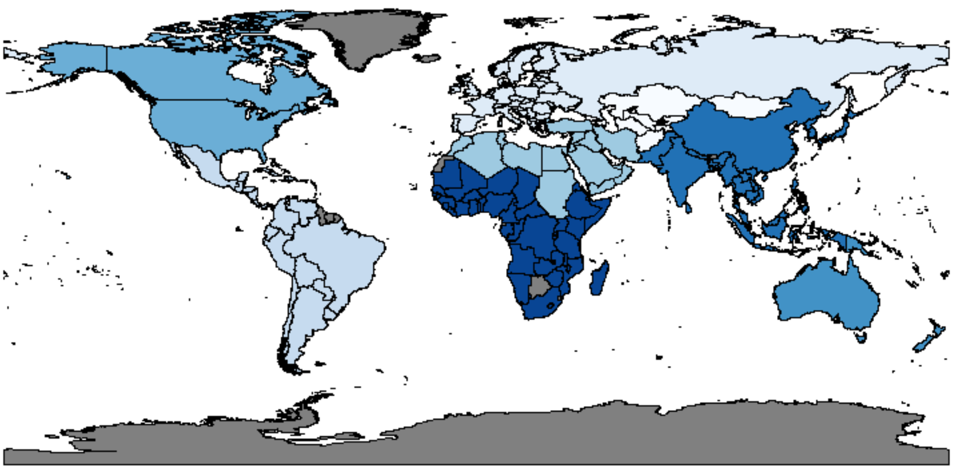
The urbanising force of global warming: The role of climate change in the spatial distribution of population

APPENDICES:
[Can be considered as Online Supplementary Material only]

Appendix A: Data overview [Corresponding to Section 2 in the paper]

Figure A.1: Map of countries included in the data set according the world regions



Note: Countries in grey are not included. All other countries are in different tones of blue, with each tone representing a different world region: The regions are: North America, Latin American & the Caribbean, Europe, North Africa & Middle East, Sub-Saharan Africa, Central Asia, South and East Asia, and Oceania.

Table A.1: Overview of all variables and data sources

Variable	Time Span	Source
I: Country-level variables		
I.1: Climatic variables		
Average temperature	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Average rainfall	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Temperature anomalies	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Rainfall anomalies	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Decennial temperature changes	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Decennial rainfall changes	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
I.2: Urban variables		
Urban rate	1960-2010	World Development Indicators (World Bank)
Urban pop in cities >1 million	1960-2010	World Development Indicators (World Bank)
Urban pop in cities <1 million	1960-2010	Constructed using World Development Indicators (World Bank)
Primacy rate	1960-2010	World Development Indicators (World Bank)
Number of cities per unit area	1960	Constructed using World Development Indicators and World Urbanisation Prospects
Average city size	1950-2015	Constructed using World Urbanization Prospects (United Nations)
I.3: Other country-level variables		
GDP per capita	1960-2010	World Development Indicators (World Bank)
Total population	1960-2010	World Development Indicators (World Bank)
Agricultural Share in GDP	1965-2010	World Development Indicators (World Bank)
II: City-level variables (for primary cities)		
Population in WUP	1950-2015	World Urbanization Prospects (United Nations)
Lights per Capita	1992-2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected
Spatial Gini coefficient in light	1992-2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected
Moran's I: spatial autocorrelation	1992-2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected
Population in GHSL	1975, 1990, 2000, 2015	Global Human Settlement Layers
Area	1975, 1990, 2000, 2015	Global Human Settlement Layers
Population density	1975, 1990, 2000, 2015	Constructed using Global Human Settlement Layers
Share of low vs. high density	1975, 1990, 2000, 2015	Constructed using Global Human Settlement Layers

Appendix B: Climate data [Corresponding to Section 2.1 in the main text]

Climate data variable definitions:

Our climatic variables are based on historical weather data, including temperature and rainfall observations, and are derived from monthly global gridded data, which have been aggregated to country means. The country-level datasets that we use were obtained from the World Bank's Climate Change Knowledge Portal (CCKP).[1] These data are simple area-weighted country means, derived from the University of East Anglia's Climate Research Unit (CRU) time-series (TS) dataset of high resolution gridded monthly climatic observations (see Harris et al. 2014). Based on these data, we construct three distinct sets of climatic variables, as follows:

Averages:

The variables *ave_rain* and *ave_temp* measure mean annual average rainfall (in meters per year) and temperatures (in degree Celsius), at the national level, over 5-year time periods. Given that our regressions include country fixed effects, when we include *ave_rain* or *ave_temp* as explanatory variables, estimation is based on the temporal variation in these measures for each country, i.e. the variation relative to that country's long-run average climate. Average annual temperatures and rainfall have been used in global analyses of the economic effects of weather variation for example in Dell et al. (2012) and Burke et al. (2015), who also implement a quadratic specification of the weather variables, similar to the one we use here.

Anomalies:

We also construct measures of rainfall and temperature *anomalies*, based on deviations of annual observations from their long run means, divided by the long run standard deviation of that variable, for each country (as used in e.g. Barrios et al., 2006, and Hendrix and Salehyan, 2012). Formally, rainfall anomalies for country i in year t are defined as:

$$rain\_anom_{it} = (ann\_rain_{it} - mean\_rain_i) \,/\, sd\_rain_i \,,$$

[1] Available from https://climateknowledgeportal.worldbank.org/download-data (last accessed on 18 June 2020).

where $mean\_rain_i$ and sd_rain_i are defined over the entire available dataset from 1901-2015. Temperature anomalies are defined similarly. These annual anomalies are then aggregated to 5-year periods to match with the urban data we are using, by taking simple 5-year means of the annual anomaly measures. The anomaly variables are standardised, with mean zero. However, the data in our sample reflect anomalies over the period 1950-2015 relative to long run trends (1901-2015). For temperature anomalies, in particular, the mean value in our sample is a bit above zero, reflecting warming over the latter part of the 20th century.

Decennial changes:

Finally, we construct measures of *decennial changes* over time in rainfall and temperature, measured as the 10-year, gradual change in average temperature or average rainfall, where averages are defined over 3-year periods at the beginning and end of each 10-year interval (as used in Peri and Sasahara, 2019). Formally, we define

$$temp\_dec\_ch_{it} \text{ as } (\Sigma_{t-2\rightarrow t}\, ann\_temp_{it}/3) - (\Sigma_{t-12\rightarrow t-10}\, ann\_temp_{it}/3)$$

The equivalent variable for rainfall, $rain\_dec\_ch_{it}$, is defined similarly. To match with our 5-year panel, we simply take the observed values of *temp_dec_ch* and *rain_dec_ch* at each fifth year, starting in 1950.

Moisture index:

We follow Henderson et al. (2017) and calculate a *moisture index* variable that captures the interaction of rainfall and temperature that is relevant for plant growth (and thus for agricultural productivity). This measure involves dividing rainfall observations by potential evapotranspiration (a non-linear function of temperature), such that rainfall observations are essentially penalised for places that are hotter, reflecting the effects of higher temperatures on moisture availability for plant growth. Potential evapotranspiration (PET) is calculated for monthly data, then aggregated to 5-year periods to match with our data. The formula for monthly PET (as used in Henderson et al., 2017), is

$$PET_i = \left(\frac{N_i}{30}\right)\left(\frac{L}{12}\right)\begin{cases} 0, T_i < 0°\text{C} \\ 16\left(\frac{10T_i}{I}\right)^{\alpha}, 0 \leq T_i < 26.5 \\ -415.85 + 32.24T_i - 0.43{T_i}^2, T_i \geq 26.5 \end{cases},$$

where T_i is the average monthly temperature in degrees Celsius, N_i is the number of days in the month, L_i is day length at the middle of the month, $\alpha = (6.75 \times 10^{-7})I^3 - (7.71 \times 10^{-5})I^2 + (1.792 \times 10^{-2})I + 0.49$, and the heat index $I = \sum_{i=1}^{12}(\frac{T_i}{5})^{1.514}$.

Each of our three sets of climatic variables (plus the moisture index) thus captures distinct aspects of weather variation; for the averages, variation in the levels of rainfall and temperature; for anomalies, variation that is large relative to typical variation for that country; and for gradual changes, gradual trends in rainfall or temperature over medium-term time scales. The moisture index captures interactions between rainfall and temperature that are likely to matter for agricultural productivity. In all cases, our weather variables are defined and included in our regressions such that we are using the variation in weather in the previous 5-year period (or in the case of the decennial change variables, over the preceding 10-year period) to explain variation in the outcomes of interest. Specifically, our rainfall observation for 1990 is defined as the average over 1985-1989.

Weighting by population and city-specific versions

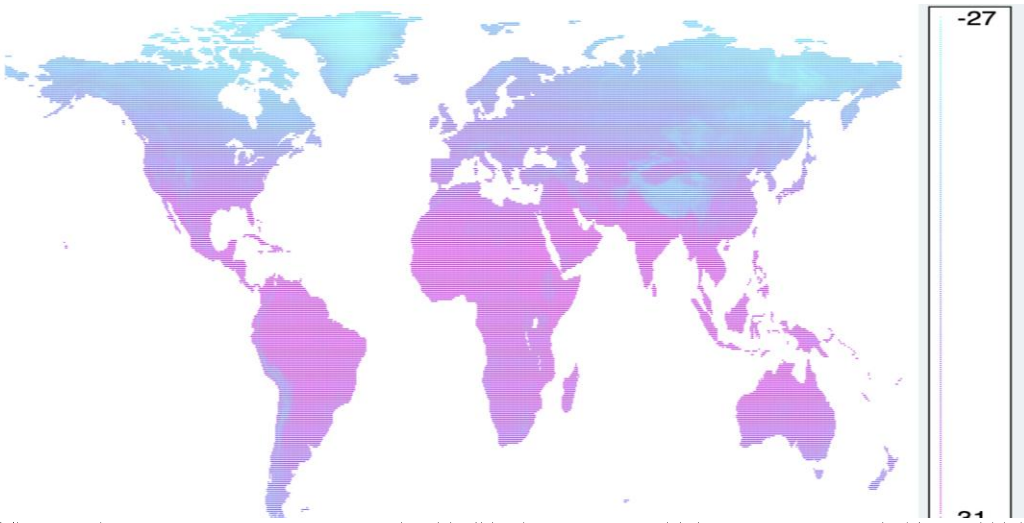
As noted in Section 2.1 of the main text, for robustness we also construct a global gridded weather dataset, merged with gridded population data, and urban area identifiers, from which we derive a number of alternative aggregations of the weather data. The gridded weather data we use for this purpose are from the CRU TS version 4.03 dataset from the University of East Anglia.[2] This is a gridded dataset of historical weather observations for 1901-2018, on a global 0.5-degree grid. These weather data were merged with gridded population data (also for a global 0.5-degree grid) from the Global Population of the World v4 dataset.[3] Urban gridcells in the data were identified using the urban area polygons from the Global Rural Urban Mapping Project (GRUMP) v1 dataset, which is based on urban extents circa 1995.[4] In practice, we identify a gridcell as

[2] The data are available from https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/ (last accessed June 2020).
[3] The data are available from https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-adjusted-to-2015-unwpp-country-totals-rev11/data-download (last accessed June 2020). We use the version of the population data adjusted to match UN country totals, and we take population estimates for the earliest available year in the data (2000).
[4] These data are available from https://sedac.ciesin.columbia.edu/data/collection/grump-v1/sets/browse (last accessed June 2020).

"urban" if the centroid of at least one urban area from the GRUMP dataset falls within that grid-cell.

For the city-level analysis reported in Section 3.3, we further construct city-specific versions of our climate variables for robustness, based on weather variation in the proximity of the city, and based on national level weather variation weighted by distance to the city. Specifically, we take coordinates of the centroid of each city in our data (the primary city, or largest urban agglomeration, in each country), from the UN WUP dataset, and calculate: a simple area-weighted aggregation of weather observations for gridcells within 500km of the city (and within national boundaries); population and distance-weighted aggregations of all gridcells in a country; and finally, population and distance-weighted aggregations of the rural (non-urban) gridcells only. Summary statistics for each of these alternative ways of aggregating the climate data, at both the national and city level, for the full sample, and by income group, are included in Table B.1.

Figure B.1: Map showing illustration of global gridded climate data



Note: The map shows average temperature at each gridcell in the year 2015, with lower temperatures in blue and higher temperatures in purple/pink. Each dot on the map represents one 0.5 degree gridcell. As the legend shows, the local average temperature in 2015 for gridcells ranges from -27 to +31 degrees C.

Table B.1: Summary stats for alternative climate variables

	World	Low	Middle	High
Panel A: National level climate variables				
Ave Rain	1.03	1.10	1.08	0.87
(St.Dev.)	(0.74)	(0.66)	(0.82)	(0.65)
Ave Temp	18.18	23.05	18.81	13.67
(St.Dev.)	(8.44)	(5.52)	(7.65)	(9.19)
Ave Rain (pop-weights)	1.09	1.20	1.04	0.85
(St.Dev.)	(0.72)	(0.61)	(0.72)	(0.53)
Ave Temp (pop-weights)	18.34	23.38	18.51	14.03
(St.Dev.)	(7.59)	(4.35)	(7.24)	(7.29)
Ave Rain (pop-weights, rural only)	1.10	1.22	1.04	0.84
(St.Dev.)	(0.71)	(0.61)	(0.71)	(0.53)
Ave Temp (pop-weights, rural only)	18.30	23.35	18.49	14.00
(St.Dev.)	(7.55)	(4.26)	(7.22)	(7.25)
Moisture	0.86	0.79	0.86	0.88
(St.Dev.)	(0.54)	(0.45)	(0.56)	(0.59)
Panel B: City level climate variables				
Ave rain (pop-weights & dist-weights)	1.02	1.23	1.02	0.81
(St.Dev.)	(0.68)	(0.64)	(0.72)	(0.53)
Ave Temp (pop-weights & dist-weights)	18.20	23.28	18.30	14.22
(St.Dev.)	(7.50)	(4.73)	(7.39)	(6.99)
Ave Rain (rural only)	1.02	1.23	1.01	0.81
(St.Dev.)	(0.68)	(0.65)	(0.72)	(0.53)
Ave Temp (rural only)	18.19	23.26	18.31	14.17
(St.Dev.)	(7.52)	(4.74)	(7.41)	(6.98)
Ave Rain (<500km)	1.05	1.15	1.09	0.87
(St.Dev.)	(0.71)	(0.63)	(0.80)	(0.57)
Ave Temp (<500km)	18.11	23.23	18.61	13.54
(St.Dev.)	(7.96)	(5.36)	(7.52)	(7.65)

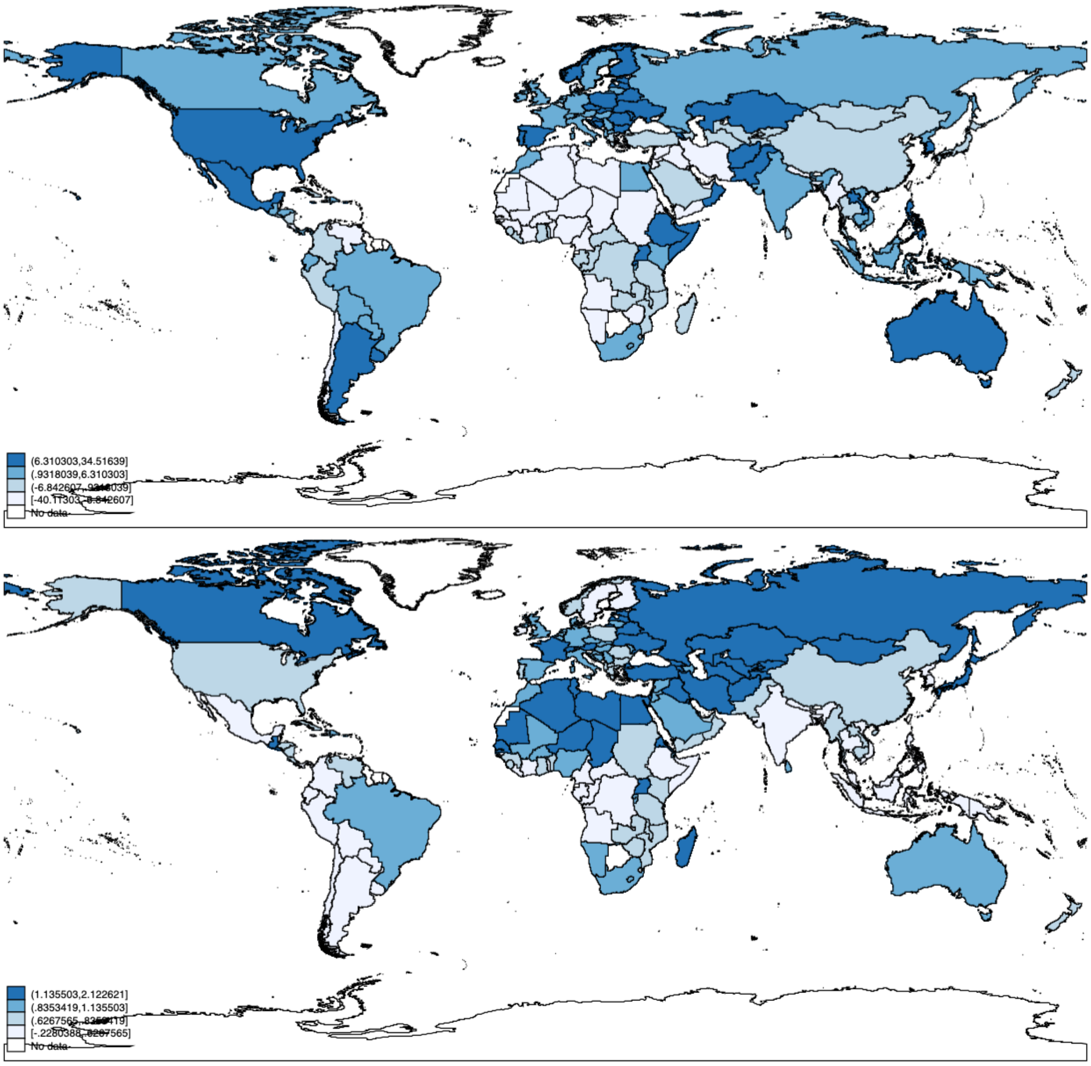
Note: The first two variables (first four rows) in the table are the (area weighted) country level average rainfall and temperature variables used in our baseline specifications, included here for comparison. The remaining rows are alternative ways of aggregating gridded climate data to the national level, as described in the text. The "rural only" variables are population weighted (and distance weighted in the case of the city-level variables), but only aggregating across gridcells that are non-urban (as per description in the text). Rainfall is measured in meters per year, and temperature in degrees Celsius.

Table B.2 Summary stats for climate data, by world region

	N Am	LATAM	Europe	Oceania	SSA	MENA	SE Asia	C Asia
Panel A: Long-run averages (1950-2015)								
Ave Rain	0.56	1.74	0.79	1.75	1.04	0.24	1.75	0.40
	(0.10)	(0.68)	(0.24)	(1.07)	(0.58)	(0.23)	(0.71)	(0.22)
Ave Temp	0.27	22.35	8.29	18.85	24.82	22.05	20.74	7.82
	(6.98)	(4.16)	(4.03)	(6.55)	(2.79)	(4.40)	(7.19)	(4.91)
Rain Anom	0.35	0.08	0.08	0.10	0.00	-0.06	0.01	0.12
	(0.61)	(0.52)	(0.46)	(0.47)	(0.65)	(0.54)	(0.54)	(0.48)
Temp Anom	0.27	0.26	0.24	0.33	0.16	0.34	0.27	0.30
	(0.72)	(0.74)	(0.70)	(0.68)	(0.88)	(0.78)	(0.82)	(0.70)
Rain_dec_ch	6.52	0.26	9.11	1.37	-1.16	-4.67	-2.99	2.25
	(22.29)	(233.70)	(90.84)	(171.37)	(104.16)	(51.06)	(197.95)	(55.04)
Temp_dec_ch	0.06	0.09	0.17	0.09	0.09	0.19	0.11	0.19
	(0.48)	(0.42)	(0.67)	(0.30)	(0.39)	(0.50)	(0.29)	(0.53)
Panel B: Long-run changes (1950-2015)								
Ave Rain	40.04	34.81	53.80	35.73	-67.81	-23.23	-24.36	5.93
	(23.18)	(174.97)	(61.39)	(43.39)	(118.06)	(32.08)	(234.68)	(17.91)
Ave Temp	0.94	0.60	1.02	0.52	0.80	1.13	0.58	1.54
	(0.35)	(0.38)	(0.37)	(0.43)	(0.39)	(0.31)	(0.29)	(0.36)
Rain Anom	1.34	0.14	0.53	0.30	-0.58	-0.52	-0.03	0.11
	(0.04)	(0.72)	(0.47)	(0.49)	(0.88)	(0.59)	(0.82)	(0.30)
Temp Anom	1.44	1.40	1.32	1.18	1.83	1.77	1.39	1.86
	(0.14)	(0.81)	(0.42)	(0.92)	(0.60)	(0.47)	(0.63)	(0.28)
Rain_dec_ch	10.54	-274.97	112.62	-21.35	44.12	-7.37	-44.23	-18.27
	(22.87)	(431.74)	(151.66)	(76.17)	(130.02)	(59.21)	(358.62)	(81.06)
Temp_dec_ch	0.69	0.41	0.15	0.37	0.15	0.67	-0.06	1.22
	(0.06)	(0.32)	(0.50)	(0.47)	(0.57)	(0.48)	(0.23)	(0.32)

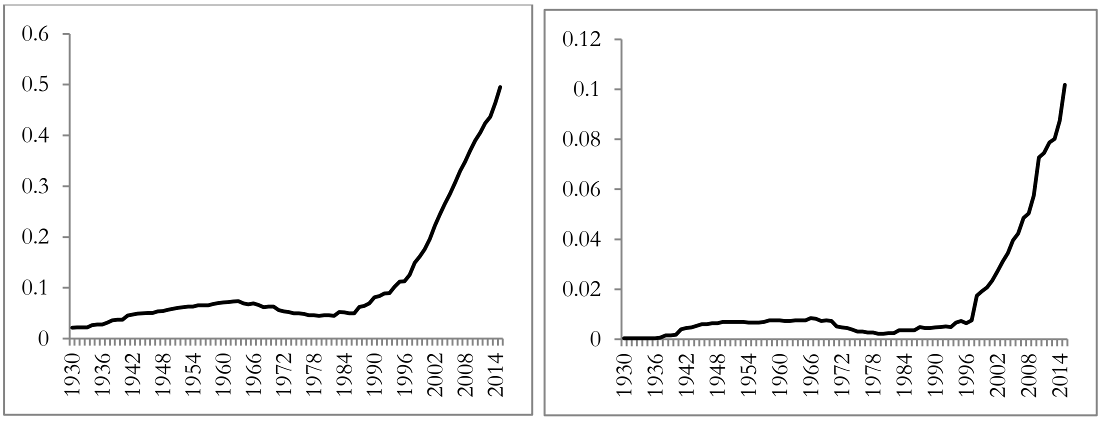
Note: The table shows mean values for each variable by world region (panel A) and long-run changes in these variables by world region (panel B). Standard deviations in parentheses. Variables are as defined in the text and here in Appendix B. For ease of interpretation, average rainfall figures are in m per year and changes in rainfall are in mm. The regions are as defined in the map in Figure A.1 in Appendix A.

Figure B.2: Maps of changes in average rainfall and temperatures, 1950-2015



Note: Top panel shows percentage changes in average annual rainfall and bottom panel shows changes in temperature (in degrees Celsius), by country, 1950-2015.

Figure B.3: Frequency of temperature anomalies



Note: Rolling 30-year average of frequency of temperature anomalies >+1 (left panel) and >+2 (right panel) for the countries in our sample. Each observation in the figures represents the average over the preceding 30-year period, such that the first observation in the chart (at 1930) represents the average over 1901-1930.

Gradual warming has a pronounced effect on the frequency of extremes

Focusing on temperature anomalies, we can observe the changing frequency of anomalies >+1, >+2, <-1, and <-2 in our data. Given how the anomaly variables are defined, a temperature anomaly >+1 represents a temperature observation (annual average temperature) more than 1 standard deviation above the mean for that country, and similarly for >+2, <-1, <-2. Warming on average might be expected to increase the frequency of higher than average temperatures, while decreasing the frequency of below average temperatures. Comparing the decade from 1901-1910, with the decade from 2006-2015, the frequency of annual temperature anomalies >+1 showed a 34-fold increase, while the frequency of annual temperature anomalies >+2 showed a 256-fold increase. These increasing frequencies are illustrated in Figure B.2. Turning to below average temperatures, the frequency of temperature anomalies <-1 declined from 28% to 0.7% over the same period, a 38-fold decline in frequency, while the frequency of temperature anomalies <-2 declined from 1.5% to 0.15%, a 10-fold decline in frequency. These figures underline how gradual warming can have dramatic effects on the frequency of more extreme observations, with a more pronounced increase in the frequency of relatively hot years.

Appendix C: Urban data [Corresponding to Section 2.2 in the main text]

Table C.1: Summary statistics of urban variables by region

	NA	LATAM	Europe	Oceania	SSA	MENA	SE Asia	C Asia
Panel A1: Country-level variables, latest available year (2010/15)								
Urb Rate	80.85	71.54	69.46	62.64	38.73	71.55	52.00	46.23
	(0.12)	(14.50)	(12.76)	(42.99)	(17.00)	(19.48)	(28.69)	(14.85)
Urb > 1m	44.47	29.76	12.77	29.79	10.34	24.55	24.34	15.56
	(0.04)	(15.51)	(10.48)	(30.11)	(10.66)	(19.62)	(29.91)	(15.28)
Urb < 1m	36.38	41.77	56.79	32.84	28.79	45.76	27.65	30.66
	(0.15)	(11.40)	(12.29)	(22.30)	(17.55)	(22.67)	(21.90)	(10.46)
Urb Largest	11.05	25.14	15.99	17.22	15.57	20.98	23.83	19.36
	(7.24)	(14.01)	(7.26)	(12.33)	(11.23)	(15.32)	(33.56)	(11.89)
Urb Non-Largest	69.80	46.39	53.48	45.42	23.13	49.65	28.16	26.86
	(7.12)	(14.67)	(14.26)	(32.74)	(10.33)	(15.89)	(19.51)	(9.46)
Primacy	13.67	35.36	23.70	30.38	38.82	30.13	35.57	40.68
	(8.93)	(15.17)	(11.59)	(6.99)	(14.39)	(14.22)	(29.86)	(15.39)
Ave. City Size	1385.51	1421.38	912.69	929.66	1249.04	1170.11	2023.18	1006.27
	(55.71)	(532.91)	(436.69)	(732.23)	(640.83)	(603.99)	(1773.57)	(374.97)
Panel A2: Variables at the primary city level, latest available year (2010/15)								
Pop	12292.98	5156.71	2454.76	1964.29	2643.47	4004.15	10195.36	1678.50
	(8909.89)	(6289.51)	(2995.25)	(2002.46)	(2938.37)	(4640.83)	(9876.78)	(1183.89)
Density	1553.51	2926.83	1712.27	2400.06	3245.51	3690.94	4816.76	3043.00
	(498.15)	(767.08)	(375.42)	(1503.95)	(1193.65)	(1695.00)	(5428.30)	(1262.67)
High dens share	86.90	90.01	77.53	87.98	92.32	86.96	80.03	87.29
	(6.79)	(9.36)	(16.91)	(8.67)	(13.20)	(11.57)	(21.98)	(13.04)
Light per capita	123.06	28.09	79.21	37.32	11.16	120.55	35.26	39.27
	(5.34)	(14.17)	(60.43)	(22.62)	(10.81)	(193.91)	(34.65)	(40.07)
Gini	37.94	29.53	29.18	19.84	25.11	38.26	37.77	32.66
	(11.37)	(5.64)	(8.34)	(6.24)	(6.99)	(9.26)	(9.36)	(9.00)
Moran's I	91.79	84.44	82.74	74.61	76.39	83.27	88.69	83.70
	(4.13)	(5.46)	(8.54)	(20.51)	(9.36)	(10.08)	(6.65)	(5.06)
Panel B1: Country-level variables, long-run changes								
Urb Rate	11.33	27.53	18.80	8.89	24.68	28.49	20.18	7.94
	(0.78)	(9.09)	(9.22)	(1.52)	(11.79)	(15.21)	(13.81)	(10.81)
Urb > 1m	10.06	10.73	2.58	5.54	6.70	5.62	7.74	4.30
	(6.07)	(10.18)	(4.86)	(5.32)	(7.10)	(10.53)	(7.36)	(7.95)
Urb < 1m	1.27	16.80	16.62	3.35	18.21	22.59	12.44	3.64
	(5.29	(6.96)	(7.62)	(5.22)	(13.25)	(14.69)	(10.02)	(4.23)
Urb Largest	2.27	7.74	3.64	4.54	9.95	2.31	5.27	4.73
	(5.89)	(9.76)	(4.25)	(5.50)	(7.31)	(12.25)	(4.94)	(7.87)
Urb Non-Largest	9.06	19.79	15.16	4.35	14.76	26.16	14.91	3.21
	(5.11)	(7.78)	(7.15)	(4.19)	(7.76)	(12.83)	(11.99)	(4.37)
Primacy	-0.15	-4.39	-1.79	0.50	0.22	-8.99	-3.17	2.92
	(5.24)	(10.06)	(4.93)	(7.78)	(17.56)	(16.30)	(8.18)	(7.88)
Ave. City Size	972.91	1181.13	397.57	691.04	1191.08	1066.96	1668.06	778.59
	(61.08)	(540.30)	(256.24)	(497.40)	(605.42)	(550.14)	(1370.84)	(401.79)
Panel B2: Variables at the primary city level, long-run changes								
Pop	5589.59	4259.25	1121.82	1408.68	2517.29	3613.72	8655.70	1314.08
	(940.67)	(5333.74)	(1475.17)	(1313.68)	(2797.07)	(4148.20)	(8043.01)	(1167.23)
Density	332.71	-457.36	-779.74	447.47	-278.98	-910.32	-829.60	305.23
	(288.98)	(1857.97)	(1973.44)	(56.32)	(1247.49)	(4691.02)	(5620.49)	(1223.69)
High dense share	13.27	-0.26	0.76	7.42	6.49	6.26	-3.24	1.42
	(7.82)	(10.15)	(11.21)	(3.63)	(14.95)	(19.73)	(22.85)	(20.68)
Light p.c.	-38.88	4.22	21.14	0.63	-0.76	-23.83	10.72	23.56
	(66.54)	(10.07)	(37.25)	(5.83)	(7.45)	(74.99)	(19.73)	(36.53)
Gini	-0.28	-5.37	-1.15	-4.69	-19.93	-2.58	-11.00	7.47
	(5.40)	(6.57)	(10.43)	(3.66)	(10.69)	(11.59)	(11.03)	(13.49)
Moran's I	-0.04	1.54	0.73	0.60	-3.71	-1.65	-0.97	6.60
	(0.44)	(4.94)	(6.06)	(5.64)	(5.62)	(3.48)	(3.51)	(7.72)

Notes: See Table 2 in the main text. The regional classifications are North America, Latin America and the Caribbean, Europe, Oceania, Sub-Saharan Africa, Middle East and Northern Africa, South East Asia, Central Asia.

Additional information on satellite data and measures for the spatial structure of cities

***Top Coding Corrected Satellite Data*:**

While satellite data of night-time lights have become established as a proxy for local economic activity in development economics in recent years (see Henderson et al., 2012, Donaldson and Storeygard, 2016), their use in urban economics has been limited. One drawback of the DMSP-OLS data, the most-often used time series data of night-time lights, is that they suffer from top-coding due to sensor saturation. This poses a problem for big cities in particular, because many pixels reach the end of the scale in terms of light intensity and appear equally bright. Inner-city differences as well as evolutions of luminosity over time cannot be measured appropriately. Bluhm and Krause (2018) propose a solution to the top-coding problem based on the observation that the world's brightest lights follow a Pareto distribution. With a geo-referenced replacement algorithm, in which top-coded pixels get assigned value from the Pareto distribution, they provide a corrected worldwide night-time lights dataset. The corrected data have been applied to the analysis of city growth and inner-city differences by, inter alia, Bluhm and Krause (2018) as well as Düben and Krause (2020).

Moran's I as Measure of Spatial Autocorrelation:

Following Moran (2015), a measure of spatial autocorrelation indicates to what extent a unit is located close of others of similar or dissimilar value. In our city application it captures whether similar light intensities cluster together and thus indicates how the city is structured. We compute Moran's I using the formula:

$$I = \frac{N}{S_0} \frac{\sum_i \sum_j w_{i,j} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

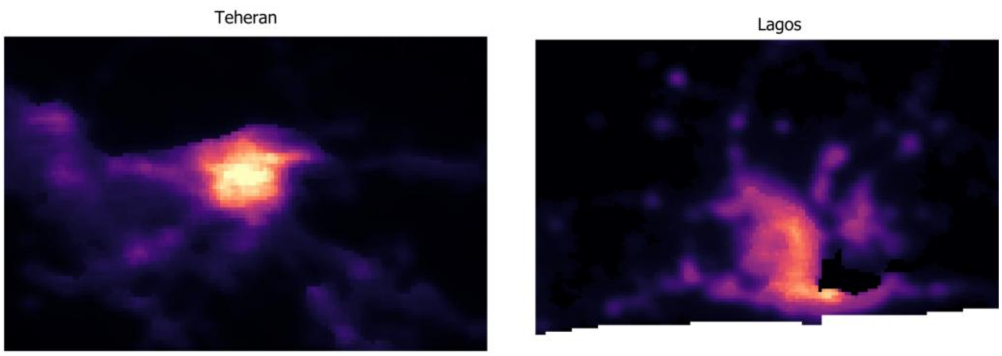
where in our case N is the number of pixels in the city, $w_{i,j}$ are elements of the spatial weights matrix (for which we use the Euclidean inverse distance matrix), S_0 is the sum of all the elements in the spatial weights matrix, x_i and x_j denote light intensities of pixels i and j, and $\bar{x}$ is the mean light intensity in the city.

Positive values of Moran's I indicate that pixels are surrounded by others of similar luminosity (positive autocorrelation), while negative values reflect a checkerboard pattern (negative autocorrelation). While light intensities within cities are known to be positively spatially correlated, there are clear differences in Moran's I across cities.

Following Tsai (2015), this can be interpreted in terms of urban structure as follows: the higher Moran's I, the more strongly monocentric the city is, while lower values are associated with polycentric structure, and ultimately fragmentation.

The two pictures below illustrate our use of the night-lights-based measure to capture the spatial structure of cities. Brighter values indicate higher light intensities (with respect to the city's maximum luminosity) and represent satellite data from 2013: Teheran, with a Moran's I of 0.9399, has a more monocentric city structure than Lagos (Moran's I of 0.8349). In Teheran, the bright city centre can easily be discerned and luminosity decreases rather gradually towards the outskirts. This happens to a much lower degree in Lagos, suggesting more fragmentation.

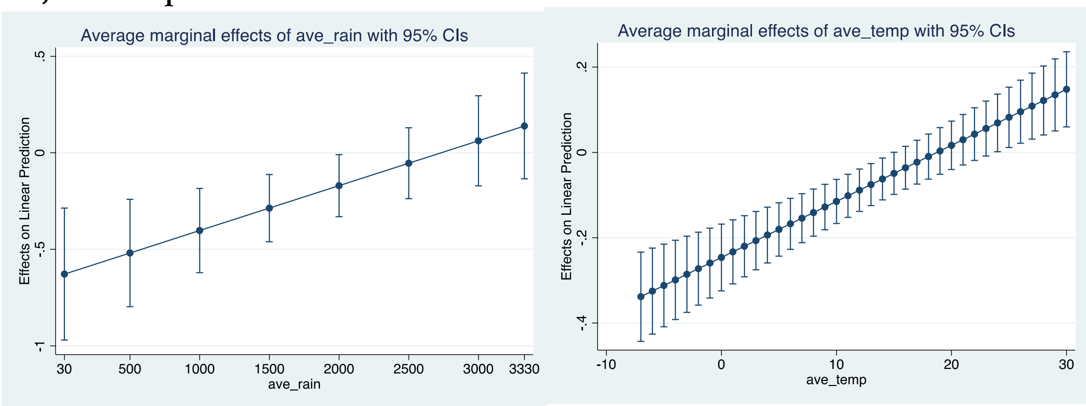
Figure C.1: Examples illustrating contrasting city structure



Note: The colours represent the light intensity with respect to the city's maximum luminosity, ranging from black (dark) over purple and red (medium-bright) to yellow (very bright). The extents of the maps are chosen for illustrative purposes, with the cut at the bottom of Lagos representing the sea.

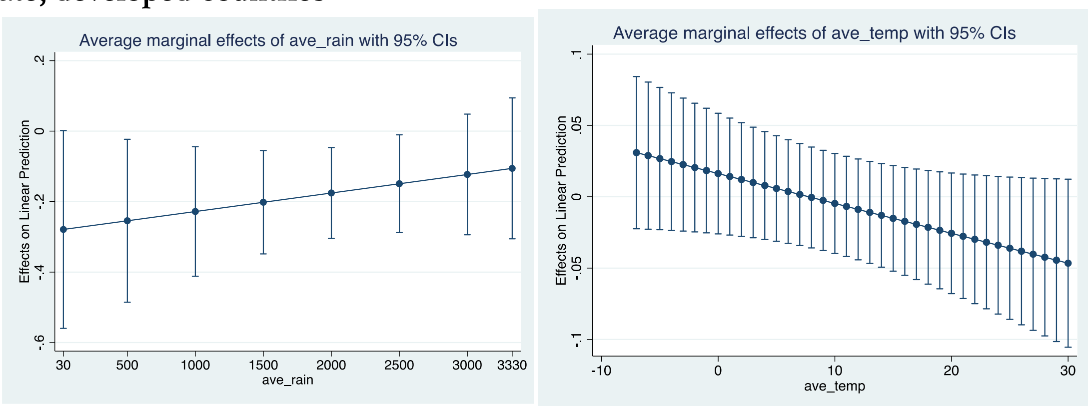
Appendix D: Climate and Urbanisation – Margins plots, additional results using alternative measures of climate, robustness checks and heterogeneity analysis [Corresponding to Section 3.1]

Figures D1: Margins plots for effects of rainfall and temperature on the urban rate, full sample



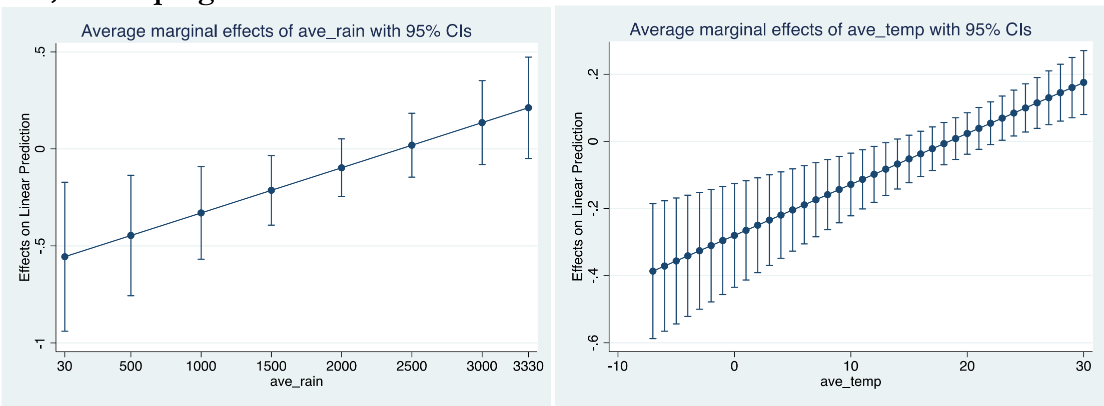
Note: The figures show the marginal effect of variation in rainfall (in mm per year, left panel) and temperature (in degrees Celsius, right panel) on the log of the urban rate, for different levels of rainfall and temperature. The marginal effects in these figures correspond to the results reported in Column 1 of Table 3 in the main text, using the full panel of countries and time periods.

Figures D2: Margins plots for effects of rainfall and temperature on the urban rate, developed countries



Note: The figures show the marginal effect of variation in rainfall (in mm per year, left panel) and temperature (in degrees Celsius, right panel) on the log of the urban rate, for different levels of rainfall and temperature. The marginal effects in these figures correspond to the results reported in Column 2 of Table 3 in the main text, for developed countries only.

Figures D3: Margins plots for effects of rainfall and temperature on the urban rate, developing countries



Note: The figures show the marginal effect of variation in rainfall (in mm per year, left panel) and temperature (in degrees Celsius, right panel) on the log of the urban rate, for different levels of rainfall and temperature. The marginal effects in these figures correspond to the results reported in Column 3 of Table 3 in the main text, for developing countries only.

Table D.1: Replicating Table 3 (Main Results, Urban Rate) weighting by population

	(1) full sample	(2) developed	(3) developing	(4) full sample	(5) developed	(6) developing
	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)
ave_rain	-0.5836***	-0.3865	-0.6875***	-0.5380***	-0.3553	-0.6372***
	(0.1809)	(0.2562)	(0.1968)	(0.1794)	(0.2556)	(0.1949)
ave_rain2	0.1020**	0.1570	0.1307**	0.0903*	0.1373	0.1187**
	(0.0506)	(0.1477)	(0.0531)	(0.0515)	(0.1487)	(0.0539)
ave_temp	-0.3357***	0.0305	-0.3520***	-0.3436***	0.0311***	-0.3640***
	(0.0526)	(0.0248)	(0.0899)	(0.0528)	(0.0251)	(0.0906)
ave_temp^2	0.0096***	-0.0011	0.0093***	0.0098***	-0.0010	0.0096***
	(0.0016)	(0.0007)	(0.0022)	(0.0016)	(0.0007)	(0.0022)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	1573	385	1188	1573	385	1188
No.Countries	143	35	108	143	35	108
R-sq. (within)	0.94	0.91	0.94	0.93	0.91	0.93

Note: Climatic variables are weighted by population. In Columns 1 to 3 rainfall and temperature observations are aggregated across all gridcells in a given country, weighted by population in each gridcell, while in columns 4 to 6 aggregation is across rural gridcells only. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D.2: Replicating Table 3 (Main Results, Urban Rate) using decennial changes and anomalies in temperature and rainfall

	(1) full sample	(2) developed	(3) developing	(4) full sample	(5) developed	(6) developing
	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)
rain_dec_ch	8.02e-06	-5.01e-05	4.07e-06			
	(3.13e-05)	(3.65e-05)	(3.26e-05)			
temp_dec_ch	0.0050	0.0151***	0.0363**			
	(0.0098)	(0.0051)	(0.0160)			
rain_anom				-0.0605***	-0.0178*	-0.0380***
				(0.0126)	(0.0098)	(0.0128)
temp_anom				0.0366**	-0.0158	0.0512***
				(0.0169)	(0.0141)	(0.0181)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	1606	396	1210	1606	396	1210
No. Countries	146	36	110	146	36	110
R-sq. (within)	0.60	0.64	0.67	0.61	0.65	0.68

Note: Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D.3: Robustness to different clustering of residuals, degree of openness and additional controls

	(1) full sample	(2) high openness	(3) low openness	(4) full sample
Dependent variable:	log(urb)	log(urb)	log(urb)	log(urb)
ave_rain	-0.6352*	-0.6294***	-0.7667**	-0.5396***
	(-0.2863)	(-0.2106)	(-0.3173)	(0.1590)
ave_rain^2	0.1162*	0.09.10*	0.1808**	0.1047***
	(-0.0600)	(-0.0478)	(-0.0765)	(0.0383)
ave_temp	-0.2462***	-0.2218***	-0.2183*	-0.1888***
	(-0.0466)	(-0.0452)	(-0.1118)	(0.0409)
ave_temp^2	0.0065***	0.0044***	0.0069***	0.0052***
	(-0.0012)	(-0.0014)	(-0.0025)	(0.0011)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Additional controls	NO	NO	NO	YES
Observations	1606	949	657	1213
No. of countries	146	126	103	143
R-Square (within)	0.918	0.623	0.651	0.64

Note: Robust standard errors (clustered by country in columns 2 to 4, and by country and time in column 1) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Additional controls include the lag of GDP pc (in logs) and total population in the country.

Table D.4: Robustness to interdependencies in temperatures and rainfall, and regional and country-specific linear trends

	(1)	(2)	(3)	(4)	(5)
	log(urb)	log(urb)	log(urb)	log(urb)	log(urb)
rain*temp	-0.0426***				
	(0.0104)				
$rain^2*temp^2$	3.38e-04***				
	(9.35e-05)				
moisture		-1.1772***			
		(0.2437)			
$moisture^2$		0.3362***			
		(0.0846)			
principal_comp			-0.7145***	-0.3336**	-0.3437***
			(0.1206)	(0.0774)	(0.0606)
$principal\_comp^2$			0.1913***	0.0721***	0.0648***
			(0.0357)	(0.0259)	(0.0186)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	NO	NO
Region-specific trends	NO	NO	NO	YES	NO
Country-specific trends	NO	NO	NO	NO	YES
Observations	1606	1581	1606	1606	1606
No. of Countries	146	144	146	146	146
R-squared	0.93	0.61	0.94	0.95	0.98

Note: principal_comp is the principal component of rain and temp, which captures 66% of the joint variance, with an eigenvalues of 1.3. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D.5: Heterogeneity of effects on urban rate, by differences in cities per unit area in 1960

	(1) full sample	(2) developed	(3) developing	(4) low income	(5) middle income	(6) high income
	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)
rain_anom	-0.0675***	-0.0176	-0.0521***	-0.0620**	-0.0329	-0.0240
	(0.0164)	(0.0142)	(0.0175)	(0.0296)	(0.0199)	(0.0153)
rain_anom*cities/area	0.2584	0.0002	0.3909	0.7482	-0.0308	0.0771
	(0.1718)	(0.0981)	(0.2645)	(0.5319)	(0.3822)	(0.0969)
temp_anom	0.0592***	-0.0065	0.0453**	-0.0222	0.0212	-0.0080
	(0.0184)	(0.0139)	(0.0189)	(0.0300)	(0.0210)	(0.0207)
temp_anom*cities/area	-0.4596**	-0.0127	0.0555	2.6150**	-0.0195	-0.1371
	(0.1834)	(0.1264)	(0.3086)	(1.1259)	(0.3414)	(0.1342)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	1,573	385	1,188	327	755	458
No. of Countries	143	35	108	44	103	60
R-squared (within)	0.62	0.66	0.69	0.81	0.70	0.52

Note: Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D.6: Heterogeneity of effects on urban rate by baseline climate, agri-share, and world region

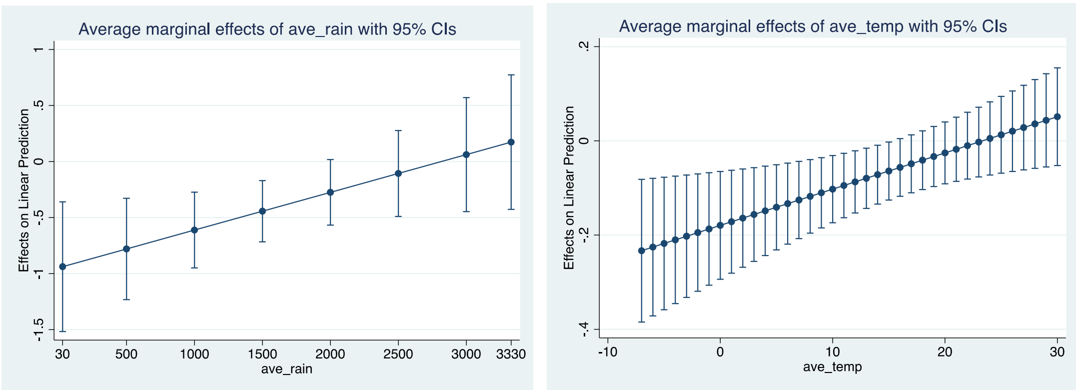
	(1) relative to baseline temperatures	(2) relative to baseline rainfall	(3) by mean agri-share	(4) by regions
	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)
rain_anom	-0.0082	-0.0814***	0.0011	-0.0411***
	(0.0225)	(0.0212)	(0.0206)	(0.0103)
temp_anom	-0.1521***	-0.0168	-0.1963***	-0.0803***
	(0.0367)	(0.0262)	(0.0281)	(0.0225)
rain_anom*temp1950	-0.0021			
	(0.0013)			
temp_anom*temp1950	0.0092***			
	(0.0016)			
rain_anom*rain1950		0.0163		
		(0.0159)		
temp_anom*rain1950		0.0380**		
		(0.0152)		
rain_anom*logagrishare_avg			-0.0160*	
			(0.0093)	
temp_anom*logagrishare_avg			0.0866***	
			(0.0102)	
rain_anom*SSA				-0.0755***
				(0.0257)
rain_anom*South_East_Asia				0.0745**
				(0.0295)
rain_anom*LATAM				0.0353**
				(0.0149)
temp_anom*SSA				0.2106***
				(0.0307)
temp_anom*South_East_Asia				0.1519***
				(0.0468)
temp_anom*LATAM				0.0657**
				(0.0254)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	1606	1606	1540	1606
No. of Countries	146	146	140	146
R-squared (within)	0.65	0.62	0.68	0.68

Note: The excluded category in Column (4) is the combination of regions not displayed in the table (NA, Europe, MENA, Central Asia and Oceania). Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix E: Results for urban structure [Corresponding to Section 3.2 in the main paper]

Figure E.1: Margins plots for effects of annual rainfall and temperature on urbanisation in large cities (top two panels) and small to medium sized cities (bottom two panels)

Marginal plots urb>1m:



Marginal plots urb<1m:

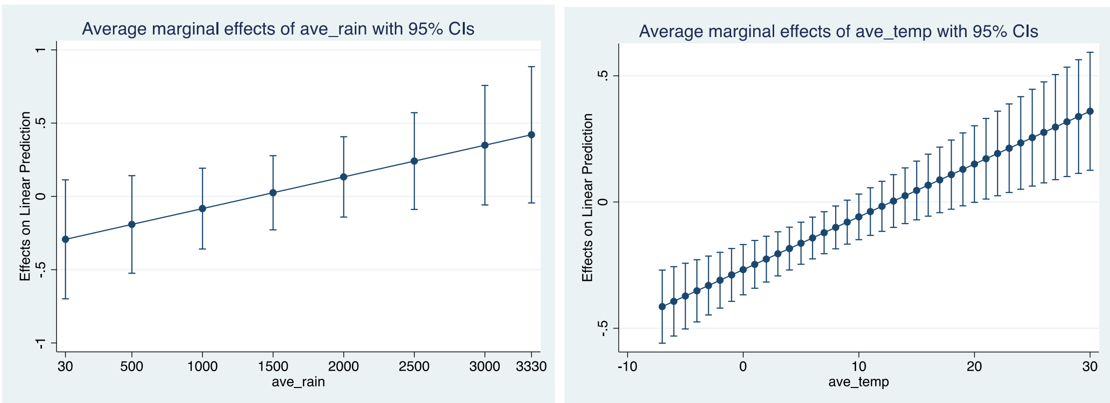
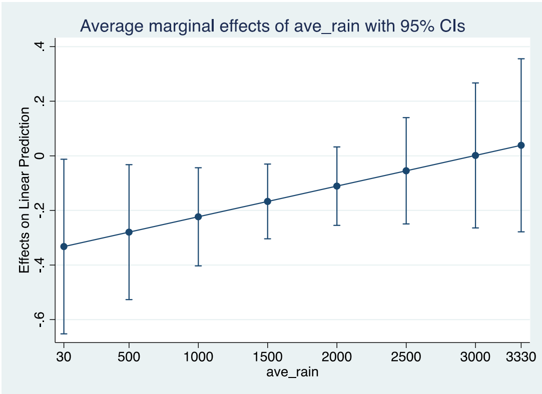


Figure E.2: Marginal plots primacy:



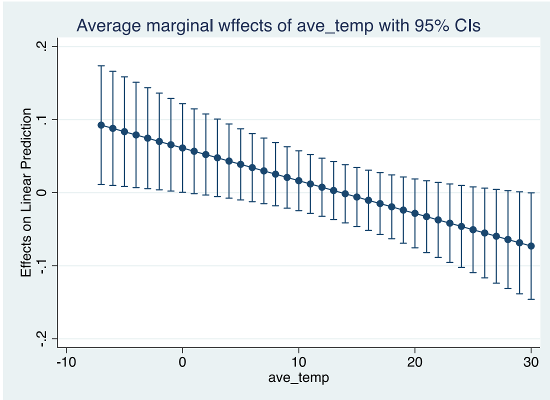


Table E.1: Heterogeneity of effects on urban structure

	(1)	(2)	(3)	(4)
Dependent variable:	Logurb>1m	Logurb<1m	logurb_largest	logurb_nolargest
rain_anom	-0.0370	-0.0380	-0.0355	-0.0369
	(0.0154)**	(0.0167)**	(0.0151)**	(0.0137)***
temp_anom	-0.0871	-0.0402	-0.0730	-0.0576
	(0.0334)**	(0.0300)	(0.0340)**	(0.0273)**
rain_anom*SSA	-0.1349	-0.0110	-0.1786	-0.0243
	(0.0423)***	(0.0306)	(0.0480)***	(0.0290)
rain_anom*SEA	0.0266	0.1356	0.0410	0.1536
	(0.0379)	(0.0536)**	(0.0410)	(0.0477)***
rain_anom*LATAM	0.0322	0.0433	0.0130	0.0446
	(0.0232)	(0.0221)*	(0.0258)	(0.0193)**
temp_anom*SSA	0.2131	0.2062	0.1814	0.2626
	(0.0479)***	(0.0492)***	(0.0412)***	(0.0475)***
temp_anom*SEA	0.1723	0.2924	0.1289	0.2679
	(0.0615)***	(0.1001)***	(0.0609)**	(0.0925)***
temp_anom*LATAM	0.0573	0.0623	0.0087	0.0767
	(0.0416)	(0.0294)**	(0.0442)	(0.0284)***
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	1221	1218	1633	1595
No. of Countries	111	111	149	146
R-squared (within)	0.548	0.527	0.483	0.525

Note: The excluded category in each case is the combination of regions not displayed in the table (NA, Europe, MENA, Central Asia and Oceania). Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix F: Results for city size, density and structure [Corresponding to Section 3.3 in the main paper]

Figure F.1: Marginal plots, city size:

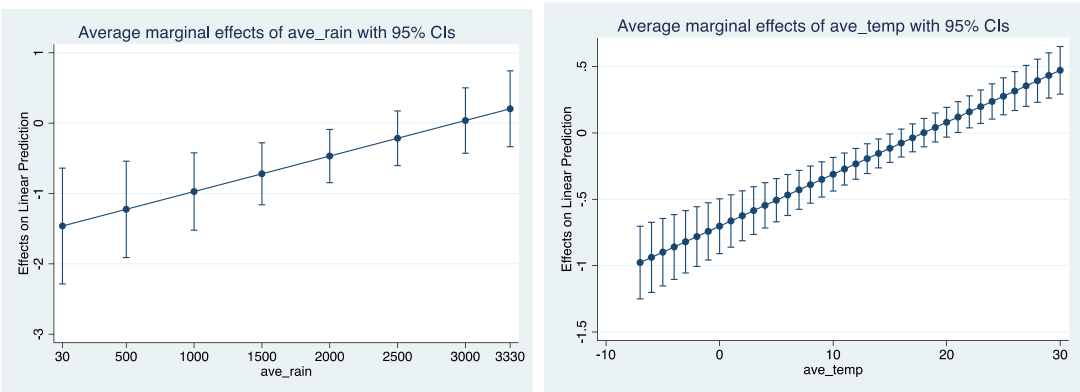


Table F.1: Robustness checks (1) to results in Table 5.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	log(pop)	log(pop)	log(pop)	log(density)	log(density)	log(density)
ave_rain	-0.8546	-0.2298	-0.4809	-0.0851	0.4546	0.1296
	(1.2515)	(1.1902)	(1.0697)	(1.2652)	(1.2096)	(1.0653)
ave_rain^2	0.0535	-0.1452	-0.0948	-0.0756	-0.2389	-0.1731
	(0.2646)	(0.2911)	(0.2705)	(0.2399)	(0.2618)	(0.2338)
ave_temp	-0.7750***	-0.8427***	-0.8464***	-0.5712***	-0.6024***	-0.6043***
	(0.1625)	(0.1708)	(0.1700)	(0.1514)	(0.1533)	(0.1534)
ave_temp^2	0.0196***	0.0220***	0.0224***	0.0104**	0.0123**	0.0126***
	(0.0048)	(0.0050)	(0.0050)	(0.0048)	(0.0048)	(0.0047)
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Observations	568	568	568	568	568	568
No. of cities	142	142	142	142	142	142

Note: Columns 1 and 4 restrict weather variation to 500 km radius around the city. Columns 2 and 5 also restrict weather variation to 500 km radius around the city but weighting by distance and population. Columns 3 and 6 do the same but excluding urban grid-cells.

Table F.2: Robustness checks (2) to results in Table 5.

	(1)	(2)	(3)	(4)
Dependent variable:	log(pop)	log(pop)	log(pop)	log(pop)
ave_rain	-2.1601**	-2.1601**	0.1770	0.1770
	(0.8948)	(0.9730)	(0.7995)	(0.7388)
ave_rain^2	0.3619*	0.3619*	-0.0391	-0.0391
	(0.2005)	(0.1831)	(0.1530)	(0.1368)
ave_temp	-0.5541***	-0.5541***	-0.2222	-0.2222
	(0.1348)	(0.1538)	(0.1461)	(0.1479)
ave_temp^2	0.0136***	0.0136***	0.0075**	0.0075**
	(0.0032)	(0.0031)	(0.0038)	(0.0033)
Year FE	YES	YES	NO	NO
City FE	YES	YES	YES	YES
City linear trends	NO	NO	YES	YES
Observations	584	584	584	584
No. of cities	146	146	146	146

Note: log(pop) using GHSL data. Robust standard errors (clustered by city in columns 1 and 3 and by city and time in columns 2 and 4) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table F.3: First-step results from Table 6.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$CitySize$	$CitySize$	$CitySize$	$CitySize$	$CitySize$
ave_rain	-0.4206**	-1.5326**	-0.4206**	-1.5326**	-1.2924***
	(0.1925)	(0.6365)	(0.1925)	(0.6365)	(0.4957)
ave_rain^2	0.0816*	0.2245	0.0816*	0.2245	0.1980*
	(4.66e-05	(0.1533)	(0.0466)	(0.1533)	(0.1187)
ave_temp	-0.3705***	-0.4949***	-0.3705***	-0.4949***	-0.4250***
	(0.0311)	(0.0826)	(0.0311)	(0.0826)	(0.0608)
ave_temp^2	0.0104***	0.0113***	0.0104***	0.0113***	0.0134***
	(0.0008)	(0.0023)	(0.0008)	(0.0023)	(0.0015)
Year FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Observations	886	436	886	436	540
No. of countries	148	146	148	146	145
R-Square	0.67	0.56	0.67	0.56	0.69

Note: *CitySize* all in logs. Columns 1 and 3 use WUP data for population. Columns 2, 4 and 5 use GHSL data. Robust standard errors (clustered by city) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table F.4: Robustness checks to results in Table 6.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Moran's I	Moran's I	Moran's I	Gini	Gini	Gini
$\widehat{CitySize}$	-0.0700***	-0.0692***	-0.0690***	-0.6333***	-0.6597***	-0.6645***
	(0.0235)	(0.0240)	(0.0239)	(0.1291)	(0.1342)	(0.1341)
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Observations	425	425	425	425	425	425
No. of countries	142	142	142	142	142	142
R-Square	0.44	0.44	0.44	0.11	0.11	0.11
F test on exc inst	45.91***	46.29***	46.32***	45.01***	46.29***	46.32***

Note: Moran´s I, Gini and *CitySize* all in logs. In columns 1 and 4, *CitySize* is estimated using weather variation in a 500km-radius around the city. I columns 2 and 4, *CitySize* is estimated using weather variation in a 500km-radius around the city but weighting by distance and population. Columns 3 and 6, *CitySize* is estimated using weather variation in a 500km-radius around the city but weighting by distance and population and excluding urban grid-cells. Robust standard errors (clustered by city) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

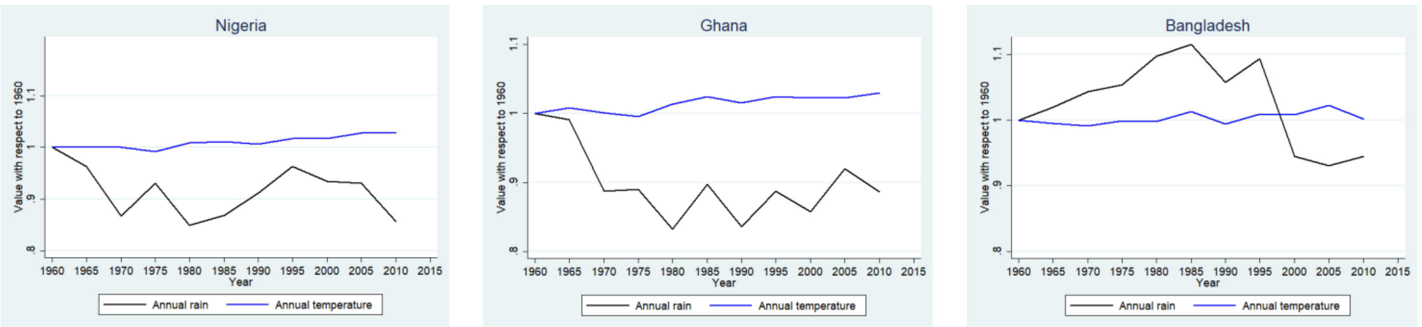
Appendix G: Case Study:

Climate Change and Urban Structure in two African and one Asian Country

Here we present a comparative case study of two Sub-Saharan African countries – Nigeria and Ghana – and one South Asian country – Bangladesh, to highlight commonalities as well as differences in the relation between climate change and urban structure.

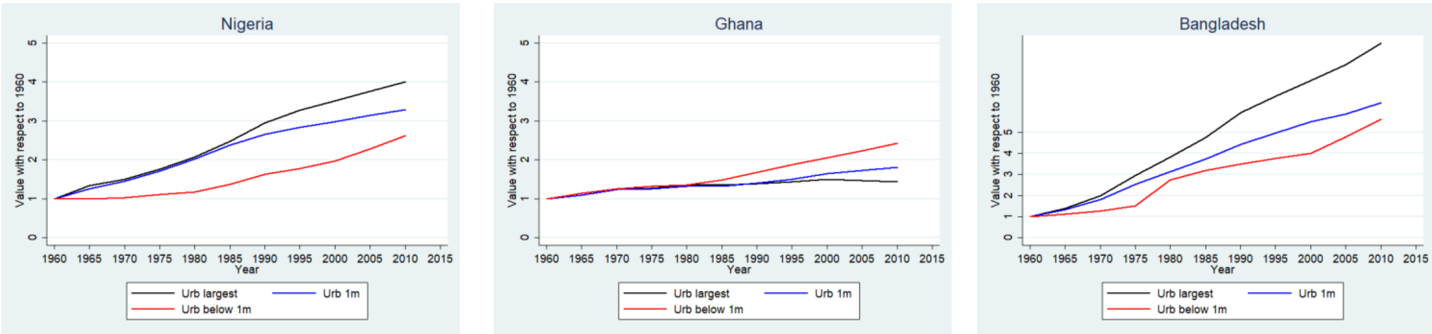
Figure G.1 shows the evolution of annual temperature and rainfall with respect to values in 1960. While the average annual temperature and its increase over time are very similar in the three countries, Bangladesh has a much wetter climate than the two African countries: the annual rainfall in 1960 was 2253mm, nearly twice as high as in Nigeria (1243mm) and Ghana (1311mm). Moreover, in Bangladesh, rainfall has substantially exceeded the initial values in some years and been below these levels in other years. In the two African countries, the trend clearly indicates less rainfall, in line with findings comparing SSA and SEA. Hence, farmers might be driven into cities by a lack of rain in SSA (i.e., Nigeria and Ghana), while both excess rain and a dearth of rain might be affecting individuals in SEA (i.e., Bangladesh).

Figure G.1: Evolution of annual rain and temperature with respect to 1960 values



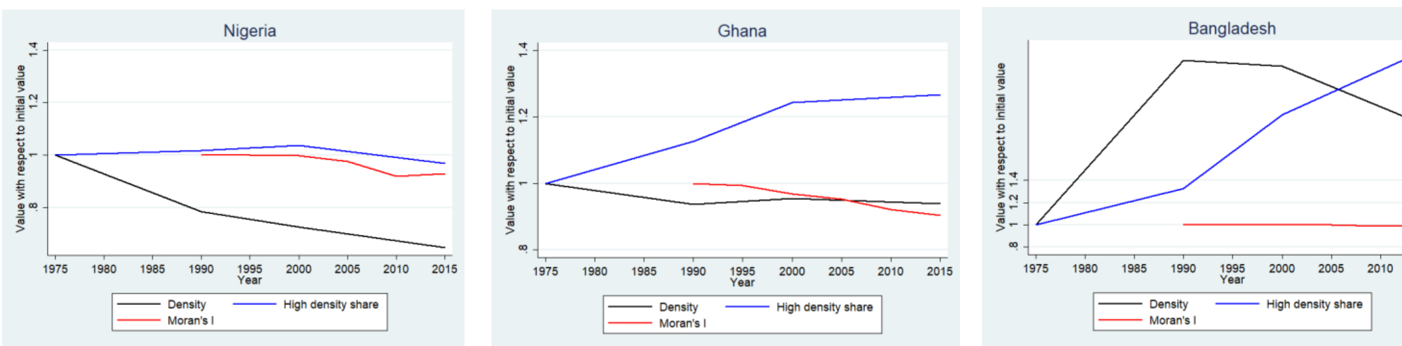
Apart from the climate conditions, these three countries show some variation in their urban structure in 1960, which might shed light on their subsequent changes in urbanization. In 1960, Bangladesh was hardly urbanized at all – its urbanization rate was 5.13% - while Nigeria had an urbanization rate of 15.41% and Ghana one of 23.25%. Despite its low urbanization rate, Bangladesh's urban population was already relatively concentrated in Dhaka, with a primacy rate of 20.52%. Ghana had a high primacy rate of 25.38%, while in Nigeria the urban population was still more dispersed (primacy rate of 10.94%).

Figure G.2: Evolution of urbanization rates in cities of various size (largest city, cities above 1m inhabitants, cities below 1m inhabitants) with respect to 1960 values



The increases in urbanization rates in cities of different size in Figure G.2 reveal that countries with low initial urbanization rates – Nigeria and in particular Bangladesh – experienced larger increases of urbanization rates across the urban structure. Whether smaller or larger cities grew more depended on the initial urban structure. In Ghana, with its comparatively mature urban structure and high primacy rate, urbanization in smaller cities has outgrown urbanization in cities above 1m and in the largest city. In Nigeria and Bangladesh, we observe the opposite: a concentration in primary cities over the last decades. The rise of Dhaka is particularly noteworthy: it has grown from a population of 508,000 in 1960 to 17.6m in 2015, fueled to some extent by its garment industry, which has attracted many migrants. But living conditions are often bad, with 60% of residents living in makeshift structures (The Economist 2019).

Figure G.3: Evolution of primary city variables (density, high density share, Moran's I) with respect to initial values (1975 or 1990)



A closer look into the structure of the primary cities (Figure G.3) reveals heterogeneous developments: Lagos's growth in population has been matched by an expansion in the built-up area, so that population density shows a decrease. Its share of high density areas remains stable. Accra's population growth in Ghana might have been more moderate, but its high-density share increased markedly and Moran's I decreased, indicating a more fragmented city structure. The higher population growth rates in smaller Ghanaian cities might help to ease the pressure on the primary city. The unique pull factor of Dhaka in Bangladesh is mirrored in the escalating density measures. Congestion, pollution and sewage are increasingly considered as severe problems. While the Dhaka city authority is now working on a plan for orderly city expansion, local authorities try to foster decentralization and migration to the country's other cities.

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