 52.3% explained variation.

# **Reverse Causality**

#### Theoretical Links: Economy $\rightarrow$ Conflict

- **Opportunity Cost Mechanism**: When gains from conventional economic activity are low, the opportunity cost for young men to engage in illicit economic activities / join rebel groups is lower (Collier and Hoeffler (1998, 2001, 2002), Miguel et al. (2004)).
- State Capacity Mechanism: Low national income and shocks limit Government capacity to maintain law and order, and invest in military, infrastructure, public administration, health and education, and to provide appropriate economic opportunity to citizens (Berman & Couttenier, 2015).

#### Theoretical Links: Conflict $\rightarrow$ Economy

- Conflict **displaces peoples**, preventing them to engage in economic activities.
- It also **destroys productive capital, state and administrative structures**, and social services needed to support complex economic activity.
- It **displaces industry and trade networks**, mindering the economic structure and stability of regions in the medium and long term.

See e.g. Cooper (2019) for a discussion of post-colonial conflicts in Africa.

References

# Why is Modeling of Reverse Causality Important?

- If the magnitude and mechanisms of reverse causality between conflict and economic conditions are not well understood, then the exclusion restriction in many IV papers estimating the effects of economic conditions on conflict may be violated
- Abstracting from reverse causality does not allow for virtuous or vicious cycles, and empirical results are thus likely to understate the true general-equilibrium effect of economic shocks on conflict and vice-versa

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# **Empirical Approach: Cross-Country Panel**

Estimate a two-way system via 2SLS using political revolutions as an instrument for conflict impacting growth and lagged food and crop production to instrument growth's impact on conflict. Instruments are taken from Buhaug et al. (2015), outcome data from Miguel & Satyanath (2011).

Both instruments are imperfect and endogenous in the long-term, but purported to limit reverse causality in the short-term.

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### Table: SUMMARY STATISTICS

Variables	Ν	Mean	SD	Min	Max	Skew	Kurt
MIG'15 - UCDP/PRIO v4-2010, >25 deaths	1,179	0.26	0.44	0	1	1.08	2.17
MIG'15 - Per cap GDP growth from PWT 7.0	1,189	0.73	9.21	-62.1	88.7	1.78	25.2
BBST - Revolutions	2,221	0.20	0.40	0	1	1.47	3.15
BBST - % growth in food prod pc since t-1	2,101	0.30	9.72	-50.5	68.3	0.84	9.89
BBST - Crops production per capita t-1	2,101	0.095	0.049	0.0029	0.31	0.78	4.34

## Table: PAIRWISE CORRELATION MATRIX

# Variable	(1)	(2)	(3)	(4)	(5)
(1) MIG'15 - UCDP/PRIO v4-2010, >25 deaths	1				
(2) MIG'15 - Per cap GDP growth from PWT 7.0	05	1			
(3) BBST - Revolutions	.46	08	1		
(4) BBST - % growth in food prod pc since t-1	02	.22	04	1	
(5) BBST - Crops production per capita t-1	06	.01	02	09	1

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### Table: Cross-Country Panel Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First 3	Stages	Reduc	ed Forms	25	SLS	2SLS	+ Lag. IV
Variables	CINC	%GDP	CINC	%GDP	CINC	%GDP	CINC	%GDP
BBST - Revolutions	0.228***	-1.670**		-2.136**				
	(0.041)	(0.785)		(0.854)				
BBST - % growth in food prod pc since t-1	0.000	0.239***	-0.000					
	(0.002)	(0.074)	(0.001)					
BBST - Crops production per capita t-1	1.426	60.789**	0.278					
	(1.611)	(28.559)	(1.658)					
MIG'15 - Per cap GDP growth from PWT 7.0					-0.001		-0.002	
					(0.005)		(0.005)	
MIG'15 - UCDP/PRIO v4-2010, >25 deaths						-9.277**		-8.905***
						(3.845)		(3.273)
Observations	1,096	1,096	1,179	1,106	1,179	1,096	1,178	1,095
R <sup>2</sup>	.681	.146	.655	.101	.005	030	.007	025
Kleibergen-Paan I M stat (H0: Underid)					6 779	13 50	9 741	13.48
Kleibergen-Paap P-Value					0.033	0.0002	0.045	0.001
Hansen J Overid, test (H0: Eq. Identified)					0.046		2.348	0.047
Hansen J P-Value					0.830		0.503	0.828
Endogeneity of Regressor (H0: Exogenous)					0.230	2.495	0.083	3.077
Endog. P-Value					0.631	0.114	0.773	0.079

Robust standard errors in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

NOTE: Country FE and Country specific time-trends included in all specifications. "2SLS + Lag. IV" indicates that the instruments were included in levels and lags, to increase the first stage r-squared. In all specifications, the error matrix is cluster-robust at the country level.

# **Empirical Approach: Gridded Panel**

Berman & Couttenier (2015) use gridded data to identify the effects of external shocks on conflict outbreak in Sub-Saharan Africa. They consider 2 shocks:

- Agricultural Commodity Price Shock: the world import value of agricultural commodities produced in each cell weighted by their share in the cells agricultural output (thus the shock is positive).
- Financial Crisis Shock: an exports-share weighted average of a dummy indicating banking crises in trading partners.

I use their measures as instruments for growth affecting conflict incidence. For the conflict  $\rightarrow$  growth channel I construct 2 own instruments, based on external political shocks, to instrument for conflict in the regression on growth:

- Political Revolutions in neighbouring countries, weighted by the distance of the cell to the border.
- **Executive elections** in neighbouring countries, weighted by the distance of the cell to the border.

References

4 different 2SLS specifications are estimated:

- (1) Simple baseline
- (2) Instruments interacted with the share of neighbouring countries where >9% of the population speak the same language
- (3) Using alternative ACLED and nightlights outcome data instead of UDCP and G-Econ
- (4) Adding all of the climate moments to both equations (partialling out the effects of climate)

Reverse Causality

Conclusion

References

## Table: SUMMARY STATISTICS

Variables	N	Mean	SD	Min	Max	Skew	Kurt
Conflict incidence, UCDP-GED	150,804	0.029	0.17	0	1	5.61	32.4
Binary, 1 for event, ACLED 1997-2010	83,670	0.042	0.20	0	1	4.54	21.6
Gross Cell Product per Capita, PPP\$ growth	28,785	20.6	26.1	-68.7	483	3.29	41.4
Nightlights calibrated, mean, growth	205,102	46.3	775	-84.6	75,803	48.7	3,187
In agr. com. shock	130,500	10.0	0.93	-6.05	12.0	-3.00	30.4
In agr. shock $ imes$ In dist. to closest port	130,500	64.0	9.75	-42.9	85.2	-1.28	7.26
Exposure to crises	223,263	0.14	0.17	0	0.88	1.86	6.07
Exp. to crises $\times$ In dist. to closest port	223,263	0.89	1.15	0	6.13	1.92	6.26
Weighted Revolutions	279,038	0.070	0.092	0	3	6.56	90.9
Weighted Nat. Elec. for Executive	317,116	0.17	0.16	0	2	6.46	62.2
Irregular Political Activity, weighted sum	259,794	0.13	0.17	0	8	7.83	136
Major Elections, weighted sum	259,785	0.23	0.23	0	6	6.94	78.9
Common language spoken by 9% of pop	335,950	0.50	0.32	0	1	-0.20	2.02
Log distance from cell centroid to int. border	362,655	4.68	1.15	0.50	7.59	-1.07	4.20

# Table: PRIO Gridded Data Regressions Using Weighted Revolutions andWeighted Executive Election Instruments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	First S %GDP	CINC	Reduc %GDP	ed Forms CINC	2SI %GDP	CINC	2SLS + %GDP	Int. IV CINC	ACLED 8	2 Nightl. CINC	2SLS + %GDP	- Clim. CINC
In agr. com. shock	-1.481	-0.072***	/****	-0.068***	/****		/0				,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	
in ugr. com: shoek	(9.374)	(0.020)		(0.018)								
Exposure to crises	27.986***	-0.008		-0.011								
	(6.708)	(0.013)		(0.013)								
Weighted Revolutions	9.839	0.002	13.726									
	(8.025)	(0.019)	(8.624)									
Weighted Nat. Elec. for Executive	-16.906	0.036	3.767									
	(16.431)	(0.030)	(20.441)									
Conflict incidence, UCDP-GED					-317.512		-141.439				-451.427	
000 0 1 0000 1					(334.653)		(100.866)				(338.519)	
GCP per Capita, PPPS growth						-0.002*		-0.000				-0.003**
Conflict incidence ACLED 1007 2010						(0.001)		(0.001)	44 579*			(0.002)
Connict medence, ACLED 1997-2010									(23.433)			
Nightlights calibrated mean growth									(20.100)	-0.012		
										(0.010)		
Dbservations P <sup>2</sup>	17,870	0.273	20,444	130,500	20,444	20,870	20,444	20,870	72,680	(2,450	2 559	16,093
Number of gid	0.500	0.215	0.570	0.270	6.826	6 968	6.826	6.968	7 268	7 245	5 1 1 9	5 370
Kleibergen-Paap LM stat. (H0: Underid.)					1.347	15.368	4.976	18.420	6.162	19.172	1.919	11.734
Kleibergen-Paap P-Value					0.510	0.000	0.290	0.001	0.046	0.000	0.383	0.003
Hansen J Overid. test (HU: Eq. Identified) Hansen I P-Value					0.027	0.007	18.679	0.017	0.196	3.780	0.104	8.283
Endogeneity of Regressor (H0: Exogenous)					2.934	0.330	0.227	0.151	6.137	7.075	15.012	0.244
Endog. P-Value					0.087	0.566	0.634	0.698	0.013	0.008	0.000	0.621

Robust standard errors in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

NOTE: Cell FE and time FE included in all specifications.

References

The instruments are weak, so I attempted to broaden their scope a bit to increase their empirical strength:

- Irregular political activity: sum of neighbouring-countries mean of revolutions, government crisis, major constitutional changes and the number of coups d'etat, weighted by cell distance to border.
- **Major elections**: sum of the neighbouring-countries mean of national elections of legislative and executive and presidential elections, weighted by cell distance to border.

Unfortunately this has not been very fruitful ...

# Table: PRIO Gridded Data Regressions using Weighted Irregular Political Activity and Weighted Major Elections Instruments

	(1) First S	(2) Stages	(3) Reduc	(4) ed Forms	(5) (6) 2SLS		(7) (8) 25LS + Int IV		(9) (10) ACLED & Nightl		(11) (12) 2SI S + Clim	
Variables	%GDP	CINC	%GDP	CINC	%GDP	CINC	%GDP	CINC	%NL	CINC	%GDP	CINC
In agr. com. shock	-0.483	-0.071***		-0.068***								
Exposure to crises	(9.497) 27.644***	-0.009		-0.011								
Irregular Political Activity, weigh. s.	(6.486) 7.346 (7.724)	(0.013)	2.811	(0.013)								
Major Elections, weighted sum	(7.724) 4.214 (6.200)	0.012*	(8.703) 7.348 (7.302)									
Conflict incidence, UCDP-GED	(0.200)	()	()		85.408 (156.820)		-172.693** (77.116)				56.052 (86.493)	
GCP per Capita, PPP\$ growth						-0.002* (0.001)		-0.000 (0.001)				-0.003** (0.002)
Conflict incidence, ACLED 1997-2010									-107.024 (83.688)			
Nightlights calibrated, mean, growth										-0.012 (0.010)		
Observations R <sup>2</sup> Number of gid	17,870 0.585	112,492 0.273	20,444 0.575	130,500 0.270	20,444 -0.040 6,826	20,870 -0.004 6,968	20,444 -0.648 6,826	20,870 0.008 6,968	72,680 0.783 7,268	72,450 -0.247 7,245	15,339 0.173 5,119	16,093 -0.025 5,370
Kleibergen-Paap LM stat. (H0: Underid.) Kleibergen-Paap P-Value Hansen J O-value (H0: Eq. Identified) Hansen J P-Value Endogeneity of Regressor (H0: Exogenous) Endog. P-Value					3.027 0.220 0.333 0.564 1.011 0.315	15.368 0.000 7.153 0.007 0.330 0.566	7.604 0.107 25.500 0.000 2.611 0.106	18.420 0.001 10.178 0.017 0.151 0.698	3.066 0.216 0.103 0.748 9.792 0.002	19.172 0.000 3.786 0.052 7.075 0.008	3.652 0.161 0.281 0.596 0.423 0.516	11.734 0.003 8.283 0.004 0.244 0.621

Robust standard errors in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

NOTE: Cell FE and time FE included in all specifications.

# Conclusion

- Climate moments can successfully predict a significant share of African growth rates and conflict incidence, but attributing this predictive power to climate alone requires strong unconfoundedness assumptions.
- Conflict onset is difficult to predict with climate alone.
- For cell-level predictions, 30-year MA's of temperature and precipitation are more important that growth rates and deviations from the average (volatility in short). Volatility is more important in country-level predictions. Drought events are not important for any predictive exercise conducted.
- Reverse causality is an important empirical issue. The literature has focussed on the channel from economic conditions to conflict, I here provided evidence for a larger channel from conflict to economic conditions, and can only weakly affirm the other channel.

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