Codebook for GAME-LIGHTS Data

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Description GAME-LIGHTS Data

Grid cell yearly GAME-LIGHTs Data used in World Development. Unit of analysis is the 0.5°x0.5° grid cell-year resolution. This file reports the GAME-LIGHTS data physical disaster intensity measures, night light emission data, and population control variable used in the regression analysis of the "weather anomalies" paper. The data is collapsed to grid cell and year from original events and monthly data.

Citation

When using the GAME-LIGHTS data, please cite:

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Primary Data Sources

This dataset builds on various datasets assembled by primary sources. If you are fully convinced you discovered an error and have checked this against the original sources, please contact us at groeschl@ifo.de. What follows is a list of sources used to assemble the datasets.

Precipitation. Monthly precipitation data in millimeters stem from the ***University of East Anglia Climatic Research Unit Time-Series [CRU TS 3.23]*** (Harris et al., 2014). The CRU provides homogenized gauge data from weather stations around the world in a consistent format. To consider seasonality, we follow the climatological literature (cp., Kraus, 1977; Nicholson, 1986) and calculate precipitation anomalies by subtracting the long-run (1979-2014) mean precipitation observed in a cell for a given month (i.e., each January, February, March) and standardize cell precipitation by dividing it by the corresponding long-run standard deviation for the cell for that particular month:

$\gamma_{i,m,t}^{prec} = \frac{x_{i,m,t}^{prec} - \bar{x}_{i,m}^{prec}}{\sigma_{i,m}^{prec}}$, where i = cell, m = month, t = year.

This indicator measures both positive and negative precipitation anomalies expressed in standard deviations from the cell mean for a specific month. We aggregate the monthly physical intensities to an annual mean intensity indicator. Before aggregating to the annual average precipitation variable, we left-censor the indicator at zero, so only months with positive precipitation deviations are considered. As weather anomalies that occur earlier in a year have a different impact than events that happen later, we take this dynamic relationship into account and calculate a rolling-window weighted annual mean, using for each month the number of months remaining in the year as its weight in year t, while taking the remainder as the weight for year t+1:

$D_{i,t}^{p} = \sum_{m=1}^{12} \left[\gamma_{i,m,t}^{p} * \frac{12-m}{12} + \gamma_{i,m,t-1}^{p} * \frac{m}{12}\right]$, where i = cell, m = month, t = year, and p = weather shock.

The resulting measure for precipitation intensity in each year is thus the time-weighted average of positive deviations from the long-run monthly mean (both in mm) in a cell, expressed in standard deviations from its cell mean.

Droughts. In addition to global precipitation, the ***University of East Anglia Climatic Research Unit Time-Series [CRU TS 3.23]*** also provides the information to compute the Standardized Precipitation-Evapotranspiration Index (SPEI). This index considers the amount of water coming in (precipitation, PRE) and the amount lost (evapotranspiration, PET), resulting in a water balance for each cell in any given month. We follow Vicente-Serrano et al. (2010) to construct a cell-specific monthly SPEI that has zero mean, a standard deviation of one and is theoretically unbounded. Negative values in the SPEI indicate drought events. Hence, to aggregate to an annual average drought indicator, we right-censor at zero and take the absolute value to obtain a drought indicator that is standardized across cells. The same rolling-window weighting by months as for excessive precipitation is applied to obtain a drought intensity measure for each cell and year.

Cold Spells. To capture anomalous cold spells, we collect gridded 0.5° resolution land surface temperatures from the ***Climate Prediction Center (CPC) of the National Oceanic and Atmospheric Administration (NOAA)***. Analogous to our measure for precipitation anomalies, temperatures are normalized by subtracting the long-run (1979-2014) cell mean temperature for a given month and dividing this by the cell's long-run standard deviation for that month: $\gamma_{i,m,t}^{temp} = \frac{x_{i,m,t}^{temp} - \bar{x}_{i,m}^{temp}}{\sigma_{i,m}^{temp}}$, where i = cell, m = month, t = year. Again, this indicator gives both positive and negative temperature anomalies. To isolate the information for cold waves, we right-censor the indicator at zero and express negative values in absolute terms. The resulting annual cold spell intensity indicator gives us the rolling-window weighted average negative deviations of surface temperature from the long-run monthly mean at the cell level measured in standard deviations from its own mean.

Storms. To create a measure for storms, we use information on monthly maximum sustained wind speeds from two distinct sources: The ***International Best Track Archive for Climate Stewardship (IBTrACS) Version v03r09*** provides the geolocation on tropical cyclone centers with respective pressure and wind speeds. The ***Global Summary of the Day (GSOD)*** statistics contain wind speeds, also of non-hurricane winds, measured at weather stations. To obtain wind speeds at the grid cell level, we fill the gaps by applying two types of spatial interpolation techniques. We use a wind field model provided and described in detail by Geiger et al. (2017) to generate continuous gridded wind fields around cyclone data from IBTrACS. This model uses available information on wind speed, pressure and direction to compute sustained winds speeds that most likely occurred in cells surrounding available data points. This provides us with the best possible wind speed estimates for cells in cyclone paths.

However, many cells do not experience a cyclone in any given month. To complete our panel in any given cell and month, we therefore combine GSOD data with a global kriging spatial interpolation algorithm (cp. Krige, 1951). As precision of resulting wind speed measures drop with distance to actual weather station measurements, we prefer wind field information on hurricanes, cyclones or typhoons – if any such event has affected the cell – to the cell's kriged station wind speed. The resulting wind speed indicator is the maximum sustained wind speed for a cell-month combination measured in knots. Again, our annual measure of wind intensity is constructed by taking the rolling-window weighted average wind speed in knots.

Other Data

Night-Light Emissions. Our raw data stem from the ***US Air Force Defense Meteorological Satellite Program (DMSP)*** and consist of composite satellite images from which the annual mean luminosity of each pixel is extracted as a digital number (DN). To obtain a useful proxy for human activity within a given location, we exclude all pixels that do not cover land surface. Following Elvidge et al. (2009), we drop all pixels in gas flaring zones. In addition, we mask areas around (active) volcanoes and known wildfires.

As on-board sensors degrade over time, the DMSP launches a new satellite every 3 to 6 years. In 12 of the 22 available years, two satellites were in orbit simultaneously. We deal with years in which more than one composite night-light image is available by choosing the satellite with the best coverage of valid nights per pixel in a given year on the basis of summary statistics for each respective satellite-year layer. If the number of valid nights for a pixel is zero (i.e., no observations in that year), it is dropped from the data. We then aggregate the cleaned night-light layers and compute the mean light intensity for the 0.5°×0.5° grid cells. Our proxy for local economic activity is thus the average annual night-time light emission at the grid cell level.

Population. Population at the pixel level is available from the ***Gridded Population of the World (GPW version 4)*** dataset provided by the Center for International Earth Science Information Network (CIESIN). The data contain 5-year target estimates based on census inputs gathered at the lowest available administrative unit. CIESIN redistribute the data from the administrative census boundaries to a uniform pixel grid by using aerial weights. We aggregate pixel data to grid cells by summing population numbers within each cell. To interpolate the years between the given 5-year periods, we assume stable exponential population growth.

Rural/Urban Classification. We use ***MODIS land-use data provided by the FAO*** for the year 2001. The data include information on the extent of urban or crop areas at a spatial resolution of 15 arc-seconds (i.e., 500 meters), obtained from MODIS satellite imagery using a supervised decision tree classification algorithm with region-specific parameters (Schneider et al., 2009). Urban land-use comprises all human-constructed elements (e.g., buildings and roads), while crop land-use comprises all kinds of cultivated fields. Pixel locations are defined according to the type of land-use they are dominated by (i.e., coverage of at least 50% of a given pixel unit). We aggregate the data to grid cell units by computing the cell level shares of each land-use pixel type.

Annual cell level GAME-LIGHTS Data

STATA file: GAME_LIGHTS_92-99.dta

- 0.5° x 0.5° grid cell-year data on night-time light emissions, excessive precipitation, droughts, cold spells, storms, and population data; simple or rolling window weighted averages for weather anomalies for the years 1992 to 1999.

STATA file: GAME_LIGHTS_00-13.dta

- 0.5° x 0.5° grid cell-year data on night-time light emissions, excessive precipitation, droughts, cold spells, storms, and population data; simple or rolling window weighted averages for weather anomalies for the years 2000 to 2013.

The two data sets have exactly the same structure and can easily be combined by using the stata code “append”.

The variable layout for this version of the data is detailed below.

objectid	cell identifier
year	year of weather anomaly
iso3_1	3-digit iso code of country 1 in cell
iso3_2	3-digit iso code of country 2 in cell
iso3_3	3-digit iso code of country 4 in cell
iso3_4	3-digit iso code of country 5 in cell
carea	geodesic cell area (in square kilometers)
lat	decimal degrees latitude (cell center)
lon	decimal degrees longitude (cell center)
tempdif_cold	yearly mean of negative temperature difference from long-run mean (abs °C, sd weight)
tempdif_cold_rolling	yearly mean of time-weighted negative temperature difference from long-run mean (abs °C, sd weight)
maxtempdif_cold_rolling	yearly maximum of time-weighted negative temperature difference from long-run mean (abs °C, sd weight)
precdif_cens	yearly mean of positive precipitation difference from long-run mean (mm/day, sd weight)
precdif_cens_rolling	yearly mean of time-weighted positive precipitation difference from long-run mean (mm/day, sd weight)

maxprecdif_cens_rolling	yearly maximum of time-weighted positive precipitation difference from long-run mean (mm/day, sd weight)
nspei3_cens	yearly mean of -1*3month standardized precipitation evapotranspiration index (SPEI) censored at 0
nspei3_cens_rolling	yearly mean of time-weighted -1*3month standardized precipitation evapotranspiration index (SPEI) censored at 0
maxnspei3_cens_rolling	yearly maximum of time-weighted -1*3month standardized precipitation evapotranspiration index (SPEI) censored at 0
combik3	yearly mean of windspeed (kt) (fields, krige3)
combik3_rolling	yearly mean of time-weighted windspeed (kt) (fields, krige3)
maxcombik3_rolling	yearly maximum of time-weighted windspeed (kt) (fields, krige3)
meanlights	average light intensity (best satellite available)
toplights	number of top-coded pixels (best satellite available)
bottomlights	number of bottom-coded pixels (best satellite available)
pop	total population (interpolated exponentially between 5-year intervals)
meancrops	percentage crops land cover
meanurban	percentage urban land cover
meansnowice	percentage snow/ice land cover

Literature

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