Climate change and its impact on education completion rates across four sub-Saharan African countries

A non-parametric approach at the community level

Citation for published version:
Delprato, M & Shephard, D 2024, 'Climate change and its impact on education completion rates across four sub-Saharan African countries: A non-parametric approach at the community level', *International Journal of Educational Development*, vol. 110, 103129, pp. 1-21. https://doi.org/10.1016/j.ijedudev.2024.103129

Digital Object Identifier (DOI):
10.1016/j.ijedudev.2024.103129

Published In:
International Journal of Educational Development

Climate change and its impact on education completion rates across four sub-Saharan African countries: a non-parametric approach at the community level

Marcos Delprato[a,*], Daniel Shephard[b]

[a] *Instituto de Investigaciones Educativas (IIE), Universidad Nacional de Chilecito, Argentina*
[b] *Moray House School of Education and Sport, University of Edinburgh, UK*

Abstract

Climate change is a leading barrier for SDG4 progress, particular across poorer regions which are more affected by it. This study estimates the impact of climate change on communities' completion rates across the life-course in four sub-Saharan African countries. Our analysis is based on 2,524 communities of four countries (i.e., Cameroon, Ethiopia, Guinea and Nigeria) using a non-parametric approach to account for heterogeneity of climate change-education linkage. We find that raising temperatures, lower rainfall, aridity and modifications on the quality of vegetation are all related to lower completion rates, with these impacts being more prominent in contextual disadvantaged communities, suggesting the urgent need for mitigating policies.

Keywords: completion rates, sub-Saharan Africa, climate change, SDG4, SDG13, non-parametric

* Corresponding author.

Email addresses: marcos.a.delprato@gmail.com (Marcos Delprato), d.shephard@ed.ac.uk (Daniel Shephard)

1. Introduction

The current impacts and future hazards of climate change caused by human activities have transformed Earth's environment with severe implications for human and planetary health (Abbass et al., 2022; Helldén et al., 2021; Masson-Delmotte et al., 2021; Mora et al., 2022). Since temperature records began, the highest average global temperature (i.e., 14.98°C) happened during the year 2023 by a wide margin, 0.17 degrees higher than the latest record of 2016 (UNEP, 2023). Also, the 10 warmest years in the 174-year record have all occurred during the last decade (2014–2023) and 2023's record temperatures were 1.18°C above the 20th-century average (of 13.9°C) (Lindsey and Dahlman, 2020; Siljander et al., 2023).

Due to climate change's far reaching impacts on ecosystems and on all parts of society, climate change's effects will be particularly relentless among the most disadvantaged groups as nearly half of the world population (between 3.3 to 3.6 billion people) live in contexts that are highly vulnerable to it (Lee et al., 2023; UNEP, 2023), be it in countries and areas which are poorer, hotter and located at lower altitude (Tol, 2018), features aligned to the realities of various African countries. Watson et al. (2019)'s estimates for ecosystems indicate that more than half of Africa's bird and mammal species could be lost and the productivity of lakes could decline by 20–30% by year 2100.

Because of widespread poverty in sub-Saharan Africa (henceforth SSA), the projected impact of climate change and degradation of ecosystems will be severe due to its strong link with poverty alleviation and food security (for a recent regional analysis, see: Adesete et al., 2023). SSA presents unique physical vulnerabilities to climate change (Serdeczny et al., 2017) given the livelihoods of a large proportion of SSA's population depend on rainfed agricultural systems. There is also a vast increase in rural-urban migration in the region (Di Falco et al., 2024) which is projected to triple, with more than half of SSA's population to be living in cities by 2035 (Cartwright, 2015), leading to an acceleration in deforestation on the back of agricultural expansion (Abernethy et al., 2016; Rudel, 2013).

The role in monitoring the actions to tackle and adapt and combat climate change (namely SDG13) is, therefore, a catalyst element behind a successful progress among other goals of the SDG agenda (e.g., Dagnachew and Hof, 2022; Xiao et al., 2023). One of the key barriers for achievement of SDG4 (education goal) is climate change because the negative impacts of climate change can be concentrated on children and women (Adesete et al., 2023; Hanna and Oliva, 2016), who are especially vulnerable to food and nutritional insecurity. Impacts of climate change in SSA can range from poverty (Tamasiga and Bakwena, 2023), malnutrition and infectious diseases (Serdeczny et al., 2017; Tirado et al., 2015; Thiede and Strube, 2020), and broad child health outcomes (Davenport et al., 2020, 2017), with these effects being spurred on by migration and conflict (Serdeczny et al., 2017).

These impacts will be translated into the educational domain since bad nutrition and poor health (Baker and Anttila-Hughes, 2020), loss in family disposable income caused by shocks that result in damage to crops and thus losses in agricultural income, will all have negative influences on educational performance. For example, Randell and Gray (2019) find that children from West and Central Africa who are exposed to below average rainfall during early life have lower attainment, 1.8 years fewer years of schooling. In a study for ten SSA countries, Yang and Fen (2023) find that cumulative exposure to climate anomalies (rainfall and temperature) during early childhood has significant negative effects on primary school completion rates (e.g., between 2.4%-10.3% due to precipitation anomalies), with these effects varying depending on socioeconomic status.

Concurrently to SSA's broad and far-reaching negative impacts of climate change for future generations, the SSA region has the lowest attaintment rates by educational level and the largest out of school (OOS) populations. For instance, regional estimates for 2020 show that the out-of-school rate was 33% at lower secondary and 48% at upper secondary and, more worryingly, these estimates have either stagnated during the last decade or have grown instead of declining (UNESCO, 2022). Hence, investigating the nexus of climate change and attainment for the SSA region is vital.

This paper adds to the empirical body of research on climate change and education for the Africa region by looking into this association for a selected group of four SSA countries (i.e., Cameroon, Ethiopia, Guinea and Nigeria) using four completion/attainment rates (primary, lower secondary, upper secondary and tertiary) and four markers of climate change (aridity, temperature, rainfall and modification on the quality of ecosystems, proxied by Enhanced Vegetation Index, EVI) with geo-localised (coordinates) data at the community level. The selection of the four SSA countries for our study is consistent with specific countries' challenges due to differential ecosystems. For instance, Ethiopia has a diverse climate and landscape, ranging from equatorial rainforest with high rainfall and humidity in the south and southwest, to the Afro-Alpine on the summits mountains and Woina Dega zones where much of the country's population is concentrated (areas of 1,500-2,500 meters), to desert-like conditions in the north-east, east and south-east lowlands (World Bank, 2021a); whereas, Nigeria, is located primarily within the lowland and humid tropics and it is overall characterised by high temperatures throughout the year, having a relatively wet coastland and highly arid northern zones (World Bank, 2021b).

We rely on a non-parametric approach at the community level to assess climate and education associations. The modelling approach followed allow us to pin down heterogeneities shaping these associations, yielding unique local estimates for the climate-completion association for each community, rather than an average association across the sample. In doing so, we extend the literature in different directions. Namely, we assess climate change-education associations across the lifecourse (from primary to tertiary); we consider the quality of ecosystems (through changes on EVI rates) impacted and modified by human activity among our set of climate change variables; we benchmark results at the community level accounting for heterogeneity and dissimilar mechanisms of communities' resilience against climate change; and, for long term implications of our analysis, we offer some forecast estimates based on different emissions scenarios in the next decades.

Specifically, in this paper, relying on data from the Demographic and Health Surveys (DHS)[1] for a set of four SSA countries (i.e., Cameroon, Ethiopia, Guinea and Nigeria), we attempt to answer the following research questions (RQ):

- RQ1. How does the impact of key climate change variables on communities vary across completion rates for different educational levels?
- RQ2. What is the role of communities' dimensions of disadvantages (be it location, poverty, women's empowerment, health status) as intermediate pathways on how climate channels educational attainment inequality?

The rest of the paper is organised as follows. Section 2 contains a literature review on the nexus of climate and environment with education attainment, giving some insights on the heterogeneity nature of this nexus. Section 3 describes the data and key indicators for the analysis. In Section 4 we describe the methodological approach. Main results are included in Section 5. In Section 6 we offer some forecast of completion rates based on emission scenarios. Section 7 includes some concluding remarks.

2. Literature review

In September of 2015, the global community, through its heads of state, committed to the Sustainable Development Goals (UNGA, 2015). The declaration declared that the 17 goals are "integrated and indivisible" with "interlinkages" being of "crucial importance" (UNGA, 2015, p. 1-2). One of those interlinkages is between climate change and education. With both the environment and the education sector being typified as complex systems (Faul and Savage, 2023; Slingo et al., 2009), their interlinkages are equally complex. To make sense of such complexity, we present a simplifying conceptual framework divided into two broad directional pathways, from climate change to education and then from education to climate change. For each of these we present conceptual pathways of influence, both direct and indirect. Drawing from the literature on the effects of education on climate change, we identify three direct and three indirect pathways of influence. We then turn to the literature on the influence of the climate on education to develop two direct and two indirect pathways –the shared elements of these pathways then constitute the focus of our empirical analysis.

2.1. Effects of education on climate

The majority of the literature on the interaction between climate change and education has focused on the influence of education on people's knowledge, attitudes, and behaviours related to climate change. The broadly optimistic trend in this literature is inspired by SDG 4.7 and "education for sustainable development", in which education is seen as contributing to increased personal and political actions to mitigate climate change or adapt to its effects (Fredriksson et al., 2020; Mochizuki and Bryan, 2015; Reimers, 2021).

Within this literature, one direct pathway runs from education to knowledge about climate change. In some instances, this knowledge transmission focuses on the scientific mechanisms that drive climate change –such as students learning how greenhouse gases trap excess heat or learning how increased temperatures can lead to increased polar ice-melt and subsequent increases in coastal flooding (Hinkel et al., 2014; Yin and Foy, 2019). A second direct pathway articulated in the literature focuses on education's role in shifting attitudes –often in addition to changes in knowledge (Czarnek et al., 2021; Kurokawa et al., 2023). This includes education's role in changing the attitudes and beliefs of climate skeptics, reinforcing learners' attitudes about the importance of changing personal and political behaviors to address climate change, and instilling attitudes about the importance of addressing climate change among learners who have not yet developed clear attitudes (e.g., young learners).The final pathway in this literature links education to changes in behaviour. Examples focused on changes in behaviour include participatory projects, political action, or institutional engagement that seek to link learning to action (Hemminki-Reijonen and Logadottir, 2021). Other interventions combined traditional educational material with behaviourally informed "nudges" to support behavioural change outcomes (Kurokawa et al., 2023).

In addition to these more direct pathways, the other streams of literature consider indirect influences from education to climate change, including negative effects. We label these indirect because there is at least one intervening step between education and climate change that lies conceptually outside of both the education and environment sectors.

The first of these is the influence of education on family planning, with more educated individuals waiting longer to have children and having fewer children (McCrary and Royer, 2011; Subbarao and Raney, 1995), albeit with some debate in the literature. This association supports less population growth and thus less of the consumption that contributes to climate change (Ray and Ray, 2011; Yahaya et al., 2020). The next indirect pathway runs from education directly to consumption before leading to climate change. In this pathway, education is associated with increased levels of consumption. For example, this can include an increased dietary footprint, as has been found in Mexico (López-Olmedo et al., 2022). Other studies have found increased education was associated with higher household level carbon footprints, for example in the context of Malaysia (Zen et al., 2022). The final and related pathway leads from education to increased economic growth to worsening climate change conditions. While the nature of the association between education and economic growth continues to be debated, there are numerous studies supporting an association between education and personal economic advancement and macroeconomic growth (Hanushek, 2013; Kamens, 2015; Psacharopoulos, 1994). Despite efforts to delink growth and climate degradation (see studies such as Hickel, 2020, 2019; Mastini et al., 2021 on degrowth to avoid/minimise climate breakdown), economic growth in most of the globe continues to be tied to worsening climate change conditions, such as increased greenhouse gas emissions (Van Den Bergh, 2017; Yusuf et al., 2020).

Taking these six pathways jointly, it is no surprise that research has often found a complex, non-linear relationship between education and environmental degradation. For example, several studies have found a u-shaped relationship in which education initially has negative effect on the environment and later has a positive effect (Cui et al., 2022).

2.2. Effects of climate on education

The relationship between climate change and education can also move in the other direction, with changes in the climate influencing educational outcomes. We outline four channels here, two direct and two indirect for this relationship from climate change to education outcomes.

While the evidence of causality remains contested, there is a growing consensus that climate change is contributing to patterns of migration and forced displacement. Increased severity and regularity of flooding and droughts can displace learners and teachers while also causing the closure of schools. In 2022, the International Displacement Monitoring Center (IDMC) estimated that more than half of the year's internal displacements (32.6 million out of 60.9 million) were related to environmental disasters (IDMC, 2023). In 2022, the continuing drought in Somalia triggered the internal displacement of 1.1 million people and in two state more than 80 schools were closed due to the drought (IDMC, 2023, p. 29).

Environmental disasters, made more frequent by climate change, can destroy schools or make them temporarily inaccessible to students. Large-scale floods provide a case-in-point. The extreme flooding in Pakistan in 2010, reduced students' access to schooling –destroying many schools, especially in rural areas (Ahmed et al., 2022). In addition, more frequent, small-scale flooding can increase absenteeism and force schools to redirect resources away ultimately reducing academic outcomes among students (Cadag et al., 2017).

Reductions in rainfall can also have indirect effects on schooling. In Kenya, experiencing rainfall reductions of one standard deviation compared to average levels during the first two years of life disrupted cognitive skill development, weaken children's health, reduced household wealth, and have negative impact on later educational progression and school expenditure (Nübler et al., 2021). Looking at rainfall during an individual's year of birth in Indonesia, Maccini and Yang (2009) found that an above average rainfall was associated with greater height, increased educational attainment, and greater household assets but only for women. They find evidence that supports a pathway from rainfall to health, to education, and then to assets.

The relationship between climate and education may be mediated through employment opportunities, or the lack there of both for adults and for children. Research in rural Zimbabwe found that the drought of 2015 to 2016 was associated with increased attainment but reduced academic performance (Nordstrom and Cotton, 2020). The authors suggested that the increase in schooling was an indirect effect of the lower opportunity cost of schooling created by the reduced occupational opportunities in agriculture or pastoralism. In Ethiopia, Randell and Gray (2016) found that patterns of rainfall and temperature during the first seven years of a child's life are most strongly associated with school attainment. They further found that the climate during the summer growing season had the most predictive power. They interpret these patterns to support an indirect model in which climate changes agricultural productivity which influences children's physiological development and later educational attainment. In India, Joshi (2019) provides additional support for the negative effects of droughts on educational outcomes, specifically children's math and reading scores. They also show more powerful negative effects for females and weaker effects when their fathers had a higher education and socio-economic status. They argue that the pattern in their data support an indirect pathway from climate to income to education.

Overall, less has been written about the effects of climate change on education, it is to this literature that our paper makes a direct contribution. From these four pathways, it is clear that droughts, floods, and agriculture all feature prominently in these pathways from climate change to education outcomes. In our analysis, we proxy these features using four different measures: aridity, land surface temperature, rainfall, and an enhanced vegetation index. We then measure the relationship between changes in these climate variables and completion rates at primary, lower-secondary, upper-secondary, and tertiary education.

3. Data

3.1. Data sources

The paper's analysis is based on Demographic and Health Surveys (DHS) data (Measure-DHS, 2023) for four sub-Sahara African countries (i.e., Cameroon, Ethiopia, Guinea and Nigeria), with key educational attaintment (i.e., completion rates) and geo-climate indicators being aggregated at the community level. The total number of communities (or sampling clusters) is 2,527, which is divided as follows: Cameroon (= 412), Ethiopia (= 557), Guinea (= 311) and Nigeria (= 1,247), with DHS years falling into the 2016-2018 period (Table 1).

The DHS program has provided technical assistance in around 90 low and lower-middle income countries, producing over 400 surveys since the 1980s, with detailed information on health, women's empowerment, nutrition, population and education themes used in various studies for the SSA region (e.g., Adedokun and Yaya, 2021; Akombi et al., 2017; Delprato and Farieta, 2023; Dietler et al., 2021). Importantly, for the cross-country study we focus on here, the DHS sampling procedure has the double advantage of country data being nationally representative as well as comparable across countries (ICF-International, 2012), permitting a cross-country evaluation of the impact of geo-climate variables on educational attainment for the sample of four countries. Furthermore, the community (or cluster) in DHS –our level of analysis– is a small contiguous area, known as a primary sampling unit (PSU), with a geographic space that corresponds to census enumeration areas and administrative divisions of a country.[2] Typically, PSU sizes can vary but contains at least 30 households, ensuring representativeness (Rutstein et al., 2006).

The working data for the empirical analysis is obtained by merging various DHS datasets.[3] We follow definitions of completion rates which are based on the WIDE dataset which, in parallel to the UIS.Stat dataset, are the frameworks to monitor the education goal (SDG4) related to attaintment. Definitions of the completion rates (at primary, lower and upper secondary, and tertiary) and the age-intervals used are included in Table 1 notes. These four rates, capturing bottlenecks at given landmarks of the educational lifecourse, are then averaged at the community level (the unit of analysis) and merged with communities' geo-location identification. Hence, we restrict our working sample to communities with geographical coordinates available (from spatial data) and with non-missing observations on key covariates.

The geographic distribution of communities with the latitude-longitude location (XY coordinates) are shown in Figure 1. DHS collects coordinates for the centroid of the survey cluster/PSU (Wilson and Wakefield, 2021) but, for confidentiality, the geo-coordinates of clusters are randomly displaced, up to two kilometres (0-2 km) for urban clusters and up to five kilometres (0-5 km) for rural clusters (Perez-Heydrich et al., 2013). Random displacement is not a limitation for our analysis as we do not engage with spatial modelling per se. Vitally for the analysis, within spatial geo-located data at the community level, there is an array of contextual variables and key climatic and environmental variables (population, footprint, droughts, temperature, precipitation, vegetation, etc.) available in the DHS spatial data repository (DHS.spatial.covariates).[4] Details on the construction of DHS spatial covariates can be found at: Mayala et al. (2018) and Boyle et al. (2020).

[Figure 1 here]

We employ four climate-related covariates in the analysis, namely: aridity (aridity index-AI), land surface temperature (LST), rainfall and the enhanced vegetation index (EVI). The AI is the ratio of annual precipitation to annual potential evapotranspiration (Greve et al., 2019); LST is a more robust indicator of temperature and a basic determinant of the terrestrial thermal behaviour (Hulley and Ghent, 2019; NourEldeen et al., 2020); and EVI is used to monitor vegetation condition and severe fluctuations of the health of ecosystems due to developmental activities and climate change (Vancutsem et al., 2021; Vijith and Dodge-Wan, 2020; Wang et al., 2023). Aridity, temperature and rainfall are measurement for the year 2015, whereas for EVI we measure rates of change for the 40-year period (1985-2015). EVI long term alterations can show ecosystems' stress and changes related to drought because of EVI's linkage with LST (Bari et al., 2021; Guha and Govil, 2021). Broadly, forest cover changes and degradation can impact on the delivery of important ecosystem services, including biodiversity richness, climate regulation, carbon storage and water supplies (Hansen et al., 2013).

The paper's contribution is to expand the body of literature of climate and environmental variables and development outcomes for the SSA region (using a selected group of four ecologically diverse countries) from an educational angle since most of existing studies for the region tends to focus on explaining health outcomes (e.g., Eissler et al., 2019; Grace et al., 2015; Thiede et al., 2022; Thiede and Strube, 2020).

3.2. Education indicators and climate explanatory variables

Sample features and summary statistics for educational attainment are displayed in Table 1. As mentioned above, the number of communities used for the analysis varies per country (from 311 in Guinea to 1,247 in Nigeria). As expected, completion rates diminish in value across the lifecourse, showing the heightened disadvantages students face to stay-in and complete educational levels in the region (e.g., Evans and Mendez Acosta, 2021; Kuepie et al., 2015; UNESCO, 2020). When considering the total sample, the reduction in the chances of completing primary against lower secondary is of 16.4%, between lower and upper secondary of 10.8%, with a largest drop after secondary and tertiary of 24.3%. In Cameroon, for instance, over three quarters of students complete primary, less than half lower secondary, one out five upper secondary and just over one out of ten students have attended at least two years of tertiary.

[Table 1]

Communities educational performance varies enormously inside countries by their geographical location. Figure 2 shows that, within each country, communities' average educational performance for the four education indicators is highly heterogenous, even within administrative areas. A visualisation of interpolations across communities completion rates from left (primary) to right (tertiary) shows that areas with darker colour (i.e., of higher educational performance) become progressively smaller in size, thereby implying close and clear defined clusters of high performance in more urbanised/larges cities.

[Figure 2 here]

In particular, consider the specific cases of Cameroon and Ethiopia for the lower secondary completion rate indicator shown in Figure 2. In the central region of Cameroon high rates are found across the southern parts (especially in the capital Yaoundé) and decreasing rates moving north within this region, while for Ethiopia (within the SSNR region) increasing rates are found towards northeastern zones. In consequence, the observed large educational attainment heterogeneity inside countries points towards the needs to account for community heterogeneity methodologically. We address this by using a local non-parametric approach (see Section 4).

Moreover, the group of plots of Figure 3 displays countries' interpolations for the four climate explanatory variables (AI, LST, rain and EVI) we use as drivers of educational inequality. Here, too, climate covariates show substantial heterogeneity due to the presence of various sub-ecosystems (e.g., tropical rainforest, savannas, mountain forest, deserts) and dissimilar pattern of development within each country[5] affecting the impact of climate change variables and fluctuations of vegetation. It is interesting to identity a country's areas where EVI rates are negative for the last four decades (lightest green colour located in the right set of maps of Figure 3), as this may indicate deforestation and the impact of human activity on the health of ecosystems. For example, in Nigeria, these hot spots can be found across the Niger Delta low-lying region in the south of the country; and, for Ethiopia, west of the capital and towards the Amhara region.

[Figure 3 here]

3.3. Summary statistics by educational performance

The empirical relevance of climate and environment association with communities' educational attainment is corroborated by the summary statistics of Table 2 (for the pooled sample), where mean values of covariates are shown by low-high values of completion rates.[6] Panel A shows that the group of weak performing communities, in comparison to those communities of high performance (and irrespective of the education indicator considered), also suffers relatively more in terms of higher aridity and temperature, smaller precipitation and changing (larger) rates of EVI. The low-high gaps decrease for completion rates at higher educational levels.

In particular, climate gaps shown in Table 2 against low performing communities are: higher LST of 1.10° (primary), 0.66° (lower secondary), 0.33° (upper secondary) and 0.03° (tertiary); higher AI between 11.85 (primary) to 3.23 (tertiary); and reduced precipitation in the range of -356 mm (primary) -57 mm (tertiary). Likewise, we observe higher rates for EVI (of 5.2%-3.15%) in communities with below average completion rates, possibly caused by combination of higher LST at a given precipitation threshold (Zhong et al., 2021).

[Table 2 here]

These raw differences validate the motivation behind our main research question, and they are in line with studies for the African region showing the trade-off between social/developmental and educational outcomes and climate and environmental variability (Davenport et al., 2017; Galway et al., 2018; Randell et al., 2022; Randell and Gray, 2019, 2016).

Table 2 also demonstrates that the degree of completion rates a community can achieve is determined by its social context. Summary statistics for an array of socio-economic, women's empowerment and health covariates (which are used later as controls in the analysis) by the two performing groups of communities are shown in Panel B of Table 2. Using primary completion rates (columns 1 and 2) as an example on the detrimental effect that broad disadvantages have on educational outcomes, a low performing community is 42% more likely to be located in rural areas than in urban areas, and 69% of poor communities fall into the low performing group but 51% in the high performing group, with low performing communities having a degree of bankarisation around 40% lower than the one observed in high performing communities. Similarly, lower women's empowerment and lower health are observed in communities with low primary completion rates in comparison to communities with primary completion rates above the mean. The gaps on rates for these two set of communities are of 14% for early marriage and of 2.3% for fertility and of 8% for stunting rates. Summary statistics for the covariates for the remaining education indicators (columns 3 to 8, Table 2) show similar patterns.

4. Methods

Because of the type of educational outcomes used in the paper as dependent variables (i.e., completion community rates, so $Y \in (0,1)$), and the fact that we do not know a priori how climate covariates may influence completion along the spectrum of communities' rates and the heterogeneity shaping these associations, we follow an agnostic approach, i.e., non-parametric regression. This approach offers, from a policy-wise perspective, some insights related to how heterogeneity behaves across the four countries yielding unique local estimates for the association of climate-completion for each community, rather than an average association across the sample. Unlike parametric estimation, nonparametric regression assumes no functional form for the relationship between outcomes and covariates (Cameron and Trivedi, 2022; Fan and Gijbels, 1996; Li and Racine, 2004), relaxing assumptions on the form of the regression function and allowing data search to find out a suitable function describing the data well (Fan, 2018).

Our parameter of interest (the conditional mean of completion rates for each country) is an unknown function $m(.)$ of the k-dimensional vector of covariates $\mathbf{x}$; that is: $\mathbb{E}(y|\mathbf{x}) = m(\mathbf{x})$ because $\mathbb{E}(\varepsilon|\mathbf{x}) = 0$, where ε is the error term. Local-linear regression estimates a regression for a subset of observations for each point in the data. In particular, we follow local linear regression with kernel (Eubank, 1999; Fan and Gijbels, 1996; Li and Racine, 2023) which is an adaptation of a general locally weighted regression in the context of kernel smoothing. That is, the aim is to estimate $m(\mathbf{x})$ at given values of $\mathbf{x}$, say $\mathbf{x}_0$ (or more broadly in an interval of observations $\mathbf{x}_i$ close to $\mathbf{x}_0$, with higher weights given to closest observations to $\mathbf{x}_0$) without imposing restrictions on the functional form of $m(.)$

Formally, kernel regression uses the local weighted average (for each country, $c =$ 1,...,4, with a total number of observations or communities N):

$$\widehat{m}(\mathbf{x}_0) = \sum_{i=1}^{N} w(\mathbf{x}_i, \mathbf{x}_0, \mathbf{h}) \times y_i \tag{1}$$

where the weights $w(\mathbf{x}_i, \mathbf{x}_0, \mathbf{h})$ increase as $\mathbf{x}_i \mapsto \mathbf{x}_0$ and decrease if the bandwidth parameter $\mathbf{h}$ increases. The weighting function is the product of kernel functions:

$$w(\mathbf{x}_i, \mathbf{x}_0, \mathbf{h}) = \prod_{j=1}^{K} w_j(\mathbf{x}_i, \mathbf{x}_0, h_j) \tag{2}$$

and with the kernel weight for given regressor jth given by:

$$w_j(\mathbf{x}_i, \mathbf{x}_0, h) = K_j\left(\frac{x_{ji} - x_{j0}}{h}\right) \Big/ \sum_{i=1}^{N} K_j\left(\frac{x_{ji} - x_{j0}}{h}\right) \tag{3}$$

and for continuous and discrete covariates Epanechnikov and Li-Racine kernel functions are used, respectively.[7]

Local linear regression, for each data point $\mathbf{x}$ (e.g., $\mathbf{x}_0$), solves the minimisation problem with respect to the constant α_0 and slope $\boldsymbol{\beta}_0$ by minimising the weighted sum of squares:

$$\min \sum_{i=1}^{N} w(\mathbf{x}_i, \mathbf{x}_0, \mathbf{h}) \times \left(y_i - \alpha_0 - (\mathbf{x}_i - \mathbf{x}_0)'\boldsymbol{\beta}_0\right)^2 \tag{4}$$

where the estimated constant $\widehat{\alpha}_0$ is the conditional mean estimate $\widehat{m}(\mathbf{x}_0)$ and the estimated slope parameter is the derivative of the mean function for each point of $\mathbf{x}$, that is: $\widehat{\boldsymbol{\beta}}_0 = \widehat{m}'(\mathbf{x}_0) \equiv \partial m(\mathbf{x}) / \partial \mathbf{x}\big|_{\mathbf{x}=\mathbf{x}_0}$. Once the minimisation is repeated over the whole range of $\mathbf{x}$, we obtain the entire mean function and its derivatives.

We estimate Eq. (4) under two specifications: (i) a null model which only includes as $\mathbf{x}$ the climate covariates $\mathbf{x}_{\text{cli}}$, and (ii) a full model where we add the remaining non-climate covariates $\mathbf{x}_{\text{non-cli}}$ (i.e., those shown in Panel B of Table 2) to gauge if relationships obtained between completion rates and climate variables hold net of contextual features of communities. We obtain the optimal bandwidth, a crucial element of non-parametric regressions, by using cross-validation (Li and Racine, 2004) which balances the trade-off between bias and variance of the mean function estimator; standard errors for the derivatives are calculated by bootstrap using $R = 400$ replications.[8]

Additionally, because of the different units of climate variables and to facilitate grasping the significance of our results (Boillat et al., 2022), estimated mean derivatives are scaled up by mean values of dependent and independent variables, and presented in terms of elasticities (evaluated at the sample mean). Namely, we report: $\left(\partial \mathbf{y} / \partial \mathbf{x}_k\right) \times \left(\bar{\mathbf{x}}_k / \bar{\mathbf{y}}\right)$, i.e., the proportional change on completion rates ($\mathbf{y}$) following from a 1% change in the given climate covariate $\mathbf{x}_k$. This procedure allows to answer RQ1, the mean effect of climate variables on completion rates. For RQ2, the sub-sample analysis, we re-run Eq. (4) by rural/urban location, poor and rich communities, communities with low-high rates of early marriage and by low-high stunting rates, which sheds light into whether climate, as a barrier of educational attainment, is more prevalent in given communities' settings.

5. Results

5.1. Main findings

This section deals with RQ1. Non-parametric, local regression kernel estimates for the four completion rates dependent variables based on Eq. (4) are presented in Table 3 (for aridity and temperature) and in Table 4 (for rainfall and EVI). Our focus is on the partial derivatives of the mean function for the four climate covariates (i.e., $\widehat{m}'(\mathbf{x}_{\text{cli}})$) under a null model (without controls: columns 1, 3, 5 and 7) and a full model (with controls: columns 2, 4, 6 and 8).[9] For reference, we also include OLS estimated coefficients for climate covariates in the Appendix (see: Tables B1 and B2).

To begin with, results of Panel A (Table 3) show an overwhelming consistency of estimates as regards to the negative impacts that increasing community aridity indices (AI) has across the four countries and for the four completion indicators. Only three out the total 16 estimates (for the full model specification) are non-statistical significant. This is expected as the AI, a combined indicator of temperature and rainfall, can capture long term weather patterns with severe bearings, especially within rural communities as aridity is strongly linked to agricultural production, food security, health, internal migration and income (Lickley and Solomon, 2018; Nhamo et al., 2019; Piemontese et al., 2019). In the pooled sample, 60% of communities are located in rural settings, reaching higher values in Ethiopia (67%) and in Guinea (76%).

[Table 3 here]

Results of Panel A (Table 3) show an important reduction on the estimated effects of AI on completion rates ($\widehat{\boldsymbol{\beta}}_{\text{AI}}$) when moving from the null specification to the full specification. For instance, for completion rates at primary level (columns 1 and 2) and at lower secondary level (columns 3 and 4), reductions on the estimated effects are of 29%-55% and 49%-68%, respectively, indicating that socio-economic context of communities heavily matters and can thus act as ecological resilience factor for the transmission of climate-educational inequalities. Still, as said above, most of the statistical power of AI remains; therefore, aridity conditions are a prevailing barrier for educational attainment, net of the array of communities' features.

First, we discuss countries' estimates based on the full specification (Table 3-Panel A; columns 2, 4, 6 and 8). Estimates are slightly decreasing when completion is measured from primary to end of secondary (with the exception of Cameroon), and, for Ethiopia, impacts are larger at upper secondary level (= -0.41) and at tertiary level (= -0.60). Impacts of AI are consistently high for Guinean communities in comparison to the other countries. In particular, in Guinea, a 1% increase on aridity above its mean value (Δaridity = 3.9) leads to a reduction of completion rates up to secondary level of 70%-86%. Whereas in Cameroon the reduction is of 35%-48% and in Nigeria of 22%-45% (with, interestingly, the impact at primary being twice as large as the impact at upper secondary in absolute terms).

Second, when we move into the land surface temperature (LST) estimates (i.e., $\widehat{\boldsymbol{\beta}}_{\text{LST}}$), for an increase in LST –shown in Panel B of Table 3, full controls– impacts are higher for Cameroon and Nigeria (outcomes: primary and lower secondary) where 0.5% increase in the average value of LST (ΔLST in the interval 0.12°-0.13°) would lead to reductions of primary completion rates of around 66%-67% and, for lower secondary completion rates, of 52%-63%. For Guinea, this pattern only holds for primary, while for Ethiopia, negative impacts are found across all four indicators (between 45% and 28%; for a ΔLST = 0.12°).

In Table 4 we present estimated elasticities for the other two explanatory variables: rainfall and EVI rate. On the one hand, in Panel A, one can see that for rainfall, and for primary and the two secondary completion rates, estimates of $\widehat{\boldsymbol{\beta}}_{\text{rainfall}}$ are positive and generally statistically significant. Larger impacts are found for Guinea and Cameroon, followed up by Nigeria and with relatively smaller impacts holding in Ethiopia. For instance, a 1% of increment in a country yearly average rainfall (Δrainfall: Cameroon of 15.5 mm, Guinea 19.3 mm and Nigeria 13.1 mm) is linked to an increment of primary completion rates in the range of 25%-42% (column 2) and of 27%-47% for lower secondary (column 4); though, for upper secondary completion rates, impacts are smaller. Hence, robust environments and increasing rainfall have overall positive associations with educational attainment, boosting communities' completion rates.

[Table 4 here]

Stable vegetation are a defining feature of healthy ecosystems. Wang et al. (2023)'s study finds that leading driving factors behind vegetation EVI fluctuations are climate, terrain and human activities, therefore, shifts in the EVI rates and long term modifications on the quality of vegetation can be detrimental for social outcomes. Panel B (Table 4) estimates of $\widehat{\boldsymbol{\beta}}_{\text{EVI-rate}}$ confirm this for the educational dimension of social outcomes. Increments of 1% in EVI rates are linked to negative impacts on completion rates; even though this is mostly true for Cameroon and Nigeria (and to a lesser extent for Ethiopia and Guinea, full models). For instance, an increment in the EVI rate of 8% (12%) in Cameroon (Nigeria) would lead to reductions on communities completion rates at primary (column 2) of 7.5% (6%) and of 24% (7.9%) for upper secondary (column 6).[10]

5.2. Impacts of climate variables by sub-samples of communities contextual disadvantages

Here, to assess RQ2, we look into dimensions or divergent pathways of dependence from climate variables to completion rates indicators, shedding light onto whether impacts are homogenous or heterogenous by communities' cumulative social barriers. Our aim is to evaluate if climate impacts are more pronounced in certain dimensions of contextual disadvantages faced by SSA communities of the four selected countries. We carry out sub-sample analyses for some of results outlined in Section 5.1 due space constraints, focusing on one climate covariate, namely: aridity. Importantly, AI condenses in one indicator both temperature and rainfall, and aridity leads to droughts which have longer onset and duration than other weather and climate events (Alpino et al., 2016). Further sub-sample analyses for temperature and rainfall are included in the Appendix (Figure D1).

Drawing on previous studies around disadvantaged populations affected by climate change (see, for instance, reviews such as Benevolenza and DeRigne, 2019;

Helldén et al., 2021, and Randell and Gray, 2019), we select four empirical dimensions of community disadvantages linked to educational's barriers for the SSA region (Bashir et al., 2018; Delprato et al., 2017; Evans and Mendez Acosta, 2021; Huisman and Smits, 2015). They are: location, poverty, women empowerment (proxied by early marriage rates) and children long-term health status (proxied by stunting), as well as topographic conditions (community altitude).

Figure 4 displays primary completion's estimates by sub-samples in terms of elasticities. In the case of Cameroon, estimated impacts are substantially dissimilar by communities' location (rural = -0.76, urban = -0.15) and by communities' altitude (altitude $\leq$ 654 m–low = -0.42, altitude $>$ 654 m–high, not significant). Also, the impact of aridity is higher in poorer communities (-0.39 versus -0.35) and in those communities with higher stunting rates (-0.37 versus -0.35), whereas by women empowerment gaps on completion rates are larger (early marriage high = -0.43, early marriage low = -0.34). For Ethiopia, a largely arid country, we only find statistical significance estimates for the group of communities located in places of low altitude (below 1764 m). For Guinea, estimates show important heterogeneity by location (rural communities = -1, and non-significant in urban communities), by degree of poverty (-0.78 against -0.54), and by stunting rates (-0.75 against -0.47), and only estimates in communities's whose altitude is below the mean (476 m) are statistically significant. In the case of Nigeria, poverty, early marriage and health are leading pathways (even larger than location, where the rural-urban gap is of 0.49), with estimates' gaps due to increasing poverty of 0.88, and of increasing early marriage and decreasing health status of 1.1 and 0.6, respectively. Further, aridity has larger impacts in high-altitude communities (above 249 m).

[Figure 4 here]

Results for the dependent variable lower secondary completion are shown in Figure 5. Compared to primary completion, in Cameroon we can now see wider gaps on $\widehat{\boldsymbol{\beta}}_{\mathrm{AI}}$ by poverty rates and by early marriage communities prevalence rates and, at the same time, by health status; thereby suggesting how socio-economic constraints and social norms become more revelant as channels of widening educational inequalities at secondary level due to aridity. For example, 0.25 and 0.79 are the differential coefficients by poverty and by early marriage groups. In the case of Ethiopia we find, as before, very few coefficients which are statistically significant; whereas for Guinea –and perhaps because of the large degree of selectivity underpinning secondary attendance– the covariate AI only has statistically significant impacts on contextual advantaged communities. In the case of Nigeria, conversely, the same dimensions of disadvantages hold as for primary level (i.e., location, poverty, women empowerment and health status), and of similar magnitudes. For instance, the impact of AI is three times as large in rural areas and in communities with high stunting rates than in their counterparts, and six times larger in poorer communities and four times higher in communities with above average rates of early marriage.

[Figure 5 here]

6. Completion rates gaps forecast by emission scenarios

In this section, we compare predictions of completion rates by the evolution of temperature and rainfall linked to three emission scenarios: low, medium and high (WB-climate-change). Emissions scenarios are based on Representative Concentration Pathway (RCP), a greenhouse concentration trajectory, measuring the total radiative forcing (cumulative measure of GHG emissions from all sources) pathway and level by 2100 (Robinson, 2020).[11] We compare estimated completion rates at the beginning and at the end of each period (first period: 2015-2034, second period: 2035-2054) and contrast them, showing the impact of alterations of temperature and rainfall on educational attainment.

Figure 6 shows estimates for these contrasts for primary completion rates.[12] First, comparison of predictions based on temperatures (top plot) clearly indicates the damaging effect that increasing temperatures would have in terms of completion rates, with higher impacts in the case of Cameroon, Guinea and Nigeria. Consider for instance the high and medium emission scenarios and their cumulative detrimental effects of higher temperatures for the two periods, from 2015 to 2054. For Cameroon the reduction on primary completion rates at the community level would range from 4.5% (medium emission scenario) to 5.8% (high emission scenario), while for Guinea primary completion rates would be reduced in the high (medium) emission scenario by 4.8% (3.1%), and in Nigeria by 5.5% (4.4%). In Ethiopia, impacts would be somewhat lower, between 1.4% and 2.2%.

[Figure 6 here]

Second, primary completion rates predictions comparison based on changes of rainfall (bottom plot) tend to show positive changes for the first period, albeit smaller in magnitude and below 0.08% (except from Nigeria). Though, interestingly, for the second period (2035-2054), impacts shift and become negative in the case of Cameroon and Guinea. Overall, this prediction exercise highlights the role that climate change and unexpected climate shocks would have for educational attainment for these four SSA countries in the next few decades, and the requirement of designing policies which may mitigate the negative climate impacts within the educational sector.

7. Conclusions

Educational progress and narrowing inequalities within educational systems of the global south as measured by SDG4 are at odds with the overreaching impacts and strains that climate change (SDG13) is placing across the health of ecosystems and different aspects of society (Dagnachew and Hof, 2022; Helldén et al., 2021;

Mora et al., 2022; Xiao et al., 2023). Because climate change is more widespread and operates more powerfully in fragile and vulnerable contexts (Adesete et al., 2023; Serdeczny et al., 2017; Tamasiga and Bakwena, 2023), with extreme weather patterns, natural hazards and food and water shortages threatening the lives of people living in poverty, assessing the nexus between climate change and education is therefore fundamental (Randell and Gray, 2019).

Even more so looking at this nexus is relevant on equity grounds because most people affected by climate change lives in low and lower-middle income countries (Lee et al., 2023). Climate change can directly impact educational outcomes due to effects on school infrastructure and personnel, via a reduction of disposable income leading to less educational investment of parents or yielding negative impacts on children's health and their cognition capabilities (Randell and Gray, 2019; Yang and Fen, 2023).

Hence, underpinned by this scenario –and based on DHS survey data with geo-located (XY coordinates) data for educational attainment rates and climate indicators for 2,524 communities of four SSA countries (that is: Cameroon, Ethiopia, Guinea and Nigeria)–, this paper investigated the effect of climate change on completion rates across the educational lifecourse (from primary up to tertiary), with the aim of obtaining specific estimates per community through a non-parametric approach accounting for the degree of communities' heterogeneity behind the climate change-education pathway. A supplementary aim of the paper was to address how the negative climate gap linked to education is also disproportionately affecting the most marginalised communities of these countries, adding a further burden to pre-existing inequalities by dimensions (or targets) of SDG4's monitoring (such as by location, poverty and gender). The paper used four climate change variables: land surface temperature (LST), rainfall, aridity and modifications on the quality of vegetation (Enhanced Vegetation Index, EVI).

7.1. Main findings

The leading findings of the paper can be summarised into three groups. First, and not surprisingly considering that most (60%) communities are located in rural areas across the sample, we find that the impact of aridity –which combines in one indicator temperature and humidity/rainfall– on completion rates is consistently negatively net of all community controls, with estimates decreasing when attainment is measured at higher educational levels. In particular, Guinea shows the largest impacts (between 70%-86% primary and secondary rates) for a 1% increment on the aridity index (AI), followed by Ethiopia (41%-60%), Cameroon (35%-48%) and Nigeria (22%-45%). In the same vein, we find negative associations of land surface temperature (LST) with completion rates accounting for controls, which are larger in Nigeria and Cameroon where increments of LST of 0.12°-0.13° are related to reduction on primary and lower secondary communities' completion rates on the range of 67%-52% and, in the case of Ethiopia, between 45% and 28%.

Second, rainfall estimated elasticities are positive and generally statistically significant across indicators and countries with smaller impacts at upper secondary.

For example, increment in precipitation in the interval 13.1 mm-19.3 m would lead to an increment in primary completion rates of 25%-42% among Cameroon, Guinea and Nigeria communities. Cumulative weather anomalies would, in the long term, modify the extent and quality of vegetation and ultimately the quality of ecosystems (Zhong et al., 2021), so EVI's changes and alterations over the last decades are also related to communities' completion rates. We find that increments of 1% in EVI rates are linked to negative impacts on completion rates, with these associations largely holding in the case of Cameroon and Nigeria.

Third, and in accordance with earlier literature on contextual pathways channeling climate change impacts (e.g., Benevolenza and DeRigne, 2019), in our sub-sample analysis for the AI we consistently find that the burden of climate change falls into most disadvantaged communities, regardless how disadvantage is captured (that is by location, poverty, social norms or health). Taking primary completion as an example, for Guinea we find large heterogeneity of AI by communities' location, only having significant effects on rural communities but not in urban communities, while in Cameroon and Nigeria the rural-urban gap on estimates is of around 0.50. Climate change effects are also larger in communities with weaker social norms and health (with higher early marriage and stunting rates). In Nigeria, for instance, differential on estimated AI elasticities are of 1.1 and 0.6 for increasing early marriage and decreasing health status, and of 0.88 due to poverty. Because of the linkage of altitude with weather patterns (Barbier, 2015), our AI's estimates show heterogeneity by communities' altitude; being only significant in low located communities (for Cameroon and Guinea) and in higher place communities (particularly in Ethiopia).

7.2. Implications for SDG4 monitoring

The empirical analysis for these four SSA countries has demonstrated why mitigation strategies for unexpected climate shocks degrading ecosystems are required to improve educational attainment in these four SSA countries, emphasising the necessity of a better parallel monitoring of SDG13 and SDG4 and their interlinkages. On the one hand, policies prioritising SDG13 targets [13] on climate action such as 13.2 ("Integrate climate change measures into national policies, strategies and planning") and 13.5 ("Promote mechanisms for raising capacity for effective climate change-related planning and management...focusing on marginalised communities") should be embedded into the frameworks of national educational policies. This policy re-configuration should start in a scaffolding manner, beginning with the groups of communities further left behind in relationship to SDG4 progress; namely, poor and rural communities which also exhibit compounded barriers for educational attainment due to malnourishment and poor health and negative social norms.

On the other hand, our forecast for the next decades clearly shows the additional set back of completion rates these countries may suffer under medium or high emission scenarios. Since the SSA region has the lowest access rate to modern energy, with energy systems being dominated by solid biomass, power generation, agriculture and non-CO2 emissions show the largest potential for climate change mitigation if good practice measures are implemented in the region (Dagnachew et al., 2021, 2017). Coal-fired power plants, for instance, are responsible for over three quarters of SSA's emissions from the power sector (IEA, 2020); consequently, shifting to renewable energy systems is very promising for the region creating a sustainable, reliable and resilient infrastructure.

Notes

1. See: DHS-overview.

2. See: DHS-sampling.

3. Namely, education completion rates and key explanatory variables used as controls are derived from PR (household recode) dataset. Women's empowerment covariates are from IR (women) dataset, while health covariates are from the IR (women dataset) and BR (birth recode dataset) and KR (children dataset). Further information of the DHS data structure can be found at: DHS-data-structure.

4. Studies using DHS geo-spatial data, can be found at: studies-DHS-GPS.

5. Ethiopia, for instance, has a diverse climate and contrasting landscapes, ranging from rainforest with high rainfall and humidity in the south and south west, to the Afro-Alpine in the center and desert areas in the north-east and east.

6. The same information per country is included in the Appendix (Figure A1).

7. Epanechnikov kernels (used for continuous covariates) are defined as: $K(z) = \big(3/4\sqrt{5}\big)(1-(1/5)z^2\big)\times \mathbf{1}\big(z \leq \sqrt{5}\big)$; and for discrete variables Li-Racine kernels are employed which are defined as follows: $K(x_i - x_0, h) = 1$ if $x_i - x_0$ and equals to h otherwise, with $0 \leq h \leq 1$.

8. Estimations are carried out using the Stata command `npregress kernel`.

9. Estimates for the control variables (or non-climate variables: $\mathbf{x}_{\text{non-cli}}$) are available from the authors upon request.

10. In Figures C1 and C2 of the Appendix, we include additional results on the impact of climate covariates and their degree of heterogeneity.

11. Values of temperature and rainfall for each period per country used in this forecast exercise are shown in the Appendix (Table E1.)

12. Table E2 includes estimates for lower and upper secondary completion rates.

13. See: SDG13-targets.

References

Abbass, K., Qasim, M.Z., Song, H., Murshed, M., Mahmood, H., Younis, I., 2022. A review of the global climate change impacts, adaptation, and sustainable mitigation measures. Environmental Science and Pollution Research 29, 42539–42559.

Abernethy, K., Maisels, F., White, L.J., 2016. Environmental issues in central africa. Annual Review of Environment and Resources 41, 1–33.

Adedokun, S.T., Yaya, S., 2021. Factors associated with adverse nutritional status of children in sub-saharan africa: Evidence from the demographic and health surveys from 31 countries. Maternal & child nutrition 17, e13198.

Adesete, A.A., Olanubi, O.E., Dauda, R.O., 2023. Climate change and food security in selected sub-saharan african countries. Environment, Development and Sustainability 25, 14623–14641.

Ahmed, R., Barkat, W., Ahmed, A., Tahir, M., Nasir, A.M., 2022. The impact of flooding on education of children and adolescents: Evidence from pakistan. Water Economics and Policy 8, 2240009.

Akombi, B.J., Agho, K.E., Merom, D., Renzaho, A.M., Hall, J.J., 2017. Child malnutrition in sub-saharan africa: A meta-analysis of demographic and health surveys (2006-2016). PloS one 12, e0177338.

Alpino, T.A., Sena, A.R.M.d., Freitas, C.M.d., 2016. Disasters related to droughts and public health–a review of the scientific literature. Ciencia & saude coletiva 21, 809–820.

Baker, R.E., Anttila-Hughes, J., 2020. Characterizing the contribution of high temperatures to child undernourishment in sub-saharan africa. Scientific reports 10, 18796.

Barbier, E.B., 2015. Climate change impacts on rural poverty in low-elevation coastal zones. Estuarine, Coastal and Shelf Science 165, A1–A13.

Bari, E., Nipa, N.J., Roy, B., 2021. Association of vegetation indices with atmospheric & biological factors using modis time series products. Environmental Challenges 5, 100376.

Bashir, S., Lockheed, M., Ninan, E., Tan, J.P., 2018. Facing forward: Schooling for learning in Africa. World Bank Publications.

Benevolenza, M.A., DeRigne, L., 2019. The impact of climate change and natural disasters on vulnerable populations: A systematic review of literature. Journal of Human Behavior in the Social Environment 29, 266–281.

Boillat, S., Ceddia, M.G., Bottazzi, P., 2022. The role of protected areas and land tenure regimes on forest loss in bolivia: Accounting for spatial spillovers. Global Environmental Change 76, 102571.

Boyle, E.H., King, M.L., Garcia, S., Culver, C., Bourdeaux, J., 2020. Contextual data in ipums dhs: physical and social environment variables linked to the demographic and health surveys. Population and environment 41, 529–549.

Cadag, J.R.D., Petal, M., Luna, E., Gaillard, J., Pambid, L., Santos, G.V., 2017. Hidden disasters: Recurrent flooding impacts on educational continuity in the philippines. International journal of disaster risk reduction 25, 72–81.

Cameron, A.C., Trivedi, P.K., 2022. Microeconometrics: methods and applications. Volume II: Nonlinear Models and Causal Inference Methods. Cambridge university press.

Cartwright, A., 2015. Better growth, better cities: Rethinking and redirecting urbanisation in africa. The New Climate Economy Working Paper .

Cui, Y., Wei, Z., Xue, Q., Sohail, S., 2022. Educational attainment and environmental kuznets curve in china: an aggregate and disaggregate analysis. Environmental Science and Pollution Research 29, 45612–45622.

Czarnek, G., Kossowska, M., Szwed, P., 2021. Right-wing ideology reduces the effects of education on climate change beliefs in more developed countries. Nature Climate Change 11, 9–13.

Dagnachew, A.G., Hof, A., Soest, H.v., Vuuren, D.v., 2021. Climate change measures and sustainable development goals. PBL Netherlands Environmenta l Assessment Agency, The Hague .

Dagnachew, A.G., Hof, A.F., 2022. Climate change mitigation and sdgs: modelling the regional potential of promising mitigation measures and assessing their impact on other sdgs. Journal of Integrative Environmental Sciences 19, 289–314.

Dagnachew, A.G., Lucas, P.L., Hof, A.F., Gernaat, D.E., de Boer, H.S., van Vuuren, D.P., 2017. The role of decentralized systems in providing universal electricity access in sub-saharan africa–a model-based approach. Energy 139, 184–195.

Davenport, F., Dorélien, A., Grace, K., 2020. Investigating the linkages between pregnancy outcomes and climate in sub-saharan africa. Population and Environment 41, 397–421.

Davenport, F., Grace, K., Funk, C., Shukla, S., 2017. Child health outcomes in sub-saharan africa: a comparison of changes in climate and socio-economic factors. Global Environmental Change 46, 72–87.

Delprato, M., Akyeampong, K., Dunne, M., 2017. Intergenerational education effects of early marriage in sub-saharan africa. World Development 91, 173–192.

Delprato, M., Farieta, A., 2023. A multilevel analysis of educational transition rates at secondary level in sub-saharan africa. PROSPECTS , 1–30.

Di Falco, S., Kis, A.B., Viarengo, M., Das, U., 2024. Leaving home: Cumulative climate shocks and migration in sub-saharan africa. Environmental and Resource Economics 87, 321–345.

Dietler, D., Farnham, A., Loss, G., Fink, G., Winkler, M.S., 2021. Impact of mining projects on water and sanitation infrastructures and associated child health outcomes: a multi-country analysis of demographic and health surveys (dhs) in sub-saharan africa. Globalization and Health 17, 70.

Eissler, S., Thiede, B.C., Strube, J., 2019. Climatic variability and changing reproductive goals in sub-saharan africa. Global Environmental Change 57, 101912.

Eubank, R.L., 1999. Nonparametric regression and spline smoothing. CRC press.

Evans, D.K., Mendez Acosta, A., 2021. Education in africa: What are we learning? Journal of African Economies 30, 13–54.

Fan, J., 2018. Local polynomial modelling and its applications: monographs on statistics and applied probability 66. Routledge.

Fan, J., Gijbels, I., 1996. Chapman hall; local polynomial modelling and its applications.

Faul, M.V., Savage, L., 2023. Systems Thinking in International Education and Development: Unlocking Learning for All? Edward Elgar Publishing.

Fredriksson, U., N. Kusanagi, K., Gougoulakis, P., Matsuda, Y., Kitamura, Y., 2020. A comparative study of curriculums for education for sustainable development (esd) in sweden and japan. Sustainability 12, 1123.

Galway, L.P., Acharya, Y., Jones, A.D., 2018. Deforestation and child diet diversity: A geospatial analysis of 15 sub-saharan african countries. Health & place 51, 78–88.

Grace, K., Davenport, F., Hanson, H., Funk, C., Shukla, S., 2015. Linking climate change and health outcomes: Examining the relationship between temperature, precipitation and birth weight in africa. Global Environmental Change 35, 125–137.

Greve, P., Roderick, M., Ukkola, A., Wada, Y., 2019. The aridity index under global warming. Environmental Research Letters 14, 124006.

Guha, S., Govil, H., 2021. An assessment on the relationship between land surface temperature and normalized difference vegetation index. Environment, Development and Sustainability 23, 1944–1963.

Gurung, R.B., Breidt, F.J., Dutin, A., Ogle, S.M., 2009. Predicting enhanced vegetation index (evi) curves for ecosystem modeling applications. Remote Sensing of Environment 113, 2186–2193.

Hanna, R., Oliva, P., 2016. Implications of climate change for children in developing countries. The Future of Children , 115–132.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., et al., 2013. High-resolution global maps of 21st-century forest cover change. science 342, 850–853.

Hanushek, E.A., 2013. Economic growth in developing countries: The role of human capital. Economics of education review 37, 204–212.

Helldén, D., Andersson, C., Nilsson, M., Ebi, K.L., Friberg, P., Alfvén, T., 2021. Climate change and child health: a scoping review and an expanded conceptual framework. The Lancet Planetary Health 5, e164–e175.

Hemminki-Reijonen, U., Logadottir, H., 2021. Reinventing climate change education. The Arctic Initiative Papers .

Hickel, J., 2019. Degrowth: a theory of radical abundance. Real-world economics review 87, 54–68.

Hickel, J., 2020. Less is more: How degrowth will save the world. Random House.

Hinkel, J., Lincke, D., Vafeidis, A.T., Perrette, M., Nicholls, R.J., Tol, R.S., Marzeion, B., Fettweis, X., Ionescu, C., Levermann, A., 2014. Coastal flood damage and adaptation costs under 21st century sea-level rise. Proceedings of the National Academy of Sciences 111, 3292–3297.

Huisman, J., Smits, J., 2015. Keeping children in school: effects of household and context characteristics on school dropout in 363 districts of 30 developing countries. Sage Open 5, 2158244015609666.

Hulley, G., Ghent, D., 2019. Taking the temperature of the Earth: steps towards integrated understanding of variability and change. Elsevier.

ICF-International, 2012. Demographic and health survey sampling and household listing manual .

IDMC, 2023. Global report on internal displacement: Internal displacement and food security .

IEA, 2020. Coal 2020: Analysis and forecast to 2025. https://www.iea.org/reports/coal-2020 .

Joshi, K., 2019. The impact of drought on human capital in rural india. Environment and Development Economics 24, 413–436.

Kamens, D.H., 2015. A maturing global testing regime meets the world economy: Test scores and economic growth, 1960–2012. Comparative Education Review 59, 420–446.

Khan, A., Chatterjee, S., Wang, Y., 2020. Urban Heat Island Modeling for Tropical Climates. Elsevier.

Kuepie, M., Shapiro, D., Tenikue, M., 2015. Access to schooling and staying in school in selected sub-saharan african countries. African Development Review 27, 403–414.

Kurokawa, H., Igei, K., Kitsuki, A., Kurita, K., Managi, S., Nakamuro, M., Sakano, A., 2023. Improvement impact of nudges incorporated in environmental education on students' environmental knowledge, attitudes, and behaviors. Journal of Environmental Management 325, 116612.

Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., Barrett, K., et al., 2023. Ar6 synthesis report: Climate change 2023. Summary for Policymakers .

Li, Q., Racine, J., 2004. Cross-validated local linear nonparametric regression. Statistica Sinica , 485–512.

Li, Q., Racine, J.S., 2023. Nonparametric econometrics: theory and practice. Princeton University Press.

Lickley, M., Solomon, S., 2018. Drivers, timing and some impacts of global aridity change. Environmental Research Letters 13, 104010.

Lindsey, R., Dahlman, L., 2020. Climate change: Global temperature. Climate. gov 16.

López-Olmedo, N., Stern, D., Bakhtsiyarava, M., Pérez-Ferrer, C., Langellier, B., 2022. Greenhouse gas emissions associated with the mexican diet: identifying social groups with the largest carbon footprint. Frontiers in nutrition 9, 791767.

Maccini, S., Yang, D., 2009. Under the weather: Health, schooling, and economic consequences of early-life rainfall. American economic review 99, 1006–1026.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M., et al., 2021. Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change 2.

Mastini, R., Kallis, G., Hickel, J., 2021. A green new deal without growth? Ecological economics 179, 106832.

Mayala, B., Fish, T.D., Eitelberg, D., Dontamsetti, T., 2018. The dhs program geospatial covariate datasets manual. Rockville: ICF .

McCrary, J., Royer, H., 2011. The effect of female education on fertility and infant health: evidence from school entry policies using exact date of birth. American economic review 101, 158–195.

Measure-DHS, 2023. Dhs overview. http://www.measuredhs.com/What-We-Do/Survey-Types/DHS.cfm .

Mochizuki, Y., Bryan, A., 2015. Climate change education in the context of education for sustainable development: Rationale and principles. Journal of Education for Sustainable Development 9, 4–26.

Mora, C., McKenzie, T., Gaw, I.M., Dean, J.M., von Hammerstein, H., Knudson, T.A., Setter, R.O., Smith, C.Z., Webster, K.M., Patz, J.A., et al., 2022. Over half of known human pathogenic diseases can be aggravated by climate change. Nature climate change 12, 869–875.

Nhamo, L., Matchaya, G., Mabhaudhi, T., Nhlengethwa, S., Nhemachena, C., Mpandeli, S., 2019. Cereal production trends under climate change: Impacts and adaptation strategies in southern africa. Agriculture 9, 30.

Nordstrom, A., Cotton, C., 2020. Impact of a severe drought on education: More schooling but less learning. Available at SSRN 3601834 .

NourEldeen, N., Mao, K., Yuan, Z., Shen, X., Xu, T., Qin, Z., 2020. Analysis of the spatiotemporal change in land surface temperature for a long-term sequence in africa (2003–2017). Remote Sensing 12, 488.

Nübler, L., Austrian, K., Maluccio, J.A., Pinchoff, J., 2021. Rainfall shocks, cognitive development and educational attainment among adolescents in a drought-prone region in kenya. Environment and Development Economics 26, 466–487.

Perez-Heydrich, C., Warren, J.L., Burgert, C.R., Emch, M.E., 2013. Guidelines on the use of dhs gps data , DHS Spatial Analysis Reports No. 8.

Piemontese, L., Fetzer, I., Rockström, J., Jaramillo, F., 2019. Future hydroclimatic impacts on africa: beyond the paris agreement. Earth's Future 7, 748–761.

Psacharopoulos, G., 1994. Returns to investment in education: A global update. World development 22, 1325–1343.

Randell, H., Gray, C., 2016. Climate variability and educational attainment: Evidence from rural ethiopia. Global environmental change 41, 111–123.

Randell, H., Gray, C., 2019. Climate change and educational attainment in the global tropics. Proceedings of the National Academy of Sciences 116, 8840–8845.

Randell, H., Gray, C., Shayo, E.H., 2022. Climatic conditions and household food security: Evidence from tanzania. Food Policy 112, 102362.

Ray, S., Ray, I.A., 2011. Impact of population growth on environmental degradation: Case of india. Journal of Economics and Sustainable Development 2, 72–77.

Reimers, F.M., 2021. The role of universities building an ecosystem of climate change education. Education and climate change: The role of universities , 1–44.

Robinson, S.a., 2020. Climate change adaptation in sids: A systematic review of the literature pre and post the ipcc fifth assessment report. Wiley Interdisciplinary Reviews: Climate Change 11, e653.

Rudel, T.K., 2013. The national determinants of deforestation in sub-saharan africa. Philosophical Transactions of the Royal Society B: Biological Sciences 368, 20120405.

Rutstein, S.O., Rojas, G., et al., 2006. Guide to dhs statistics. Calverton, MD: ORC Macro 38, 78.

Schoumaker, B., 2013. A stata module for computing fertility rates and tfrs from birth histories: tfr2. Demographic Research 28, 1093–1144.

Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M., Perrette, M., Reinhardt, J., 2017. Climate change impacts in sub-saharan africa: from physical changes to their social repercussions. Regional Environmental Change 17, 1585–1600.

Siljander, R., Cederlöf, M., Skoglund, K., Herronen, V., 2023. Annual climate report 2023 .

Slingo, J., Bates, K., Nikiforakis, N., Piggott, M., Roberts, M., Shaffrey, L., Stevens, I., Vidale, P.L., Weller, H., 2009. Developing the next-generation climate system models: challenges and achievements. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 367, 815–831.

Subbarao, K., Raney, L., 1995. Social gains from female education: a cross-national study. Economic development and cultural change 44, 105–128.

Tamasiga, P., O.H.A.A., Bakwena, M., 2023. The inter-relationship between climate change, inequality, poverty and food security in africa: A bibliometric review and content analysis approach. Sustainability 15, 5628.

Thiede, B.C., Ronnkvist, S., Armao, A., Burka, K., 2022. Climate anomalies and birth rates in sub-saharan africa. Climatic Change 171, 5.

Thiede, B.C., Strube, J., 2020. Climate variability and child nutrition: Findings from sub-saharan africa. Global Environmental Change 65, 102192.

Tirado, M., Hunnes, D., Cohen, M., Lartey, A., 2015. Climate change and nutrition in africa. Journal of Hunger & Environmental Nutrition 10, 22–46.

Tol, R.S., 2018. The economic impacts of climate change. Review of environmental economics and policy .

UNEP, 2023. Emissions gap report 2023. https://www.unep.org/resources/emissions-gap-report-2023 .

UNESCO, 2020. Global education monitoring report 2020: Inclusion and education: All means all. 92310038 .

UNESCO, 2022. New estimation confirms out-of-school population is growing in sub-saharan africa. UNESCO Digital Library Policy Paper.

UNGA, 2015. Transforming our world: the 2030 agenda for sustainable development .

Van Den Bergh, J.C., 2017. A third option for climate policy within potential limits to growth. Nature Climate Change 7, 107–112.

Vancutsem, C., Achard, F., Pekel, J.F., Vieilledent, G., Carboni, S., Simonetti, D., Gallego, J., Aragao, L.E., Nasi, R., 2021. Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. Science Advances 7, eabe1603.

Vijith, H., Dodge-Wan, D., 2020. Applicability of modis land cover and enhanced vegetation index (evi) for the assessment of spatial and temporal changes in strength of vegetation in tropical rainforest region of borneo. Remote Sensing Applications: Society and Environment 18, 100311.

Wang, G., Peng, W., Zhang, L., Zhang, J., Xiang, J., 2023. Vegetation evi changes and response to natural factors and human activities based on geographically and temporally weighted regression. Global Ecology and Conservation , e02531.

Watson, R., Baste, I., Larigauderie, A., Leadley, P., Pascual, U., Baptiste, B., Demissew, S., Dziba, L., Erpul, G., Fazel, A., et al., 2019. Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the intergovernmental science-policy platform on biodiversity and ecosystem services. IPBES Secretariat: Bonn, Germany , 22–47.

Wilson, K., Wakefield, J., 2021. Estimation of health and demographic indicators with incomplete geographic information. Spatial and Spatio-temporal Epidemiology 37, 100421.

World Bank, 2021a. Climate risk profile: Ethiopia .

World Bank, 2021b. Climate risk profile: Nigeria .

Xiao, H., Liu, Y., Ren, J., 2023. Synergies and trade-offs across sustainable development goals: A novel method incorporating indirect interactions analysis. Sustainable Development 31, 1135–1148.

Yahaya, N.S., Hussaini, M., Bashir, A.B., 2020. Population growth and environmental degradation in nigeria. Academic journal of economic studies 6, 31–35.

Yang, X., Fen, K., 2023. Mapping the cumulative effects of climate change on children's education in ten african countries. Paper commissioned as part of the GEM Report Fellowship Programme in 2022 .

Yin, L., Foy, P., 2019. Constructing the timss 2019 environmental awareness scales. Methods and Procedures: TIMSS .

Yusuf, A.M., Abubakar, A.B., Mamman, S.O., 2020. Relationship between greenhouse gas emission, energy consumption, and economic growth: evidence from some selected oil-producing african countries. Environmental science and pollution research 27, 15815–15823.

Zen, I.S., Uddin, M.S., Al-Amin, A.Q., Majid, M.R.B., Almulhim, A.I., Doberstein, B., 2022. Socioeconomics determinants of household carbon footprint in iskandar malaysia. Journal of Cleaner Production 347, 131256.

Zhong, R., Wang, P., Mao, G., Chen, A., Liu, J., 2021. Spatiotemporal variation of enhanced vegetation index in the amazon basin and its response to climate change. Physics and Chemistry of the Earth, Parts A/B/C 123, 103024.

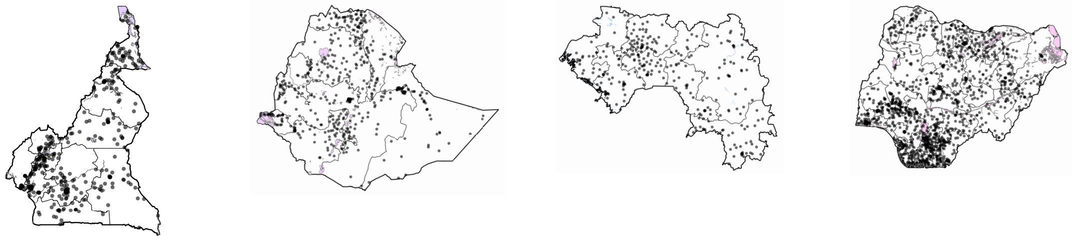


Figure 1: Location of communities in the working sample

Notes: (1) Countries left to right: Cameroon, Ethiopia, Guinea and Nigeria.

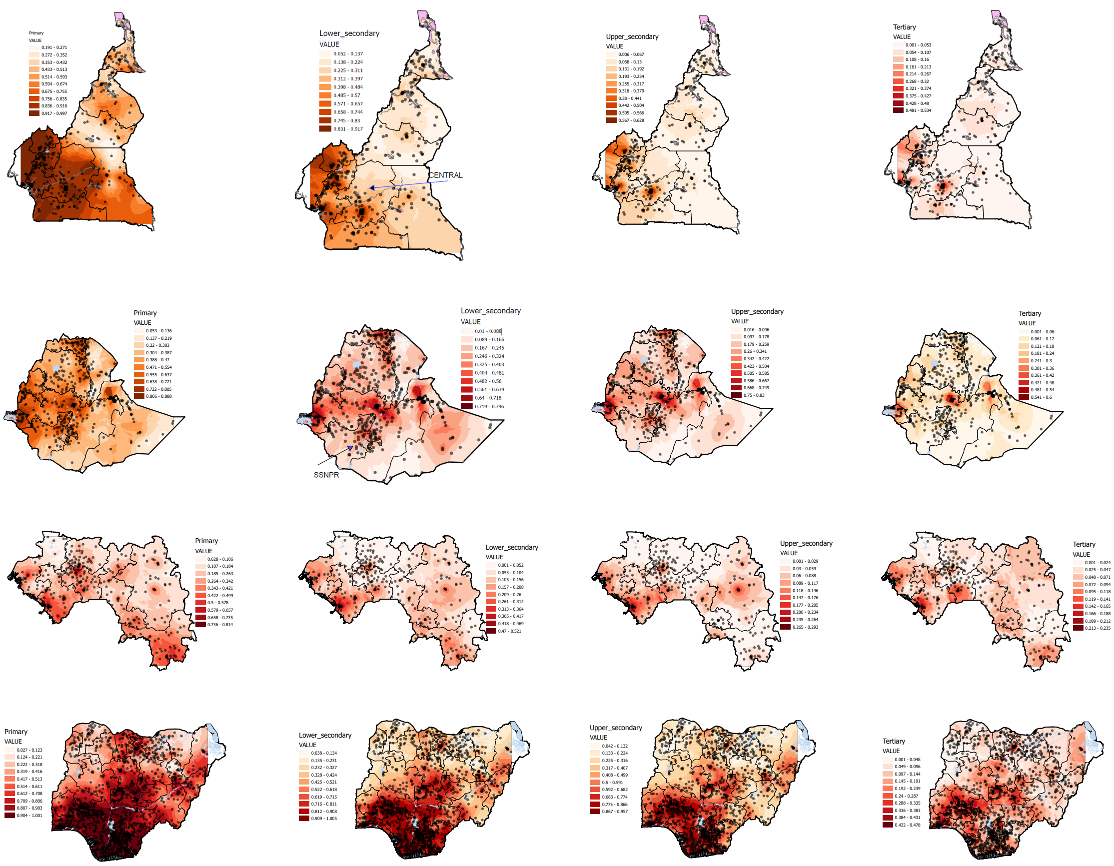


Figure 2: Completion rates distribution/prediction

Notes: (1) Data interpolations to obtain smooth maps are obtained using the interpolation Empirical Bayesian Kriging (EBK). (2) Countries names per row: Cameroon, Ethiopia, Guinea and Nigeria.

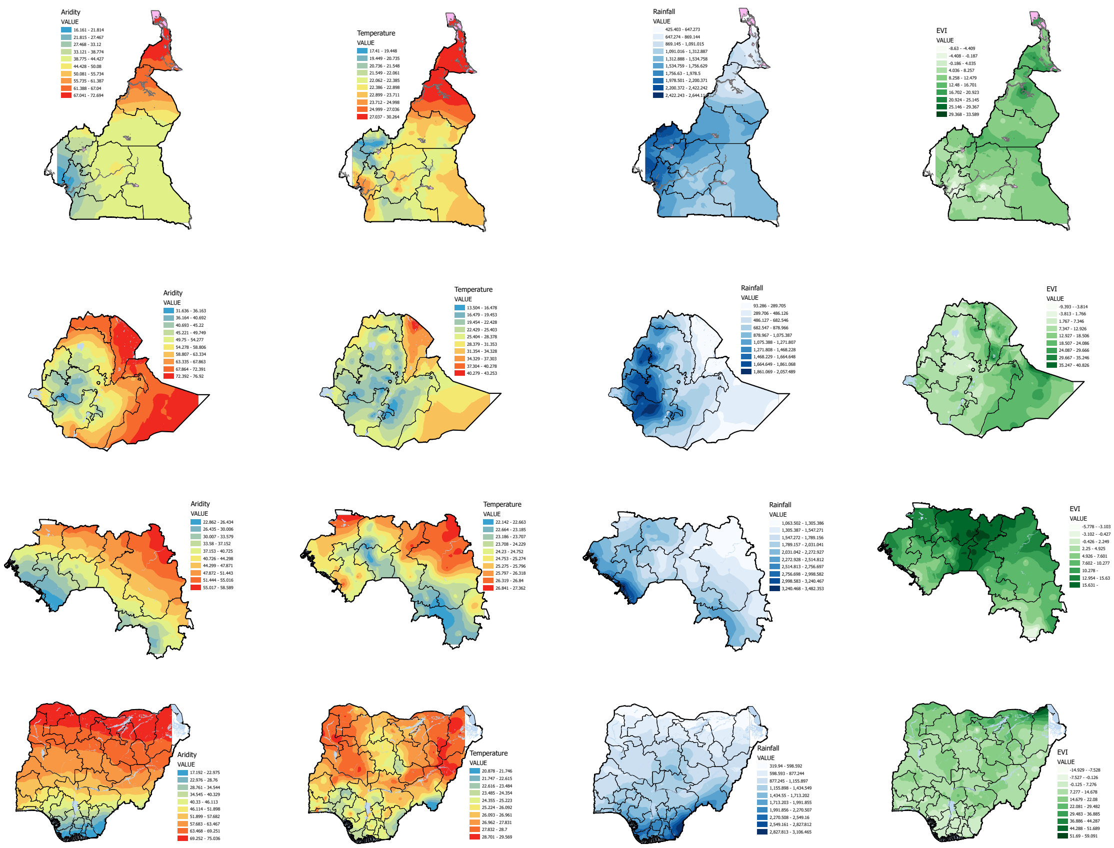


Figure 3: Climate variables distribution/prediction

Notes: (1) Data interpolations to obtain smooth maps are obtained using the interpolation Empirical Bayesian Kriging (EBK). (2) Countries names per row: Cameroon, Ethiopia, Guinea and Nigeria.

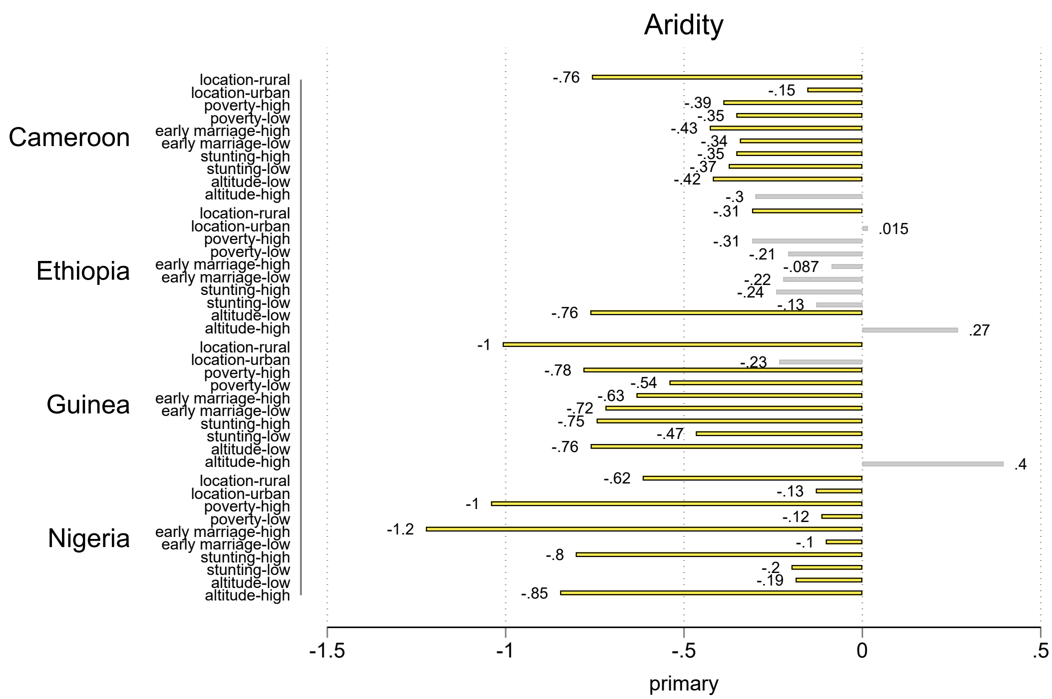


Figure 4: Estimates (elasticities) for primary completion of climate variables by community's disadvantages and location

Notes: (1) Light colour bars denote non-statistically significant estimates.

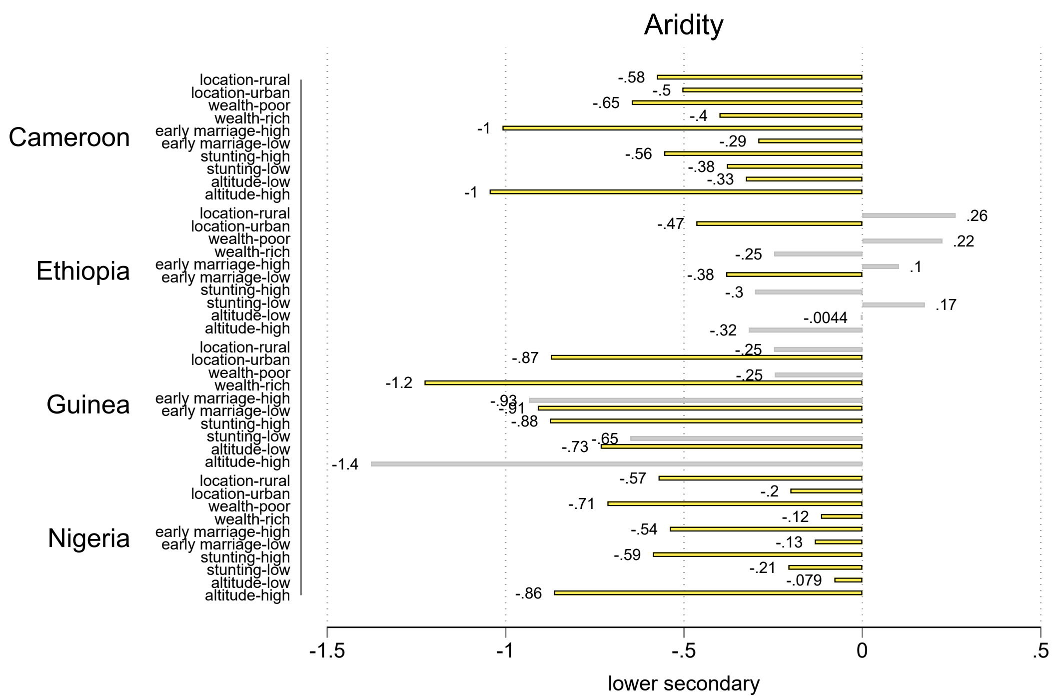
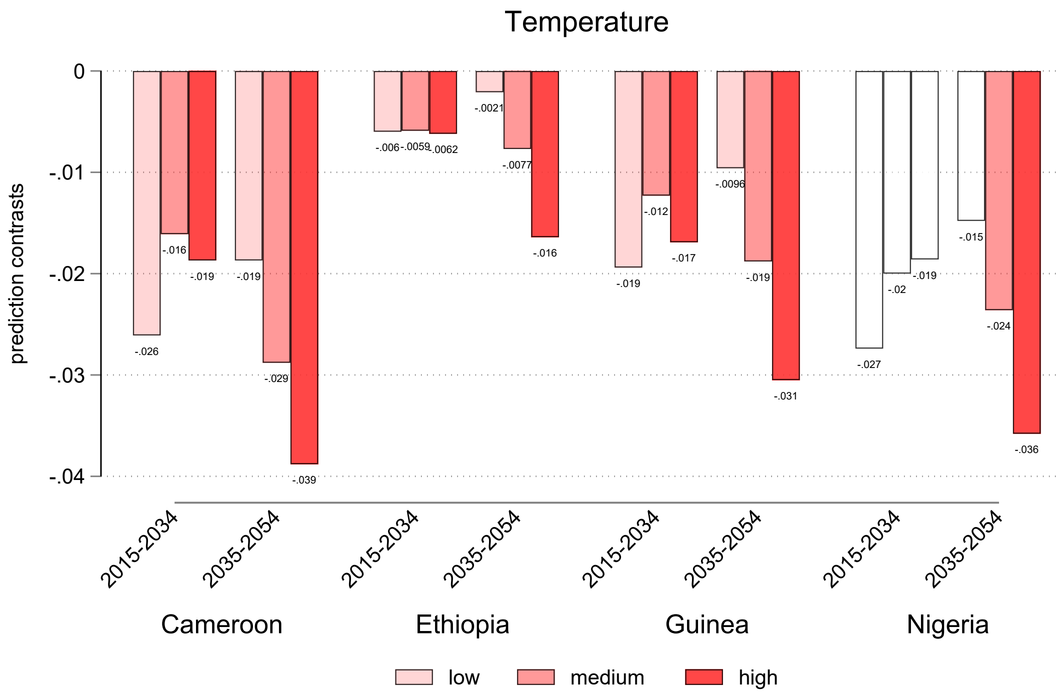


Figure 5: Estimates (elasticities) for lower secondary completion of climate variables by community's disadvantages and location

Notes: (1) Light colour bars denote non-statistically significant estimates.



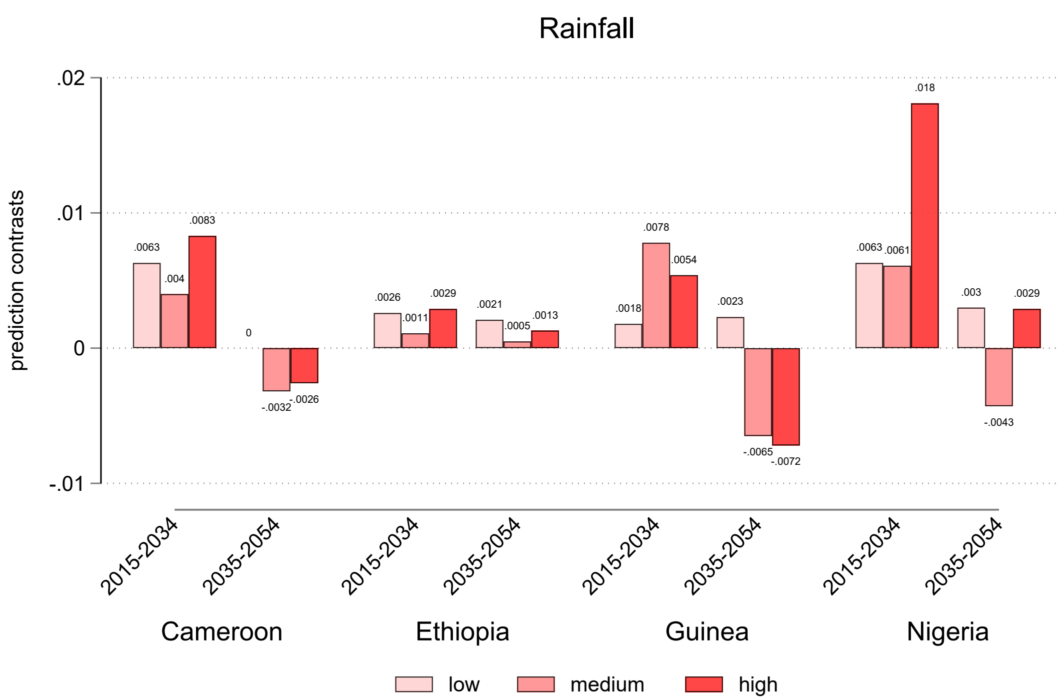


Figure 6: Contrast on prediction for primary completion rates by emission scenarios

Notes: (1) White coloured bars denote non-statistically significant estimates.

Table 1: List of countries and mean value for completion rates

Country	Year	Primary	Lower secondary	Upper secondary	Tertiary
		(1)	(2)	(3)	(4)
Cameroon	2018	0.786	0.479	0.202	0.113
N		412	412	412	412
Ethiopia	2016	0.533	0.344	0.330	0.171
N		557	557	556	556
Guinea	2018	0.323	0.144	0.067	0.057
N		311	309	310	311
Nigeria	2018	0.768	0.666	0.564	0.174
N		1247	1244	1244	1245
Total sample		0.664	0.501	0.392	0.149
N		2527	2522	2522	2524

(1) Number of communities with XY coordinates. (2) The age intervals for calculating the different completion rate indicators are as follows: primary completion (finishing primary school age+1, finishing primary school age+5); lower secondary completion (finishing lower secondary school age+1, finishing lower secondary school age+5); upper secondary completion (finishing upper secondary school age+1, finishing upper secondary school age+5); tertiary completion (finished 2 years of higher education for the age group 25-29).

Table 2: Summary statistics for completion indicators by community climate characteristics and other covariates. Whole sample

	Primary		Lower secondary		Upper secondary		Tertiary	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Climate variables								
Aridity	57.65	45.80	55.64	45.60	53.29	46.81	51.39	48.16
Temperature - land surface	25.84	24.75	25.51	24.85	25.31	24.98	25.17*	25.14*
Rainfall	1110.80	1446.71	1164.31	1455.22	1242.19	1409.43	1300.46+	1357.69+
EVI rate	14.26	9.24	13.60	8.99	13.23	8.74	12.23	9.09
Panel B - Other covariates								
Rural location	0.87	0.45	0.85	0.40	0.82	0.37	0.77	0.31
Poverty	0.69	0.51	0.68	0.49	0.67	0.48	0.64	0.47
Bank account	0.26	0.44	0.27	0.46	0.28	0.47	0.32	0.46
Early marriage	0.54	0.40	0.54	0.39	0.52	0.38	0.49	0.40
Fertility rate	6.90	4.60	6.68	4.41	6.48	4.31	6.15	4.21
Stunting rate	0.32	0.24	0.32	0.23	0.30	0.23	0.29	0.24
Infant mortality rate	0.08	0.07	0.08	0.07	0.07	0.07	0.07+	0.07+
Altitude	761.26	623.38	765.70	597.15	719.74	624.63	694.28++	639.96++
N	950	1,581	1,717	1,360	1,344	1,187	1,639	892

(1) Low/high values for completion rates are defined by mean values of each dependent variable per country. All t-test between low and high groups are statistically significant at 1%, expect from those denoted by + (at 5%), ++ (at 10%), and * (non-statistically significant). (2) Climate variables (Panel A). (a) The Aridity Index (AI) denotes the ratio of annual precipitation to annual potential evapotranspiration, with the AI varying between 0 (most arid) to 300 (most wet). We reversed the AI scale, so larger values denotes more aridity. (b) Land surface temperature (LST) is the radiative skin temperature of the land derived from solar radiation. We employ LST because is a fundamental aspect of climate change as it is a basic determinant of the terrestrial thermal behavior (see: Hulley and Ghent, 2019; Khan et al., 2020). (c) The Enhanced Vegetation Index (EVI) is used for global monitoring of vegetation condition by providing information about the variability in stature, growth and vigor of the vegetation across a region (Gurung et al., 2009), and it is used to monitor vegetation condition and severe fluctuations due to developmental activities and climate change (Vijith and Dodge-Wan, 2020). The EVI varies between 0 (least vegetation) and 10000 (most vegetation). (d) Aridity, temperature and rainfall are measurement for the year 2015, whereas for EVI we measure rates of change for the he 40-year period (1985-2015). (e) For more details on climate, environment and geographical covariates measurement see, DHS report: Mayala et al. (2018). (3) Other covariates (Panel B). (a) Poverty is defined by the community proportion of households in the bottom two quintiles wealth distribution. (b) Early marriage (proportion of girls married before age 18). (c) Infant mortality rates (if the child died before first birthday) and community fertility rates are calculated using the Stata module tfr2 (Schoumaker, 2013).

Table 3: Non-parametric kernel estimates (elasticities), null and full models. Climate covariates: aridity and temperature

	Primary		Lower secondary		Upper secondary		Tertiary	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Aridity (AI)								
Cameroon (N = 412)								
$\widehat{\boldsymbol{\beta}}_{\mathrm{AI}}$	-0.5312***	-0.3592***	-0.9568*	-0.4879***	-1.3263***	-0.4545***	-1.2055***	-0.0675
SE	(0.0007)	(0.0008)	(0.0061)	(0.0008)	(0.0006)	(0.0007)	(0.0005)	(0.0005)
R^2	0.343	0.478	0.363	0.535	0.168	0.423	0.086	0.359
Ethiopia (N = 557)								
$\widehat{\boldsymbol{\beta}}_{\mathrm{AI}}$	-0.3235**	-0.231*	0.6872	-0.123	0.7752	-0.4135**	0.9753	-0.6037**
SE	(0.0013)	(0.0012)	(0.0032)	(0.0011)	(0.0034)	(0.0010)	(0.0028)	(0.0008)
R^2	0.019	0.586	0.054	0.630	0.073	0.646	0.078	0.605
Guinea (N = 311)								
$\widehat{\boldsymbol{\beta}}_{\mathrm{AI}}$	-1.314***	-0.7753***	-2.2237***	-0.8603***	-2.0488***	-0.7068*	-2.0119***	-0.4261
SE	(0.0018)	(0.0014)	(0.0016)	(0.0009)	(0.0010)	(0.0007)	(0.0009)	(0.0008)
R^2	0.105	0.517	0.116	0.565	0.056	0.476	0.065	0.367
Nigeria (N = 1,247)								
$\widehat{\boldsymbol{\beta}}_{\mathrm{AI}}$	-1.0203***	-0.4557***	-1.203***	-0.388***	-1.0467***	-0.228***	-0.6501***	0.9868***
SE	(0.0007)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0007)	(0.0004)	(0.0005)
R^2	0.434	0.689	0.421	0.732	0.301	0.647	0.084	0.466
Panel B - Temperature (LST)								
Cameroon (N = 412)								
$\widehat{\boldsymbol{\beta}}_{\mathrm{LST}}$	-0.6541***	-1.3285****	-1.0452***	-1.0449***	0.6926	-0.1033	2.1599**	1.0301*
SE	(0.0074)	(0.0044)	(0.0052)	(0.0047)	(0.0056)	(0.0036)	(0.0045)	(0.0025)
R^2	0.326	0.502	0.294	0.500	0.217	0.409	0.162	0.362
Ethiopia (N = 557)								
$\widehat{\boldsymbol{\beta}}_{\mathrm{LST}}$	-0.6201***	-0.7871***	-0.6029***	-0.5641**	-0.6371***	-0.9059***	-0.5224*	-0.849**
SE	(0.0030)	(0.0037)	(0.0027)	(0.0034)	(0.0029)	(0.0033)	(0.0020)	(0.0025)
R^2	0.104	0.573	0.108	0.609	0.098	0.615	0.090	0.602
Guinea (N = 311)								
$\widehat{\boldsymbol{\beta}}_{\mathrm{LST}}$	-0.8968	-1.7958**	2.7392*	-0.7061	5.5501**	3.6228**	4.8872**	2.4551
SE	(0.0126)	(0.0102)	(0.0095)	(0.0079)	(0.0062)	(0.0048)	(0.0046)	(0.0045)
R^2	0.038	0.523	0.057	0.638	0.059	0.557	0.050	0.396
Nigeria (N = 1,247)								
$\widehat{\boldsymbol{\beta}}_{\mathrm{LST}}$	-2.9979***	-1.3469***	-3.2669***	-1.2686***	-2.761***	-0.6573**	-1.2068**	3.6712***
SE	(0.0050)	(0.0049)	(0.0055)	(0.0049)	(0.0064)	(0.0055)	(0.0039)	(0.0040)
R^2	0.230	0.697	0.205	0.716	0.141	0.628	0.010	0.469
Full controls	No	Yes		No	No	Yes	No	Yes

(1) Non-parametric local linear regression. Kernels: for continuous variables (Epanechnikov) and for discrete variables (Liracine). Bandwidths are obtained by cross-validation. (2) Bootstrapped standard errors (SE) in parenthesis using 400 repetitions. (3) Estimates are presented in terms of elasticities: $[\partial \mathbf{y}/\partial \mathbf{x}_k)] \times [\bar{\mathbf{x}}_k/\bar{\mathbf{y}}]$. (4) Null models only include the specific climate covariate, and the full models include the set of controls of Table 2, Panel B. (5) Significance levels: * p $\leq$ 0.10, ** p $\leq$ 0.05, ***p $\leq$ 0.01.

Table 4: Non-parametric kernel estimates (elasticities), null and full models. Climate covariates: rainfall and EVI rate

	Primary		Lower secondary		Upper secondary		Tertiary	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Rainfall								
Cameroon (N = 412)								
$\widehat{\beta}_{\text{rainfall}}$	0.4617***	0.2512***	-0.0459	0.4055***	1.1505***	0.3635**	0.6681***	-0.1687
SE	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	0.419	0.428	0.336	0.519	0.209	0.417	0.104	0.360
Ethiopia (N = 557)								
$\widehat{\beta}_{\text{rainfall}}$	0.1262**	0.0869**	0.1699*	0.0329	0.2237**	0.0914*	0.2054	0.1229
SE	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	0.031	0.559	0.038	0.618	0.045	0.638	0.042	0.593
Guinea (N = 311)								
$\widehat{\beta}_{\text{rainfall}}$	0.335	0.4274***	0.4481	0.5721**	0.0342	0.1913	0.5673	0.0134
SE	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	0.072	0.506	0.097	0.545	0.070	0.465	0.034	0.360
Nigeria (N = 1,247)								
$\widehat{\beta}_{\text{rainfall}}$	0.7764***	0.3093***	0.9222***	0.2712***	0.9091***	0.1782***	0.4778***	-0.3601***
SE	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	0.420	0.690	0.395	0.710	0.285	0.630	0.071	0.485
Panel B - EVI rate								
Cameroon (N = 412)								
$\widehat{\beta}_{\text{EVI-rate}}$	-0.1433***	-0.0753***	-0.2925***	-0.1128***	-0.4211***	-0.2402***	-0.5759***	-0.2516***
SE	(0.0018)	(0.0012)	(0.0019)	(0.0016)	(0.0019)	(0.0013)	(0.0012)	(0.0011)
R^2	0.201	0.399	0.222	0.495	0.248	0.446	0.211	0.389
Ethiopia (N = 557)								
$\widehat{\beta}_{\text{EVI-rate}}$	-0.0703*	0.0339	-0.0521	0.0631	-0.1297**	-0.0156	-0.2217**	-0.0489
SE	(0.0017)	(0.0011)	(0.0018)	(0.0011)	(0.0017)	(0.0011)	(0.0013)	(0.0009)
R^2	0.063	0.468	0.083	0.560	0.094	0.549	0.095	0.539
Guinea (N = 311)								
$\widehat{\beta}_{\text{EVI-rate}}$	-0.5023***	-0.1142	-0.8344***	-0.2449*	-0.799***	-0.1219	-0.7059**	-0.0501
SE	(0.0028)	(0.0024)	(0.0025)	(0.0018)	(0.0015)	(0.0012)	(0.0017)	(0.0013)
R^2	0.163	0.575	0.204	0.603	0.125	0.565	0.127	0.382
Nigeria (N = 1,247)								
$\widehat{\beta}_{\text{EVI-rate}}$	-0.2719***	-0.0605***	-0.3423***	-0.0664***	-0.4073***	-0.0792***	-0.3525***	0.0913*
SE	(0.0010)	(0.0009)	(0.0010)	(0.0008)	(0.0012)	(0.0009)	(0.0009)	(0.0008)
R^2	0.206	0.486	0.222	0.562	0.204	0.539	0.046	0.315
Full controls	No	Yes		No	No	Yes	No	Yes

(1) Non-parametric local linear regression. Kernels: for continuous variables (Epanechnikov) and for discrete variables (Liracine). Bandwidths are obtained by cross-validation. (2) Bootstrapped standard errors (SE) in parentheses using 400 repetitions. (3) Estimates are presented in terms of elasticities: $[\partial \mathbf{y}/\partial \mathbf{x}_k)] \times [\bar{\mathbf{x}}_k/\bar{\mathbf{y}}]$. (4) Null models only include the specific climate covariate, and full models include the set of controls of Table 2, Panel B. (5) Significance levels: * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$.

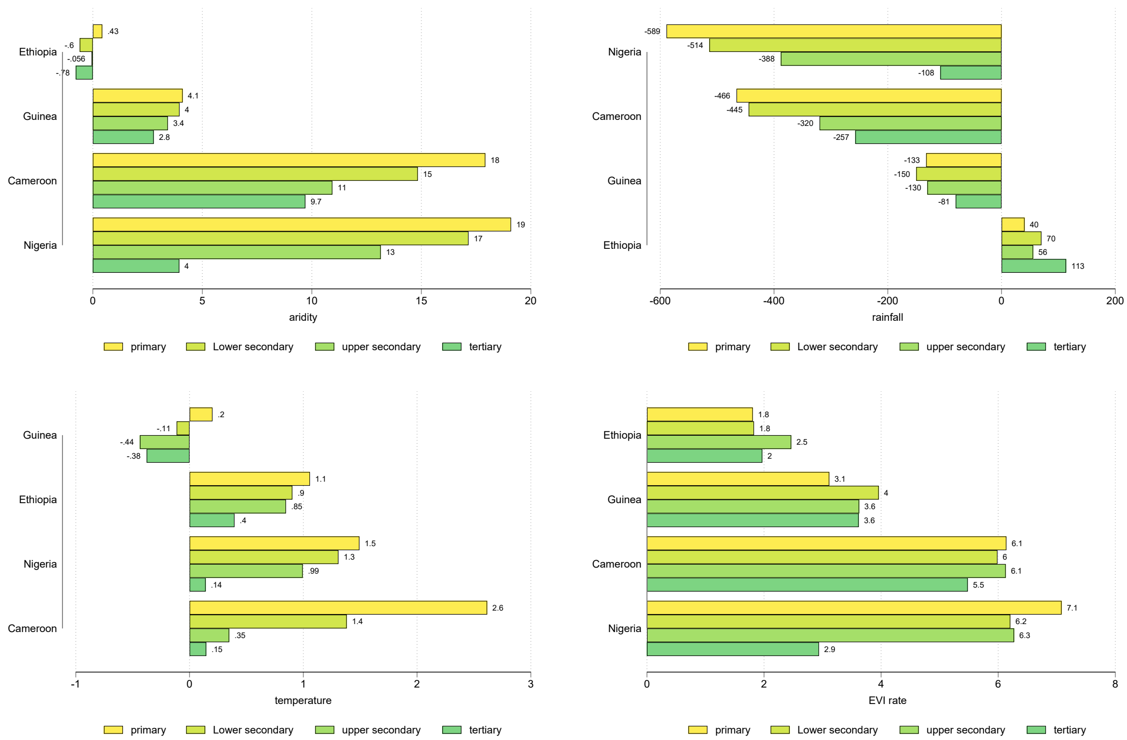


Figure A1: Climate variables gaps by high-low values of communities' completion rates of each country

Notes: (1) High group consists of communities whose completion rate is above the country mean of the completion rate, and low group if equal or below the mean.

Table B1: OLS estimates, null and full models. Climate covariates: aridity and temperature

	Primary		Lower secondary		Upper secondary		Tertiary	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Aridity								
Cameroon (N = 412)								
coefficient	-0.0105***	-0.0065***	-0.0113***	-0.0061***	-0.0065***	-0.0027***	-0.0033***	-0.0006
SE	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
R^2	0.3302	0.4932	0.2797	0.5401	0.1633	0.4087	0.0817	0.3394
Ethiopia (N = 557)								
coefficient	-0.0024*	-0.0025**	-0.0004	-0.0012	-0.0011	-0.0025**	-0.0001	-0.0019**
SE	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.0067	0.4209	0.0001	0.5210	0.0014	0.5358	0.0000	0.4957
Guinea (N = 311)								
coefficient	-0.0107***	-0.0065***	-0.0078***	-0.0035***	-0.0033***	-0.0012*	-0.0027***	-0.0005
SE	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.0894	0.5088	0.0830	0.5450	0.0403	0.3790	0.0296	0.3238
Nigeria (N = 1,247)								
coefficient	-0.0111***	-0.0057***	-0.0116***	-0.0042***	-0.0096***	-0.0015**	-0.0016***	0.0036***
SE	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
R^2	0.3149	0.5301	0.3074	0.5849	0.2060	0.5476	0.0142	0.3358
Panel B - Temperature								
Cameroon (N = 412)								
coefficient	-0.0428***	-0.0429***	-0.0297***	-0.0236***	-0.0100***	-0.0036	-0.0026	0.0032
SE	(0.005)	(0.004)	(0.005)	(0.005)	(0.003)	(0.004)	(0.002)	(0.003)
R^2	0.1995	0.5122	0.0705	0.5056	0.0142	0.3891	0.0019	0.3393
Ethiopia (N = 557)								
coefficient	-0.0136***	-0.0194***	-0.0086***	-0.0103***	-0.0086***	-0.0140***	-0.0036*	-0.0071***
SE	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
R^2	0.0406	0.4454	0.0158	0.5281	0.0157	0.5453	0.0048	0.4970
Guinea (N = 311)								
coefficient	-0.0132	-0.0278***	0.0158	-0.0017	0.0149**	0.0101**	0.0100**	0.0043
SE	(0.012)	(0.010)	(0.010)	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)
R^2	0.0041	0.4939	0.0100	0.5318	0.0238	0.3821	0.0120	0.3243
Nigeria (N = 1,247)								
coefficient	-0.0891***	-0.0451***	-0.0848***	-0.0316***	-0.0689***	-0.0137***	-0.0064*	0.0254***
SE	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)
R^2	0.2056	0.5316	0.1652	0.5836	0.1079	0.5484	0.0023	0.3309
Full controls	No	Yes	No	Yes	No	Yes	No	Yes

(1) Null models only include the specific climate covariate, and full models include the set of controls of Table 2, Panel B. (2) Robust standard errors in parentheses. (3) Significance levels: * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$.

Table B2: OLS estimates, null and full models. Climate covariates: rainfall and EVI rate

	Primary		Lower secondary		Upper secondary		Tertiary	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Rainfall								
Cameroon (N = 412)								
coefficient	0.4249***	1.2071***	-0.0297***	-0.0236***	0.0002***	0.0001***	0.0001***	-0.0000
SE	(0.040)	(0.125)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.1943	0.4426	0.0705	0.5056	0.1115	0.4005	0.0372	0.3379
Ethiopia (N = 557)								
coefficient	0.5127***	0.7442***	-0.0086***	-0.0103***	-0.0000	0.0000**	-0.0000*	0.0000*
SE	(0.029)	(0.097)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.0014	0.4224	0.0158	0.5281	0.0013	0.5333	0.0049	0.4926
Guinea (N = 311)								
coefficient	0.1331**	0.8342***	0.0158	-0.0017	0.0000*	0.0000	0.0000	0.0000
SE	(0.063)	(0.154)	(0.010)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.0283	0.4953	0.0100	0.5318	0.0168	0.3781	0.0079	0.3230
Nigeria (N = 1,247)								
coefficient	0.3372***	0.7539***	-0.0848***	-0.0316***	0.0003***	0.0000**	0.0000***	-0.0001***
SE	(0.025)	(0.050)	(0.006)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.2942	0.5375	0.1652	0.5836	0.1687	0.5484	0.0086	0.3269
Panel B - EVI rate								
Cameroon (N = 412)								
coefficient	-0.0136***	-0.0063***	-0.0164***	-0.0066***	-0.0127***	-0.0064***	-0.0077***	-0.0037***
SE	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.1568	0.4275	0.1683	0.5034	0.1779	0.4256	0.1265	0.3618
Ethiopia (N = 557)								
coefficient	-0.0043***	0.0008	-0.0037***	0.0010	-0.0055***	-0.0009	-0.0032***	-0.0005
SE	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.0176	0.4158	0.0130	0.5205	0.0275	0.5308	0.0163	0.4907
Guinea (N = 311)								
coefficient	-0.0155***	-0.0033	-0.0137***	-0.0033*	-0.0063***	-0.0008	-0.0055***	-0.0006
SE	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.1018	0.4862	0.1366	0.5380	0.0779	0.3762	0.0647	0.3236
Nigeria (N = 1,247)								
coefficient	-0.0156***	-0.0041***	-0.0170***	-0.0037***	-0.0164***	-0.0035***	-0.0045***	0.0013**
SE	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.1707	0.5062	0.1805	0.5751	0.1644	0.5512	0.0305	0.3094
Full controls	No	Yes	No	Yes	No	Yes	No	Yes

(1) Null models only include the specific climate covariate, and full models include the set of controls of Table 2, Panel B. (2) Robust standard errors in parentheses. (3) Significance levels: * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$.

Appendix C–Climate impacts degree of heterogeneity within each country and by the prevalence of communities' completion rates

Results of Tables 3 and 4 are average estimates $\left(\sum_{i=1}^{N} \widehat{m}'(\mathbf{x}_i)\right)$. A more nuanced understanding of how each climate variable impacts on educational attainment can be gained by plotting each community estimated partial derivative, showing the degree of within-country heterogeneity of the climate-completion rates associations. Here, we discuss temperature-related covariates.

Figure C1 displays these densities. In the first plot for aridity, we can see that, for primary and lower secondary completion, the range of estimates for Guinea and Cameroon are quite narrow, with a wider heterogeneity and more spread of AI estimates in the case of Ethiopia and Nigeria (which is even larger). For upper secondary we find a similar pattern, though AI densities tend to overlap around mean effects. The densities of communities' derivatives for temperature (displayed in second bottom plot) markedly show that Nigeria's relationships of LST with primary and lower secondary completion rates are well below the other countries, while for upper secondary its heterogeneity increases and there is a shift of Ethiopia's impacts (below Cameroon), more aligned with Nigeria's derivatives. Again, the shape of distributions of specific impacts at each country's communities resembles the ones for AI. Overall, we find that impacts tend to be more homogeneous across Cameroon and Guinea and there are more heterogeneous in the case of Ethiopia and (largely) Nigeria.

Furthermore, a way to look deeper into the roots of heterogeneity behind effects of climate on communities' educational attainment is to simultaneously compare communities' specific impacts and community completion rates values. In other words, to assess whether or not there are higher (lower) observed effects of climate covariates in communities with weaker (stronger) educational performance.

In Figure C2 we assess this. For aridity and temperature, plots show a clear upward tendency for Ethiopia and Nigeria; hence, communities mostly negative affected by aridity in terms of primary and lower secondary completion rates are those with low attainment. Whereas, on the contrary, for Cameroon and Guinea the fitted lines are flat (primary) or point downwards (lower secondary). For EVI rate, we find decreasing tendencies (in Cameroon and Nigeria), therefore suggesting that communities with larger attainment have also larger (in absolute terms) impacts driven by alterations on their EVI rates.

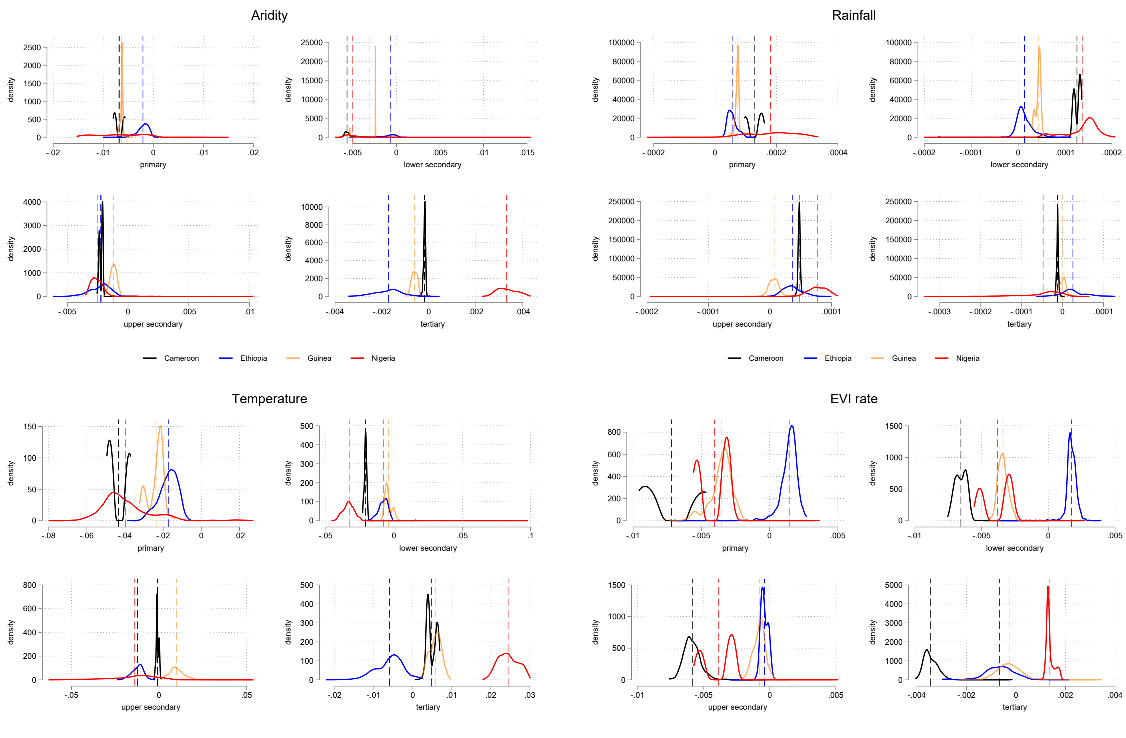


Figure C1: Climate variables non-parametric communities estimates (derivatives) densities

Notes: (1) Kernel densities of country average derivatives are shown with dotted vertical lines.

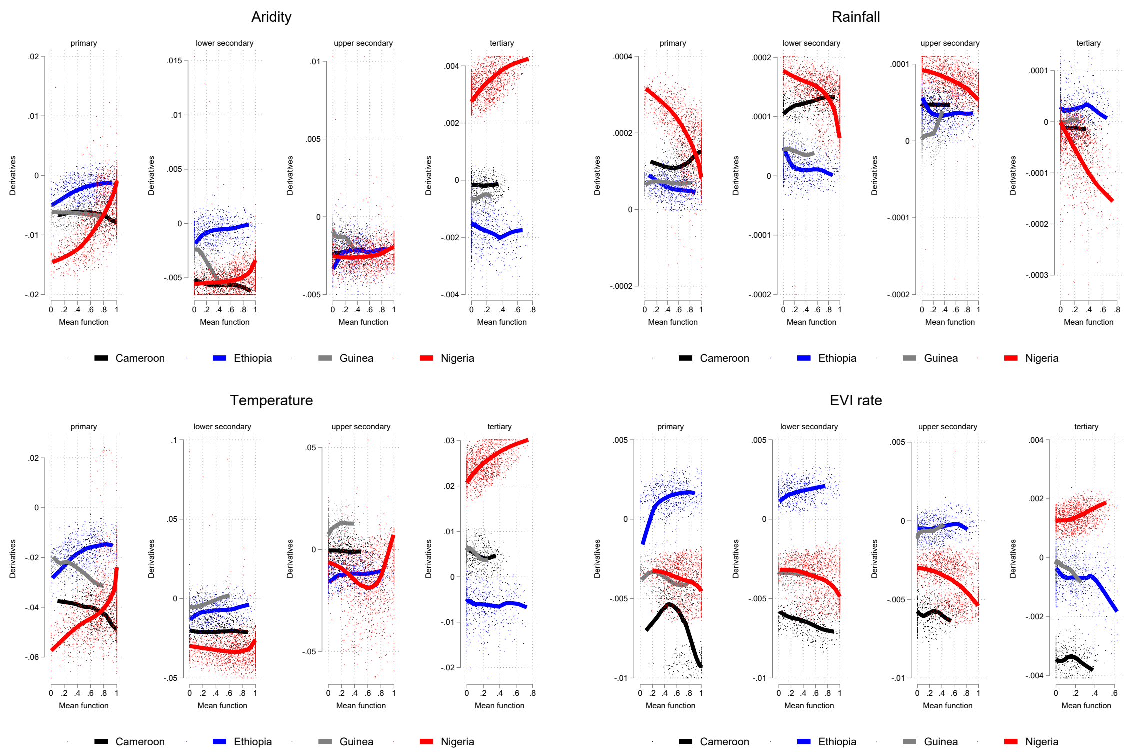


Figure C2: Communities estimated mean functions (completion rates) and derivatives of climate variables

Notes: (1) Scattered plots of estimated communities derivatives and values of the estimated rates (mean function) for communities. (2) Thick lines shown are local linear regressions between them.

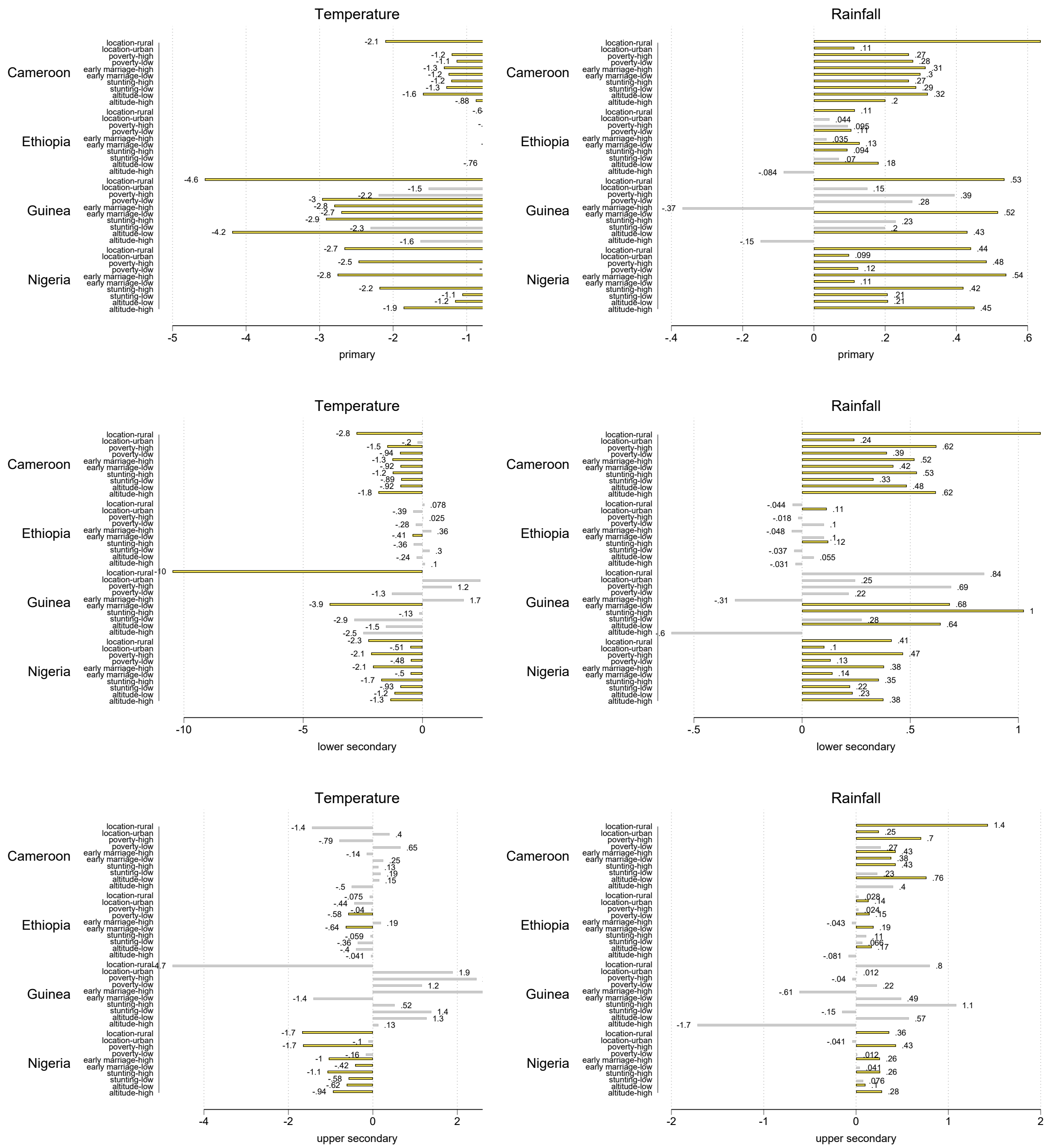


Figure D1: Estimates (elasticities) for climate variables temperature and rainfall by community's disadvantages and location

Notes: (1) Light colour bar denote non-statistically significant estimates.

Table E1: Temperature and rainfall forecast based on different emission scenarios

Country	Emission scenario	2015	2034	2035	2054	Period 2015-2034	Period 2035-2054
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A- temperature							
Cameroon	low	25.26	25.86	25.76	26.19	0.6	0.43
Ethiopia	low	23.83	24.26	24.42	24.56	0.43	0.14
Guinea	low	26.71	27.4	27.33	27.65	0.69	0.32
Nigeria	low	27.66	28.3	28.32	28.59	0.64	0.27
Cameroon	medium	25.35	25.72	25.8	26.46	0.37	0.66
Ethiopia	medium	23.87	24.29	24.36	24.87	0.42	0.51
Guinea	medium	26.8	27.24	27.37	27.98	0.44	0.61
Nigeria	medium	27.7	28.13	28.28	28.91	0.43	0.63
Cameroon	high	25.34	25.77	26	26.89	0.43	0.89
Ethiopia	high	23.9	24.34	24.48	25.5	0.44	1.02
Guinea	high	26.78	27.38	27.57	28.46	0.6	0.89
Nigeria	high	27.72	28.11	28.37	29.18	0.39	0.81
Panel B - rainfall							
Cameroon	low	1830.61	1881.35	1867.63	1867.65	50.74	0.02
Ethiopia	low	1039.62	1103.21	1050.21	1103.71	63.59	53.5
Guinea	low	1800.59	1826.11	1775.47	1807.86	25.52	32.39
Nigeria	low	1127.29	1159.13	1141.26	1156.96	31.84	15.7
Cameroon	medium	1817.99	1850.36	1883.61	1857.26	32.37	-26.35
Ethiopia	medium	1032.5	1058.65	1074.37	1086.74	26.15	12.37
Guinea	medium	1768.57	1874.58	1864.12	1775.23	106.01	-88.89
Nigeria	medium	1123.56	1153.99	1183.99	1161.23	30.43	-22.76
Cameroon	high	1824.07	1890.81	1912.39	1891.18	66.74	-21.21
Ethiopia	high	1045.41	1118.36	1096.58	1129.31	72.95	32.73
Guinea	high	1755.65	1828.85	1827.8	1729.94	73.2	-97.86
Nigeria	high	1124.8	1219.13	1189.35	1205.44	94.33	16.09

(1) Data source for climate variables forecast are from: WB-climate-change. (2) Temperature is the average mean surface air temperature over the aggregation period, and rainfall is aggregated accumulated precipitation (in mm). (3) Emissions scenarios are based on the Representative Concentration Pathway (RCP), a greenhouse concentration trajectory, measuring the total radiative forcing (cumulative measure of GHG emissions from all sources) pathway and level by 2100. Low (RCP2.6), medium (RCP4.5) and high (RCP8.5). For details, see: Robinson (2020).

Table E2: Contrast on predictions of completion rates by scenarios for temperature and rainfall changes

	Emissions (period: 2015-2034)			Emissions (period: 2035-2054)		
	Low	Medium	High	Low	Medium	High
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Temperature						
Primary						
Cameroon	-0.0261***	-0.0161***	-0.0187***	-0.0187***	-0.0288***	-0.0388***
Ethiopia	-0.006***	-0.0059***	-0.0062***	-0.0021***	-0.0077***	-0.0164***
Guinea	-0.0194***	-0.0123***	-0.0169***	-0.0096***	-0.0188***	-0.0305**
Nigeria	-0.0274	-0.02	-0.0186	-0.0148	-0.0236***	-0.0358**
Lower secondary						
Cameroon	-0.0127***	-0.0078***	-0.0091***	-0.0091***	-0.0140***	-0.0190***
Ethiopia	-0.0008	-0.0008	-0.0009	-0.0003	-0.0015	-0.0036
Guinea	0.0197	0.0122	0.0173	0.0095	0.0113	0.0102
Nigeria	-0.011	-0.0044	-0.0041	-0.0049	-0.0037	0.0424*
Upper secondary						
Cameroon	-0.0008	-0.0004	-0.0005	-0.0006	-0.001	-0.0014
Ethiopia	-0.0040***	-0.0039***	-0.0041***	-0.0014***	-0.0051***	-0.0109***
Guinea	-0.0061	-0.002	-0.0054	-0.0084	-0.01	-0.0376
Nigeria	0.0017	-0.0015	-0.0056	0.0047	0.0123	0.0095
Panel B - Rainfall						
Primary						
Cameroon	0.0063***	0.0040***	0.0083***	0.0000***	-0.0032***	-0.0026***
Ethiopia	0.0026*	0.0011*	0.0029*	0.0021*	0.0005*	0.0013*
Guinea	0.0018***	0.0078***	0.0054***	0.0023***	-0.0065***	-0.0072***
Nigeria	0.0063***	0.0061***	0.0181***	0.0030***	-0.0043***	0.0029***
Lower secondary						
Cameroon	0.0064***	0.0041***	0.0084***	0.0000***	-0.0033***	-0.0026***
Ethiopia	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000
Guinea	0.0010*	0.0042*	0.0029*	0.0012*	-0.0035*	-0.0038*
Nigeria	0.0045***	0.0044***	0.0134***	0.0022***	-0.0032***	0.0022***
Upper secondary						
Cameroon	0.0023**	0.0015**	0.0031**	0.0000**	-0.0012**	-0.0009**
Ethiopia	0.0016	0.0007	0.0018	0.0013	0.0003	0.0008
Guinea	-0.0002	-0.0005	-0.0005	-0.0002	0.0005	0.0007
Nigeria	0.0026***	0.0025***	0.0078***	0.0013***	-0.0018***	0.0013***

(1) Data source for climate variables forecast are from: WB-climate-change and emissions scenarios are based on Representative Concentration Pathway (RCP), a greenhouse concentration trajectory, measuring the total radiative forcing (cumulative measure of GHG emissions from all sources) pathway and level by 2100. Low (RCP2.6), medium (RCP4.5) and high (RCP8.5) (see: Robinson (2020)). (2) Non-parametric local linear regression. Kernels: for continuous variables (Epanechnikov) and for discrete variables (Liracine). Bandwidths are obtained by cross-validation, and statistical significance is based bootstrapped standard errors using 400 repetitions. (3) Models control for the array of covariates of Table 2, Panel B. (4) Significance levels: * p $\leq$ 0.10, ** p $\leq$ 0.05, ***p $\leq$ 0.01.