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EXPLORING THE SHORT-TERM AND LONG-TERM RELATIONSHIPS BETWEEN CLIMATE AND HUMAN DEVELOPMENT

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Exploring the Short-Term and Long-Term Relationships between Climate and Human Development

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Abstract

How global warming affects human development is a central question for economists as well as social scientists. While most of the literature has focused on the impact of rainfall and temperatures on individual well-being, precipitations alone do not capture the actual soil water availability, which also depends on the potential evaporation of the water. This paper considers shocks in precipitation, temperature, and an original measure of soil aridity to exploit the association between climate warming and Human Development. While precipitations do not have a significant long-term impact on human development growth, both temperature and potential evapo-transpiration shocks affect two of the three determinants of the Human Development Index, namely life expectancy at birth and education.

Key words: Human Development, Weather Shocks, Soil Aridification, Africa

1 Introduction

Understanding the effects of human-induced climate changes on economic and social development is critical for achieving policy interventions to counterbalance economic losses

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of less developed countries, which will pay the highest price of a warmer and drier climate. However, climate does affect economic development in many ways. The economic literature has focused mainly on income and social disparities across countries, while considerably less attention has received spatial disparities within countries.

A growing body of literature is focusing on within-country uneven economic development in the climate change discussion. Diffenbaugh and Burke (2019) have investigated whether global warming has affected the recent evolution of income inequality between countries finding that anthropocentric climate changes have increased economic inequality between countries. Nevertheless, climate warming might affect human development through different dimensions, often neglected in the economic literature. For instance, rising temperatures have been associated with higher lower infant health and higher infant mortality (Banerjee and Maharaj, 2020; Geruso and Spears, 2018) this leads to a reduction in life expectancy in more vulnerable areas of the world. Moreover, weather shocks are negatively associated with children's education (Pellerin, 2000) mainly through an increase in child labor (Colmer, 2021; Myers and Theytaz-Bergman, 2017; Boutin, 2014). Finally, global warming has also been associated with lowering income (Burke et al., 2015) in particular for developing countries relying on agriculture (Zhang et al., 2017). In the economic geography literature, Dall'Erba and Domínguez (2016) and Dall'Erba et al. (2021) have focused on the impact of climate change on the productivity and trade of US agriculture, while Conte et al. (2021), Castells-Quintana et al. (2021) and Bosetti et al. (2021) focus on the distribution of population across urban-rural areas, even in terms of local migration patterns. Finally, Pan et al. (2020) focuses on the future joint impacts of climate and land use changes on the Yangtze river economic belt, in China.

In this paper, we first assess the relationship between climate variability and a measure of human development within a country and then explore the determinants of such a relationship. To investigate whether global warming has affected human development, we combine historical climatic variables such as precipitation, temperature, and potential evapotranspiration with sub-national Human Development Indexes (HDI)[1].

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[1] Differences between human development and income growth have been a crucial issue in the recent economic literature (Rodionov et al., 2018; Ranis et al., 2006). Several measures of social development which go beyond the mere economic area have been developed. For instance Ram (1992) is the first paper to show that despite being highly correlated, the GDP per capita and the index of human development (HDI) revealed a striking difference, that is, intercountry inequality in real income is high. At the same time, that in HDI is extremely low. Ranis et al. (2000) empirically shows how countries that initially favored economic growth over human development eventually performed poorly on health and education.

Our research contributes to the literature in two main directions. The first and most important relates to the climate indicator we employ. Most of the economic effects of global warming literature has focused on precipitation and temperature shocks. Here we instead use a soil-water availability index, the Potential Evapotranspiration (PET), that considers the combined effects of precipitation, humidity, temperature, UV radiations, among other climate variables. This accounts for the fact that the impact of rainfall on the growing cycle of a plant depends on the extent to which water can be retained by the soil (Harari and Ferrara, 2018). The second contribution of the present study relates to the investigation of the main determinants through which climate variations affect the human development of a small area of the world. To understand this, we estimate the relationship between our climate variables and each of the three dimensions that compose the HDI, namely life expectancy at birth, gross national income, and completed years of education by taking as units of observation sub-national administrative units[2] for a period between 1990 and 2015.

We assemble a panel dataset covering about 1564 administrative units in 135 countries from 1990 to 2015. By combining sub-national human development data from Jahan et al. (2017) with an original measure of soil aridification, which is obtained interacting precipitation, humidity, and temperature data from the gridded Climatic Research Unit (CRU) Time-series (TS). First, we estimate the relationship between annual and long-term variations in climate variables (i.e., precipitation, temperature, and PET) and human development using OLS. Our benchmark specification is conditional on subnational district fixed effects and country-specific time trend so that we identify changes in the human development index relative to a district's historical mean. We find that: first, there is a significant local-level relationship between annual precipitation and temperature shocks and human development. According to our most conservative specification, a one standard deviation shock in precipitation and temperature during year t is associated with an eleven and eight percentage point increase in HDI, respectively. Second, the relationship appears to be concave (i.e., considerable higher amounts of precipitation and higher temperatures

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On the other hand, countries with good HDI and poor economic growth performed better in the long term. Finally, Prados de la Escosura (2015) discussed how the economic gap between OECD and the rest of the world widened throughout the 20^{th} century, with the differences growing remarkably after the 1970s, when the rest of the world fell behind the OECD in terms of life expectancy and education.

[2] We consider a total of 1,565 administrative units, defined as those belonging at the second level of administration (i.e., "admn 2"). These sub-national units correspond to provinces or counties.

are negatively associated with the local human development). Third, when evaluating the 25-year relationship between climate variations and local human development, rainfalls and temperature do not significantly explain development, while soil aridification affects significatnly HDI. Our estimates indicate that one standard deviation increase in PET over the period 1990-2015 is associated with a decrease of 27.7 percentage points in the Human Development Index. Forth, we further extend the analysis to investigate the relationship between climate and each of the determinants of the human development index. In particular, we document a strong and positive relationship between standard climate variables (i.e., precipitation and temperature) and life expectancy and income at the local level, thus confirming the conclusions drawn in the relevant economic literature (Dell et al., 2012; Burke et al., 2015). However, our estimates show the opposite effects of Potential Evapotranspiration.

The remainder of the paper is organized as follows: in Section 2, we summarize the differences between precipitations and soil aridification, while in n Section 3 we present the analytical framework to estimate the annual relationship between rainfall, PET, and human development. In Section 4, we present the data used for the construction of the Aridity Index and describe each of the dimensions composing the Human Development Index. Section 5 discusses the results of the short- and long run relationships between climate variables, PET and HDI. In Section 6 we address which of the three dimensions composing the HDI is the most affected by the process of desertification. Finally, Section 7 concludes.

2 Precipitation and Soil Aridification

The economic literature on the climate impact on socio-economic development has focused on precipitation and temperature shocks in Africa and South-East Asia as primary climate variables. Maccini and Yang (2009) and Kudamatsu et al. (2012) show that individuals who, during their childhood, were exposed to greater amounts of precipitation and shorter drought periods had positive long-term impacts in terms of health and living standards compared to their peers. Jayachandran (2006) is yet another example of how rainfall shocks explain variations in wages and migration waves in agriculture-intensive rural India. Although the aforementioned studies are only the most relevant and recent papers dealing with the relationship between rainfalls and socio-economic well-being, a vast literature has confirmed the positivity and significance of such effect. Interestingly enough, more recently, the effect of precipitation and temperature on human development has been found to be non-linear, prompting at the existence of a tipping point where the sign of the relationship becomes negative [3].

According to current projections on weather changes in the upcoming decades, average rainfall at the global level is foreseen to rise (Cherlet et al., 2018). In particular, the increase in precipitation will be more pronounced at high and mid-latitudes and in tropical regions (Kirtman et al., 2013; Donat et al., 2016).

Given the results obtained in the existing empirical literature one may be tempted to infer a positive effect of climate change. However, three elements need to be taken into account. First, the non-linearity of the relationships between climate variables and economic development implies that the size of the forecasted climate change will define the sign of the impact at local level. Second, although climate is defined by geophysical interactions on a global scale, the socio-economic impacts need to be analysed at a local scale. Third precipitations alone do not capture actual soil water availability, depending on concurring factors such as land quality, solar radiations, temperature, air humidity, and wind speed.

As a result, the effective water availability of these areas is not certain, and a precise measure of land dryness is needed. We use a measure of Potential Evapo-Transpiration (PET), which considers the combination of two sources of soil water loss: soil surface evaporation[4] and reference crop transpiration[5] (Allen et al., 1998). Following Rind et al. (1990) and Cherlet et al. (2018), we assume PET as an indication of local aridity.

To better visualize this crucial aspect Figure 1 shows that for the period 1990-2015, most areas of the world have experienced increased precipitation compared with their historical mean (Panel A). Nevertheless, zones that have experienced increases in precipitation have also been accompanied by higher evaporation levels (Panel B)[6]. In particular, during the historical period (1900-1980), the global average monthly precipitation was 1.82 millimeters, while the present-day average (1990-2015) is 1.85 millimeters, with an increase

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[3] The effects of precipitation and temperature on human development are not linear. Burke et al. (2015) and Dasgupta et al. (2020) suggest a significant non-linear relationship between income growth and inequality and local mean temperature

[4] The process whereby liquid water is converted to water vapor and removed from the evaporating surface

[5] The vaporization of liquid water contained in plant tissues and the vapor removal to the atmosphere

[6] This is particularly visible in Africa and the Middle East, large parts of Latin America, and South-East Asia

of 0.03 millimeters per month, or 1.65%. Conversely, during the historical period (1900-1980), the global average monthly PET was 1.83 millimeters, while the present-day average (1990-2015) is 1.88 millimeters, with an increase of 0.05 millimeters per month, or 2.73% (Fu et al., 2016). Along these lines, Malpede and Percoco (2021) examine the effects of human-induced desertification on economic growth and find over the period 1990–2015, aridification reduced the GDPs of African and Asian countries by 12% and 2.7%, respectively.

In this paper, we aim to investigate the relationship between climate and local development. To the best of our knowledge, our research is the first to assess such (non-linear) relationship at global level with local data and to extend the analysis to consider the impact of all dimensions of HDI: education, life expectancy and income.

3 Methodology

In this section, we present the analytical framework for discussing the relationship between climate change and human development. Our methodology consists in estimating a short run and a long run relationship between climate and HDI with its components.

The estimation of the effects of climate variations on the human development in the short run follows the same logic of Diffenbaugh and Burke (2019); Burke et al. (2018, 2015) :

$$\begin{aligned} \Delta Y_{i,c,t} = \alpha + \beta_1 \ P_{i,c,t} + \beta_2 \ P^2_{i,c,t} + \beta 3 \ PET_{i,c,t} + \delta_1 \ T_{i,c,t} + \delta_2 \ T^2_{i,c,t} + \\ + \sigma_t + \omega_i + \rho_c \ \tau + \epsilon_{i,c,t} \end{aligned} \tag{1}$$

We denote with $\Delta Y_{i,c,t}$ the change in the Human Development Index (HDI) of subnational district i, of country c, from year $t-1$ to year t. $P_{i,c,t}$ indicates the average annual amount of precipitation of district i in country c at year t and is expressed in millimeters. To account for non linear relationship between precipitation and HDI, we include $P^2_{i,c,t}$ which indicates the average annual precipitation in millimeters of grid i in country c at time t squared. The variable $PET_{i,c,t}$ instead, indicates the annual potential evapo-transpiration of grid i in country c at year t and is expressed in millimeters. In addition, we also control for average annual mean surface temperature $T_{i,c,t}$ and its squared value denoted as $T^2_{i,c,t}$.

Finally, the model considers year fixed effects, denoted with σ_t, district fixed effects denoted with ω_i, and country linear trends in order to account for country specific trends over time; this is denoted with $\rho_c \, \tau$. Equation (1) is estimated by using OLS.

In addition to the annual relationship we estimate the long term relationship between climate and human development. This models implies a cross sectional equation, and is detailed below:

$$\Delta Y_{i,c} = \alpha + \beta_1 \, \overline{P}_{i,c} + \beta_2 \, \overline{P}^2_{i,c} + \beta 3 \, \overline{PET}_{i,c} + \delta_1 \, \overline{T}_{i,c} + \delta_2 \, \overline{T}^2_{i,c} + \mu_c + \epsilon_{i,c} \tag{2}$$

Here we denote with $\Delta Y_{i,c}$ is the long-term change in the Human Development Index (HDI) of sub-national district i, of country c, from year 1990 to year 2015. $\overline{P}_{i,c}$, $\overline{PET}_{i,c}$, and $\overline{T}_{i,c}$ indicate the 25-year average HDI, precipitation, PET and temperature at district i of country c from 1990 to 2015. As in equation 1 we also account for non linear long term relationship between average precipitation and HDI and we include $\overline{P}^2_{i,c}$ indicating the squared average amount of precipitation over the period 1990-2015. Similarly, we include the squared average local temperature denoted as $\overline{T}^2_{i,c}$. These variables capture long-run changes in climate, attenuating year-to-year fluctuations and only isolating a 26-year trend. Finally, the model considers country fixed effects denoted with μ_c. We estimate equation 2 via OLS.

Variable $\Delta Y_{i,c}$, capturing the 25-year change in the HDI, is constructed as follows:

$$\Delta Y_{i,c} = \overline{Y}_{i,c,2015} - \overline{Y}_{i,c,1990} \tag{3}$$

where the average term $\overline{Y}_{i,c,t}$ is defined as follows:

$\overline{Y}_{i,c,t} = \frac{1}{5} \sum_{K=1}^{5} Y_{i,c,t+1-k}$

These are five-year averages of annual average HDI. In other words, the variable $\overline{Y}_{i,c,2015}$ is the average of the HDI during the period 2010-2015. Similarly, $\overline{Y}_{i,c,1990}$ is the average of the HDI during the period 1990-1995. Consequently, $\Delta Y_{i,c}$ captures long-run changes in the HDI, attenuating year-to-year fluctuations and only isolating a 25-year trend.

4 Data Description and Summary Statistics

4.1 Climate Data

Precipitation, Potential Evapotranspiration, and temperature data are provided by the gridded Climatic Research Unit (CRU) Time-series (TS) version 4.00. Original climate data are expressed at a monthly level and extent for the period 1901-2015. The data are provided on high-resolution (0.5 degrees × 0.5 degrees) grids. Precipitation and PET[7] are expressed in millimeters (mm/month), while the surface temperature is expressed in °C. Total precipitation amounts range from a minimum of zero millimeters per month to a maximum of 91 millimeters per month. Potential Evapotranspiration ranges from a minimum of zero millimeters per month to a maximum of 24.5 millimeters per month. Finally, the annual mean surface temperature ranges from a minimum of -20 °C to a maximum of 37.7 °C. A total of 36,172 observations were collected for the years 1990 to 2015. Tables 1 and 2 report summary statistics for weather variables and human development dimensions, respectively.

4.2 The local HDI and its determinants

The concept of human development was first introduced in 1990 with the first Human Development Report (Haq, 1990). The latter introduced a new approach for expanding the richness of human life, rather than simply the richness of the economy in which human beings live. It is, therefore, an approach focused on people and their opportunities and choice (Haq, 1990).

The Human Development Index (HDI) was constructed to have a numerical representation of human development. The HDI is a summary measure of average achievement in three critical dimensions of human development (rather than a single one as in the case of the GDP): i) the health dimension, ii) the education dimension, and iii) the living standard dimension. The HDI is the geometric mean of normalized indices for each of the three dimensions. Each dimension composing the HDI is assessed by one or more specif variables. Specifically, the health dimension is assessed by life expectancy at birth; the education dimension is measured by the mean of years of schooling for adults aged 25 years and more

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[7] PET is calculated by the method proposed by Penman (1948), and different variables are considered, such as atmospheric humidity, solar radiation, and wind, all potentially affected by climate change (Salem et al., 1989).

and expected years of schooling for children of school entering age. Finally, the income dimension is measured by the logarithm of the gross national income per capita[8].

Similarly to its original definition, the HDI is an average of the sub-national values of the three dimensions outlined above. In its official version, these dimensions are measured with the following indicators: Education measured with the variables "Mean years of schooling of adults aged 25 and above" and "Expected years of schooling of children aged 6"; health measured with "Life expectancy at birth" and standard of living measured with "Gross National Income per capita (PPP, 2011 US$)". Our database comprises 1564 sub-national administrative units for which human development data is available annually from 1990 to 2015. Details about the estimation procedure can be found in the Human Development Report (Jahan et al., 2017).

4.2.1 Education Index

The Education dimension is computed using two different measures of schooling years. The first measure is the Mean years of schooling of adults aged 25 and more (henceforth, MYS). It ranges from a minimum of zero years of education to a maximum of 15 years. The sources are Eurostat, the Global Data Lab[9], and UNDP. Additional sources were used to compute the LIFEX (those can be found in the Appendix). The second measure is the Expected education years of schooling (EYS) which consists of the number of years of schooling a child of school entrance age can expect to receive if prevailing patterns of age-specific enrollment rates persist throughout the child's schooling life. It ranges from a minimum of zero years of education to a maximum of 18 years. The sources are Eurostat, GDL-AD, UNDP. Additional sources used to compute the education index can be found in the Appendix. Lacking for HICs outside EU.

The Global Data Lab computes the average years of schooling for each sub-national administrative unit by taking for each region the average number of years of education completed by adults aged 25 and over in the survey and census datasets.

To assess whether climate variations are negatively associated with individuals' health, we use data on life expectancy at birth. These data are recorded at the administrative

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[8] The use of the logarithm of the GNI per capita reflects the diminishing importance of income with increasing GNI

[9] The GDL-AD provides sub-national development indicators for Low and Middle-Income Countries starting from 2016. The data is downloadable at (`https://www.globaldatalab.org/areadata`)

level for each country and are available starting from 1990. To assess whether climate variations are negatively associated with individuals' level of education, we use data on the number of completed years of schooling for adults aged 25 and more. It ranges from a minimum of zero years of education to a maximum of 15 years. These data are recorded at the administrative level for each country and are available starting from 1990 (Smits and Permanyer, 2019). To assess whether climate variations are negatively associated with the average individual income for each district, we use data on the natural logarithm of the Gross National income per capita (LGNIc) also derived from Smits and Permanyer (2019).

4.2.2 Life Expectancy Index (LIFEX)

The Health dimension of the HDI is the life expectancy index at birth (LIFEX). This index is defined as the total number of years newborn children would live if subject to the mortality risks prevailing for the cross-section of the population at the time of their birth. The LIFEX ranges from a minimum of 20 to a maximum of 85. The sources are Eurostat, GDL-AD, and UNDP. Additional sources were used to compute the LIFEX (those can be found in the Appendix).

For High-Income Countries (HICs) and some Middle-Income Countries (MICs), sub-national values of LIFEX were based on data derived from national statistical offices and Eurostat. For most of the Low and Middle-Income Countries (LMICs), data were derived from the GDL-AD.

4.2.3 Standard of Living

The standard of living dimension of the HDI is represented by the natural logarithm of the Gross National income per capita (LGNIc). Smits and Permanyer (2019) define it as the (Log of the) sum of the value added by all resident producers in a given administrative unit. LGNIc is based on Purchasing Power Parity (PPP) and is expressed in 2011 USD. It ranges from 100 USD to a maximum of 75,000 USD. The sources are Eurostat, GDL-AD, UNDP. Additional sources used to compute the LGNIc can be found in the Appendix. For High-Income Countries (HICs) and some middle-income countries (MICs), sub-national values of LGNIc were based on data derived from national statistical offices and Eurostat. However, for most Low and Middle-Income Countries (LMIc), data on the standard of living were not available. In such cases, Smits and Permanyer (2019) derived it from the GDL-AD. A detailed description of the computation of the LGINc is found in the Appendix.

4.2.4 Construction of the HDI

Having presented the three dimensions used to compute the HDI, we now describe the simple formula that defines the HDI.

The first step is the computation of each of the three dimension indices for the administrative unit i at year t. To do that the following formula is used:

$$\text{Dimension Index}_{i,t} = \frac{AV_{i,t} - \text{Min. Value}_t}{\text{Max. Value}_t - \text{Min. Value}_t} \tag{4}$$

The minimum and maximum values are the so-called 'goalposts', which are used to ensure that the dimension indices' values remain between 0 and 1 (see Table 2). For life expectancy at birth, the UNDP goalposts are 24 and 85, and for the standard of living, they are 100 and 75,000. For expected years of schooling, they are 0 and 18, and for mean years of schooling 0 and 15. To obtain the dimension index for education, the geometric mean of the separate indices for expected years of schooling and mean years of schooling is taken. To compute the HDI based on the three-dimension indices, the geometric mean of the three indices is taken[10]:

$$\text{SHDI}_{i,t} = (\text{Education}_{i,t} \cdot \text{Health}_{i,t} \cdot \text{Income}_{i,t})^{\frac{1}{3}} \tag{5}$$

5 Baseline results

Results of the relationship between annual variations of climate variables and the local human development index are reported in Table 3. The regressors of interest are Prec, defined as the average level of precipitation during the year t, Temp, defined as the average surface temperature in year t; and PET, defined as the average level of potential evapotranspiration during year t. Higher values of the variable Prec correspond to higher rainfall in year t. Higher values of the variable Temp correspond to higher average temperatures in year t. Conversely, higher values of the variable PET correspond to lower “effective” water availability in year t. We also check for a non-linear relationship between precipitation and

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[10] For a few regions, the value of one of the education indicators was higher than the maximum goalpost. In these cases, Smits and Permanyer (2019) indicate that the values were capped at the goalpost levels.

human development by including the variable Prec^2, defined as the quadratic term of the average level of precipitation during the year t. Similarly, we include the variable Temp^2, defined as the quadratic term of the average surface temperature in year t. Equation 1 also includes district and time fixed effects and country-specific linear trends.

Column (1) of Table 3 considers the whole sample of sub-national districts for the whole world and shows the contemporaneous relationship between precipitation and temperature and local human development. It indicates the positive relationship between annual variations in precipitation levels and average temperature and human development. In particular, one standard deviation increase in precipitation during year t is associated with an 8 percentage point increase in the Human Development Index in the same year. Similarly, one standard deviation increase in average temperature during year t is associated with an increase of 8 percentage points in the Human Development Index in the same year. Moreover, the relationship appears to be concave (i.e., considerable higher amounts of precipitation and higher temperatures are negatively associated with the local human development). These results do not statistically change when we include year-fixed effects (column 2) and country-specific time trends (column 3). In column 4, we include the contemporaneous effects of PET. This inclusion does not appear to affect the relationship between precipitation and temperature and local human development. However, the sign is negative, although non-significant for the PET. This is no surprise since annual variations in PET are not common as precipitations. Instead, the increasing PET is a process occurring over decades. For this reason, we expect a negative relationship between PET and HDI when estimating equation 2, which is reported in the next section.

Results of the relationship between long-term variations of climate variables and the local human development index are reported in Table 4. This time, the regressors of interest are $\overline{Pre}$, indicating the average amount of precipitation of district i, in country c, over 25 years expressed in millimeters, $\overline{Temp}$, indicating the average temperature of district i in country c over the 25-year period expressed in degree Celsius, and $\overline{PET}$, indicating the average annual amount of PET of district i, in country c, over the 25 years expressed in millimeters. Higher values of the variable $\overline{Pre}$ correspond to higher average rainfall over the period 1990-2015. Higher values of the variable $\overline{Temp}$ correspond to higher average temperatures over the period 1990-2015. Conversely, higher values of the variable $\overline{PET}$ correspond to lower "effective" water availability over the period 1990-2015. As in equation 1, we also check for a non-linear relationship between precipitation and human development by including the variable$\overline{Pre}^2$, defined as the quadratic term of the average level of precipitation over the period 1990-2015. Similarly, we include the variable $\overline{Temp}$, defined as the quadratic term of the average surface temperature over the period 1990-2015. Equation 2 also includes district and time fixed effects and country-specific linear trends.

Column (1) of Table 4 considers the whole sample of sub-national districts for the whole world and shows the 25-year relationship between precipitation and temperature and local human development. Unlike the results obtained for the short run analysis, the estimates of the relationship between long-term changes in precipitation and human development lose significance. These results are qualitatively robust to the inclusion of year-fixed effects (column 2) and country-specific time trends (column 3). Column (4) shows a negative and significant relationship between long-term variations in PET and local human development. In particular, one standard deviation increase in PET over the period 1990-2015 is associated with a decrease of 17.9 percentage points in the Human Development Index.

Taken together, these results suggest that while precipitations are an essential determinant of Human Development in the short run when considering long run climate variations, the effect of climate on HDI is likely to work through soil aridification.

As a robustness check of the estimates we also implement a second model to assess the long term relationship between climate and human development. In this model we construct the change in the Human Development Index from 1990 to 2015 for each district i of country c, and estimate the relationships between long term variations in climate variables and variations of the HDI. Results of this further check are reported in Table A.1 in the Appendix.

6 Evidence on health, education and income

Having established the significant adverse effects of soil aridification on within-country human development, we proceed to investigate which of the three dimensions composing the HDI constitutes the main driver. Several studies provide valuable insights on the effects of climate variation on income (Zhang et al. (2017); Burke et al. (2015)) and individual health, focusing primarily on infant mortality (Banerjee and Maharaj (2020)) and education attainment (Colmer, 2021).

We estimate equations 1 and 2 where ΔY this time denotes the annual and 25-year change in the Human Development Index for district i of country c, respectively.

Tables 5 and 6 report results of the contemporaneous and long terms relationship between climate and local life expectancy, completed years of education and gross national income. Column (1) of Table 5 considers the whole sample of sub-national districts for the whole world and includes year fixed effects and country-specific time trends. It shows the contemporaneous relationship between precipitation and temperature and life expectancy expressed in years. A strong and positive relationship emerged between the annual variations in precipitation and expected years of life. The same conclusions are shown for temperature. In particular, one standard deviation increase in precipitation during year t is associated with an increase of 0.4 years in life expectancy in the same year. Similarly, one standard deviation increase in average temperature during year t is associated with an increase of 0.3 years in life expectancy in the same year. The concavity of the relationship is confirmed (i.e., considerable higher amounts of precipitation and higher temperatures are negatively associated with the life expectancy at the local level). These results do not statistically change when we also include the variable PET (column 2). Column (3) of Table 5 shows the contemporaneous relationship between precipitation and temperature and completed years of education expressed in years. This time, it appears that short-term climate variations do not affect education. These results do not statistically change when we also include the variable PET (column 4). Column (5) of Table 5 shows the contemporaneous relationship between precipitation and temperature and local income expressed as the natural logarithm of the gross national income. Once again, a strong and positive relationship emerges between the annual variations in precipitation and local income level. On the other hand, annual temperature variations do not seem to be related to variations in the GNI. In particular, one standard deviation increase in precipitation during year t is associated with an increase of 0.4 years in life expectancy in the same year. Similarly, one standard deviation increase in average temperature during year t is associated with an increase of 0.3 years in life expectancy in the same year. The concavity of the relationship is confirmed (i.e., considerable higher amounts of precipitation are negatively associated with income at the local level). These results do not statistically change when we also include the variable PET (column 6).

Taken together, these results show a strong positive relationship between standard climate variables (i.e., precipitation and temperature) and life expectancy and income at the local level, thus confirming the conclusions drawn in the relevant economic literature

(Dell et al., 2012; Burke et al., 2015). However, the opposite effects of the Potential Evapotranspiration of the soil emerge (column 2).

Concerning the relationship between long term variations of climate variables and determinants of the sub-national human development, Table 6 shows a negative and significant relationship between PET and life expectancy and completed years of education, while a negative but less robust relationship with our measure of local income.

As for the relationship between climate and HDI, we perform a robustness check of the estimates of the relationship between climate variables and each determinant of the HDI. We construct the change in the life expectancy, year of education and GNI from 1990 to 2015 for each district i of country c, and estimate the relationships between long term variations in climate variables and variations of the three determinants of the HDI. Results of this further check are reported in Table A.2 in the Appendix and reinforce the conclusions drawn in this article.

7 Conclusions

Recent economic literature has addressed the issue of the impacts of climate change on economic development, focusing mainly on standard economic activities. This paper investigates the effects of climate change on human development. Our results indicate that, while precipitations and temperature are associated with a higher human development index at the sub-national level, the inclusion of the Potential Evapotranspiration of the land partly offset the benefits of higher precipitation levels. We also show that these effects are more pronounced for economies that extensively rely on the agricultural sector. Finally, we argue that the two principal mechanisms through which climate impacts human development are income and life expectancy, suggesting that the channels through which desertification impacts human development are the reduction in agricultural production and the associated malnutrition exposing children to higher mortality rates. Our conclusions shed light on the practical economic impacts of climate variations.

Our results point at three policy implications: a) the effect of climate change needs to be analysed at local level, where also adaptation and mitigation policies need to be implemented; b) climate is not only a matter of changes in the atmosphere, but also on the ground, with soil aridification affecting significantly socio-economic well-being in the long-run; c) in some cases, climate change will affect human health not necessarily by affecting income.

Future research is expected to be directed towards the local channels of transmission driving the impact of soil aridification on development and in this respect, the analysis of the impact on the composition of agricultural production and new crop and technology adoption to cope with terrain degradation may prove to be interesting from a research perspective and useful for policy making.

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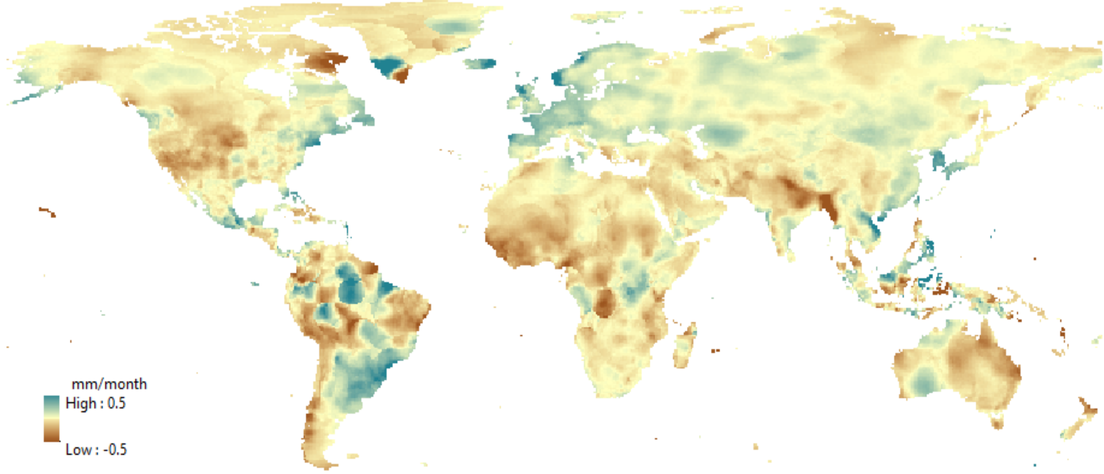
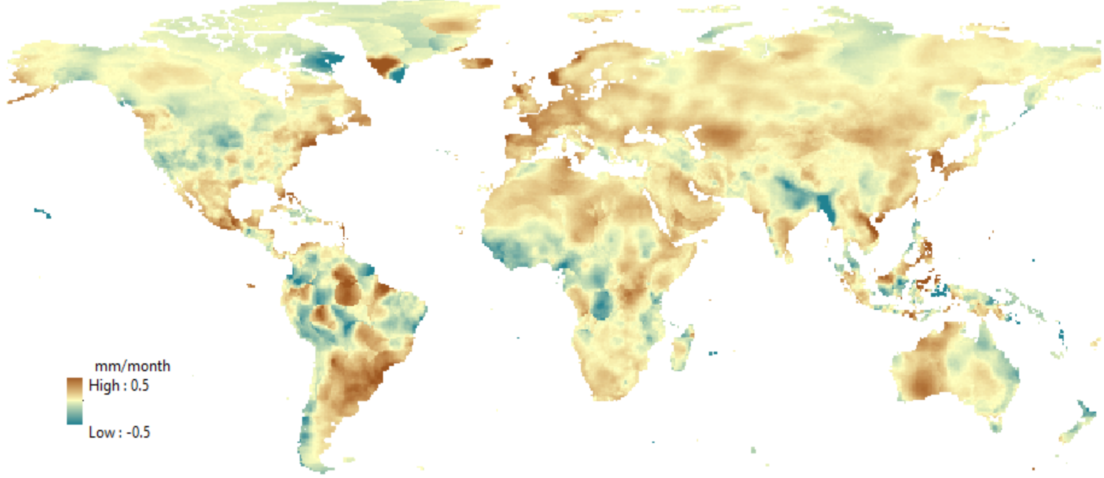
8 Figures and Tables

Figure 1: Global distributions of changes (mm/month) in (A) Precipitation, and (B) PET, taken as the difference between the present day (1990–2015) and the historical average (1900–1980)

Panel A: Precipitation changes



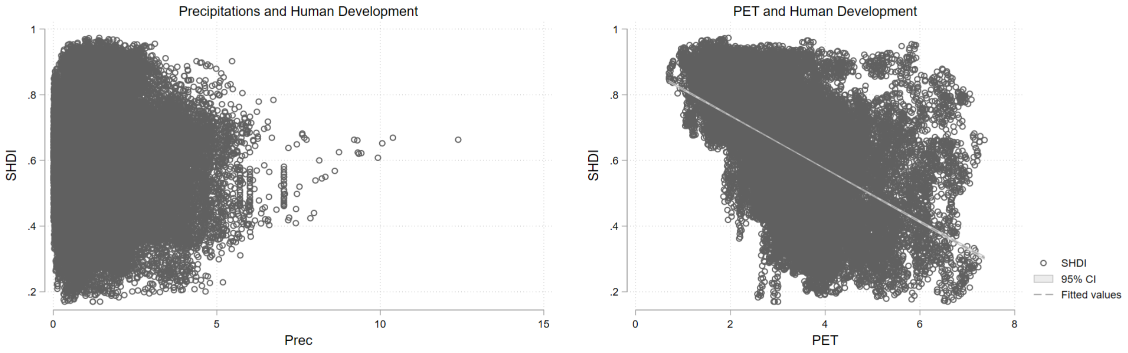
Panel B: PET changes



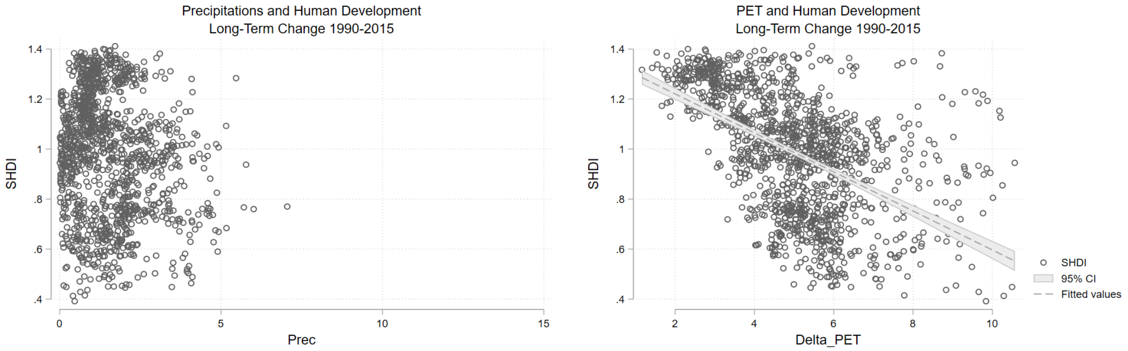
In Panel A, lighter cells identify areas with average precipitations in present day (1990-2015) higher than historical average (1900-1980). In Panel B, darker cells identify areas with average PET in present day (1990-2015) higher than historical average (1900-1980). *Notes: Secular data for precipitation and PET are retrieved from Fu et al. (2016)*

Figure 2: Correlation between climate variables and sub-national human development index.

Panel A: Annual variations



Panel B: Long-Term variations (1990-2015)



Panel A shows the correlation between annual variations in precipitations (left) and PET (right) expressed in mm/year and annual variations in HDI. Panel B shows the correlation between long-term (1990-2015) variations in precipitations (left) and PET (right) and HDI.

The graph on the left hand side shows the negative relationship between Potential Evapotranspiration and Human development for the African continent. Results are obtained considering year-to-year variations from 1990 to 2015. The graph on the right hand side is obtained considering the long term change over the 25-year period. This represents the long term relationship between PET and human development.

Based on these data, on the other hand we do not see a strong correlation between variations in precipitations and human development.

Figure 3: Long term change in the Subnational Human Developemnt Index (1990-2015)

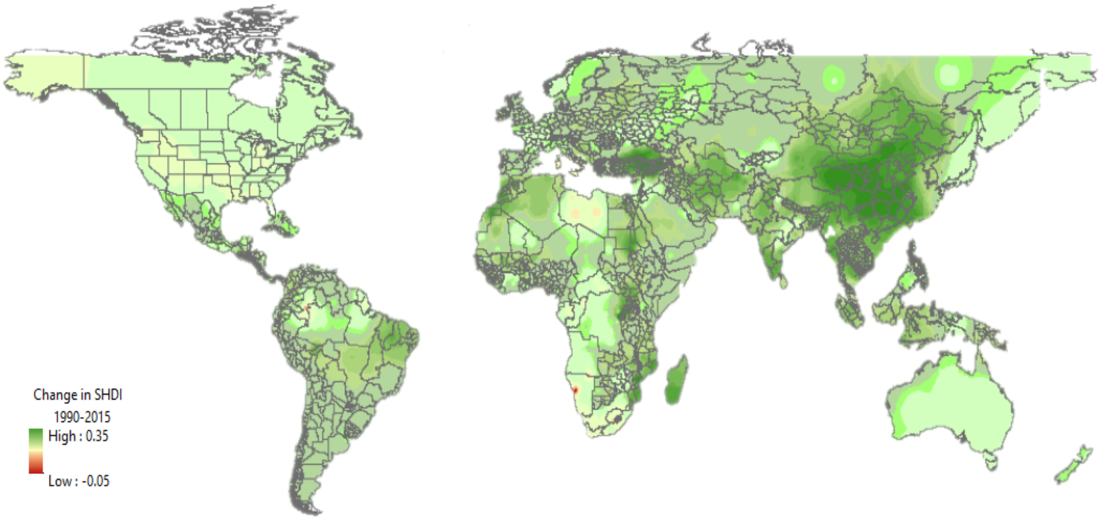


Figure 4: Long term change in the Life Expectancy Index (1990-2015)

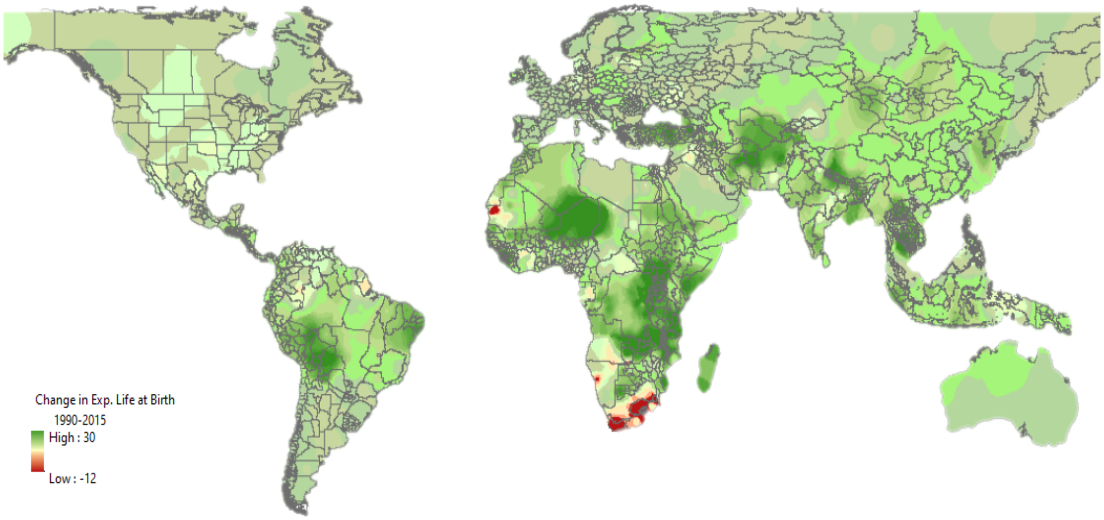


Figure 5: Long term change in completed years of education (1990-2015)

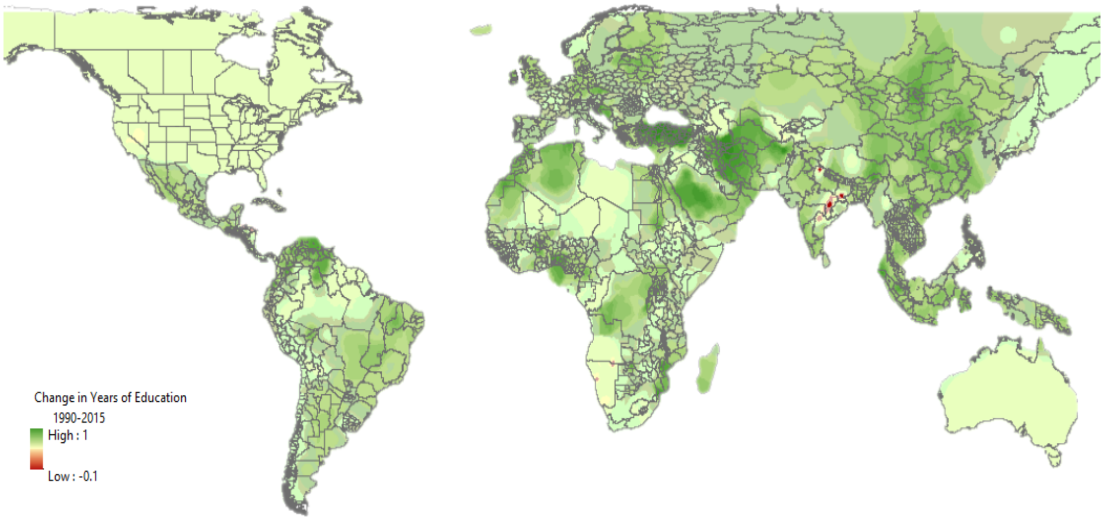


Figure 6: Long term change in the Gross National Income, GNI (1990-2015)

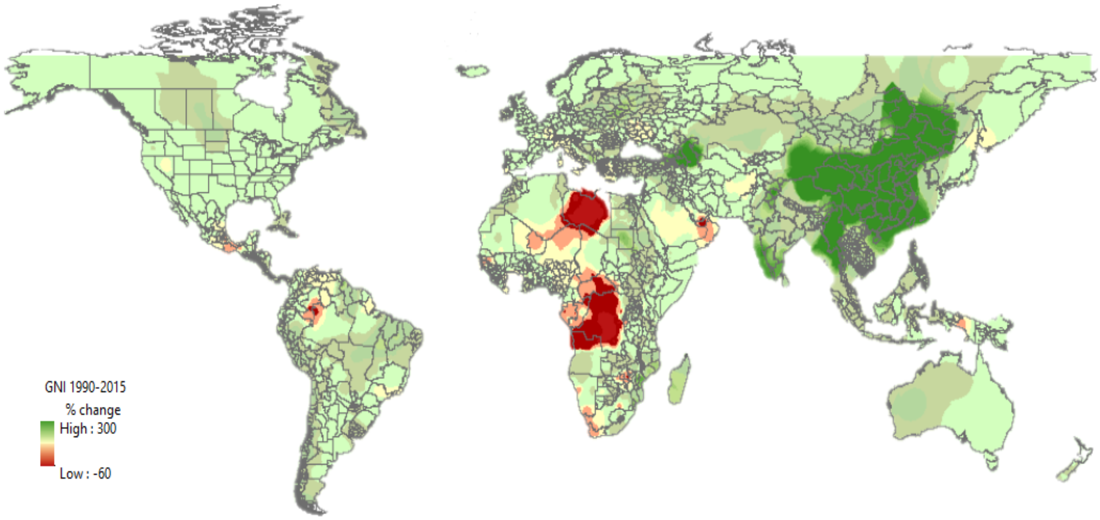


Table 1: Summary Statistics, Climate Variables, Panel Data Sample

Variable	**Unit**	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Precipitation	mm./month	36,172	1.638	1.193	0.003	12.381
PET	mm./month	36,172	3.375	1.112	0.702	7.362
Temperature	$^{\circ}C$	36,172	18.71	8.36	-19.91	36.58

Table 2: Summary Statistics, Sub-national Human Development Dimensions, Panel Data Sample

Variable	**Unit**	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
HDI	0-1 index	36,172	0.624	0.176	0.17	0.973
Life Exp.	years	36,172	67.63	9.91	24.72	84.52
Mean School. Years (25-64)	years	36,172	6.74	3.42	0.17	14.55
Exp. School. Years	years	36,172	11.37	3.59	0.34	15
GNI	thousands of 2011 USD	36,172	7,961	34.329	100.03	74,896

Table 3: Annual Climate-HDI Relationship

	(1)	(2)	(3)	(4)
Prec	0.0010***	0.0005**	0.0005**	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Prec^2	-0.0002***	-0.0001***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Temp	0.0000***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Temp^2	0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PET				-0.0006
				(0.0013)
Observations	36,172	36,172	36,172	36,172
R^2	0.0097	0.1281	0.1298	0.1301
Number of districts	1,564	1,564	1,564	1,564
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Country time trends	N	N	Y	Y

Notes: This table shows results of the estimation of equation 1. Each observation is a district/year. Standard errors in parenthesis. Columns 1 through 4 corrected for clustering at the district level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 4: Long-Term Climate-HDI Relationship

	(1)	(2)	(3)	(4)
$\overline{Pre}$	0.0004	0.0004	0.0004	0.0007
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$\overline{Pre^2}$	-0.0024	-0.0024	-0.0026	-0.0049**
	(0.0021)	(0.0021)	(0.0021)	(0.0024)
$\overline{Temp}$	0.0005*	0.0005*	0.0005	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
$\overline{Temp}^2$	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\overline{PET}$				-0.0170***
				(0.0057)
Observations	1,307	1,307	1,307	1,307
R^2	0.0113	0.0113	0.0151	0.0229
Number of districts	1,564	1,564	1,564	1,564
Controls	Y	Y	Y	Y
District FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Country time trends	N	N	Y	Y

Notes: This table shows results of the estimation of equation 2

Notes: This table shows results of the estimation of equation 2. Each observation is a district/year. Standard errors in parenthesis. Columns 1 through 4 corrected for clustering at the district level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 5: Annual Relationship between Climate and HDI Determinants

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Life Exp.	Life Exp.	Education Years	Education Years	LGNIc	LGNIc
Prec	0.0375**	0.0650***	-0.0000	0.0001	0.0009**	0.0009**
	(0.0152)	(0.0176)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Prec^2	-0.0071***	-0.0097***	-0.0000	-0.0000	-0.0003***	-0.0003***
	(0.0021)	(0.0024)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Temp	0.0034**	0.0031**	0.0001**	0.0001**	0.0000	0.0000
	(0.0014)	(0.0014)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Temp^2	-0.0000	-0.0000	-0.0000**	-0.0000**	0.0000**	0.0000*
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PET		-0.0276**		-0.0033		-0.0033
		(0.0125)		(0.0020)		(0.0024)
Observations	36,172	36,172	36,172	36,172	36,172	36,172
R^2	0.3072	0.3081	0.0813	0.0815	0.1201	0.1202
Number of districts	1,564	1,564	1,564	1,564	1,564	1,564
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Districts FE	Y	Y	Y	Y	Y	Y
Country Trends	Y	Y	Y	Y	Y	Y

Notes: Each observation is a district/year. Standard errors in parenthesis. Columns 1 through 6 corrected for clustering at the district level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 6: Long-Term Relationship between Climate and HDI Determinants

	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{Pre}$	0.0380	0.0416	-0.0000	0.0006	0.0010*	0.0009
	(0.0291)	(0.0306)	(0.0008)	(0.0008)	(0.0005)	(0.0006)
$\overline{Pre}^2$	-0.2144*	-0.2408*	0.0010	-0.0038	-0.0065***	-0.0063**
	(0.1243)	(0.1427)	(0.0033)	(0.0038)	(0.0023)	(0.0027)
$\overline{Temp}$	0.0354*	0.0385*	0.0009*	0.0014***	0.0000	0.0005
	(0.0193)	(0.0210)	(0.0005)	(0.0006)	(0.0004)	(0.0004)
$\overline{Temp}^2$	-0.0014*	-0.0014*	-0.0001***	-0.0001***	-0.0000	-0.0000**
	(0.0008)	(0.0008)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\overline{PET}$		-0.0362		-0.0066***		-0.0156**
		(0.0962)		(0.0025)		(0.0065)
Observations	1,307	1,307	1,307	1,307	1,307	1,307
R^2	0.0071	0.0072	0.0159	0.0215	0.0196	0.0266
Number of districts	1,564	1,564	1,564	1,564	1,564	1,564
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Districts FE	Y	Y	Y	Y	Y	Y
Country Trends	Y	Y	Y	Y	Y	Y

Notes: Each observation is a district/year. Standard errors in parenthesis. Columns 1 through 6 corrected for clustering at the district level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

A.1 Data Appendix

A.1.1 Construction of the HDI

The Subnational Human Development Index used in this study are a translation of the UNDP's official HDI and GDI (hdr.undp.org) to the sub-national level. Data are publicly available through the Global Data Lab Project (Smits and Permanyer, 2019).

The HDI is an average of the sub-national values of three dimensions: education, health and standard of living. In its official version defined at the national level, these dimensions are measured with the following indicators: Education measured with the variables "Mean years of schooling of adults aged 25 and above" and "Expected years of schooling of children aged 6"; health measured with "Life expectancy at birth" and standard of living measured with "Gross National Income per capita (PPP, 2011 US$)". Details about the estimation procedure can be found in the Human Development Report (Jahan et al., 2017).

To construct the HDI for the period 1990-2018, Smits and Permanyer (2019) computed the sub-national variation in these indicators and applied it to their national values derived from the UNDP website. For computing the sub-national values, basically two different data sources were used: indicators derived from the Area Database of the Global Data Lab and indicator data obtained from statistical offices. The indicators derived from the GDL Area Database are the major source of data for low and middle income countries (LMICs) and those obtained from statistical offices for high-income countries (HICs).

Because life expectancy and Gross National Income per capita (GNIc) are not readily available in the household surveys and census datasets from which the GDL Area Database is constructed, their sub-national values for LMICs had to be estimated. For life expectancy, this was done on the basis of data on under-five mortality and for GNIc on the basis of household wealth. To measure household wealth, the International Wealth Index (IWI) was used, an indicator of household's standard of living based on asset ownership, housing quality and access to public services (Smits and Steendijk, 2015).

For years for which sub-national data for one or more indicators was missing, the values of these variables were estimated by linear interpolation between the preceding and succeeding year for which this information was available. If interpolation was not possible, the sub-national values of the nearest year were used. The sub-national variation obtained in this way was subsequently applied to the UNDP national values, so that for each year in the period 1990-2017 the (population weighted) mean of the sub-national values is in line with the UNDP values. Further information on the construction of the HDI Database can be found in Smits and Permanyer (2019); Permanyer and Smits (2020).

The Global Data Lab

The Global Data Lab provides since 2016 freely downloadable sub-national development indicators for Low and Middle Income Countries (LMICs) through its Area Database[11]. These indicators are constructed by aggregation from representative survey and census datasets. The major data sources used by GDL for this purpose are Demographic and Health Surveys[12], UNICEF Multiple Indicator Cluster Surveys[13], and datasets from population censuses distributed by IPUMS International[14]. These sources provide large samples, often 50,000 to 100,000 or more respondents, containing information on all household members. For LMICs for which these sources are not available, GDL uses other country-specific surveys, such as the Afrobarometer or the Americas barometer surveys[15], which include only adults instead of complete households. For most LMICs, GDL-AD provides the two indicators needed for creating the educational index, mean years of schooling and expected years of schooling. However, the indicators needed for the health and income dimensions are usually not available in the required form in household survey and census datasets. The sub-national values of these indicators for LMICs are therefore estimated using data on child mortality and household wealth that is derived from GDL-AD.

Education and LIFEX

When only educational attainment data was available, the HDI is computed considering the corresponding years of schooling. In case of missing data, LIFEX was estimated using information on child mortality. This is the case for most of the LMICs. Given that household surveys and censuses generally do not contain information on LEXP, sub-national values of this indicator were for these countries estimated based on information on under-5

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[11] `https://www.globaldatalab.org/areadata`

[12] `https://www.dhsprogram.com`

[13] `http://mics.unicef.org`

[14] `https://international.ipums.org`

[15] The Afrobarometer is retrievable at the following address: `http://www.afrobarometer.org`, the Americas barometer is retrievable at the following address: `http://www.americasbarometer.org`

mortality (U5M). To estimate LEXP on the basis of U5M, Smits and Steendijk (2015) constructed a regression model that explained the variation in national LEXP derived the UNDP database on the basis of national U5M scores derived from GDL-AD.

Standard of Living

In case of missing data, LGNIc was estimated on the basis of IWI scores. Indeed, for most LMICs, data on standard of living were not available. Therefore Smits and Permanyer (2019) derived it from the GDL-AD. Given that household surveys and censuses for LMICs often do not contain information on income and, if they do, this information is not very reliable in poor areas, sub-national values of LGNIc were estimated based on household wealth. For this purpose, the International Wealth Index (IWI) was used, which measures household wealth on the basis of information on asset ownership, housing quality and access to public services. The IWI scale runs from 0 to 100, with 0 meaning ownership of none of the assets and bad quality housing and services and 100 indicating ownership of all assets and best quality housing and services. To estimate LGNIc for the sub-national regions on the basis of IWI, a regression model was constructed that explained the variation in national LGNIc derived from the UNDP database on the basis of national IWI scores derived from GDL-AD.

A.2 Robusteness of Estimates

We also implement a second model to assess the long term relationship between climate and human development. This models implies a cross sectional equation, and is detailed below:

$$\Delta Y_{i,c} = \alpha + \beta_1 \; P_{i,c} + \beta_2 \; P_{i,c}^2 + \beta 3 \; PET_{i,c} + \delta_1 \; T_{i,c} + \delta_2 \; T_{i,c}^2 + \mu_c + \epsilon_{i,c} \tag{6}$$

Here we denote with $\Delta Y_{i,c}$ the change in the Human Development Index from 1990 to 2015 for district i of country c. $\Delta P_{i,c}$ indicates the change in average annual amount of precipitation of district i in country c over the 25-year period and is expressed in millimeters. As in 1 we also account for non linear relationship between change precipitation and HDI and we include $\Delta P_{i,c}^2$ indicating the change in the average annual amount of precipitation in millimeters of grid i in country c squared. The variable $\Delta PET_{i,c}$ instead, indicates the change in annual potential evotranspiration of grid i in country c from 1990 to 2015 and is expressed in millimeters. In addition, we also control for the 25-year change of annual mean surface temperature $\Delta T_{i,c}$. Finally, the model considers country fixed effects denoted with μ_c. We estimate equation (6) via OLS.

We construct these variables capturing the 25-year change as follows:

$$\Delta Y_{i,c} = \overline{Y}_{i,c,2015} - \overline{Y}_{i,c,1990} \tag{7}$$

$$\Delta P_{i,c} = \overline{P}_{i,c,2015} - \overline{P}_{i,c,1990} \tag{8}$$

$$\Delta PET_{i,c} = \overline{PET}_{i,c,2015} - \overline{PET}_{i,c,1990} \tag{9}$$

$$\Delta T_{i,c} = \overline{T}_{i,c,2015} - \overline{T}_{i,c,1990} \tag{10}$$

The average terms, $\overline{Y}_{i,c,t}$, $\overline{P}_{i,c,t}$, $\overline{PET}_{i,c,t}$, and $\overline{T}_{i,c,t}$ are defined as follows:

$\overline{Y}_{i,c,t} = \frac{1}{5} \sum_{K=1}^{5} Y_{i,c,t+1-k}$, $\qquad$ $\overline{P}_{i,c,t} = \frac{1}{5} \sum_{K=1}^{5} P_{i,c,t+1-k}$

$\overline{PET}_{i,c,t} = \frac{1}{5}\sum_{K=1}^{5} PET_{i,c,t+1-k}, \qquad \overline{T}_{i,c,t} = \frac{1}{5}\sum_{K=1}^{5} T_{i,c,t+1-k}$

where $Y_{i,c,2015}$, $P_{i,c,2015}$, $PET_{i,c,2015}$, and $T_{i,c,2015}$ indicate the annual average HDI, the annual average precipitation, PET and temperature at district i of country c in year 2015. These are five-year averages of annual average HDI, precipitations, PET and temperatures. Similarly $Y_{i,c,1990}$, $P_{i,c,1990}$, $PET_{i,c,1990}$, and $T_{i,c,1990}$ indicate the annual average HDI, the annual average precipitation, PET and temperature at district i of country c in year 1990. These are five-year averages of annual average HDI, precipitations, PET and temperatures. As a result, equations 7, 8, 9, and 10 measure changes in average HDI, precipitations, PET, and average temperature over 25 years as these are differences between year 2015 and 1990. These variables capture long-run changes in climate, attenuating year-to-year fluctuations and only isolating a 25-year trend.

Results of the relationship between long-term variations of climate variables and the local human development index are reported in Table A.1. This time, the regressors of interest are ΔPrec, indicating the change in the average annual amount of precipitation of district i, in country c, over 25 years expressed in millimeters, ΔTemp, indicating the change in average annual temperature of district i in country c over the 25-year period expressed in degree Celsius, and ΔPET, indicating the change in the average annual amount of PET of district i, in country c, over the 25 years expressed in millimeters. Higher values of the variable ΔPrec correspond to higher average annual rainfall over the period 1990-2015. Higher values of the variable ΔTemp correspond to higher average temperatures over the period 1990-2015. Conversely, higher values of the variable ΔPET correspond to lower "effective" water availability over the period 1990-2015. As in equation 1, we also check for a non-linear relationship between precipitation and human development by including the variable ΔPrec^2, defined as the quadratic term of the average level of precipitation over the period 1990-2015. Similarly, we include the variable ΔTemp, defined as the quadratic term of the average surface temperature over the period 1990-2015. Equation 6 also includes district and time fixed effects and country-specific linear trends.

Column (1) of Table A.1 considers the whole sample of sub-national districts for the whole world and shows the 25-year relationship between precipitation and temperature and local human development. Unlike the results obtained for the short run analysis, the estimates of the relationship between long-term changes in precipitation and human development lose significance. These results are qualitatively robust to the inclusion of year-fixed effects (column 2) and country-specific time trends (column 3). Column (4) shows a negative and significant relationship between long-term variations in PET and local human development. In particular, one standard deviation increase in PET over the period 1990-2015 is associated with a decrease of 27.7 percentage points in the Human Development Index.

Taken together, these results suggest that while precipitations are an essential determinant of Human Development in the short run when considering long run climate variations, the effect of climate on HDI is likely to work through soil aridification.

Table A.1: Robustness: Long-Term local Climate-HDI Relationship

	(1)	(2)	(3)	(4)
ΔPrec	0.0006	0.0005	0.0006	0.0010*
	(0.0005)	(0.0005)	(0.0005)	(0.0006)
ΔPrec^2	-0.0024	-0.0025	-0.0028	-0.0091*
	(0.0046)	(0.0046)	(0.0046)	(0.0053)
ΔTemp	0.0010	0.0011	0.0012	0.0025***
	(0.0007)	(0.0007)	(0.0007)	(0.0009)
ΔTemp^2	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔPET				-0.0266**
				(0.0126)
Observations	1,307	1,307	1,307	1,307
R^2	0.0148	0.0163	0.0184	0.0240
Number of countries	135	135	135	135
Controls	Y	Y	Y	Y
District FE	N	N	Y	Y
Country time trends	N	Y	Y	Y

Notes: This table shows results of the estimation of equation 6. Each observation is a district/year. Standard errors in parenthesis. Columns 1 through 4 corrected for clustering at the district level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table A.2: Long-Term Relationship between Climate and HDI Determinants

Dependent variable:	(1) Life Exp.	(2) Life Exp.	(3) Education Years	(4) Education Years	(5) LGNIc	(6) LGNIc
ΔPrec	-0.0048	0.0120	0.0008	0.0015*	0.0009	0.0010
	(0.0256)	(0.0269)	(0.0007)	(0.0008)	(0.0006)	(0.0007)
ΔPrec^2	0.0381	-0.2081	0.0002	-0.0101	-0.0097*	-0.0109*
	(0.2183)	(0.2503)	(0.0064)	(0.0073)	(0.0053)	(0.0061)
ΔTemp	-0.0021***	-0.0021***	-0.0001***	-0.0001***	-0.0000	-0.0000**
	(0.0007)	(0.0007)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔTemp^2	0.0958***	0.1247***	0.0013	0.0025**	0.0002	0.0010
	(0.0339)	(0.0368)	(0.0010)	(0.0011)	(0.0008)	(0.0010)
ΔPET		-0.3377**		-0.0141***		-0.0241*
		(0.1687)		(0.0049)		(0.0146)
Observations	1,307	1,307	1,307	1,307	1,307	1,307
R^2	0.0107	0.0141	0.0215	0.0284	0.0147	0.0172
Number of countries	135	135	135	135	135	135
Controls	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Country time trends	Y	Y	Y	Y	Y	Y

Notes: Each observation is a district/year. Standard errors in parenthesis. Columns 1 through 6 corrected for clustering at the district level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

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