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Green Lights: Quantifying the economic impacts of drought

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Green Lights:

Quantifying the economic impacts of drought

Peter Fisker*

August 29, 2014

Abstract

This study investigates the effect of drought on economic activity globally using remote sensing data. In particular, predicted variation in greenness is correlated with changes in the density of artificial light observed at night on a grid of 0.25 degree latitude-longitude pixels. I define drought as greenness estimated by lagged variation in monthly rainfall and temperature. This definition of drought performs well in identifying self-reported drought events since 2000 compared with measures of drought that do not take greenness into account, and the subsequent analysis indicates that predicted variation in greenness is positively associated with year-on-year changes in luminosity: If a unit of observation experiences a predicted variation in greenness that lies 1 standard deviation below the global mean, on average 1.5 - 2.5 light pixels out of 900 are extinguished that year. Finally, an attempt is made to estimate the global cost of drought.

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1 Introduction

It is important to study the economic consequences of natural disasters both at the micro and macro level. At the micro level because natural disasters affect people's daily lives and hamper their ability to escape from poverty; at the macro level there is more discussion about the size and even the direction of the effects. Recent evidence, however, suggests that repeated exposure to disasters may constitute a boundary to growth in some countries (e.g. Hsiang and Jina, 2014).

Drought is the most devastating type of natural hazard. According to the Emergency Database (EM-DAT), droughts have killed 11.7 million people since the beginning of the 20$^{\text{th}}$ century; more than earthquakes, floods, storms and volcanic eruptions combined.[1] These numbers include only 647 registered occurrences of drought-disasters, but every year there are many more areas of the world where low rainfall and high temperatures lead to low incomes and general hardship for people living off the land.

Global warming is causing hotter and more extreme weather across the globe. Recently, a report from the Intenational Panel on Climate Change (IPCC)[2] warned that a warmer climate will decrease crop yields in especially the tropical parts of the world, and that - coupled with population growth - global warming could lead to widespread food insecurity. The tropical parts of the world also tend to include poorer countries, so the impacts of climate change are likely to fall disproportionately on poorer nations and on poorer, agrarian households within those nations (see e.g. Skoufias et al., 2011).

Agencies that promote economic development look increasingly towards ways of helping poor countries cope with drought. One way to increase poor

[1] http://www.EMDAT.be
[2] http://www.ipcc.ch/report/ar5/wg2/

farmers' resilience towards drought is the provision of so-called *weather index based insurance*. The World Bank, the Food and Agriculture Organization of the UN and FewsNet are among the leaders in developing insurance schemes that automatically trigger a payment if defined proxy for drought is below a certain threshold. Often this proxy is simply rainfall measured at a single weather station. In order to extend the programs beyond the near vicinity of weather stations, researchers focus more and more attention on remote sensing in order to obtain a detailed drought indicator with high spatial and temporal resolution in remote, rural areas.

The contribution of this paper is two-fold: firstly, I develop a purely satellite-based drought indicator with many of the same properties as the most frequently used existing station-based measures and evaluate the different indicators across drought years. Secondly, I investigate the economic impacts of drought by correlating it with changes in the density of artificial light observed at night at a grid of 0.25 degree latitude-longitude globally. Results show that if a unit of observation experiences a predicted variation in greenness that lies 1 standard deviation below the global mean, on average 1.5 - 2.5 light pixels out of 900 are extinguished that year.

The remainder of the paper is organized as follows: section 2 goes through the most commonly used measures of drought in the field of development economics while outlining their shorcomings and arguing how the use of remote sensing might remedy some of these. The different ways of measuring drought are then tested in order to see how they perform in identifying officially registered drought occurences under various circumstances. Finally, using satellite-based observations only, section 3 attempts to quantify the economic impacts of drought.

2 Measuring drought from outer space

This part of the paper outlines some of the most commonly used drought measures starting with those based on in-situ (i.e. weather station) observations before focusing on the properties of the Normalized Difference Vegetation Index (NDVI), which is only recorded from space. While adding valuable information about greenness (and thus vegetation density) compared to the land-based indexes, there are also disadvantages related to the NDVI. Section 2.2 attempts to combine information on rainfall and temperature with greenness in order to construct a drought index that is both precise and reliable across time and space using remote sensing data only. Finally section 2.3 compares the performance of the different drought indicators across years that are officially registered as being hit by drought in a specific region and years where no droughts are registered.

2.1 Existing measures of drought

This section focuses on providing an overview of drought measures starting with the early land-based indexes before gradually moving towards remote sensing.

2.1.1 Land-based

The Palmer Drought Severity Index (PDSI) was first published in 1964. It is based on a calculation of supply and demand of soil-moisture using rainfall and temperature as input variables. The PDSI has been critized for using arbitrary algorithms and lacks the element of periodicity, which means that it doesn't catch shorter droughts as well as longer droughts.

As a response, the Standardized Precipitation Index (SPI) was suggested in the late 1980's introducing different times scales over which water deficits accumulate in order to separate e.g. hydrological, environmental, and agricultural droughts. The fact that SPI is based solely on precipitation has lead researchers to develop the Standardized Precipitation-Evapotranspiration Index (SPEI) which is based on the SPI calculation procedure but includes temperature as one of the input variables in order to estimate the difference between rainfall and potential evapotranspiration.

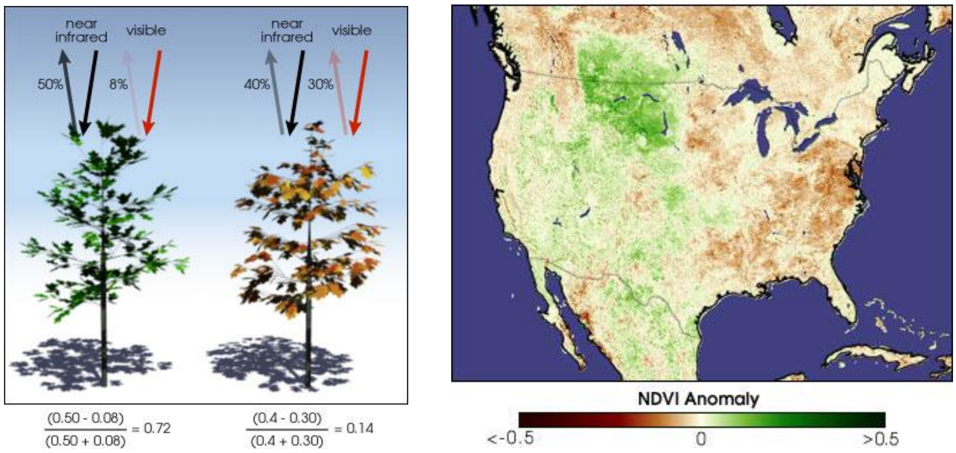
All of the above suffer from the following two shortcomings: weather stations are scarce in many developing countries where droughts often hit and how rainfall and temperature translate into plant-mass (and thus crop yields or food for cattle) is very circumstatial - it depends on rivers and irrigation, soil types, altitude, ruggedness and so forth.

2.1.2 Satellite-based

From space it is possible to obsverve the surface of the earth and measure the light that is emitted at different wavelenghts. Vegetation indexes such as the Normalized Difference Vegetation Index translate visible red and near infrared radiation into a decimal number between -1 and 1 which describes the greenness of a specified geographical area. In order to use NDVI as a proxy for drought, it is common to calculate the anomaly, i.e. the deviation from a long-run average for a specific time of the year. Figure 2.1 shows on the left how NDVI is calculated as the ratio between near infrared radiation and visible red radiation; a higher index value is related to a greener land surface. The map on the right show NDVI anomalies in North America for a specific month, where it is clear that there is a drought in the east while some of the north western experience a month that is greener than expected.

NDVI data is obtained from the MODIS Terra satellite. It has been

Figure 2.1: Normalized Difference Vegetation Index



Source: earthobservatory.nasa.gov.

orbiting Earth daily since 2000, and here we employ a pre-processed product[3] made publicly available by NASA that has a temporal resoulution of one month and a spatial resolution of 0.05 degrees (3 arc minutes or around 5.8 km at the equator). It is later aggregated to 0.25 degrees in order to match the resolution of the rainfall data and reduce the number of observations. In the end we have a data frame with 1440x720 obervations over 180 months.

The images used in this analysis are so-called monthly maximum value composits. Since all athmospheric influence lowers NDVI, NASA stores only the highest greenness-value for each pixel over the period, where most pixels are recorded daily. This way cloud cover is filtered out in almost all cases.

It is not unproblematic to use NDVI as a proxy for drought, however. Year-on-year variation in greenness might be caused by other factors than the climatic. As an example, deforestation quickly reduces the greenness of an area without being associated with drought. On the contrary, deforestation is often a sign of increased economic activity in a region. Broadly speak-

[3]Mod13c2

ing, all factors that are non-climatic but affect the greenness of the planet will create noise in the picture of NDVI anomalies as a drought indicator. Most of these factors would be anthropogenic and, apart from deforestation, include changes in cultivation, irrigation and urban expansion. Anomalies in NDVI is therefore seldomly used in index-based crop insurance schemes. McLaurin and Turvey (2011) conclude that the relationship between NDVI and other drought indicators is dependent on location-specific characteristics and that NDVI should not be applied widely into insurance desings. To our knowledge, observations of NDVI are today only being used directly for index insurances in a couple of places among pastoralists (see Chantarat et al., 2013).

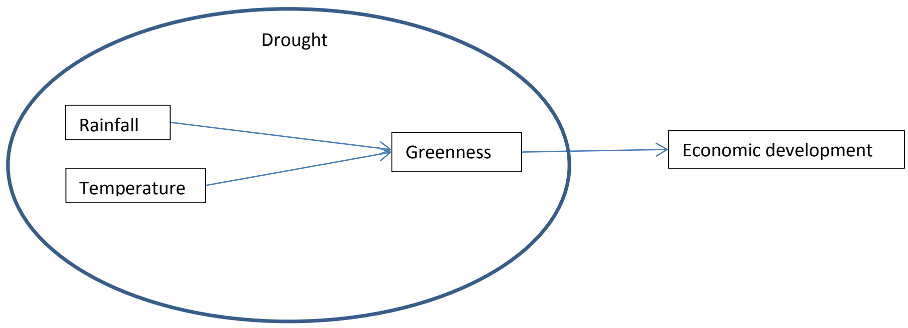
2.2 Predicted greenness

The main contribution of this part of the paper is to exploit the variation in greenness in combination with rainfall and temperature to obtain a drought measure that is more precise than existing global drought indicators, consitent across time and space, and easily accessible and updateable from satellite data.

This measure, which I shall dub *predicted greenness*, is obtained from regressing monthly variation in NDVI on lagged monthly variation in rainfall and temperatures. By this procedure, only the variation in NDVI that is caused by climatic factors is considered, whereas the noise described above is filtered out. Furthermore, the measure improvemes on existing drought indexes such as the SPEI, by adding weights to the summation of lagged variation in rainfall and temperature which are determined by their correlation with the variation in NDVI.

Usually, anomalies are calculated for each observation as the deviation in

Figure 2.2: Basic idea behind predicted greenness



Predicted greenness is a measure of drought that uses the variation in greenness caused by variation in rainfall and temperature.

a time period from the historical average. However, in this case we use data from 2000-2012, so a historical average is not obtainable. One possibility would be to focus on the latest years only, say 2010-2012, and then compare with the average for the 2000-2010 period. But this would mean a dramatic loss in the number of observations and general variation in the data. Instead, in order to avoid bias in the regressions in section 3, the focus is year-on-year changes, as will be described in more detail below.

2.2.1 Data

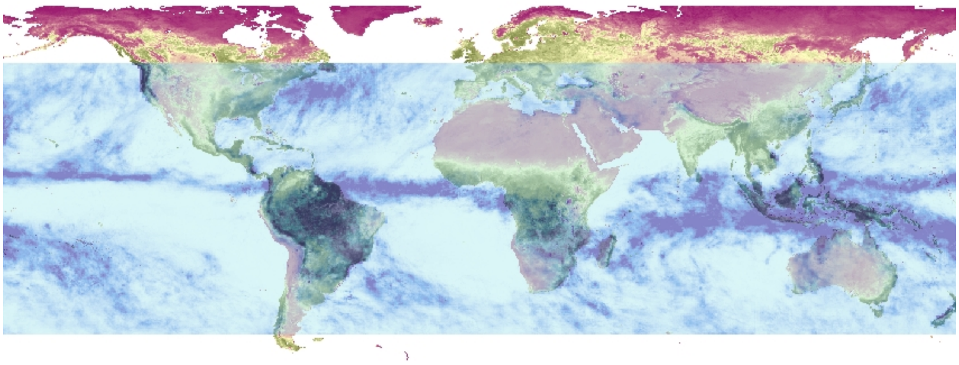
This section describes the data on land surface temperature and rainfall that will be used along with the variation in NDVI in the first-stage regression. All the data that is being used at this stage has a temporal resolution of one month.

Land surface temperature: Like NDVI, land surface temperature is measured from space globally using the MODIS Terra satellite, and again, the product in use has a spatial resolution of 0.05 degrees.[4] Year-on-year

[4]The observations are available starting from February 2000 through the gridded product Mod11c3

changes in both daytime and nighttime temperatures are included in the model. On average, it is expected that daytime temperatures affect greenness negatively since hotter means drier in most parts of the world. Nighttime temperatures are likely to affect greenness positively, however, since cold also becomes a serious constraint for plant growth when moving away from the equator.

Figure 2.3: Geographical extent of NDVI, temperature and rainfall data.



The analysis is limited to the central blue rectangle since this is where the satellite based rainfall data is available.

Rainfall: While greenness is best seen from above, rainfall is harder to measure using satellites. This study uses data from the Tropical Rainfall Measuring Mission (TRMM)[5] which to our knowledge is the most precise and valid remote sensing estimate of rainfall for the relevant period. In terms of spatial extent and resolution, the TRMM data is not as good as our measures of greenness and land surface temperature. It includes pixels of 0.25 degrees and only covers the 'tropical' areas of the world, i.e. a band stretching from 50 degrees north to 50 degrees south. However, the spatial resolution seems sufficient for our purpose and the exclusion of the areas

[5] http://trmm.gsfc.nasa.gov/

furthest away from the equator is a price we have to pay and a fact to be aware of when interpreting the results.

2.2.2 Model

I model the link between year-on-year change in NDVI and the climatic background variables for every month using up to 11 lags so that it is only what has happened during the preceding year that is included. The first stage relationship in pixel i for year t and month m can be written as follows:

$$\Delta_t NDVI_{itm} = \gamma_0 + \sum_{n=0}^{11} (\gamma_{1n}\Delta_t P_{it,m-n} + \gamma_{2n}\Delta_t Td_{it,m-n} + \gamma_{3n}\Delta_t Tn_{it,m-n}) + \epsilon_{itm} \tag{2.1}$$

where P is precipitation, Td is daytime land surface temperature and Tn is nighttime land surface temperature. Δ_t indicates a year-on-year change, so for each variable that has this operator, the previous year's value has been subtracted.

2.2.3 Results

Table 2.1 and figure 2.4 show the results of applying equation 2.1 to the global monthly data set of NDVI, rainfall and temperatures. As can be read, year-on-year changes in rainfall affect year-on-year changes in NDVI mostly in the month prior to the observation of NDVI whereas temperature changes have the largest effect on NDVI changes when looking at the same month. This is probably because plants take some time to transform rainfall into biomass whereas extreme heat or cold has a more immediate effect the color of leaves.

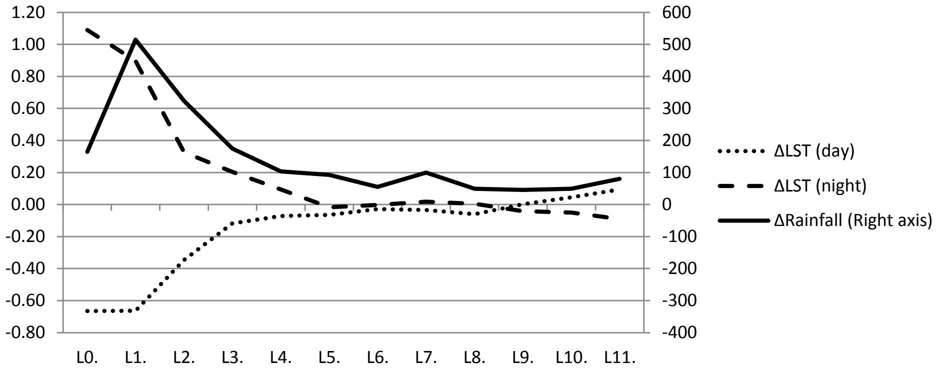
Using a standard linear prediction technique, $\Delta_t \widehat{NDVI}_{itm}$ represents

Table 2.1: Lagged monthly correlations between year-on-year changes in rainfall, temperature and NDVI globally

Lags (months)	Δ_t Rainfall		Δ_t LST (day)		Δ_t LST (night)	
0	164.79***	(1.428)	-0.66***	(0.001)	1.09***	(0.002)
1	514.77***	(1.432)	-0.66***	(0.001)	0.89***	(0.002)
2	323.70***	(1.432)	-0.34***	(0.001)	0.32***	(0.002)
3	174.63***	(1.431)	-0.11***	(0.001)	0.20***	(0.002)
4	103.50***	(1.431)	-0.07***	(0.001)	0.09***	(0.002)
5	92.60***	(1.432)	-0.06***	(0.001)	-0.00***	(0.002)
6	54.85***	(1.432)	-0.02***	(0.001)	-0.01*	(0.002)
7	99.79***	(1.433)	-0.03***	(0.001)	0.01***	(0.002)
8	49.04***	(1.433)	-0.06***	(0.001)	0.00***	(0.002)
9	45.77***	(1.434)	0.00*	(0.001)	-0.04**	(0.002)
10	49.56***	(1.435)	0.04***	(0.001)	-0.04***	(0.002)
11	80.36***	(1.432)	0.09***	(0.001)	-0.08***	(0.002)

Dependent variable: $\Delta NDVI_t$. Robust standard errors in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1% levels, respectively. 25 climate zone dummies included, N = 19,795,008, R^2= 0.1167

Figure 2.4: Lagged monthly correlations between year-on-year changes in rainfall, temperature and NDVI globally



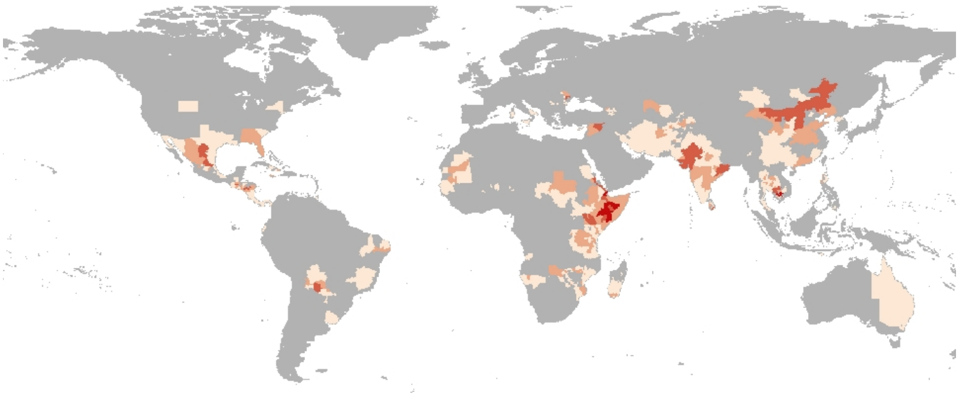
the drought indicator that will be used in section 3 after aggregating from months to years.

2.3 Identifying droughts

So far the section has been concerned with variation in climatic variables as a continous measure of drought. But droughts are often seen as a discrete phenomenon; either there is a drought or the situation is *normal.* A drought can be defined as a period of unusually dry conditions leading to water shortages or reduced plant growth, that might turn into a disaster for the people living in drougt-affected areas.

This section compares the deviation from the long-run average of different indicators of drought across years that are registered as being hit by drought. Figure 2.5 shows all droughts that have been officially registered betweem 2000 and 2012 at the sub-national level according to the Global Disaster Identifier Number (GLIDE) database[6]. Colors indicate the frequency from 1 (beige) to 6 (dark red).

Figure 2.5: Frequency of droughts registered in the GLIDE database



Beige represents provinces or districts with 1 registered drought in the period; dark red represents 6.

A drought is considered to be officially *registered* when it is contained in the GLIDE database and is geographically delimited based on information contained in that database about the specific parts, regions or districts of a country that are hit by drought. Obviously, self-reported droughts suffer from a number of selection biases, but here they will serve as a crude division rule that will be used for comparison of different gridded drought indicators.

[6]Maintained by the Asian Disaster Reduction Center (ADRC) in collaboration with ISDR, CRED, UNDP, IFRC, FAO, World Bank, OFDA/USAID, LA Red, and OCHA/ReliefWeb. A GLIDE number is generated for all disaster events with the aim being that the number is then attached to all databases documenting the same disaster thereby linking the various information sources. Source: EMDAT

Table 2.2 contains the Z-scores of a list of drought indicators. All have been normalized to a mean of zero and a standard deviation of 1 for the period 2000-2012 in order to be comparable. Basically, what we see is that all indicators react to a change between a normal year and a registered drought-year. Starting from the left, the columns below *globally* show the difference on these indicators between normal years (No drought) and a registered drought year (Drought) across the globe. Predicted greenness is the measure that shows the largest difference between normal and drought.

Table 2.2: Comparison of average anomalies of monthly key variables by drought incidence

	Globally		Semi-arid zones		Croplands	
Z-scores	No Drought	Drought	No Drought	Drought	No Drought	Drought
NDVI	0.00	-0.49	0.00	-0.59	0.00	-0.44
Rainfall	0.00	-0.18	0.00	-0.24	0.00	-0.10
LST_day	0.00	0.30	0.00	0.36	0.00	0.45
LST_night	0.00	-0.09	0.00	-0.10	0.00	-0.05
Predicted greenness	0.00	-0.59	0.00	-0.74	0.00	-0.45
1-m SPEI	0.00	-0.18	0.00	-0.15	0.00	-0.23
6-m SPEI	0.00	-0.36	0.00	-0.38	0.00	-0.56
12-m SPEI	0.00	-0.36	0.00	-0.47	0.00	-0.65
Observations	41.9 mio.	59,967	4.19 mio.	15,416	1.22 mio.	1,948

The rest of the table contains similar comparisons, but for semi-arid climate zones and croplands respectively. Maps A.1 and A.2 in the appendix show the areas that are referred to. When only looking at the semi-arid zones (columns 3-4), there is generally a larger difference between drought and non-drought years for all but the SPEI whereas in cropland areas (colums 5-6) the difference is smaller.

In general, SPEI reacts stronger to droughts in areas of cropland and less in the semi-arid zones. This might be due to the fact that it is based on observations from weather stations and these are more densely distributed when there is a high population density and degree of development. Thus in the semi-arid zones there is in general longer distances between the stations and more interpolation and smoothing is required. See map of weather stations behind the SPEI in appendix A.

3 Quantifying economic impacts of drought

This part of the paper turns to the second research question: what are the economic impacts of drought? Firstly the empirical strategy is presented, then the results at the global level, and finally an attempt is made to put numbers on the cost of drought.

3.1 Empirical strategy

In order to answer the question of how drought affects global economic development, the first step is to obtain good quality data on both aspects. While the paper so far has centered around estimating drought precisely and consistenly across the globe using satellite data, here a similarly precise and consitent measure of economic development is presented. Secondly, the econometric specification is outlined before turning to the results.

3.1.1 Lights at night

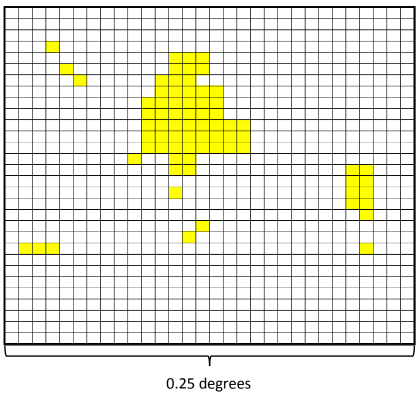
Measures of economic activity, such as gross domestic product (GDP), is typically only constructed for rather large administrative units, such as provinces of a country. Furthermore, it is not always measured in the same way across the world, and finally, measurement errors in GDP are not uncorrellated with the level of economic development.

This study therefore employs an increasingly popular measure of local economic activity, first advocated by Henderson et al. (2012), namely the density of artificial lights at night, or luminosity, as some authors prefer to call it. The data is downloadable in different versions from the Defense

Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) providing pictures of Earth at night between 20:30 and 22:00 local time. Naturally occuring lights such as fires and aurora are filtered out, and the data that is available at the yearly level is a composite image, where only stable lights are included and observations of cloud cover are dropped.

As previously mentioned, this study uses pixels of 0.25 degrees[7] as the unit of analysis whereas the pixels containing information on artificial lights at night are only 0.008 degrees[8]. There are thus 900 light pixels per unit of analysis. This allows for the construction of an indicator of economic development that measures the share of lit light-pixels within the larger unit of analysis. This method is inspired by Michalopoulos and Papaioannou (2013) and is thought to be better than taking the average amount of light emitted in a unit because it puts more weight on the variation that takes place in darker, less developed regions of the world.

Figure 3.1: Illustration of light measure



Luminosity is here defined as the share of light pixels that are lit within one unit of analysis. In this case the share of lit pixels is 75/900 = 8.3%

As shown by Henderson et al. (2012) among others, there is a strong

[7] 15 arc minutes around 28 km at the equator

[8] 30 arc seconds or around 1 km at the equator

correlation between changes in luminosity and changes in GDP per capita at a sub-national level. For this particular purpose, there are even more arguments why the measure is useful: Most areas where drought has a profound impact on people's lives are in poor countries in the warm parts of the world, and these are also areas where trustworthy GDP figures at the subnational level are harder to find.

3.1.2 Model

Turning to the econometric specification, the relationship between drought and economic development for pixel i in year t can be stated as follows:

$$\Delta Lights_{it} = \alpha + \sum_{s=0}^{5} \beta_s \Delta \widehat{NDVI}_{i,t-s} + \epsilon_{it} \tag{3.1}$$

Where $\Delta Lights_{it}$ is the share of lit sub-pixels in pixel i and year t. $\Delta \widehat{NDVI}_{it}$ is the predicted values of model 1 aggregated from monthly to yearly values:

$$\Delta \widehat{NDVI}_{it} = \sum_{m=1}^{12} \Delta_t \widehat{NDVI}_{itm} \tag{3.2}$$

In focusing on year-on-year changes in predicted greenness, model 3.1 controls for all time-invariant factors that might affect change in luminosity. The error term ϵ_{it} is clustered at the country level allowing for correlation between the errors within a country while holding on to an assumption of no correlation between countries.

3.2 Results

This section contains the results of a regression analysis that is based on equation 3.1. Table 3.1 includes the results of regressing changes in luminosity on predicted changes in greenness with 0 (column a) to 5 (column

f) lags. It shows that predicted changes in greenness has a clear positive effect on changes in luminosity between year t and $t-1$. The effect persists in the first lag (with around half the size), but then disappears when more lags are added. This suggests that drought does not affect economic growth permanently, but could have an observable effect on the levels of economic activity if the repeatedly hit the same regions.[9]

Table 3.1: Changes in light and predicted greenness

	a	b	c	d	e	f
$\Delta\widehat{NDVI}_{it}$	0.17**	0.24***	0.26***	0.25**	0.26**	0.34***
	(0.07)	(0.09)	(0.09)	(0.10)	(0.11)	(0.12)
$\Delta\widehat{NDVI}_{i,t-1}$		0.15***	0.17**	0.14**	0.12**	0.28***
		(0.04)	(0.07)	(0.06)	(0.06)	(0.10)
$\Delta\widehat{NDVI}_{i,t-2}$			-0.04	-0.09**	-0.12***	0.11
			(0.08)	(0.04)	(0.04)	(0.07)
$\Delta\widehat{NDVI}_{i,t-3}$				0.07	0.02	0.24*
				(0.09)	(0.12)	(0.13)
$\Delta\widehat{NDVI}_{i,t-4}$					-0.06	0.13
					(0.08)	(0.09)
$\Delta\widehat{NDVI}_{i,t-5}$						0.08
						(0.15)
Constant	0.03	-0.01	0.05	-0.03	-0.06	0.15***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.04)
N	1,605,344	1,440,490	1,281,234	1,128,323	980,150	834,878
R^2	.0011	.0016	.0072	.0025	.0028	.0034

Dependent variable: $\Delta Lights_t$. Standard errors clustered at country level in parentheses. Clustering at province or district level yields similar result, but with higher levels of significance. Including country-dummies does not affect results.

Quantitavely, the main result from table 3.1 is that if a given 0.25*0.25 degree pixel experiences a predicted change in greenness that lies 1 standard deviation above the global mean, on average an extra 1.5 - 2.5 light pixels out of 900 are lit that year. This is likely to reflect increased economic activity associated with higher agricultural productivity, more hydropower generation or migration away from areas hit by drought to greener regions. Likewise if an area is subject to drought in the sense that the predicted change in greenness lies 1 standard deviation below the global average, between 1.5

[9]For a discussion of the long-run impacst of natural disasters on economic growth, see Hsiang and Jina (2014).

and 2.5 fewer pixels are lit.

3.3 The cost of drought

Looking again at the map in figure 2.5 showing the frequency of droughts registered in the GLIDE database, we now take a look at how luminosity has changed in these areas compared to the rest of the world. On average, across the extent of this analysis, luminosity increases 0.017% each year. In areas where at least one drought has been recorded in a given year, luminosity has decreased 0.23% those years. In other words, 2 out of the 900 light-pixels that are contained in each unit of observation are extinguished.

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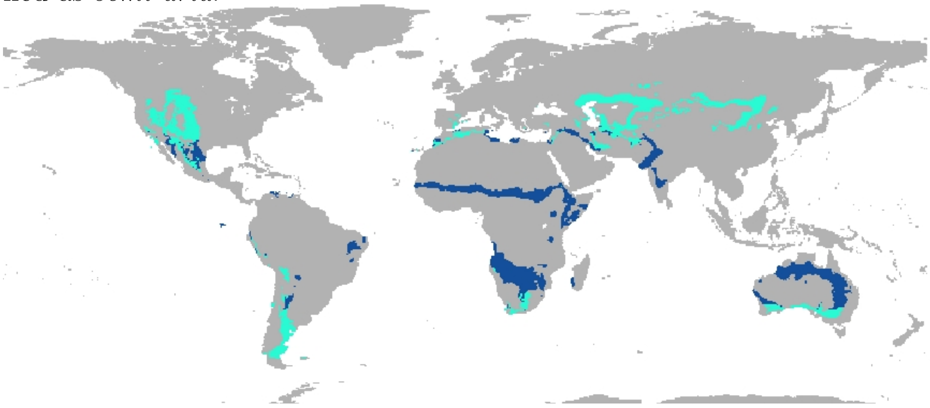
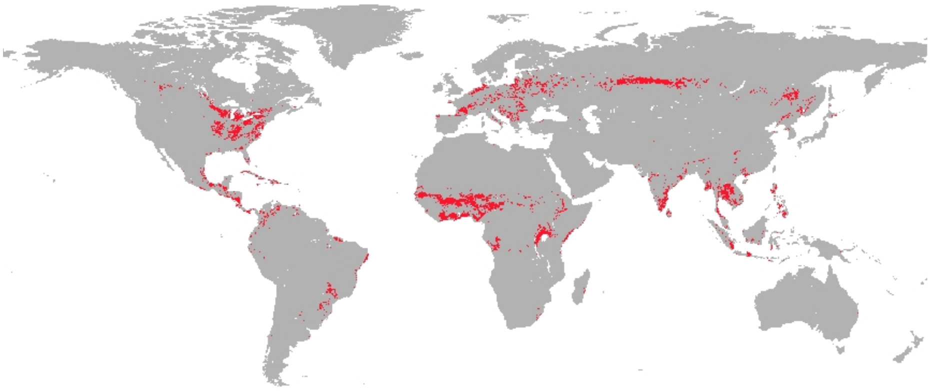
A Maps

Figure A.1: Geographical extent of the Koppen-Geiger climate zones classified as *semi-arid*.



Blue areas cover the hot semi-arid zones and teal the cold semi-arid zones.

Figure A.2: Global croplands



Pixels where the majority of sub-pixels are classified as *croplands* by MODIS Terra.

Figure A.3: Weather stations used for calculation of the SPEI index: