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The impact of climate change on incomes and convergence in Africa

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*Highlights (WITHOUT author details)

Highlights

- Accounting for the three dimensions of risks: exposure, vulnerability and hazards; we estimate climate-induced losses in African countries.
- With historical losses up to 15 percent of GDP per capita growth, most African economies are poorly adapted to their climatic conditions.
- Western and Eastern African countries are projected to be the most affected countries on the continent.
- Inequalities between countries are projected to widen in the high warming scenario compared to those in the low and without warming scenarios.
- Solutions include raising mitigation ambition, addressing adaptation deficits and generalizing a special treatment for the most vulnerable.

Abstract

Climate change is projected to detrimentally affect African countries' economic development, while income inequalities across economies is among the highest on the planet. However, it is projected that income levels would converge on the continent. Hitherto there is limited evidence on how climate change could affect projected income convergence, accelerating, slowing down, or even reversing this process. Here, we analyze convergence considering climate-change damages, by employing an economic model embedding the three dimensions of risks at the country-level: exposure, vulnerability and hazards. The results show (1) with historical mean climate-induced losses between 10 and 15 percent of GDP per capita growth, the majority of African economies are poorly adapted to their current climatic conditions, (2) Western and Eastern African countries are projected to be the most affected countries on the continent and (3) As a consequence of these heightened impacts on a number of countries, inequalities between countries are projected to widen in the high warming scenario compared to inequalities in the low and without warming scenarios. To mitigate the impacts of economic development and inequalities across countries, we stress (1) the importance of mitigation ambition and Africa's leadership in keeping global mean temperature increase below 1.5°C, (2) the need to address the current adaptation deficit as soon as possible, (3) the necessity to integrate quantitatively climate risks in economic and development planning and finally (4) we advocate for the generalization of a special treatment for the most vulnerable countries to access climate-related finance. The analysis raises issues on the ability of African countries to reach their SDGs targets and the potential increasing risk of instability, migration across African countries, of decreased trade and economic cooperation opportunities as a consequence of climate change – exacerbating its negative consequences.

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1. Introduction

With income disparities between richest and poorest countries on the African continent ranging from 20 to 50, economic convergence is of uttermost importance when planning and financing development. Convergence is a long-standing debate in economic literature with the main question being as to whether the poorest countries converge towards the richest ones thanks to higher productivity and economic growth (denominated beta-convergence by Barro and Sala-I-Martin, 1995). The main measure of economic convergence is GDP per capita measured in PPP terms (Sala-i-Martin, 2006), even though more recent literature has also investigated convergence in Human Development Index (Asongu, 2014). Over the period from 1950 to nowadays, the gap in income between high-income countries and lower-income regions (here Africa, Asia, Latin America) has remained constant at about 80 percent, with the difference in income levels measured as a percentage of developed countries' incomes (Rodrik, 2011). A significant academic effort went into explaining the sources of the absence of income convergence between high and lower-income countries across the World. Hitherto, to the best of our knowledge, no study has investigated the potential impacts of climate variability and change on income convergence.

Climate variability and change have detrimental consequences on economic and social development in African countries. Droughts in the Sahel in the 1970s led to steep double-digit decreases in countries' GDP and agricultural value-added (Berg, 1976), intertwined with the human and social consequences owing to the large number of casualties incurred by droughts as well as flooding events (CRED, 2017). Further, an increasing number of studies have shown that economies, and especially African ones, are not only sensitive to climate-related disasters but also to year-to-year changes in climatic variables (Abidoye & Odusola, 2015; Barrios, Bertinelli, & Strobl, 2010; Dell, Jones, & Olken, 2012a).

With the intensifying consequences of climate change in the coming years and decades (Niang et al., 2014), this paper explores whether attaining the Sustainable Development Goal (SDG) of "decent work and economic growth" and facilitating income convergence between countries could become more challenging. The present analysis therefore analyses the extent to which climate variability and change is a meaningful determinant to consider in the economic debate on economic convergence and whether owing to current vulnerability and exposure patterns, climate change could lead to an accelerated income convergence or divergence across African countries.

The consequences of climate-related disasters are dependent on several parameters: the intensity of the hazard itself, and also the current vulnerability and exposure of the affected system (Crichton, 1999). With projected climate change displaying uneven modifications in precipitation and temperature patterns across the African continent, combined with different economic structure and vulnerability, the consequences on income convergence are intricate to predict. Therefore, improving the scientific understanding of the consequences of climate-related disasters on African countries' economic development in the coming decades is of significant importance. This is particularly important for policy-planning in the areas of development and adaptation to climate change at the national level, the allocation – i.e. climate finance – of scarce financial resources across countries as well as mitigation ambition at the global level.

Hitherto, studies have mostly focused on the effects of temperature on economies (M. Burke, Hsiang, & Miguel, 2015; Dell et al., 2012a; Moore & Diaz, 2015), using global or continental panel regressions, providing limited understanding of the vulnerability and risk dynamics at the country-level. In addition, precipitation (including droughts and flooding events) is largely overlooked by being considered either as a control variable, or ignored in some cases. The objective of this study is twofold. First, it consists in further understanding the historical vulnerability of African economies to both precipitation (including extreme precipitation events) and temperature fluctuations in order to estimate the extent to which countries are adapted to their current climatic conditions. The second objective is to apply this improved understanding to estimate more comprehensively the projected impact of climate change on economies at the country-level in the perspective of African countries' economic convergence. The model developed for this paper underlying the economic analysis dynamically satisfies the three dimensions of disaster and climate risks by considering exposure, vulnerability and hazards (Crichton, 1999; IPCC, 2012, 2014). Furthermore, at the difference of earlier publications focusing on Africa as a continent (Millner & Dietz, 2011; W. Nordhaus, 2011; OECD, 2015), the analysis of the impacts of climate-related disasters and climate change is performed at the national level. On the basis of this country-level analysis, the effects of climate change on income convergence and divergence between countries are discussed. The effects of climate variability and change are introduced separately for each region and country between 2015 and 2050 in a low and a high warming scenario.

The paper is planned as follows. Section 1 reviews the literature on economic convergence and climate change in Africa. The Section 2 presents the methodology and data used for the assessment. Section 3 displays the results of the analysis. Finally, section 4 discusses the results and introduces the policy implications of the main findings while section 5 concludes.

1. Literature review

The topic analysed in this paper builds on several separate streams of scientific literature. It touches upon inequality and income convergence and the impacts of climate change on economic development, with a specific focus on the African continent. The novelty of the paper lies in the connection made between these two issues by estimating the extent to which climate change impacts could impede the progress towards economic convergence between African economies.

Scholars have widely studied the issue of income convergence, particularly with the objective to assess the trends and conditions under which low- and middle-income countries' level of wealth would converge towards high-income countries. Answering the question of the effectiveness of income convergence remains largely dependent on the data and methods used to conduct such assessment (Magrini, 2004). Observing the historical convergence between European regions and U.S. States, Barro and Sala-I-Martin, (1991) could conclude that States and regions were converging and the process of convergence would occur – even though its pace was slow. According to Sachs and Warner (1995), convergence to occur is conditional to the implementation of "reasonably efficient economic policies", which include property rights protection and openess to trade. This policy condition is a prerequisite to establish "higher-than-average" growth of lower income countries to converge towards higher income ones (Sachs & Warner, 1995). The policy conditions highlighted intend to foster productivity growth in low-income countries to accelerate their economic development path – and therefore closing the "convergence gap" (Rodrik, 2011). As convergence depends on fostering productivity in low-income economies, facilitating the structural transition towards high productivity sectors in the industry and services are indispensable to lock-in the convergence benefits (Rodrik, 2011).

More recently, it was observed that convergence does not occur systematically and could actually be limited to a group of neighboring regions or countries (Magrini, 2004). This observation for the last 10 years is confirmed by more recent literature, which concludes that there is slow – if not a lack of – progress in bridging the income gaps between low- and high-income countries (Johnson & Papageorgiou, 2018; Rodrik, 2011).

Specific to African economies, a study observed that Western African countries were forming a "convergence club" characterized by a convergence in income per capita and a reduction of the standard deviation of income over the recent decades (Jones, 2002). Finally, moving away from income as a measure of economic convergence, a recent study showed that the Human Development Index converged at a faster rate than its sole income component (Asongu, 2014). At the microeconomic level, a study on livestock in three regions of Ethiopia has shown that rainfall deficits tend to reduce asset – particularly livestock ownership – inequalities as wealthier herders progressively sell their assets to smooth the negative impacts of the dry spells on their households (Thiede, 2014). Beyond inequality measured in terms of assets and livestock, households not able to dissave their capital were exposed to large negative consequences maintaining them in poverty (Thiede, 2014).

To date, the large majority of employment in Sub-Saharan Africa is in the agricultural sector, which accounts for about 57 percent of the workforce, but only 16 percent of the GDP of the region (World Bank, 2018). This discrepancy underlines the vulnerability and poverty endemic to the sector, which displays a value added per capita 6 to 7 times lower than for the other sectors of the economy (World Bank, 2018). This high sectoral vulnerability and socioeconomic importance explain the large amount of climate change related literature on the African continent primarily focusing on the agricultural sector. Numerous publications have modelled and estimated the potential impacts of climate change on agriculture in Africa. The large majority of the publications conclude that the production of the main staples is projected to decrease (Calzadilla, Zhu, Rehdanz, Tol, & Ringler, 2013; Schlenker & Lobell, 2010; Thornton, Jones, Ericksen, & Challinor, 2011; Waha et al., 2017). For example, a study published in 2012 estimated the mean risk on yield across the African continent as follows: -10 percent for Millet, -17 percent for Wheat, -5 percent for Maize and -15 percent for Sorghum (Knox, Hess, Daccache, & Wheeler, 2012). Rice production, another staple food in Africa, particularly in the Western Africa could also experience some drastic consequences. Without implementation of adaptation options, irrigated rice yields in the dry season could decrease by up to 45 percent; adaptation measures could lead to a lower but still very significant decrease of 15 percent (Oort & Zwart, 2017). Considering the importance of these crops in terms of caloric intake and income generation for farming households, the projected decreases could lead to severe consequences on economic and social development (Serdeczny et al., 2016).

Climate change could also have negative impacts on labour productivity in all African regions by increasing the number of lost days measured by daily temperature exceeding the "wet bulb globe temperature" (WBGT) threshold set at 22.5°C for non-acclimatized persons and 26°C for acclimatized ones. In the 2050s in a high warming scenario (SRES A2), the number of lost working days due to high temperature could increase by 3.4 percentage points in Western Africa from already one of the highest in the World with 40.3 percent of lost days per year (Kjellstrom et al., 2009).

In an analysis of potential hotspots of vulnerability, it was found that most severe consequences of projected climate change would actually coincide with regions showing pre-existing high socioeconomic vulnerability, mostly characterized by high poverty rates and population density (Müller, Waha, Bondeau, & Heinke, 2014). Even though some of the climatic conditions currently experienced on the African continent are unprecedented (e.g. the drought conditions in the Sahel -

Carré et al., 2018), limiting global warming below 1.5°C by the end of the century would reduce the occurrence of climate-related extremes such as heat waves compared to a scenario in which global mean temperature reaches 2.0°C by 2100 (Nangombe et al., 2018). Lessening the occurrence of such extremes could have significant benefits in avoiding social and economic impacts (Nangombe et al., 2018).

Within the large number of parameters that could have an influence on economic convergence, the role of climate has been largely overlooked. For example, in a review of the literature on the determinants of economic convergence, several socioeconomic and geographical variables have been identified such as criminality, the level of development of neighbouring countries, sociology, political structure or cultural heritage (Rey & Janikas, 2005). To date, one of the rare considerations of climate in the factors affecting income convergence is higher temperature from one U.S. State to another considered as an amenity positively influencing state-to-state migration rate, a key driver of income convergence (Barro and Sala-I-Martin (1991).

The current research proposes a new perspective in an attempt to bridge the gap between climate change and income convergence research.

2. Methodology and data

2.1. Model framework

To measure historical and future disaster and climate-related risks to which African countries could be exposed, the economic framework is developed following the concept of "risk triangle" (Crichton, 1999), consistent with the conceptual definition of disaster and climate risk in the IPCC SREX (IPCC, 2012). The concept of "risk triangle" defines risk as the combination of three components: hazard intensity and frequency, exposure, and vulnerability. Each component conceptually determines the length of the edges of the triangle. The economic framework developed for this analysis therefore integrates these three components:

- Hazard: The model accounts for the intensity and frequency of precipitation and temperature extremes as well as mean temperature and precipitation levels. The intensity of precipitation and temperature extremes is integrated by using gridded monthly precipitation and temperature for both historical (as in Chaney, Sheffield, Villarini, & Wood, 2014) and projected time periods (Hempel, Frieler, Warszawski, Schewe, & Piontek, 2013).

- Exposure: the economic exposure of African countries to hazards is approximated by weighting the overall country area with population density, considering that more densely populated areas produce higher economic output and hence have a higher exposure. An approach tested and verified in earlier publications (e.g. Nordhaus, 2006).
- Vulnerability: Country-level historical sensitivity to precipitation and temperature, means and extremes, provides the proxy for vulnerability. This is estimated by a non-linear regression model, which measures the sensitivity of GDP per capita to contiguous levels of precipitation intensity and temperature. It follows the concept of vulnerability curves largely used for other types of natural disaster assessments (e.g. earthquakes in Rossetto & Elnashai, 2003).

The risk triangle approach originates from the insurance industry and is still largely used in disaster risk assessment (Murnane, Simpson, & Jongman, 2016).

The guiding principle underlying the projections and therefore econometric estimation is that hazards of the same intensity (here precipitation and temperature) will have effects of similar magnitude expressed in change in GDP per capita in the future as they had in the recent past (from 1980-2014, the period on which the regression is performed). This guiding principle is directly based on the concept of climate analogues, widely used in the climate change economics literature (Burke et al., 2015; Du et al., 2017; Hallegatte, Hourcade, & Ambrosi, 2007). The econometrically-inferred coefficients for GDP per capita in relation to a given intensity of precipitation and temperature are called sensitivity and provide the proxy in this paper for the vulnerability of GDP per capita to climate-related hazards.

2.2. Empirical approach

The past and future effects of climate-related disasters and climate change on GDP at the country level are estimated using an econometric approach (see details on the theoretical framework in Annex 1). The sensitivities are inferred using a piecewise multivariate regression model (Equation 1), which uses the common logarithm of GDP per capita ($\dot{Y}_{it}$) for country *(i)* and at time *(t)*, as dependent variable. Segments (noted *l*) of precipitation intensity ($X_{it,l}$) as well as the variation of temperature against a historical mean ($T_{it} - \bar{T}_h$) - with *h* being the reference period, noted $\dot{T_{it}}$ are the independent climatic variables. To allow for a variation of the effect of weather and climate across different climatic zones (Mendelsohn, 2016), temperature is integrated in the model employing its deviation from the historical mean. Precipitation is expressed using the Standardized Precipitation Index (SPI - Seiler, Hayes, & Bressan, (2002); Vicente-Serrano & López-Moreno, (2005); Wu, Svoboda, Hayes, Wilhite, & Wen, (2007)). The approach using a precipitation index to measure historical risk on macroeconomic output has been developed by Brown, Meeks, Ghile, & Hunu, (2013) and described as: "*a precise measure of precipitation variability that has qualities that make it superior for identifying associated impacts than other methods typically used, such as spatially averaged or population weighted precipitation*" (p.5, 2013). According to the authors, using a precipitation index has the ability to "*preserve the spatial and temporal variability of precipitation*" (p.5, 2013). Furthermore, SPI has the ability to capture both the occurrence of extreme dry or droughts events (H Wu, Svoboda, Hayes, Wilhite, & Wen, 2007), as well as extreme wet or flood events (Seiler et al., 2002; Wang, Chen, Chen, Liu, & Gao, 2017). SPI is recommended by the World Meteorological Organization (WMO) for the characterization of meteorological droughts (World Meteorological Organization, 2012).

A panel regression is employed for the African countries of the region noted *r*:

$$\log\widetilde{(Y_{it})} = \sum_{l=1}^{n} \beta_{rl}\,(X_{it,l})^2 + \pi_{r1}\dot{T_{it}} + \pi_{r2}\dot{T_{it}}^{\,2} + \gamma V_{it,s} + \phi_i + \theta_t + {\theta_t}^2 + \varepsilon_{it}$$

Equation 1

Where ϕ_i is the country time-invariant fixed effect, $V_{it,s}$ is a set of control variables, $\theta_t + {\theta_t}^2$ is a nonlinear time trend representing unexplained time variant effects affecting all the countries in the panel and ε_{it} is the error term clustered at the country-level (time-variant factor). The quadratic time trend allows for controlling for long-term time influences on GDP per capita, which results from year-to-year growth in marginal output (Durlauf, Johnson, & Temple, 2005; J. M. Wooldridge, 2011).

The regression is run for a 35-year panel from 1980 to 2014 for all the African countries (for which socioeconomic data is available). The main consideration that lead to this temporal selection relates to data availability. The availability of socioeconomic data before 1980, including in the World Bank's World Development Indicator database, remains limited.

2.3. Country-level model calibration

As described above, sensitivities of GDP per capita to temperature and precipitation are inferred for a panel of African countries in the period 1980-2014 (N=910). However, African countries display large differences in GDP per capita. For example, the GDP per capita of South Africa and Equatorial Guinea are 20 and 50 times higher than Burundi's GDP per capita in 2015 (World Bank, 2018). As a consequence of this large variability of income and presumably of vulnerability to changes in temperature and precipitation (Brooks, Adger, & Kelly, 2005; Ward & Shively, 2012), the temperature and precipitation sensitivity inferred from the continental panel may underestimate vulnerability in the poorest countries and, by contrast, overestimate it in the richest ones. To address this potential bias, the model is calibrated for each country (as in Gomme & Rupert, 2007 for macroeconomic models). Annex 1 provides the details of the calibration method.

2.4. Projections

The projections up to 2050 are realized using the sensitivity coefficients inferred by the regression model and subsequent calibration ($\beta_{i,s,l}$ for precipitation intensity and $\pi_{i,s,1}$ and $\pi_{i,s,2}$ for temperature levels). Extent to the same range of precipitation intensity and temperature deviation from the historical mean are provided by the grid-level bias-corrected projections of five Global Circulation Models (GCM) (more details on the models and the bias-correction process can be found here: Hempel et al., 2013 and Annex 1). The GDP-per-capita deviation induced by future climate is computed in two scenarios, the RCP8.5 scenario (called high warming) and the RCP2.6 scenario (called low warming) from 2015 to 2050. For every year, country, climate model (five GCMs from the CMIP5 database) and scenario (RCP8.5 and RCP2.6), the model generates 10 macroeconomic risk effect estimates, therefore 50 for every year, country and scenario. This large number of estimates allows for sensitivity and distribution analysis of the results. We measure future economic risk induced by climate change compared to a 10-year reference period, centred around 2010 (here 2006-2015). The results are available for each African country, for which historical and projected socioeconomic indicators and climate data are available[1].

Unweighted and population-weighted Gini and Atkinson inequality coefficients are computed for each model and scenario projection from 2015 to 2050 to observe the effects of climate change on income convergence across African countries. The equations used to estimate inequality coefficients over time are available in the respective publications from Atkinson and Gini (Atkinson, 1970; Gini, 1912).

3. Results

3.1. Regression analysis

3.1.1. Vulnerability to extremes and optimal climatic conditions

Based on the regression model described above (data and methodology section), we investigate the non-linear effects of different levels of precipitation intensity, from severely-extremely dry (values of SPI below -1.5) to severely-extremely wet (above +1.5) events and of temperature. Table 1 shows the results of the regression for the current (first column) and lagged effect (1-year, 5-year and 10-year in columns 2 to 4). The climate data from the NCEP database are weighted for population density using CIESIN data for year 2000 (CIESIN - Columbia University, 2016), GDP per capita data are from the World Development Indicators (World Bank, 2018), control variables and sources are described in the annex to this paper. To mitigate the issue of endogeneity between the economic variables used as control such as government spending and the dependent variable GDP per capita, one-year lagged values of the control variables are used (Felbermayr & Gröschl, 2014).

	Dependent variable:			
	GDP per capita (log)			
	Current	**1-year lag**	**5-year lag**	**10-year lag**
Precipitation				
Extreme & Severe dry	-0.0001^{***} (0.00001)	-0.0001^{***} (0.00001)	-0.00004^{***} (0.00001)	-0.00002^{*} (0.00001)
Moderately dry	-0.0001^{***} (0.00002)	-0.0001^{***} (0.00002)	-0.00002 (0.00002)	-0.00003^{**} (0.00001)

[1] The analysis was conducted for 40 countries with sufficient socioeconomic and climate data availability.

Near normal dry	-0.00004*** (0.00001)	-0.00003** (0.00001)	-0.00002 (0.00001)	-0.00001 (0.00001)
Normal dry	-0.00002 (0.00001)	-0.00001 (0.00001)	-0.00001 (0.00001)	-0.00001 (0.00001)
Normal wet	-0.00001 (0.00001)	-0.00001 (0.00001)	-0.00001 (0.00001)	-0.00001 (0.00001)
Near normal wet	-0.00002* (0.00001)	-0.00002** (0.00001)	-0.00002 (0.00001)	-0.00000 (0.00001)
Moderately wet	0.00001 (0.00002)	0.00002 (0.00002)	0.00002 (0.00002)	-0.00000 (0.00001)
Extreme & Severe wet	-0.0001*** (0.00003)	-0.0001** (0.00003)	-0.00005 (0.00003)	0.00002 (0.00003)
Temperature				
Linear Temp.	0.019 (0.014)	0.015 (0.012)	0.011 (0.011)	0.008 (0.011)
Squared temp.	-0.028** (0.014)	-0.023* (0.013)	-0.023* (0.012)	-0.019* (0.011)
Control variables				
GFCE (lag.)	0.001 (0.001)	0.001 (0.001)	0.002* (0.001)	0.003*** (0.001)
Governance (cur. / lag.)	-0.015 (0.022)	-0.009 (0.021)	0.002 (0.021)	0.002 (0.019)
External debt (lag.)	-0.018** (0.008)	-0.018** (0.008)	-0.025** (0.012)	-0.018 (0.011)
ODA (lag.)	-0.004 (0.054)	0.013 (0.050)	0.051 (0.051)	0.079* (0.042)
Remittances (lag.)	-0.004*** (0.001)	-0.004*** (0.001)	-0.002*** (0.001)	-0.0005 (0.0004)
Oil price (lag.)	-0.00004 (0.0002)	-0.0002 (0.0002)	0.00002 (0.0003)	0.0002 (0.0003)
Trade openness (lag.)	0.0003 (0.0003)	0.0005 (0.0003)	0.001* (0.0003)	0.001** (0.0002)
Observations	910	882	756	605
R^2	0.371	0.380	0.407	0.487
Adjusted R^2	0.328	0.336	0.359	0.439
Note:				*p**p***p<0.01

Table 1 Regression results for GDP per capita (log) as dependent variable using precipitation (top-tier), temperature (middle-tier) and the control variables (bottom-tier). From the left column to the right column time-lagged are column 1- no lag, column 2- 1-year lag, column 3- 5-year lag, column 4- 10-year lag. Authors' computation based on NCEP population-weighted precipitation and temperature data. The reported standard errors are Newey-West heteroskedastic and autocorrelation corrected (HAC), with 7 lags (Newey & West, 1987). Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

In relation with the socioeconomic variables influencing per capita income, only two are statistically significant at a level below 5 percent. Both external debt (5 percent level) and remittances (1 percent level) have a negative influence on income per capita. The effect of external debt on income per capita is consistent with the economic literature (Clements, Bhattacharya, & Nguyen, 2003; Pattillo & Ricci, 2011). The effect of remittances of income growth is also inferred negative. The literature on the effects of remittances on economic growth produces results both in favour and disfavour of remittances as a driver of economic growth (Catrinescu, Leon-Ledesma, Piracha, & Quillin, 2009; Clemens & Mckenzie, 2014). Interestingly, trade openness only appears to have a positive statistically significant effect with a lag of 5 to 10 years. The positive effect to trade openness in mitigating the negative consequences of natural disasters has also been observed in earlier publications (Felbermayr & Gröschl, 2014). The other socioeconomic factors considered in the econometric analysis as potential drivers of economic growth in the regression model do not appear to have a statistically significant influence on the outcome. They include: Oil prices, ODA, Governance and Government Spending.

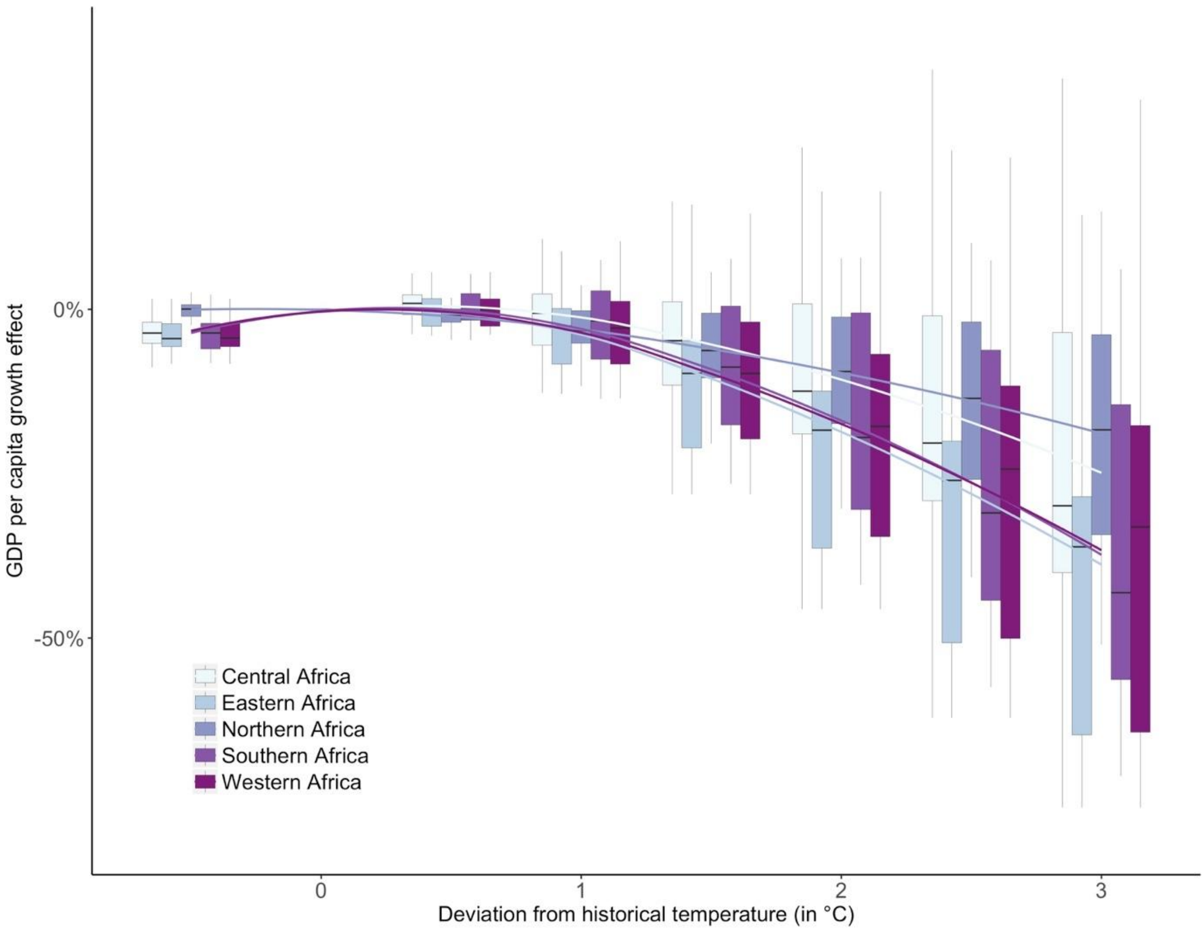

Figure 1 Growth effect (in log) of increasing temperature deviation from -0.5 to +3ºC degrees above the historical mean for Africa countries – each region is represented by one colour.

As described in the methodology section, the effect of temperature on income per capita is integrated using a quadratic function. Based on the estimated parameters (π_{r1} *and* π_{r2}) and the country-level calibration, simulations are run for different level of temperature deviation to the historical temperature from -0.5°C to 3°C (Figure 1). The figure presents the results for the five African regions separately. The regions which display the highest vulnerability and therefore risk on GDP per capita growth are Eastern and Southern Africa, at the opposite Northern Africa exhibits the lowest risk from temperature. Despite these differences in the level of risks at higher temperature, all the regions have an optimal temperature level in the range of 0.3 and 0.5°C above the countries' historical mean temperature.

The results from the regression for temperature are however different from recent publications investigating the effect of temperature change on macroeconomic indicators. Recent publications have defined the optimal temperature – as an absolute temperature – ranging for developed countries from about 6ºC (Du et al., 2017) to 13ºC (M. Burke et al., 2015) and also 13ºC for developing countries (M. Burke et al., 2015). In this paper, we estimate the optimal temperature level not absolutely but relatively to each country's historical mean in the period from 1951 to 1980. For the countries in the panel, the optimal deviation from the historical temperature is about 0.33ºC [0.11;0.85] above the panel's historical mean in the 1951-1980 period. Normalized temperature is recommended as a more appropriate measure to evaluate the effect of temperature on macroeconomic indicators (Mendelsohn, 2016). Firstly, the deviation from the mean temperature allows for the effect of temperature to vary across different climate, without setting an absolute temperature level expected to fit all countries whatever their current climate and economic structure. Secondly, it may avoid a bias induced by the nonlinearity of the temperature effects using fixed-effect estimation (Mendelsohn, 2016).

As mentioned above, for the Sub-Saharan African countries the optimal mean deviation is about 0.3 degrees above the historical mean for the effects of temperature in the current year. For the one-year lagged sensitivity, the optimal deviation is at the same level. However, the upper bound of the range slightly increases for the 1-year lagged temperature sensitivity, from 0.85ºC in the current year to above 1.0ºC in the subsequent year.

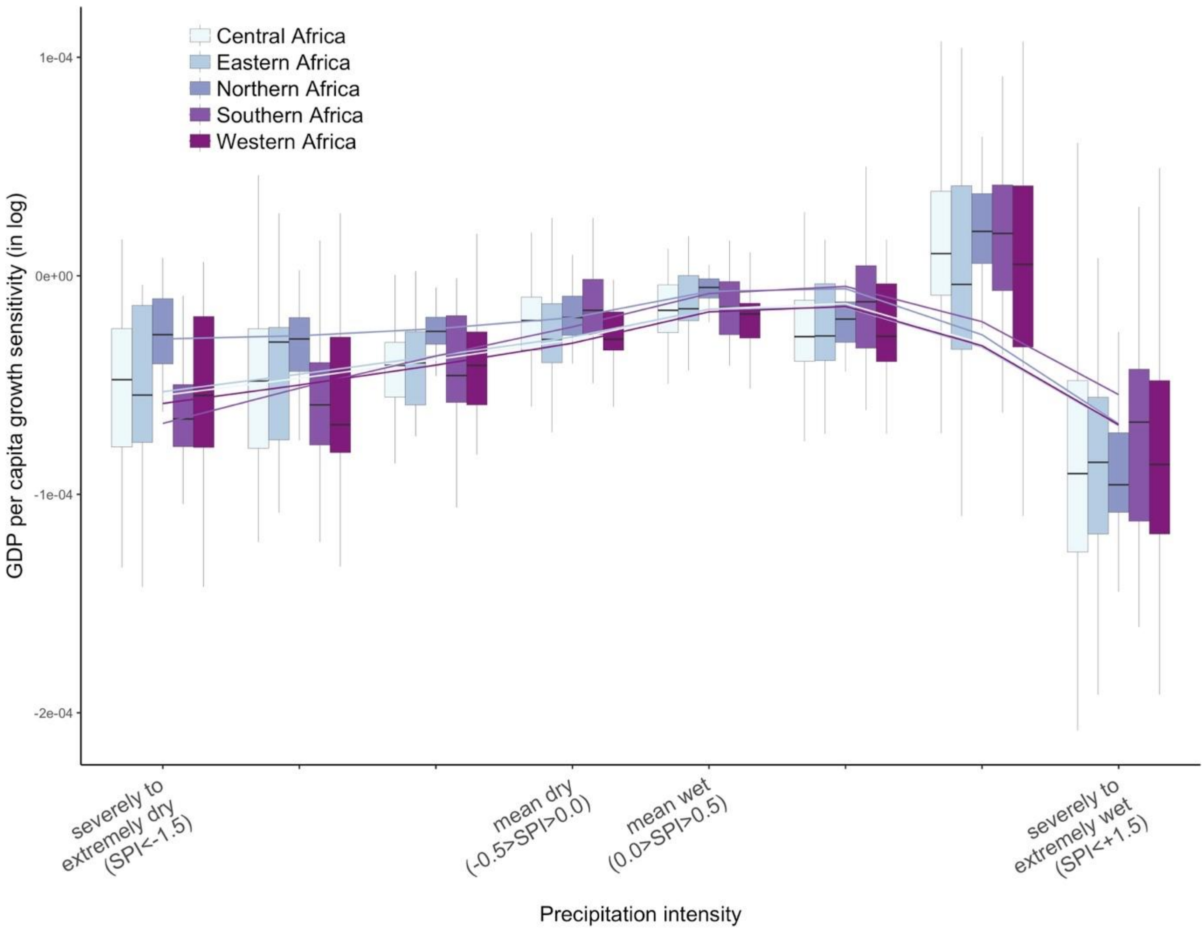

Figure 2 Sensitivity of GDP per capita growth (in log) to levels of precipitation intensity measured using SPI from severely & extremely dry (left-hand side of the x-axis) to severely & extremely wet (right-hand side) for Africa countries from the different regions – each region is represented by one colour. The boxplots represent the median (bold black line), the coloured area represents the interquartile range and the whiskers the 95% interval. The lines connecting the boxes are the result of the locally weighted scatterplot smoothing (loess) and are only illustrative.

For current and 1-year lagged model results, the sensitivity of GDP per capita to the effects of different segments of precipitation intensity describe a concave relationship (Figure 2). The sensitivity of GDP per capita to the most extreme values of SPI, indicating the exposure of the country to extremely dry and wet events, are negative, largely below the sensitivity of GDP per capita for SPI values ranging from -1.5 to 1.5. The concavity of the relationship indicates the possibility of an optimal level of precipitation above and below which the economy performs less favourably.

The results of the regression analysis indicate that the sensitivity of GDP per capita to the occurrence of severely-extremely dry events is lower in comparison to the sensitivity to severely-extremely wet events. The effects of precipitation follow a concave pattern with a possible optimal precipitation level being the “near normal wet” and the “moderately wet” categories of the SPI, indicating that African countries optimally perform economically when the level of precipitation is above the countries' mean precipitation level. This situation in which economies outperform in above-average precipitation years is confirmed by interactions with public servants in ministries in e.g. Senegal, Malawi or Ghana as well as earlier publications (Jerven, 2014). This distance between the optimal precipitation level and the mean precipitation level of the countries could be interpreted as a measure of the precipitation adaptation deficit (Burton, 2004; Fankhauser & McDermott, 2014).

The long-term effects of extremely wet and dry events follow a different pattern. The results of the regression analysis show that one year after the extremely dry or wet events, the sensitivity remains unchanged. Five years after the occurrence, the negative sensitivities are halved, highlighting a progressive recovery after severely-extremely dry and wet events affecting the countries. Finally, 10 years after the occurrence, in the case of severely-extremely wet events, the regression displays positive but not statistically significant results, while severely-extremely dry events lead to persistently negative sensitivity. This long-term positive sensitivity of severely-extremely wet events potentially highlights the beneficial economic-only consequences of capital destruction and reconstruction as hypothesized in earlier publications (S. Hallegatte & Przyluski, 2010). Overall, with time passing after the occurrence of extreme events, the relationship between intensity and sensitivity of the economy progressively decreases – becoming less and less concave (see Annex 3).

Furthermore, as the regression results indicate, a number of climatic and socioeconomic parameters have the potential to influence GDP per capita. To measure the relative importance of each of the parameters or group of parameters compared to others at explaining changes in GDP per capita, we employ the ratio of effect standard deviation (method described in Silber, Rosenbaum, & Ross, 1995). We consider two types of influences, first the effects of climate variables compared to socioeconomic variables and second the effects of precipitation compared to temperature. The ratio of effect of the climate variables (temperature and precipitation) against the control variables and time trend shows the decreasing influence of climate variables on GDP per capita over time. While a ratio of 1 would imply that climate variables and socioeconomic variables equally explain the variation of GDP per capita, the current-year ratio is 0.32 [95% confidence interval 0.232-0.451] and decreasing to 0.17

[95% confidence interval 0.099-0.291] for the 10-year lagged consequences. These results show that despite the lack of adaptation to their current climatic conditions, economic outcomes in Africa are largely influenced by non-climatic factors. For the climate variables, the ratio of effects of temperature and precipitation is 0.52 [0.234-1.154], implying that precipitation has a greater influence than temperature on GDP per capita in the period 1980-2014. The relatively larger influence of precipitation on GDP per capita compared to temperature highlights the importance of considering both temperature and precipitation in econometric analyses of the effects of climate variability on economic outcomes.

3.2. Historical climate-induced economic impacts

In recent decades, African countries have experienced significant losses from climate-related disasters. Scientific understanding of these contemporary losses, linked to countries' limited adaptation to their climatic conditions, is still limited. The losses were estimated at about 0.3 percent of GDP for low-income countries in the period 2001-2006 and 0.1 percent for high-income countries (IPCC, 2012). The economic analysis performed in this paper allows for a preliminary estimate of the historical effects of precipitation and temperature on African economies. The Figure 3 shows estimates of mean deviations in percentage of GDP per capita growth that occurred in the period from 1986 to 2015, as a consequence of the limited adaptation of African countries to fluctuations in their precipitation and temperature patterns.

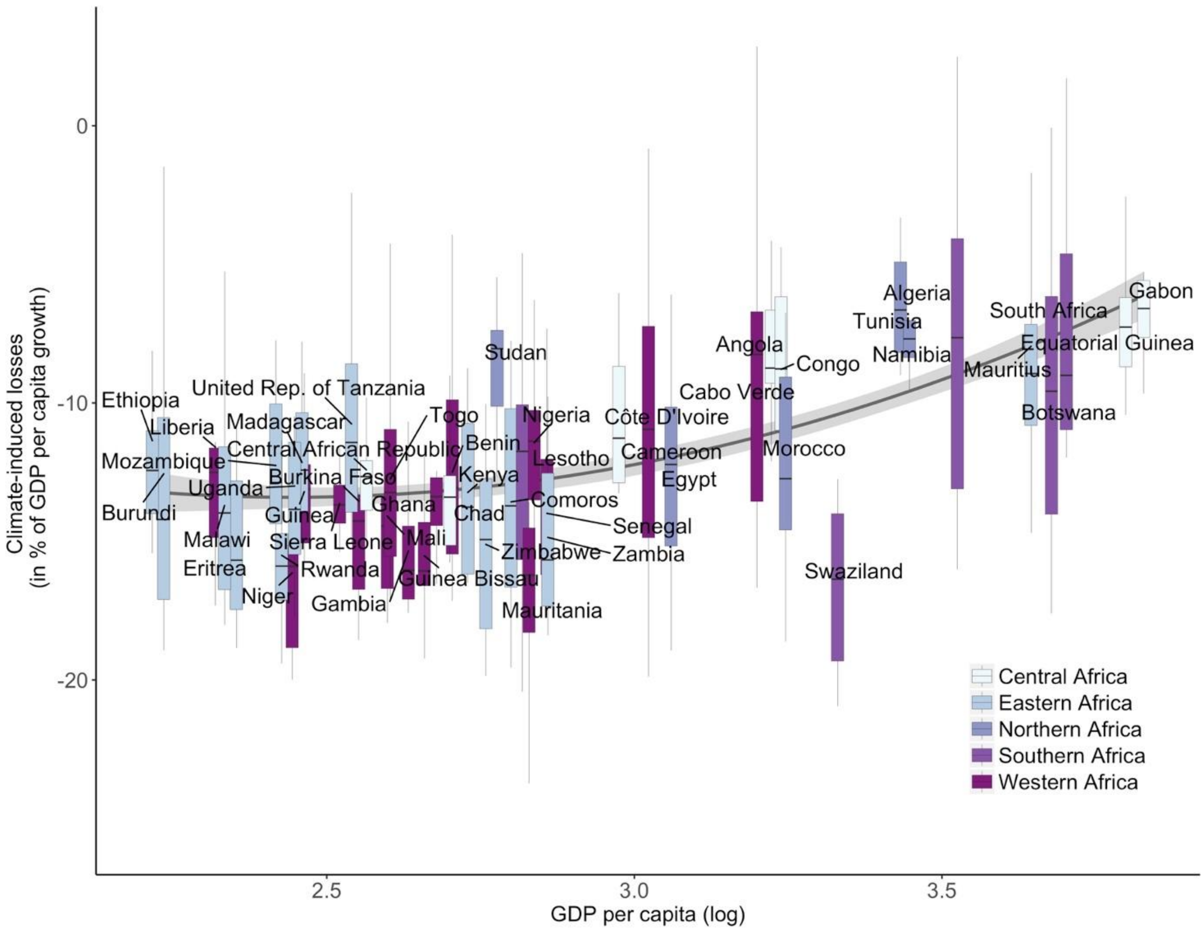

Figure 3 Annual climate-induced (precipitation and temperature combined) losses in the period 1986-2005 measured in percentage of GDP per capita growth.

The majority of African countries has average annual losses, induced by climate variability, ranging on average from -15 to -10 percent in GDP per capita growth over the 1986-2015 period. Depending on the GDP per capita growth baseline, the cumulative reduction could range from 5 to 15 percent over this 30-year period. This suggests that the countries' lack of adaptation to their current climatic conditions is already negatively affecting economic development and delaying African countries' path to emergence. The range of estimates of 5 to 15 percent lower GDP per capita as a consequence of this limited adaptation is consistent with earlier studies, which estimated losses to about 8 percent in GDP over the 1970-2010 period (World Bank & United Nations, 2011) or a decrease by about 15 percent in GDP per capita – only as a consequence of precipitation – over the period 1960 to 2000 (Barrios et al., 2010). The estimates also highlight that resource-rich and / or countries with higher GDP per capita tend to have experienced lower negative consequences from climate variability. Even though the econometric analysis and modelling does not provide detailed evidence of the channels through which climate variability affects economic growth, several of them can be hypothesised. It could include the structure of the economy and employment in the economy (Dell, Jones, & Olken, 2012b), or the distribution of population between rural and urban areas (Henderson, Storeygard, & Deichmann, 2015). The structure of the economy could indeed play a major role in the magnitude of the losses experienced by the countries. The countries, which experienced the least loss in the historical period appear to be (1) countries with large natural resource endowment for example oil resources: Congo, Gabon, Equatorial Guinea, Angola or Sudan or diverse mineral resources: Botswana; (2) countries with strong services sector such as tourism in Cabo Verde or Mauritius; (3) or countries with diversified economy in the industry and services sectors like South Africa. The rest of the countries in Africa, in which agriculture played (and still plays for the majority of them) a major economic and employment role are the countries most affected by climate-related losses in the historical period.

This contemporary occurrence of losses induced by climate-related disasters is a consequence of an "adaptation deficit" (Bhave, Conway, Dessai, & Stainforth, 2016; Fankhauser & McDermott, 2014). Its existence and its already measurable large impacts economically and socially justify alone active involvement of governments and their supporters in the effective implementation of climate-resilient development plans and policies, even independently from future climate change.

3.3. Future climate-induced economic risks

The optimal temperature and precipitation sensitivity coefficients, filtered from the country-level model calibration, are used to estimate future climate-induced macroeconomic risk for each country in two different warming scenarios (RCP2.6, *low warming*; and RCP8.5, *high warming*). The GDP per capita growth risk estimated for the period 2015 to 2050 is adjusted against the reference period (here 2006-2015) to measure any further risks compared to current climate and socioeconomic conditions. The projected risk accounts for the effects of precipitation and temperature in the current year, without the lagged consequences. As the model produces economic risk as a change in percentage of GDP growth, we include risks estimates in both scenarios to the SSP2 GDP per capita growth projections.

The shared socioeconomic pathways (SSPs) are scenarios describing "plausible alternative evolutions" of the economy and society at the global level and modelled at the national level. These scenarios are developed to be combined with assumptions of future climate change and policy responses to assess future climate change impacts. In this study, a pathway of GDP per capita is used as an economic development baseline to estimate the potential impacts of changes in precipitation and temperature induced by future climate change on African countries' GDP per capita trajectories (Riahi et al., 2017). We use the SSP2 GDP per capita projections for both warming scenarios, this shared socioeconomic pathway (SSP) implies "intermediate challenges" and represents a "moderate pathway" compared to the other SSPs (Dellink, Chateau, Lanzi, & Magné, 2015). Furthermore, using a consistent SSP between the low and high warming scenarios also allows for a more precise comparison of the sole impacts of climate change on economic development in African countries.

Figure 4 displays the results of the GDP per capita deviation risk projections in the low and high warming scenarios for all African countries (Africa) and the countries of the five African regions. The results are shown as a deviation from the GDP per capita baseline in the SSP2 scenario.

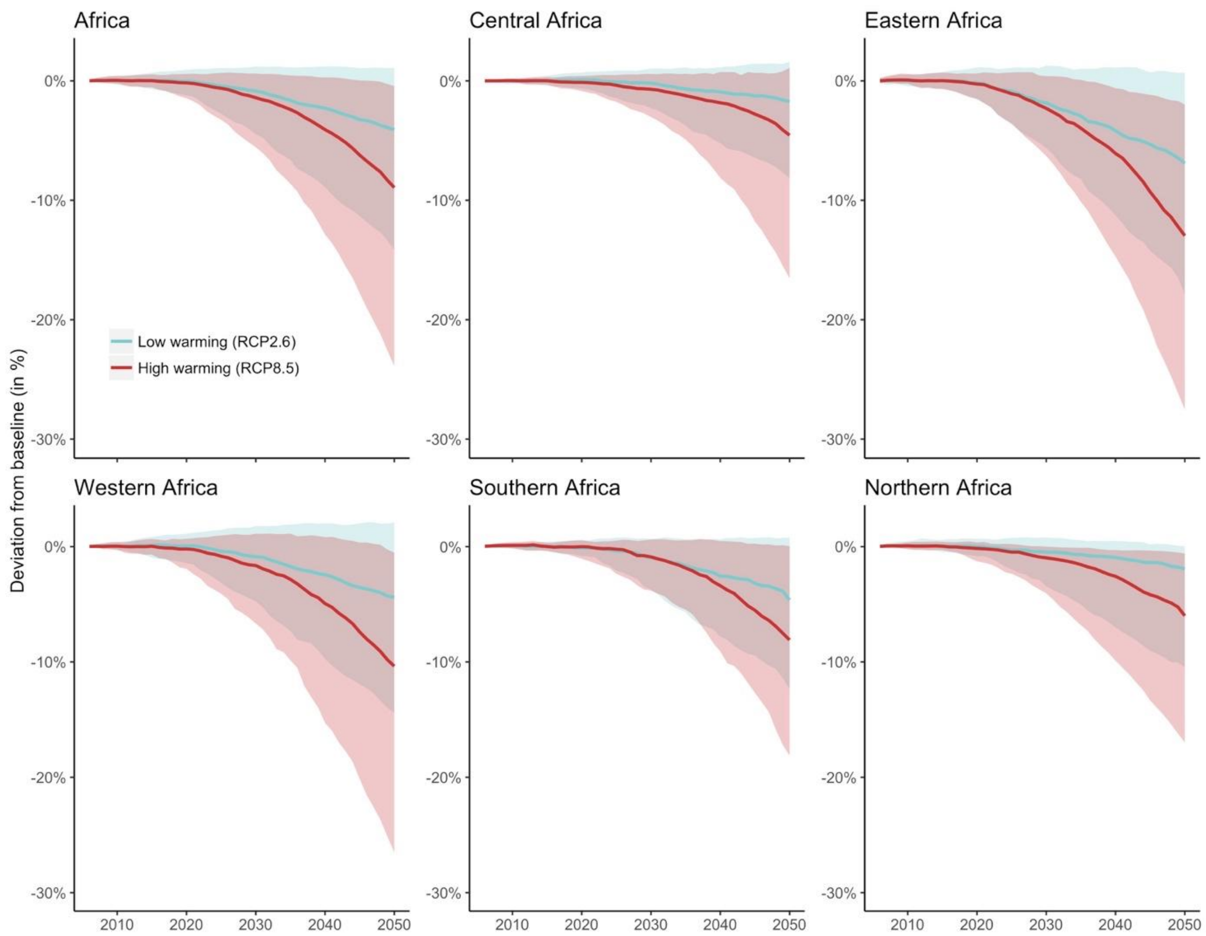

Figure 4 GDP per capita growth risk measured as a deviation from a GDP per capita baseline (here SSP2) in African countries and regions for the period 2005-2050 under a low (RCP2.6 - blue) and high warming (RCP8.5 – red) scenario.

The projections clearly show that the effects of future changes on precipitation and temperature may adversely affect GDP per capita growth in every African region. Western Africa and Eastern Africa are projected to be the most affected regions in both warming scenarios with above 10 percent median reduction in GDP per capita in the high warming scenario by 2050. In comparison, the Northern, Southern and Central African regions would be the least affected with projected deviation below 10 percent in GDP per capita compared to the baseline and limited to below 5 percent in Central African countries. High warming would have particularly severe consequences on African economies as the regional median macroeconomic risks are almost twice as high as in the low warming scenario by 2050. Macroeconomic risks induced by climate-related disasters and climate change are at a relatively similar level between 2010 and 2030, even though the risk measured in the high warming scenario is already higher than in the low warming scenario (a detailed assessment of the deviation between scenarios was not conducted in the current study).

As Table 2 shows, the median GDP per capita risk is between 0 and 2.6 times higher in the high warming scenario in 2030, in Southern African and Central African countries, respectively.

Region	Scenario	25th percentile	Median	75th percentile
Eastern Africa	RCP2.6	-1,42%	-0,19%	0,53%
	RCP8.5	-1,94%	-0,70%	0,20%
Central Africa	RCP2.6	-4,18%	-1,85%	0,20%
	RCP8.5	-4,79%	-2,30%	-0,33%
Northern Africa	RCP2.6	-2,48%	-0,47%	0,50%
	RCP8.5	-2,96%	-0,97%	-0,26%
Southern Africa	RCP2.6	-2,83%	-0,97%	0,22%
	RCP8.5	-2,67%	-0,89%	0,16%
Western Africa	RCP2.6	-3,06%	-0,87%	0,89%
	RCP8.5	-4,77%	-1,64%	0,33%

Table 2 GDP per capita growth risk, measured as a deviation from a baseline scenario, for the countries of the five different African regions in the low (RCP2.6) and high warming (RCP8.5) scenarios in 2030.

After 2030, the spread between the scenarios widens rapidly. Between 2030 and 2050, the negative consequences in the high warming scenario are almost twice as high compared to the losses in the low warming scenario. This highlights the very rapid negative impacts on economic growth and GDP per capita of unchecked emissions in the second quarter-century. It is also worth noting that the results displayed in the figure above may potentially strongly underestimate the projected economic risks as the lagged consequences on GDP per capita are not accounted for in the projections.

3.4. Divergence and convergence under climate change

Building on the country-level estimates of the future impacts of climate change on economic growth per capita in African countries, we analyse whether the projected changes could lead to positive or negative consequences of the ability of African economies to converge. Over the last decades, convergence has been observed globally, mostly induced by the fast development trajectory of the "emerging" countries such as China, India, Brazil and other Latin American countries (Ravallion, 2014).

We use two inequality indices (Gini and Atkinson) to measure income convergence across African countries. The objective of this analysis is to estimate the effect of future climate change on Africa's income convergence against the same SSP2 socioeconomic baseline for GDP per capita growth, which actually projects a rapid income convergence on the African continent. The GDP per capita baseline projects a decreasing Gini index (as well as Atkinson index) from about 0.5 in 2015 to 0.37 in 2050 for the population-weighted Gini index and from 0.61 to 0.47 for the non-weighted Gini index. GDP per capita in the low and high warming scenario is estimated for the period 2015-2050 using the SSP2 scenario as a baseline (Dellink et al., 2015).

As a consequence of climate change, particularly in the high warming scenario, the inequalities between African countries are projected to decrease at a lower rate than in the baseline scenario, implying a probable delayed convergence. In the high warming scenario, convergence could be delayed by 10 to 11 years (median), for the Gini and Atkinson index, respectively and up to 19 years for the upper bound of the 95 percent confidence interval of the Atkinson index. The median delay for the low warming scenario ranges from 5 years (Gini index) to 7 years (Atkinson index). As Figure 5 shows, mean population-weighted and non-weighted inequality is projected to increase in the low warming and in the high warming scenarios compared to the baseline scenario.

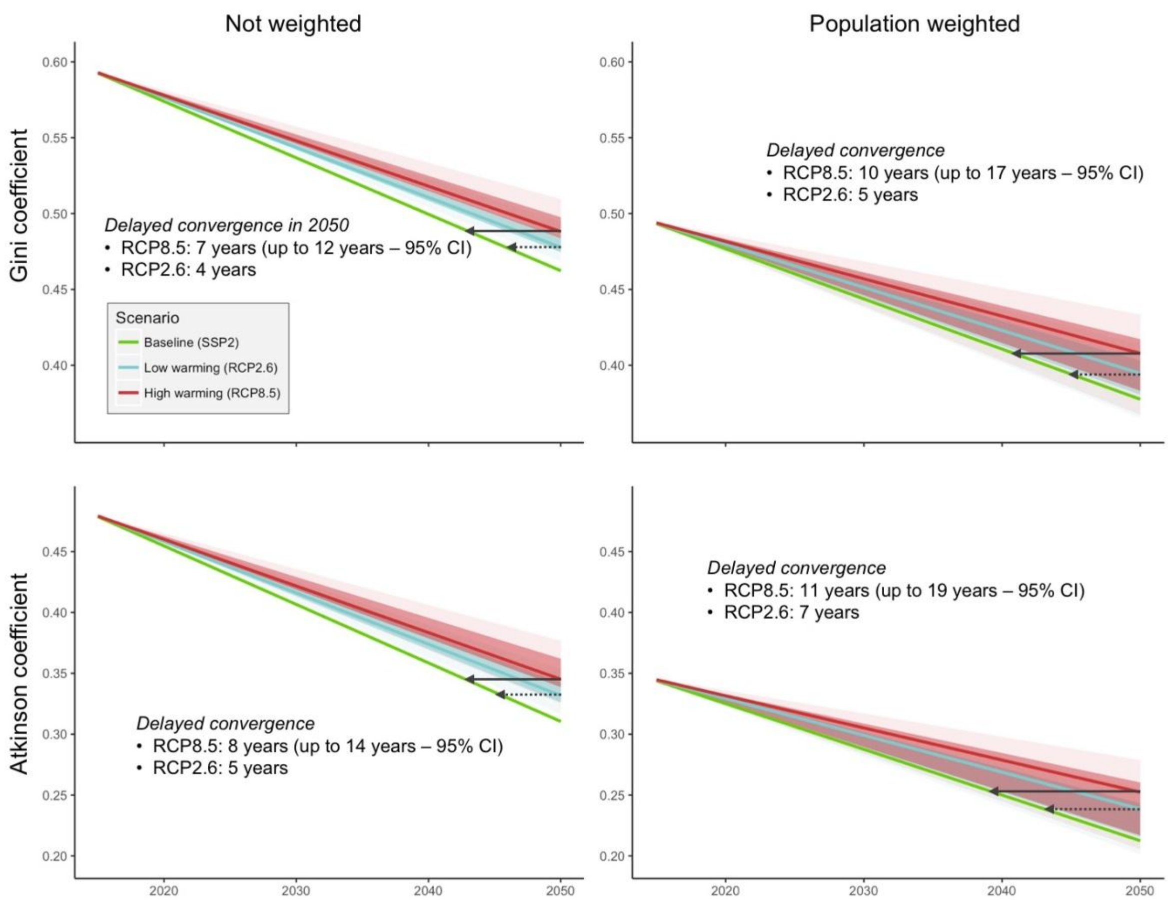

Figure 5 Gini and Atkinson inequality indices (not weighted – right, and population weighted – left) compared in the low warming (blue line RCP2.6) and high warming (red line RCP8.5) compared to inequality in the baseline scenario (green line). The arrows represent the delayed convergence in 2050, in the low warming (dotted line) and high warming scenario.

Even though the scale of the change is different depending on the index and weight used for the measure of inequality, both indices and weight show a slower income convergence between African countries as a consequence of global warming, which is all the more remarkable given the relatively short time horizon (35 years to 2050). It is important to note a key difference in the results between inequalities weighted or not with population. Despite the lower values measured for the population-weighted inequality index, it appears that the delay in income convergence will be larger when population is accounted for. Countries with large population, still with a large share of population living from agriculture, like Ethiopia (median at about -15.0 percent in RCP8.5), Kenya (-12.9 percent) or Niger (-14.9 percent) may be particularly affected by future climate change. It highlights that countries with small population and large natural resource endowment (e.g. Gabon, Equatorial Guinea) and more resilient economic structure (e.g. dependency of the service sector), are projected be significantly less affected in comparison with large countries with a significant share of their population concentrated in the agricultural sector. This interpretation of the projections on the pace of weighted and non-weighted income convergence as a results of climate change are consistent with the distribution of losses across countries observed in the climate-induced losses in the 1986-2015 period (Figure 3).

4. Discussion and policy implications

This results on the historical and projected consequences of climate variability and change on economic development in African countries shed the light on four key policy implications discussed below: (1) the benefits of mitigation in limiting the magnitude of the economic impacts; (2) the urgent need to address the existing adaptation deficit; (3) the required integration of climate risks in development planning and (4) the generalization of a specific treatment for the most affected to mitigate the inequality consequences.

Benefits of mitigation

In line with our analysis, more recent publications (M. Burke et al., 2015; Du et al., 2017) tend to indicate that earlier assessments of the effects of climate change on economic development were underestimates, as also pointed out in Stern (2013). The results presented in the paper highlight the early benefits of mitigation action between a low warming and a high warming pathway. In the majority of the countries and regions, the economic impacts between warming scenario start diverging in the 2030s. By 2050, the impact in the high warming scenario are almost twice as high as in the low warming scenario. The underestimates of the potential losses and the doubling in impacts in the high warming scenario have two very important implications for policymakers on the African continents and globally. First, African governments should attach more importance to stringent mitigation policies primarily for the largest emitters but also for themselves. The planned revision of the Nationally Determined Contributions (NDCs) in 2020 could be an excellent opportunity for policy-makers from African countries to show their leadership by raising the level of ambition and pressing other countries to follow suit. Raising ambition and implementing measures in line with the Paris Agreement objective of 1.5°C would be the best yardstick of this leadership. The second implication resides in the necessary revision of the main economic models (PAGE, DICE and FUND) used to estimate the Social Cost of Carbon (SCC). These three models tend to largely underestimate losses induced by future climate change leading to particularly low SCC, which provides only limited incentives for public and private investors to prioritize low-carbon technologies against carbon-intensive ones.

Addressing the adaptation deficit

As pointed out in the analysis of the historical losses induced by climate variability, African countries are poorly adapted to their current climatic conditions. The results of the econometric analysis clearly show the distance between optimal temperature and precipitation levels and the current climatic conditions of the countries. As shown in the projections, the deficit in adaptation to the changing climatic conditions will only worsen as temperature and precipitation progressively diverge from their historical patterns. The magnitude of the current adaptation deficit and the losses it incurs should be integrated in development and adaptation planning at the project and strategic levels. The quantitative integration of historical adaptation deficit and its impact on economic development, using diverse decision-making tools for climate change adaptation (Dittrich, Wreford, & Moran, 2016), should be performed along the future consequences of climate change. Accounting for both adaptation deficit and future adaptation needs could reduce the level of uncertainty involved with such assessments and accelerate the implementation of measures intended at fostering resilience.

Integrating climate change in development planning

As highlighted in the analysis of the historical loss induced by climate variability, building resilience would have direct and clear benefits on economic development – independently from the magnitude of the future emission scenarios, climate sensitivity and impacts of climate change. However, due to the current lack of economic evidence available in the Ministries of Economics, Finance or Planning, climate variability and climate change are still addressed as environmental issues and treated separately from the mainstream development debate. However, African governments are the first investors in their own economic, human and social development – by very far. Therefore, providing governments, in particular the Ministries of Economics and Development Planning, with the ability to measure current and future climate-induced risks on their economy, to plan development in light of the magnitude and on-set of key climate risks and impacts is a prerequisite for effective climate-resilient development. Owing to the magnitude of the projected impacts, addressing climate change will require the leadership and support from the main public and private economic and financial (including banks, for example) decision-makers. In the absence of more quantitative approaches to mainstream climate-related risks in development planning policies, efforts to build resilience risk to remain scattered with limited systemic effects and hinder countries and communities' ability to develop.

Specific treatment

The results of the analysis on the consequences of climate change on income convergence sheds light on a potential slowdown in the reduction of inequalities across African countries. The additional burden incurred by climate variability and change requires a specific attention from the international community to facilitate and accompany the development of the most vulnerable and affected countries. Some International Financial Institutions (IFI) have already integrated this specific need of the most vulnerable countries. For example, the Green Climate Fund (GCF) allocates at least 50 percent of its funding dedicated to adaptation to particularly vulnerable countries, which include Least

Developed Countries (LDCs), Small Island Development States (SIDS) and African States (GCF decision B.06/06). The World Bank Group has a similar strategy to facilitate access to financing by Small States particularly those vulnerable to natural disasters and climate change, making the Group "the largest provider of climate and disaster-resilience-related investment finance". Also, the International Fund for Agricultural Development (IFAD) integrates a parameter accounting for countries' vulnerability (including to climate change) in its Performance-Based Allocation System (IFAD 2017/8/W.P.2). Such specific treatment and funding allocation towards the currently and projected most affected countries by the impacts of climate-related disasters and climate change could contribute to alleviate the additional burden borne by these countries. To this end, experience could be shared between IFIs and country-level social and economic assessment of the current and future impacts of climate change could become more available to facilitate this integration by IFIs. Finally, making this integration possible could also entail the modification of the allocation methodology of the main development banks to integrate current and projected impacts of climate change on development trajectories.

5. Conclusions

While rapid and sustained economic growth should support the poorest countries and populations in Africa converging with the richest countries on the continent, the projections of inequality across countries on the two warming scenarios show otherwise. Even though climate change is not projected to increase inequalities or reverse income convergence between African countries, it is projected to significantly slow these processes. The slowdown in inequality reduction particularly highlights the uneven distribution of climate-change-induced impacts, with for example the Sahel countries being among the most affected by temperature and precipitation extremes in both climate change scenarios, in conjunction with already vulnerable economies and communities. In addition to the lack of efficient economic policies, impeding among others open trade and the protection of private property rights (Sachs & Warner, 1995), un-mitigated climatic consequences could be added to the already-long list of factors limiting African economies to converge, within the continent and with high-income countries. Economic convergence is however a strong factor of economic and social stability – in terms of migration (Black, Natali, & Skinner, 2005), as well as conflicts on the continent (Alesina & Perotti, 1996), but also a factor of prosperity as countries with similar levels of development can further develop comparative advantages and further engage in trade, decreasing the price of goods and services to the benefits of the population (Rodrik, 2011).

Finally, the findings recall the importance of several aspects of the Paris Agreement (UNFCCC, 2015), and have relevance for its implementation. On the mitigation side, the results tend to support the global coordinated effort envisaged in the agreement to mitigate greenhouse gas emissions in line with the 1.5ºC limit to global warming. Our analysis shows that reducing future warming to the lowest technically and economically feasible level minimizes the risk of significant negative macroeconomic impacts of climate change and development rollback throughout the first half of the 21st century. The projected negative macroeconomic impacts are significantly smaller, and possibly more manageable, when global mean temperature increase remains below two degrees and very close to 1.5°C (the low warming scenario, RCP2.6). On the adaptation and finance side of the Paris Agreement, the results show something else equally important in a quantitative sense: the projected negative macroeconomic impacts are still significant even if warming is limited close to 1.5°C on a mid-century timescale. For the affected economies, this implies significant adaptation needs to avoid potentially large economic losses. This strong connection between the warming levels resulting from mitigation efforts and the current and future needs for adaptation may need to be further accounted for the implementation arrangements of the Paris Agreement relating to adaptation and international climate finance.

Overall, the current analysis shows that achieving sustainable development will require coordinated action across and within high- and middle- and low-income countries on emission mitigation as well as climate resilience. Unchecked warming levels, in line with current emission trends, would lead to detrimental social and economic impacts, which could severely hamper the future capacity of African countries to adapt and cope with the negative consequences of climate change. This would in consequence lead to a further increase in the losses, entangled in a downward spiral of risk and vulnerability, bringing the objective of a sustainably developed world without poverty totally out of reach.

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Supplementary information

Annex 1 Theoretical framework

Using a Cobb-Douglas production function, economic output for a given period, or time step (z), within a longer time period (t, such as $z \in t$) and unit of production (u) within a country's territory (i such as $u \in i$) is defined as a function of total factor productivity (A), capital stock (K), labour stock (L) and the capital elasticity of substitution (α). Capital stock in time t is defined as the capital stock in the previous period, net of depreciation given by the effective depreciation rate of capital over one-time step (δ) and increased by total investment (I).

$$Y_{u,z} = A_{u,z}\left(K_{u,z}^{\alpha} L_{u,z}^{1-\alpha}\right) = A_{u,z}\left[(1-\tilde{\delta})K_{u,z-1} + I_{u,z-1}\right]^{\alpha} L_{u,z}^{1-\alpha}$$

Equation 2

Building on the above Cobb-Douglas production function and the empirical framework from Dell et al., (2012), Moore & Diaz, (2015) and Burke, Hsiang, & Miguel, (2015), the impacts of climate-related events ($C_{u,z}$) are integrated into climate-adjusted macroeconomic output $\widetilde{Y_{u,z}}$. Equation 2 shows the reduced form of the equation over a period of time (z), with $g_{u,z}$ representing growth unaltered by climate-related disasters and γ_0 being the sensitivity of macroeconomic output to climate-related events ($C_{u,z}$):

$$\widetilde{Y_{u,z}} = Y_{u,z-1}(1 + g_{uz} + \gamma_0 C_{u,z})$$

Equation 3

The majority of recent empirical analyses have focused on the effects of temperature on economic outputs. In this model specification, we analyse both the effects of temperature and precipitation. Most empirical models integrate absolute annual precipitation as a control variable. However, particular climate and econometric specifications have enabled empirical analyses of the effects of precipitation using panel regression (Brown, Meeks, Ghile, & Hunu, 2013). Therefore, in contrast to earlier theoretical models in which either temperature or precipitation were analysed, we integrate and distinguish between the effects of precipitation and temperature. Precipitation is expressed using the Standardized Precipitation Index (SPI - Seiler, Hayes, & Bressan, (2002); Vicente-Serrano & López-Moreno, (2005); Wu, Svoboda, Hayes, Wilhite, & Wen, (2007)). The approach using a precipitation index to measure historical risk on macroeconomic output has been developed by Brown, Meeks, Ghile, & Hunu, (2013) and described as: "*a precise measure of precipitation variability that has qualities that make it superior for identifying associated impacts than other methods typically used, such as spatially averaged or population weighted precipitation*" (p.5, 2013). According to the authors, using a precipitation index has the ability to "*preserve the spatial and temporal variability of precipitation*" (p.5, 2013). Normalized precipitation using the SPI index is noted $\hat{P}_{u,z}$. SPI has the ability to capture both the occurrence of extreme dry or droughts events (H Wu, Svoboda, Hayes, Wilhite, & Wen, 2007), as well as extreme wet or flood events (Seiler et al., 2002; Wang, Chen, Chen, Liu, & Gao, 2017). SPI is recommended by the World Meteorological Organization (WMO) for the characterization of meteorological droughts (World Meteorological Organization, 2012). In this study, we use one-month SPI, aggregated over a year as described below. Other indices can be explored as well, fulfilling at least two conditions for the purpose of projecting climate-adjusted GDP per capita. An index must demonstrate the ability to: (1) represent a proxy for drivers of climate-related impacts and (2) have a basis in the literature in terms of climate projections. Calculating SPI is relatively simple and does not depend on temperatures directly, which is an advantage in our study, where temperatures are used as an independent variable as well. It must be noted, however, that drought projections under climate change are sensitive to the choice of index (E. J. Burke & Brown, 2008; Taylor et al., 2012). At least across Africa, the projected patterns of increased drought in SPI seem to resemble closely those in a more complex, composite index such as the Palmer Drought Severity Index (Taylor et al., 2012). In the model, temperature is specified using the temperature deviation $\dot{T}_{u,z}$ from its historical mean in the reference period, for each grid cell, to allow for a better representation of the specific temperature sensitivity of each country (Mendelsohn, 2016). In the following equation, π_0 and β_0 represent the sensitivity of macroeconomic output to temperature and precipitation, respectively. Therefore, Equation 3 becomes:

$$\widetilde{Y_{u,z}} = Y_{u,z-1}(1 + g_{u,z} + [\pi_0 \dot{T}_{u,z} + \beta_0 \hat{P}_{u,z}])$$

Equation 4

Following Burke et al., (2015) and Schlenker & Roberts, (2009), we aggregate output for each sub-period z in Equation 4 over time t, so that $g_{u,z}$ becomes here $g_{u,t}$. Each unit of territory is exposed to different levels of intensity, from mean to extremes, of temperature $\dot{T}_{u,z}$ and precipitation $\hat{P}_{u,z}$ in *t*, at each time step *z* as a consequence of seasonality and climate variability. Therefore, we transform the climate parameters in an integral to capture the different levels of intensity; ranging from minimum to maximum temperature $[min(\dot{T}_{u,z});\ max(\dot{T}_{u,z})]$ or precipitation index $[min(\hat{P}_{u,z});\ max(\hat{P}_{u,z})]$ in the period.

$$\widetilde{Y_{u,t}} = Y_{u,t-1}(1 + g_{u,t} + \left[\int_{min(\dot{T}_{u,z})}^{max(\dot{T}_{u,z})} h_i(\dot{T}_{u,z})d\dot{T}_{u,z} + \int_{min(\hat{P}_{u,z})}^{max(\hat{P}_{u,z})} p_i(\hat{P}_{u,z})d\hat{P}_{u,z}\right])$$

Equation 5

In Equation 5, $h_i$and p_i respectively represent a function of the effects of temperature and precipitation on aggregate economic output (as in M. Burke et al., 2015; Schlenker & Roberts, 2009). Aggregating over the territory of country *i*, we obtain:

$$\widetilde{Y_{\iota,t}} = Y_{i,t-1}(1 + g_{it} - \left[\int_{u\in i}\int_{min(\dot{T}_{u,z})}^{max(\dot{T}_{u,z})} h_i(\dot{T}_{u,z})d\dot{T}_u du + \int_{u\in i}\int_{min(\hat{P}_{u,z})}^{max(\hat{P}_{u,z})} p_i(\hat{P}_{u,z})d\hat{P}_{u,z} du\right])$$

Equation 6

We approximate the double precipitation integral by first defining *z* as a month and binning SPI (in this case 8 bins *l* covering the SPI range from extreme/very dry conditions to extreme/very wet conditions). For temperature only, annual mean deviation is integrated, similarly to M. Burke et al., (2015). This presents some challenges, which are further discussed in the robustness and sensivitiy analyses section and discussions section of the paper. We therefore obtain:

$$\widetilde{Y_{\iota t}} = Y_{i,t-1}(1 + g_{it} - \left[\frac{\sum_{z=1}^{12}\left[\frac{\sum_{u=1}^{n} d_u\left(\sum_{l=1}^{8}\beta_{i,l}\hat{P}_{z,l}\right)_u}{\sum d_u}\right]_t}{\mathrm{Z}} + \int_{u\in i}\int_{min(\dot{T}_{u,t})}^{max(\dot{T}_{u,t})} h_i(\dot{T}_{u,t})d\dot{T}_u du\right])$$

Equation 7

With *Z* being the number of time steps in *t*, here 12.

Burke, Hsiang, & Miguel, (2015) approximate the double temperature integral using a quadratic function of temperature such as: $\int_{u\in i}\int_{-\infty}^{+\infty} h_i(\dot{T}_{u,t})d\dot{T}_u du = \pi_1\dot{T}_{\iota t} + \pi_2\dot{T}_{\iota t}^{\ 2}$. Where $\pi_1$and π_2 are the sensitivity coefficients of GDP per capita to the deviation of temperature compared to the reference period mean. This transformation assumes the existence of a "kink", at which the economy performs optimally. To avoid this assumption, Du, Zhao, & Huang, (2017) apply a piecewise multivariate regression. Interestingly, despite the use of a multivariate regression, the observed relationship between temperature bins and GDP per capita also describes an optimum – for both the USA and European countries to which they applied their methods.

We simplify Equation 7 with the parameter $X_{i,t,l}$. This parameter is defined as a percentage of population density-weighted country area, which measures the number of units or weighted units on the total number of units in the country, exposed to a value or a range of $\hat{P}_l$, such as:

$$X_{i,t,l} = \frac{\sum d_{u,\hat{P}_{t,l}}}{\sum_{u=1}^{m} d_u} / \mathrm{Z}$$

Equation 8

$X_{i,t,l}$ represents the percentage of population-weighted area in a country *(i)* at a specific time period *(t)* that is exposed to the same range of intensity *(l)* of a derived precipitation index. It is used as independent variable in the econometric model. The percentage of area exposed to *(l)* can also be defined as the percentage of spatial units having an index value within a specified range of intensity *(l)* to the total number of grid points within a country for a given period of time (*t*). Replacing in Equation 7 the precipitation component by a term depending on $X_{it,l}$ and the temperature component by the quadratic function mentioned above, the following simplified form of the temperature and precipitation adjusted production function is obtained:

$$\widetilde{Y_{it}} = Y_{i,t-1}(1 + g_{it} - \left[\sum_{l=1}^{8} \beta_{i,l}(X_{i,t,l}) + \pi_1 \dot{T_{it}} + \pi_2 \dot{T_{it}}^2\right]$$

Equation 9

Considering that the precipitation exposure parameters $\sum_{l=1}^{8} X_{i,t,l}$ is equal to 1, $X_{i,t,l}$ is squared to avoid multicollinearity. We derive the regression model from the above equations. Temperature and precipitation sensitivities are inferred from Equation 9 for log GDP per capita. A panel regression is employed for the African countries composing the region noted *r*:

$$\widetilde{\log(Y_{it})} = \sum_{l=1}^{n} \beta_{rl} \, (X_{it,l})^2 + \pi_{r1} \dot{T_{it}} + \pi_{r2} \dot{T_{it}}^2 + \gamma V_{it,s} + \phi_i + \theta_t + \theta_t^{\,2} + \varepsilon_{it}$$

Equation 10

Where ϕ_i is the country time-invariant fixed effect, $V_{it,s}$ is a set of control variables, $\theta_t + \theta_t^{\,2}$ is a nonlinear time trend representing unexplained time variant effects affecting all the countries in the panel and ε_{it} is the error term clustered at the country-level (time-variant factor). The quadratic time trend allows for controlling for long-term time influences on GDP per capita, which results from year-to-year growth in marginal output (Durlauf, Johnson, & Temple, 2005; J. M. Wooldridge, 2011).

The time-lagged model is specified as below:

$$\widetilde{\log(Y_{i,t})} = \sum_{l=1}^{n} \beta_{r,l,t-\Delta t} \, (X_{i,t-\Delta t,l})^2 + \pi_{r1,t-\Delta t} \dot{T}_{i,t-\Delta t} + \pi_{r2,t-\Delta t} \dot{T}_{i,t-\Delta t}^{\;2} + \gamma V_{i,t} + \phi_i + \theta_t + \theta_t^{\,2} + \varepsilon_{i,t}$$

Equation 11

Calibration

The regression (Equation 11) is performed for a given panel of countries. The calibration is performed in three steps. In a first step a normally distributed ensemble of coefficients is generated following the coefficients and standard errors inferred from the regression. In a second step modelled GDP per capita is calculated using the generated coefficients over the historical period. In a third step, for each individual country the 10 "best-fitting" coefficients are filtered, for which the Mean Average Percentage Error (MAPE) over the historical period is the lowest.

For this analysis, we generate 5000 draws, within two standard errors around the mean value of the panel coefficients (noted with the index *r*). GDP per capita for the period 1980-2014 are estimated using the 5000 generated coefficients. The filtering is performed for each country individually using MAPE. This filtering leads to the selection of 10 different values for each of the regression coefficients. MAPE is among the most commonly used forecast accuracy indicator (Gneiting, 2009). Using MAPE may lead to some computing and selection issues, particularly when values are below 1

(Makridakis, 1993). However, we do not use MAPE to quantify the forecast accuracy of the regression and calibration but to select the sets of coefficients that best explain the historical variations of GDP per capita; as a consequence, outlying MAPE values would be excluded from the filtering. The calibration method leads to the inference of β_i and π_i coefficients (with the index i – for each country individually) at the national level from panel regression coefficients (initially noted with r). Figure 6 displays the range of MAPE for the 10 "best-fitting" sets of coefficients for each country as well as the number of observations for each country, against which the calibration was performed.

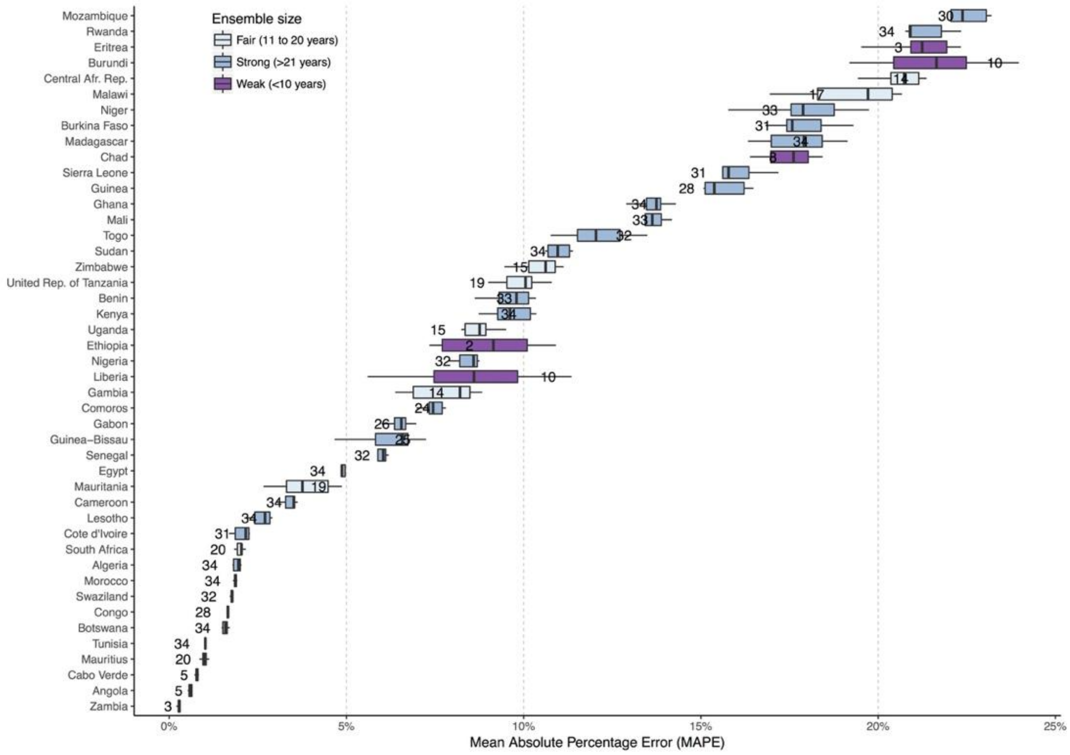

Figure 6 Range of Mean Absolute Percentage Error (MAPE) for the 10 "best-fitting" sets of sensitivity coefficients for each African country resulting from the panel regression and country-level model calibration.

Future economic risk (R) is computed on a yearly basis for GDP per capita through the following equation, with $\dot{t}$ in the reference period (here 2006-2015 centred around 2010). A future time period is denoted f:

$$R_{i,f} = \sum_{l=1}^{n} \beta_{i,l} \left(X_{i,f,l}\right)^2 + \pi_1 \dot{T}_{i,f} + \pi_2 \dot{T}_{i,f}^{\,2} - \left[\frac{1}{Z}\sum_{z=1}^{Z}\sum_{l=1}^{n} \beta_{i,l} \left(X_{i,\dot{t},l}\right)^2 + \pi_1 \dot{T}_{i,\dot{t}} + \pi_2 \dot{T}_{i,\dot{t}}^{\,2}\right]$$

Equation 12

Z is the total number of years in the reference period $\dot{t}$. In Equation 12, the parameter $R_{i,\dot{t}} = \frac{1}{Z}\sum_{z=1}^{Z}\sum_{l=1}^{n}\beta_{i,l}\,(X_{i\dot{t},l})^2 + \pi_1\dot{T_{it}} + \pi_2\dot{T_{it}}^2$ measures the mean economic risks in the reference period (R) used to de-mean future economic risks in both warming scenarios. After subtracting the aggregate risk for the reference period, the projections for the period 2015-2050 only account for climate variability and climate change effects additional to climatic conditions prevailing in the reference period. R is here expressed in the GDP-per-capita growth rate.

5.1.1. Robustness and sensitivity analyses

We carry out a sensitivity analysis of the effects of temperature on the regression outcomes – as presented in Table 2 – using different specifications such as linear and squared temperature only, cubed temperature with and without control variables. This additional analysis is conducted to understand whether and to which extent the specifications of temperature influence the regression outcome – particularly for precipitation intensity. This is particularly important to also understand the extent to which the specifications of temperature may influence the future projections when temperature deviation exceeds the regression period (1980-2014) temperature deviation. We investigate four additional model specifications: linear (with controls), squared (with controls), cubic (with controls) and finally quadratic (without controls). The results of the robustness analysis are displayed in Table 3.

	Dependent variable:				
	GDP per capita (log)				
	Quadratic (with control)	**Linear (with control)**	**Squared only (with control)**	**Cubic only (with control)**	**Quadratic (no control)**
Precipitation					
Ext. & Severe dry	-0.0001*** (0.00001)	-0.0001*** (0.00001)	-0.0001*** (0.00001)	-0.0001*** (0.00001)	-0.0001*** (0.00004)
Moderately dry	-0.0001*** (0.00002)	-0.0001*** (0.00002)	-0.0001*** (0.00002)	-0.0001*** (0.00002)	-0.0001*** (0.00003)
Near normal dry	-0.00004*** (0.00001)	-0.00004*** (0.00001)	-0.00004*** (0.00001)	-0.00004*** (0.00001)	-0.0001*** (0.00003)
Normal dry	-0.00002 (0.00001)	-0.00002 (0.00001)	-0.00002 (0.00001)	-0.00002 (0.00001)	-0.0001*** (0.00002)
Normal wet	-0.00001 (0.00001)	-0.00001* (0.00001)	-0.00001 (0.00001)	-0.00001 (0.00001)	-0.00003*** (0.00001)
Near normal wet	-0.00002* (0.00001)	-0.00002** (0.00001)	-0.00002** (0.00001)	-0.00002** (0.00001)	-0.0001*** (0.00002)
Moderately wet	0.00001 (0.00002)	0.00001 (0.00002)	0.00001 (0.00002)	0.00001 (0.00002)	-0.00004 (0.00004)
Ext. & Severe wet	-0.0001*** (0.00003)	-0.0001*** (0.00003)	-0.0001*** (0.00003)	-0.0001*** (0.00003)	-0.00004 (0.00004)
Temperature					
Linear Temp.	0.019 (0.014)	-0.001 (0.009)			-0.028 (0.018)
Squared temp.	-0.028** (0.014)		-0.017* (0.010)		-0.007 (0.015)
Cubed temp.				-0.004 (0.006)	
Control variables					
GFCE (lag.)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	
Gov. (cur. / lag.)	-0.015 (0.022)	-0.018 (0.023)	-0.016 (0.022)	-0.018 (0.022)	

External debt (lag.)	-0.018** (0.008)	-0.018** (0.008)	-0.018** (0.008)	-0.018** (0.008)	
ODA (lag.)	-0.004 (0.054)	-0.009 (0.055)	-0.008 (0.055)	-0.009 (0.055)	
Remittances (lag.)	-0.004*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	
Oil price (lag.)	-0.00004 (0.0002)	0.00003 (0.0002)	-0.0001 (0.0002)	-0.00000 (0.0002)	
Trade openness (lag.)	0.0003 (0.0003)	0.0004 (0.0003)	0.0004 (0.0003)	0.0003 (0.0003)	
Observations	910	910	910	910	1,476
R^2	0.371	0.365	0.369	0.366	0.164
Adjusted R^2	0.328	0.322	0.326	0.322	0.131
Note:					*p**p***p<0.01

Table 3 Sensitivity analysis for GDP per capita (log) as dependent variable using precipitation (top-tier), temperature (middle-tier) and the control variables (bottom-tier) using different temperature and control specifications. Regressions based on NCEP population-weighted precipitation and temperature data. The reported standard errors are Newey-West heteroskedastic and autocorrelation corrected (HAC), with 7 lags (Newey & West, 1987). Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

For all temperature and control specifications, the concave pattern of precipitation is preserved with extreme / very dry and extreme / very wet events yielding negative impacts on GDP per capita. However, the level of statistical significance of the extreme / very wet events is much lower for the quadratic model without control compared to the models with controls. This difference in statistical significance may highlight the importance of government spending, debt or trade (and the other control variables used in the panel regression) as mitigators of the negative consequences of extreme / very wet events on GDP per capita growth, consistently with previous studies such as (Felbermayr & Gröschl, 2014).

Furthermore, for annual mean temperature deviations ranging from -0.5 to +3°C, which include about 98% of the observations in the period 2015-2050 in five climate models and two warming scenarios (RCP2.6 and RCP8.5 – and 96% in the RCP8.5 scenario only), the model specifications display similar economic risks within this range. With the exception of the linear specification, which shows almost constant risks over the 2015-2050 period, all four model specifications estimate temperature-induced risk range from -0.13 and -0.2 (in log base 10) while 66% statistical uncertainty distribution ranges from +0.05 and -0.35 (see Annex 3). Confirming the robustness of the econometric approach, all models with control variables show consistent results for the control variables.

Annex 2 Climate scenario description

The IPCC Working Group 1 assessed in the Fifth Assessment report (AR5) four different scenarios of changes in Earth's heat balanced induced by human activities, mostly from greenhouse gas emissions.

The four scenarios are called Representative Concentration Pathways (RCP), the highest of the four scenario or RCP8.5 represents the business-as-usual scenario (Riahi et al., 2011) with is characterised by a significant reliance on coal for energy supply, moderate economic growth and population growth. The RCP8.5 scenario could lead to a global mean temperature increase of about 4.8°C [3.5 to 6°C] above pre-industrial levels by the end of the 21st century.

To embed the full spectrum of projected climate change, the second scenario used in this analysis is the RCP2.6 scenario. In this scenario, global mean temperature increases by about 1.7°C [1.3°; 2.0°C] by the end of century above pre-industrial levels. The RCP2.6 scenario displays the lowest warming of all the RCPs modelled by the IPCC in the Fifth Assessment Report. In this paper RCP8.5 is referred to as an "High warming" and RCP2.6 as a "Low warming".

Temperatures in the high and low warming scenarios start to diverge by the 2030s, and grow rapidly throughout the century.

Land areas are projected to experience a higher warming than the oceans, particularly towards the poles. However, considering the limited fluctuations of temperature in the tropics and sub-tropics, the warming expressed relative to natural annual variability is higher in the tropics and sub-tropics than in the other regions of the global. These regions will therefore move earlier than others into climatic conditions outside their historical local patterns (Coumou & Robinson, 2013; Diffenbaugh & Scherer, 2011; IPCC, 2013; I Mahlstein, Knutti, Solomon, & Portmann, 2011; Irina Mahlstein, Hegerl, & Solomon, 2012).

Annex 3: Temperature and precipitation lagged effects

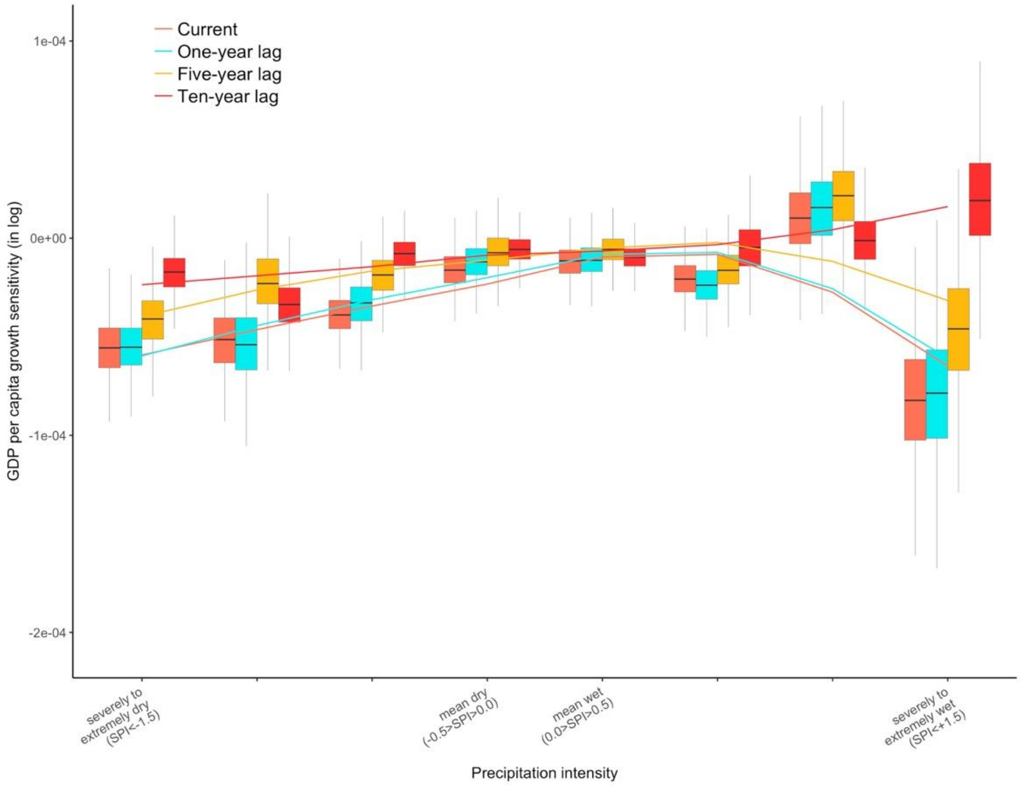

Figure 7 Sensitivity of GDP per capita growth (in log) to levels of precipitation intensity measured using SPI from severely & extremely dry (left-hand side of the x-axis) to severely & extremely wet (right-hand side) for Africa countries from the different regions – each colour illustrates different lag periods: current (orange), one-year (blue), five-year (yellow) and ten-year (red). Regressions based on NCEP population-weighted precipitation and temperature data. The reported standard errors are Newey-West heteroskedastic and autocorrelation corrected (HAC), with 7 lags (Newey & West, 1987). The boxplots represent the median (bold black line), the coloured area represents the interquartile range and the whiskers the 95% interval. The lines connecting the boxes are the result of the locally weighted scatterplot smoothing (loess) and are only illustrative.

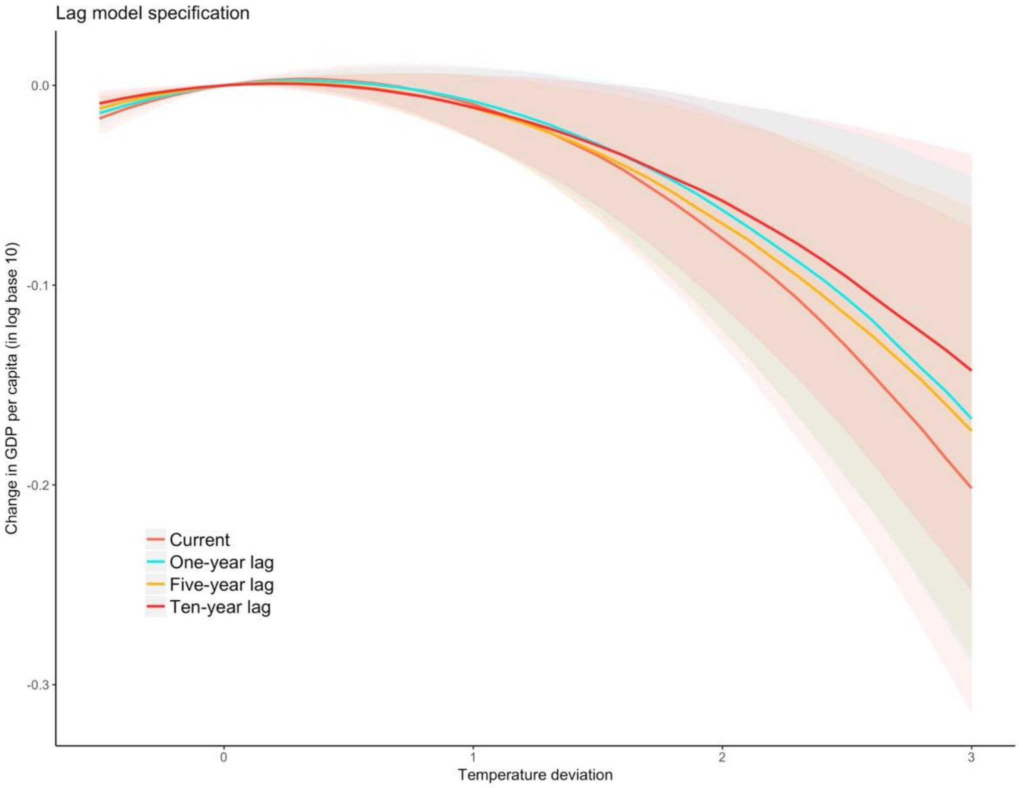

Figure 8 Growth effect (in log) of increasing temperature deviation from -0.5 to +3ºC degrees above the historical mean for Africa countries – each colour illustrates different lag periods: current (orange), one-year (blue), five-year (yellow) and ten-year (red). Regressions based on NCEP population-weighted precipitation and temperature data. The reported standard errors are Newey-West heteroskedastic and autocorrelation corrected (HAC), with 7 lags (Newey & West, 1987).. The boxplots represent the median (bold black line), the coloured area represents the interquartile range and the whiskers the 95% interval. The lines connecting the boxes are the result of the locally weighted scatterplot smoothing (loess) and are only illustrative.

Influence of the model specifications on the regression coefficients

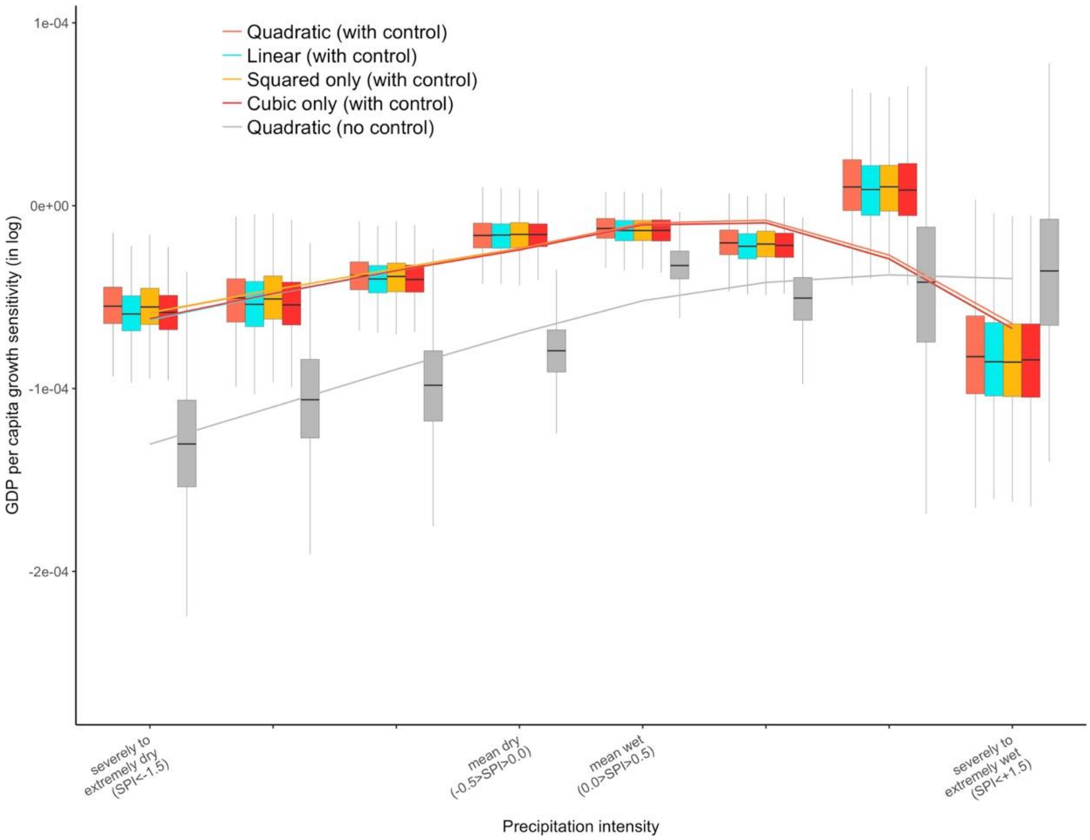

Figure 9 Sensitivity of GDP per capita growth (in log) to levels of precipitation intensity measured using SPI from severely & extremely dry (left-hand side of the x-axis) to severely & extremely wet (right-hand side) for Africa countries from the different regions – each colour illustrates different temperature and control specifications quadratic with controls (brown), linear with controls (blue), squared temperature with controls (orange), cubed temperature with controls (red) and the quadratic specification without control (grey). Regressions based on NCEP population-weighted precipitation and temperature data. The reported standard errors are Newey-West heteroskedastic and autocorrelation corrected (HAC), with 7 lags (Newey & West, 1987).. The boxplots represent the median (bold black line), the coloured area represents the interquartile range and the whiskers the 95% interval. The lines connecting the boxes are the result of the locally weighted scatterplot smoothing (loess) and are only illustrative.

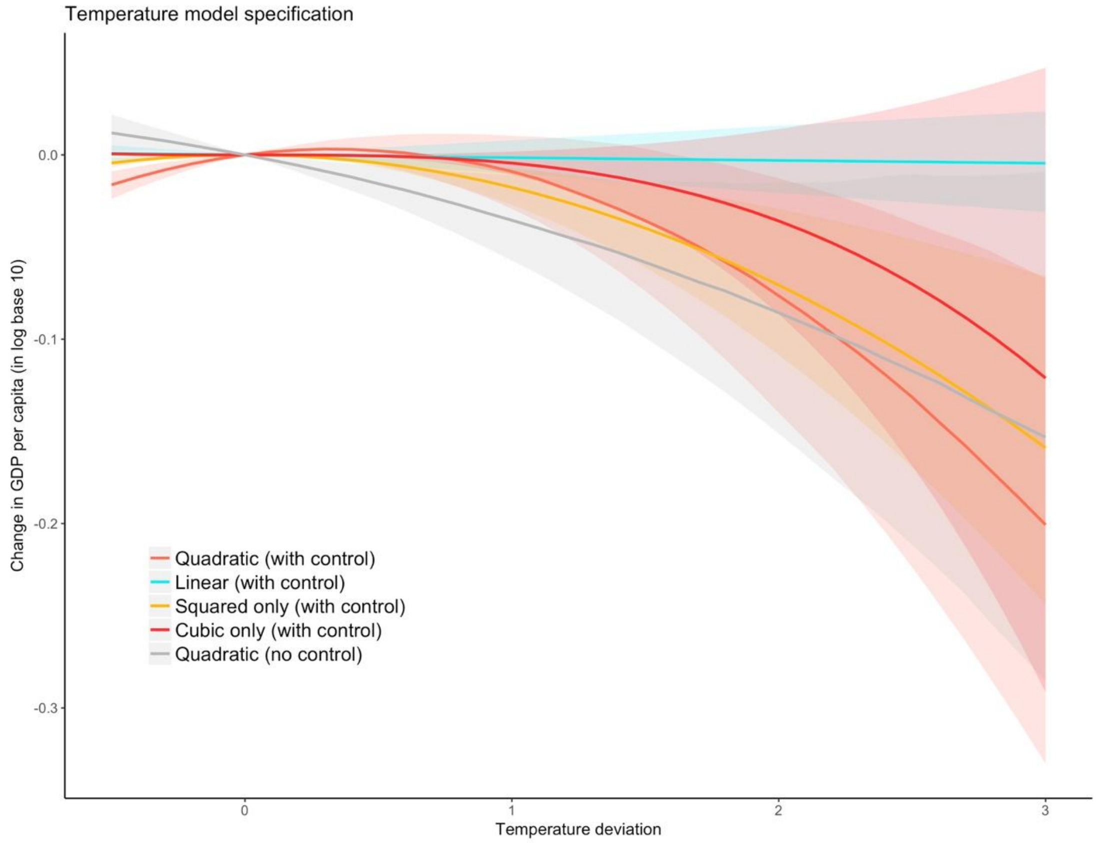

Figure 10 Growth effect (in log) of increasing temperature deviation from -0.5 to +3ºC degrees above the historical mean for Africa countries – each colour illustrates different temperature and control specifications quadratic with controls (brown), linear with controls (blue), squared temperature with controls (orange), cubed temperature with controls (red) and the quadratic specification without control (grey). Regressions based on NCEP population-weighted precipitation and temperature data. The reported standard errors are Newey-West heteroskedastic and autocorrelation corrected (HAC), with 7 lags (Newey & West, 1987).

Annex 4: Socioeconomic and climate data

Data type	Specific data	Data source
Climate data	- Historical precipitation and temperature - Projected precipitation and temperature	NCEP (Kalnay et al., 1996) gfdl-esm2m, hadgem2-es, ipsl-cm5a-lr, miroc-esm-chem, noresm1-m (Hempel et al., 2013)
Socioeconomic data	- GDP per capita - Int. Oil price - Governance index - Government final consumption expenditures - Remittances - Total external debt stock - Trade openness ((I+M)/Y) - ODA	World Development Indicators – WDI (World Bank, 2018) International Energy Agency Polity IV project (Marshall, Jaggers, & Gurr, 2014) WDI (World Bank, 2018) WDI (World Bank, 2018) WDI (World Bank, 2018) WDI (World Bank, 2018) WDI (World Bank, 2018)

Table 4 Socioeconomic and climate data

***Acknowledgements**

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