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Does the Environment Matter for Poverty Reduction?

The Role of Soil Fertility and Vegetation Vigor in Poverty Reduction

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Abstract

The debate on the environment-poverty nexus is inconclusive, with past research unable to identify the causal dynamics. This paper uses a unique global panel data set that links (survey and census derived) poverty data to measures of environmental quality at the subnational level. The analysis uses vegetation vigor as a proxy for above-ground environmental quality and soil fertility as proxy for below-ground environmental quality. Rainfall is used to account for endogeneity issues in an instrumental variable approach. This is the first global study using quasi-experimental methods to uncover to what degree environmental quality matters for poverty reduction. The paper draws three main conclusions. (1) The environment matters for poverty reduction. The panel regression suggests that a 10 percent increase in vegetation vigor is associated with a poverty headcount ratio reduction of nearly 0.7 percentage point in rural areas, and 1 percentage point in Sub-Saharan Africa. A 10 percent increase in soil quality leads to a roughly 2 percentage point decrease in poverty rates in rural areas and in Sub-Saharan Africa. (2) The effects of environmental quality on poverty are stronger than its effects on average income, suggesting that the poor benefit disproportionately from environmental quality. (3) In situ environmental quality improvements are pro-poor, in contrast to urbanization. Although urbanization has highly significant and sizable correlations with GDP per capita, it is not significantly correlated with poverty reduction.

This paper is a product of the Environment and Natural Resources Global Practice . It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/research. The authors may be contacted at mheger1@worldbank.org.

Does the Environment Matter for Poverty Reduction?

The Role of Soil Fertility and Vegetation Vigor in Poverty Reduction

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1. Introduction

The world had 1 billion fewer people living in poverty in 2013 compared to 1990 (measured in monetary terms; World Bank, 2016). While poverty remains unacceptably high (using a poverty line of 1.90$/day, 10.7 percent of the world population are still poor[1]) and challenges remain, these aggregate numbers suggest that significant progress has been made in the past decades. What factors are responsible for the observed decline in poverty headcounts? Human capital formation, economic growth, trade, and institutional strengthening have been suggested as important drivers. Much ink has been spilled on these human development and macro-economic drivers of poverty reduction (see e.g. Gennaioli et al, 2015). Less emphasis has been placed on the role of the environment in poverty reduction.

Most of the world's poor live in rural areas and depend heavily on agricultural or environmental income to make a living (Barbier and Hochard, 2016; Olinto et al., 2013). This includes timber and non-timber forest products; both formally and informally (for an overview, see e.g. Angelsen and Wunder, 2003). Environmental quality is important for both agricultural and environmental income, as healthier ecosystems increase agricultural and environmental yields.

Early empirical studies have identified declining soil fertility and poverty to be related at an aggregate level (Krishna et al., 2006; Barrett & Swallow, 2006). More recently, Barrett and Bevis (2016) find that national GDP per capita is positively correlated with soil nutrient balances in 36 Sub-Saharan African countries for which data are available. Barbier & Hochard (2016) find that around a quarter of people living in low-income countries reside on severely degraded land and that a lower share of people on degraded lands is associated with higher economic growth as well as lower poverty. While prior studies all point towards positive relationships, the evidence cannot be interpreted as causal.

The theoretical channels behind the suggested positive relationship are rather intuitive. The most important productive asset determining land productivity for the rural poor is soil, which grows the crops and delivers the ecosystem services that allow for either selling in the market or consumption. There is extensive literature on the relationship between agricultural productivity and soil fertility. For instance, the water storage capability of soil is an important determinant of plant growth (Wong and Asseng, 2006). Louwagie et al. (2009) find that shallow soils, stoniness or chemical issues such as salinity or acidity are negatively correlated with crop yields. There is also a third channel: The topographical conditions of the soil (elevation, steepness, etc.) affect soil erosion and accessibility by humans and machinery (e.g. Duran Zuazo, 2008). For an overview, see Mueller et al. (2010). Thus, we conclude that locations with good soils are likely to have high agricultural potential and thus have absolute advantage in producing high-value perishable vegetables and other crops.

On the other hand, poor soils may have negative implications for poverty reduction through three mechanisms (Barrett and Bevis, 2016): First, poor and degraded soils have negative effects on agricultural and environmental income. Reduced income on a micro level has not only contemporaneous negative effects on income and poverty on the macro level, but also makes it harder for a household to access nutrients to boost soil productivity in the future. Such links can be self-reinforcing: poor soil constrains capital accumulation and low capital accumulation inhibits investments in improving soils (Eswaran et al., 1997; Barrett & Bevis, 2015).

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[1] Calculated using the World Bank's WDI data set for the year 2016.

Second, poor and degraded soils are characterized by soil micronutrient deficiencies, which in turn can result in dietary mineral deficiencies affecting human health negatively (Barrett & Bevis, 2015). Reduced health outcomes in turn have negative consequences for productivity and asset accumulation (which in turn could have been leveraged for increased income and consumption allowing for an escape from poverty). This relationship may exist directly for households who self-consume their agricultural output, but also indirectly for low income households who purchase food on the market.

Third, poor soils offer weak insurance of farm assets from risk. Higher levels of risk – either from rainfall, pests, or market prices – often inhibit poor households from investing in higher-productivity livelihoods (Carter & Barrett, 2006). Poor soils offer weak insurance, and even exacerbate this low-risk, low-investment trap. Weather shocks such as droughts occur more often in soils with limited water-holding capacity (Garrity et al., 2010). Furthermore, pests and weeds, which decimate cropland in Sub-Saharan Africa, are more common in low-nutrient and degraded soils (Ayongwa et al., 2011). While the connection between soils and agricultural risk is not well explored, it is likely that good soils reduce the vulnerability to weather shocks such as droughts and promote investment in higher-productivity livelihoods (Barrett & Bevis, 2015).

However, three recent empirical studies call into question the positive impact of environmental quality on poverty reduction. Okwi et al. (2007), using a spatial lag model, find that even if Kenya's soil was at the highest quality for Kenya's circumstances everywhere, it would only lead to a 1 percentage point decrease in the poverty rate.[2] Yamano and Kijima (2010) find that soil fertility only had a positive relationship with poverty in Kenya, but not in Uganda or Ethiopia. They also find that while soil fertility is positively related with crop-income, it is negatively related with non-crop income. Wantchekon & Stanig (2015) find a "curse of good soil" using geology and colonial infrastructure as instruments in a study of regional scope, arguing that good soil has negative causal effects on poverty reduction. They find that high quality soil was counter-productive for poverty reduction and constituted a curse for development. They conclude that more attention should be given to infrastructure and human capital formation, relative to the environment.

An additional issue is the possible two-way relationship between environmental quality and poverty. Environmental quality can influence poverty (reduction), but poverty (reduction) can also influence environmental quality (Barbier, 2010). In addition, many factors shape the poverty-environment nexus, including demography, culture, and institutions (Leach and Mearns, 1995). Due to potential simultaneity and intervening drivers, the causal effect of environmental quality on poverty reduction (and vice-versa) has been difficult to identify, with most of the literature describing correlations (Duraippah, 1998; Suich et al., 2015).

While notable exceptions exist (e.g. Alix-Garica et al., 2015), prior studies are location or country-specific, and do not inform on how the relationship differs by biome or geographic region. Despite these limitations, the body of evidence generally points towards positive relationships between environmental quality and poverty reduction (Sandker et al., 2012). In West Africa, Sedda et al. (2015) find negative co-movements between multidimensional poverty measures and vegetation vigor (as proxied by NDVI); meaning more poverty was found in places with less vegetation vigor. However, these results are merely

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[2] At the same time, however, they also found that poverty rates of Western Province would be lowered by almost 10 percentage points if soil fertility were improved from poor to good in locations that have poor soils.

correlative. Suich et al. (2015) review the evidence of research into the relationship between ecosystem services and poverty alleviation and conclude that "a considerable gap remains in understanding the links between ecosystem services and poverty, how change occurs, and how pathways out of poverty may be achieved based on the sustainable utilisation of ecosystem services."

The main contribution of this paper is to provide causal estimates of the impact of environmental quality on poverty reduction. In addition, insights into the importance of environment relative to other factors such as infrastructure development or urbanization will be discussed. In particular, several contributions to existing literature are offered: (a) We use a global subnational data set, (b) we use monetary poverty rates that emerge from survey and census estimations rather than highly modeled measures that may induce multicollinearity with the explanatory variables, (c) we use not one, but three different measures of environmental quality, one for soil fertility and two for vegetation vigor, and (d) we do not draw evidence from cross-sectional evidence only (which likely suffers from omitted variable bias), but also exploit variance over time by implementing a panel fixed effects model. With these methodological refinements, we obtain results that underline the importance of soil and vegetation quality in poverty reduction.

2. Empirical Strategy

a. Data

We create a unique geospatial data set linking environment and natural resource measures to poverty and other human development indicators at the subnational level. The geographical unit of analysis of the data set is the administrative unit 1 level, commonly referred to as "province" level, because this is the finest-grained level at which the poverty data set is available.[3] This rich data set allows us to specify a range of different models to examine the relationship of environmental quality (and degradation) and poverty.

Poverty and GDP per capita (outcome measures)

The measurement of poverty we use is the headcount ratio of people falling below $1.90 per day. Even though this is a narrow definition of poverty,[4] it is the official international poverty line and allows us to draw from country poverty maps that the World Bank has helped produce over the last 30 years. We "stitch together" a global map of sub-national poverty measures and pool several years of observations for several countries, creating an unbalanced poverty panel (see table 6 for the detailed descriptive statistics on the poverty observation frequency by country). For the panel specifications, we use the countries in table 6 that have repeated poverty observations. For the cross-sectional specification, we use the latest available observation per country.

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[3] Certain poverty maps were available at the administrative unit 2 level, commonly referred to as the "district" level. However, time-series data– necessary for furnishing a panel data set – were only available at the province level.

[4] There are other very useful measures of poverty such as the Multidimensional Poverty Indicator (MPI), which is also available regionally (see Alkire et al, 2015).

Gross Domestic Product per capita[5] is our second outcome indicator. We compute this variable using GDP data from Gennaioli et al. (2015) and population data from the Gridded Population of the World (GPW) data set (CIESIN, 2016).[6]

Environmental quality – soil fertility and vegetation vigor (explanatory measures)

We use three different measurements to proxy environmental quality. Two measure vegetation vigor, and one measures soil fertility:

a) Net Primary Productivity (NPP), as our first measure of vegetation vigor, and
b) the Normalized Difference Vegetation Index (NDVI), as our second measure of vegetation vigor for a robustness specification.
c) topsoil carbon content (content of carbon in the 30cm of soil layer from the top), as a measure of soil fertility

NPP is the rate at which an ecosystem accumulates biomass. It measures how much carbon dioxide plants take in during photosynthesis minus how much carbon dioxide is released during respiration. Hence, it is an indicator for how much of the absorbed carbon becomes part of leaves, roots, stalks or tree trunks. NPP data are captured via the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Terra and Aqua satellites. The data are provided in grid format. We use the average value per province in our computations.

NDVI is a satellite image–based measurement of environmental quality. It measures the "greenness", i.e., the relative density and health of vegetation of the planet's surface. This index shows where and how much green leaf vegetation was growing during a certain period. It uses red and near infrared light spectrum data captured by NASA's Terra satellite to compute a monthly indicator of vegetation quality for about 10km² cells. Again, we use the province averages.[7] Generally, it has been found that NPP is a better measure of biomass productivity and biodiversity (see for instance Xu et al., 2012; Phillips et al., 2008) which is why we use NPP for our main specifications and NDVI data in a robustness check.

Soil carbon content is an important measure of plant productivity. It is the percentage of carbon contained in the organic matter in the soil. It is the result of, e.g., decomposing plant and animal residues, root exudates or both living and dead microorganisms. Topsoil carbon content refers to the organic carbon measured in the top 30cm of the soil. It is a major determinant of plant growth and agricultural productivity (see for instance Lal, 2004). Hiederer & Kochy (2012) use the Harmonized World Soil Database (HWSD) to compute global soil organic carbon estimates on a subnational level. The Joint Research Centre

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[5] Strictly speaking, we measure GRP (Gross Regional Product) rather than GDP (Gross Domestic Product) since our unit of analysis is not the nation state required, but rather the province within a nation-state. However, because it is more conventional to refer to such economic activity as GDP, we stick to this nomenclature.
[6] It is noteworthy that even though GPW data are highly modeled, using for example land use and night lights data for micro-simulated observations at the high-resolution grid-cell level, aggregating the data up to the aggregate admin1 level should retrieve the original data, which are solely based on survey- and census-based information.
[7] Both the NPP and NDVI data sets can be obtained via the NASA MODIS Terra website under https://modis.gsfc.nasa.gov/ .

of the European Commission provides this georeferenced data set including both topsoil and subsoil carbon measurements via the European Soil Data Centre (ESDAC) upon request.

These indicators of environmental quality are used together with a set of common control variables to model two dependent variables, namely poverty and GDP per capita.

Instrumental variable (measure that delivers exogenous variation)

Mean average annual rainfall is employed as the instrument for annual changes in vegetation vigor (NPP & NDVI) and topsoil carbon. The data are sourced from the Climatic Research Unit in the National Center of Atmospheric Research (NCAR, 2017). The data set contains geographically gridded multiple weather time series from 1901 onwards. We use averages per year and province. A detailed discussion of the validity of using rainfall as an instrument is provided in the research design section.

Control variables

We use a variety of highly relevant control variables to isolate the effect of soil fertility and vegetation vigor on our dependent variables. This is particularly important in the cross-sectional specifications, as they do not have the luxury of province fixed effects. To capture the effect of different terrains, a topographic ruggedness index is employed. This index (see Nunn & Puga, 2012) is given by the square root of the sum of the squared differences in elevation between a given point on the earth surface and the eight points that lie 30 arc-seconds away in the eight major directions of the compass (North, North-East, East, etc.). Hence, the ruggedness index captures small-scale terrain irregularities based on elevation differences.

We also include land use categories (i.e. cropland, forest land, grass land, urban land or other) in the regression. Each *LU* indicator is measured as a share of the total geographic area. The original data are provided as global raster files with a spatial resolution of 300m by the Land Cover (LC) project of the Climate Change Initiative (CCI) led by the European Space Agency (ESA).

Soil type is a categorical variable that is used as a control variable in the cross-sectional specifications. There are 12 different categories of soil types: Alfisol, Andisol, Ardisol, Emtisol, Gelisol, Histosol, Inceptisol, Mollisol, Oxisol, Spodosol, Ulisol, and Vertisol. Additionally, where there is no soil, the area may be classified as either rock or sand. These soil categories are the result of millennia old geological and ecological processes and are a crucial determinant of soil quality. While a province may have several soil types, we assign the most prevalent soil type to each province. This classification using the aforementioned 12 + 2 soil types follows the soil classification system of the USDA system of soil taxonomy.

We include road density (mean kilometers of roads per province) and population as standard control variables. In contrast to similar works, we do not rely on population data that are modeled using land use or night light data (e.g. Amaral et al., 2005). Such data sets might raise severe endogeneity issues when acting as an explanatory variable for environmental quality. On our level of aggregation, we can rely on census and survey estimates, which greatly minimizes this risk of endogeneity. A detailed description of all variables, including data sources, can be found in table 1. For summary statistics, please refer to table 5 in the appendix.

Table 1: Variable Overview

Variable	Description	Units	Source
pov_hcr	Poverty Headcount Rate ($ 1.90 PPP)	%	WB
gdp	Gross Regional Product	USD	Gennaioli et al., 2015
npp	Net Primary Productivity	gC/m^2	NASA
ndvi	Normalized Difference Vegetation Index	Index (-1 to 1)	NASA
soil	Soil carbon content of the topsoil	tons per hectare	European Comission (JRC)
soil_type	Soil classification	1 -14 categories	NRDC
cropshare	Share of area cropland	%	CCI
forshare	Share of area forest	%	CCI
grassshare	Share of area grassland	%	CCI
urbanshare	Share of are urban	%	CCI
rugged	Ruggedness Index	Index (0 to 1,000,000)	Nunn & Puga, 2012
roaddensity	Road Density	mean of lengths in km per provicen	PBL GeoNetwork
precipitation	Mean precipitation	millimeters per month	CRU
population	Estimate of number of people	persons	GPW

b. Research design

Previous attempts to estimate the effect of environmental quality on poverty suffer from both omitted variables bias and simultaneity (as discussed above). Changes in environmental quality such as degradation of soil or degradation of vegetation vigor (through e.g. application of fertilizers) are endogenous explanatory variables, meaning that OLS would produce biased and inconsistent effect estimates and the coefficients would be correlated with the error term. To overcome these methodological challenges, we use simultaneous equation models with instrumental variables (see e.g. Greene, 2003 or Wooldridge, 2010).

For vegetation vigor, we specify a panel regression as we can exploit time series of NPP, NDVI, and rainfall. This allows us to create an unbalanced panel[8] as described in specification (1) below. In the case of below ground environmental quality, our measure of soil stored carbon is unfortunately time-invariant. Therefore, we specify a cross-sectional regression. Similarly, we have variation over time regarding the poverty headcount ratio, but we can only make use of our proxy of regional economic activity (GDP) measured at one point in time. To account for omitted variables that may drive the relationship between soil and poverty, we include a battery of control variables.

Starting with the panel specification, the reduced-form empirical models estimated are:

[8] It is unbalanced because of the poverty measure, where some countries have more years of subnational poverty observations than others. Moreover, the years for which subnational poverty measures are available vary from country to country. For details, see table 6 in the Appendix. Environmental variables are available for all years, with complete coverage.

Panel specification of the vegetation vigor determinants of poverty

The panel is specified as

$$\mathrm{Pov}_{i,t}=\alpha+\beta_1\mathrm{vegetation}_{i,t}+\beta_2\mathrm{LU}_{i,t}+\beta_3\mathrm{pop}_{i,t}+\mu_c+\theta_t+\mu_c{*}\,\theta_t+\epsilon_{i,t} \quad (1)$$

where *i* denotes province, *c* denotes country, and *t* denotes year. The dependent variable p*ov* measures the poverty headcount rate. The explanatory variables are vegetation quality (NPP or NDVI), a vector of the five land use categories, population, country fixed effects (μ_c), year fixed effects (θ_t) and country-specific time trends ($\mu_c * \theta_t$), as controlling for unobserved heterogeneity across countries and time is crucial. We use province-clustered standard errors, which account for within-country clustering of errors. NPP, NDVI, and population enter the model as log-transformed measures.

We are interested in the intensive margin of vegetation[9] and control for the extensive margin. An increase in vegetation vigor of a province may be driven by territorially expanding vegetation, or by intensifying the vegetation vigor within bounded areas. By controlling for land use change trends, we attempt to control for changing patterns in land uses (the extensive margin) and isolate the effect of intensifying the plant productivity in each land use (the intensive margin).

Model (1) identifies the potential effect of the environment exploiting variation over time. However, unlike NPP and NDVI data, subnational GDP data as well as soil fertility data are time-invariant, meaning that the effects of soil fertility on poverty and GDP can only be assessed using spatial variation. The same holds true for the effects of vegetation vigor on GDP.

Cross-sectional specifications (soil fertility as determinant of poverty & GDP)

$$Pov_i = \alpha + \beta_1 soil_i + \beta_2 LU_i + \beta_3 pop_i + \beta_4 rug_i + \beta_5 road_i + \mu_c + \theta_t + \epsilon_i \quad (2)$$

$$GDP_i = \alpha + \beta_1 soil_i + \beta_2 LU_i + \beta_3 pop_i + \beta_4 rug_i + \beta_5 road_i + \mu_c + \theta_t + \epsilon_i \quad (3)$$

where *GDP* measures GDP per capita and *soil* refers to the measure of soil quality. *LU* is a vector of shares of the five land use categories. *pop* refers to population, r*ug* refers to ruggedness and r*oad* refers to the road density of the province under consideration. μ_c are country fixed effects and θ_t are year dummies, capturing that our poverty observations are from different years.[10] ϵ_i refers to the error term. GDP per capita, population, ruggedness, road density and precipitation enter the model as log-transformed measures. Our cross-sectional specifications exploit within-country inter-province variation in

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[9] Changes in environmental quality, as proxied by changes in NPP or NDVI, can have many origins: they can be caused by climatic, ecological, geochemical, and human influences on the biosphere. In other words, the vegetation changes can be driven by bad land management, overexploitation of renewable resources such as forests, the destruction of biodiversity, droughts, and climate change (Nemani et al., 2003; Ainsworth et al., 2012). Here, we evaluate the effects of changes in environmental quality on the pace of poverty reduction, but without disentangling the origins of these changes, which may have come from any of these sources and are a subject for future scrutiny. Environmental changes driven by human behavior are the reason for endogeneity concerns, which we seek to overcome using an IV approach.

[10] To be clear, these are not time fixed effects, but rather controls for the different years of the poverty maps used (we always use the poverty measures for the last year available).

environmental quality in estimating potential effects on poverty rates (model 2) and on GDP per capita (model 3).

We use a suite of highly relevant and geospatially heterogenous control variables to reduce the problem of omitted variables bias (which was much less of an issue with the panel specification). For instance, controlling for land use categories is important, as another reason for why our environmental quality measures change is due to changing LU patterns rather than due to changes in vegetation quality driven by rainfall, which we are interested in isolating. To control for different levels of infrastructure across provinces, we use road density (average km of roads per province). Controlling for ruggedness is crucial, as terrain ruggedness may on the one hand be connected to higher levels of poverty due to difficulties regarding agricultural land use and on the other hand may even have positive correlations with poverty reduction due to historical reasons (see Nunn & Puga, 2012).

As a robustness check we also carry out spatial econometrics exercises. To minimize the risk of biased estimates due to neglected spatial dependence of our data and to gain additional robustness, we specify spatial Durbin models to account for both the possibility of spatially lagged dependent and explanatory variables. In addition, we run Moran's I tests on the residuals of the second-stage regressions of selected IV specifications (results not shown). The results are robust to this explicit modeling of spatial dependence, however, the estimated coefficients become quantitatively smaller.

Instrumental variables approach for both the panel and the cross-sectional specifications

An instrumental variable design is employed to control for the possible endogeneity of soil fertility and vegetation vigor on poverty. We use rainfall (as sources of exogenous variation for soil fertility), NPP, and NDVI (for a similar research design, see for instance Kiuri, 2016).

To qualify as a good instrument, the candidate variable must be (a) strongly associated to the endogenous variable (in our case environmental quality as proxied by soil fertility and vegetation vigor), (b) not affect the outcome variable (in our case poverty and GDP) through any channel other than through environmental quality, and (c) it must be (as-if) randomly assigned (see e.g. Angrist & Pieschke, 2015).

Condition (a) is easily met by the instrumental variable rainfall. The annual variations in the rainfall measure are one of the most crucial determinants of vegetation vigor and biomass productivity (see several papers in the agronomic literature such as Vlam et al., 2014 and Schippers et al., 2015). This is confirmed by the strength of the first-stage regressions that are provided in the appendix. Precipitation influences above ground biomass by affecting inter alia seed germination, seedling growth, and plant phenology (see e.g. Kang et al., 2013; Liu et al., 2014; Yan et al., 2014). Many studies have used rainfall as a predictor of biomass productivity. Furthermore, precipitation is also the main input factor in Revised Universal Soil Loss Equation (RUSLE) models (see e.g. Angulo-Martínez and Beguería, 2009; Hernando and Romana, 2015) and in the GIS-based Universal Soil Loss model (Angima et al., 2003; Fu et al., 2005; Lufafa et al., 2003).[11]

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[11] These studies show that rainfall intensity and duration are the most important factors affecting soil erosion. Ziadat et al. (2013) further show that soil erosion could occur at a relatively small intensity on wet soils because of subsequent rainfall events.

There have been several debates on the validity of rainfall as an instrument, particularly on criterion (b), which we reviewed carefully (see below). We argue, recognizing that the perfect instrument does not exist, that our paper is probably the one among the reviewed lot that is best positioned to use rainfall as an instrument. This is mostly because in our case rainfall is much more closely linked to our treatment variables vegetation growth and soil stored carbon than any other treatment variable used in the literature, but also because the exclusion criterion (b) is unlikely violated. Many studies have recently shown the relationship of this measure with many other variables, which in turn might be related to poverty and welfare. Sarsons (2015) for example finds evidence from India that rainfall might affect welfare through other channels, namely transportation and the ability to organize, particularly during extreme events, calling into question the findings of the seminal IV papers from e.g. Paxson (1992), Miguel et al. (2004), Miguel (2005), Yang & Choi (2007). Concretely, the concern with using rainfall as an IV for the case of this paper is that extreme rainfall events (such as flooding) can lead to the destruction of property and affect poverty, outside the channels of soil fertility and vegetation changes. The same rationale applies to droughts, that they for example kill livestock due to heat stress in addition due to reduced vegetation vigor. We overcome the flooding and drought identification threat by excluding extreme rainfall events from our main IV specifications (titled 'no outlier' specifications in the results section). Furthermore, by including road density and ruggedness we control for the transportation identification threat. An empirical indication that this exclusion restriction holds is that the OLS specification indicates that rainfall is not a statistically significant predictor in its own right (in addition to NPP, NDVI and soil fertility being in the specification) of poverty rates or GDP per capita.

There is no way to fully avail the identification strategy of possible violations using rainfall, as there may yet even other channels which we have not pondered and which have not yet been discussed in the literature, through which rainfall may affect welfare, although that may be said of any IV. We argue that if there is a fitting case for using rainfall as an IV, using it for isolating the exogenous variation in environmental quality is probably the best candidate. Rainfall is perhaps the most important determinant of plant growth, particularly so in areas with little irrigation.

In low-income and middle-income countries, economies are particularly dependent on the primary sector such as agriculture and forestry. We argue that increased quantities of rainfall increase crop yields and the environmental services from surrounding ecosystems, a mechanism which is especially strong in Sub-Saharan Africa, where only 4% of area cultivated is equipped for irrigation as compared to for instance 28% in North Africa (see You et al., 2010). We rely on the same logic, but instead instrument plant growth directly. Therefore, we posit that annual mean rainfall only affects poverty through biomass productivity, and that outside this channel it has no effect on poverty reduction. To emphasize the theoretical efforts made to ensure the restriction holds, we again stress the additional control variables and excluded extreme rainfall events mentioned above.

Condition (c), the as-if random assignment criterion, is met because rainfall is randomly assigned. Mean rainfall is an exogenous event to province *i*; even if climate change alters rainfall patterns, it does so on a global scale, and it is hardly attributable to province *i*'s actions alone.

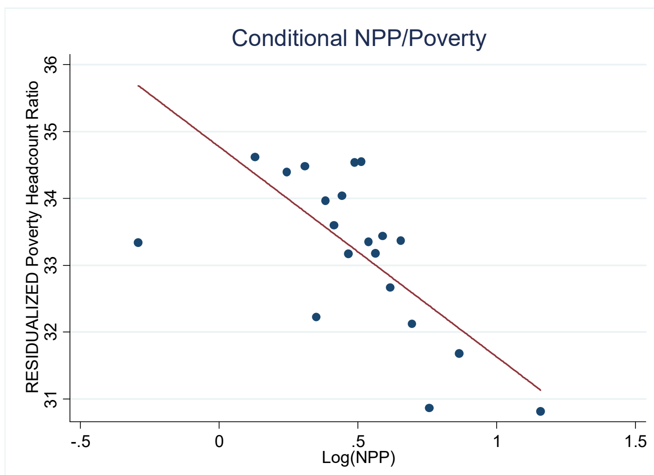
3. Results

We detail three main findings: (1) Environmental quality – both above-ground as well as below-ground – has significant and sizeable negative effects on poverty, particularly in rural areas and in Sub-Saharan Africa. (2) The relationship between environmental quality and GDP per capita is less strong, and only significant in certain specifications, suggesting that environmental quality is particularly important for the poor, compared to the average income earner. (3) In-situ environmental quality improvements are pro-poor, in contrast to urbanization. While urbanization has highly significant and sizeable correlations with GDP per capita, it is not significantly correlated with poverty reduction, unlike environmental quality, which is significantly correlated with both.

a. Panel Fixed Effects evidence

The correlation between concurrent environmental quality changes and poverty reduction are strong (see figure 1). The graph shows the conditional relationship of vegetation vigor (as measured by Net Primary Productivity) and poverty after controlling for other possible predictors of poverty in the panel specification. It can be clearly seen that increasing vegetation vigor is associated with accelerated poverty reduction.

Figure 1: The relationship between changes in vegetation & poverty reduction



Note: Each dot represents an equally sized bin of observations (grouped over the x-axis). Within these bins, the average of the x- and y-variable is computed and used in a scatterplot. The plot gives the conditional effect of log(NPP) on the residualized poverty headcount ratio after controlling for several covariates. They are created by running OLS regressions equivalent to table 2, specification 1.

However, it does not appear as if environmental quality causally influences poverty reduction for the average province in our global sample, as shown in table 2 (despite the OLS specification (1) being significant, the IV specifications (4) and (5) are not). Environmental quality however is much more important for poorer and more rural areas, as shown by specification (2) and (3). In fact, among rural areas and Sub-Saharan Africa, poverty is reduced significantly by vegetation vigor increasing, as shown by specifications (6) & (7). The panel results show that an increase of vegetation vigor (NPP) by 10 percent in rural areas reduces poverty rates by almost 0.7 percentage point. In Sub-Saharan Africa, the effects were even larger, such that a 1 percent increase in NPP resulted in a 1.3 percentage point increase in poverty rates. Similarly, increases in vegetation vigor as measured by NDVI resulted in poverty rate reductions in rural areas (see robustness check in appendix). The reasons for such significant and sizeable effects in Sub-Saharan Africa and rural areas has likely to do with livelihoods there being more dependent on the environment, among other reasons that are discussed below.

Using the data variation available and assuming a linear relationship, we find that the effects of NPP range between a reduction of the poverty headcount ratio by 4.8 percentage points (in times of extremely large increases in vegetation) and an increase in the poverty headcount ratio of around 3 percentage points (in times of a large decrease in vegetation vigor). In that sense, the effects we find are significantly larger than the effects suggested in Okwi et al. (2007). The interquartile range of the effects is -0.28 percentage points and +0.39 percentage points for the rural areas.

Table 2: Panel Specification - Dependent Variable - Poverty Headcount Ratio

VARIABLES	(1) OLS	(2) OLS - SSA	(3) OLS - rural	(4) IV	(5) IV - No outliers	(6) IV - rural	(7) IV - SSA
NPP	-4.176***	-2.658*	-3.468***	-0.961	0.0297	-6.703**	-13.08***
	(1.214)	(1.360)	(1.325)	(2.466)	(3.300)	(2.756)	(4.641)
NPP * SSA		-6.195***					
		(2.178)					
NPP * Rural			-1.301				
			(0.990)				
Precipitation	1.523	1.328	1.509				
	(1.323)	(1.330)	(1.318)				
Share Cropland	9.783***	7.941**	9.845***	8.623**	8.945*	6.755	22.99*
	(3.481)	(3.544)	(3.490)	(3.836)	(4.584)	(5.396)	(12.31)
Share Urban	-0.540	-1.383	-1.191	0.207	2.643	-25.53***	-872.4***
	(7.007)	(7.189)	(7.103)	(7.216)	(7.153)	(9.615)	(248.8)
Share Grassland	-1.584	-2.982	-2.383	-1.696	-2.761	13.78	-89.30*
	(5.330)	(5.404)	(5.413)	(5.327)	(6.095)	(10.38)	(49.61)
Share Forest	3.666	1.670	2.226	0.557	-1.076	0.0652	20.22
	(4.105)	(4.176)	(4.258)	(5.426)	(6.215)	(7.226)	(14.31)
Population	-1.850***	-1.812***	-1.897***	-1.825***	-2.030***	-1.102**	-9.812***
	(0.570)	(0.574)	(0.569)	(0.554)	(0.627)	(0.546)	(1.613)
Ruggedness	1.875***	1.669***	1.925***	1.545***	1.498***	3.024***	-0.883
	(0.417)	(0.424)	(0.418)	(0.485)	(0.521)	(0.548)	(2.133)
Road Density	-2.897***	-2.874***	-2.904***	-3.085***	-3.115***	-5.015***	-0.323
	(0.801)	(0.823)	(0.808)	(0.826)	(0.969)	(1.229)	(2.271)
Constant	47.60***	53.66***	49.01***	42.06***	53.31***	14.43	195.9***
	(10.13)	(10.48)	(10.16)	(13.30)	(14.37)	(12.65)	(29.28)
Observations	2,736	2,736	2,736	2,736	1,478	1,360	189
R-squared	0.744	0.747	0.745	0.742	0.759	0.820	0.445
Country FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Country trend	YES	YES	YES	YES	YES	YES	YES

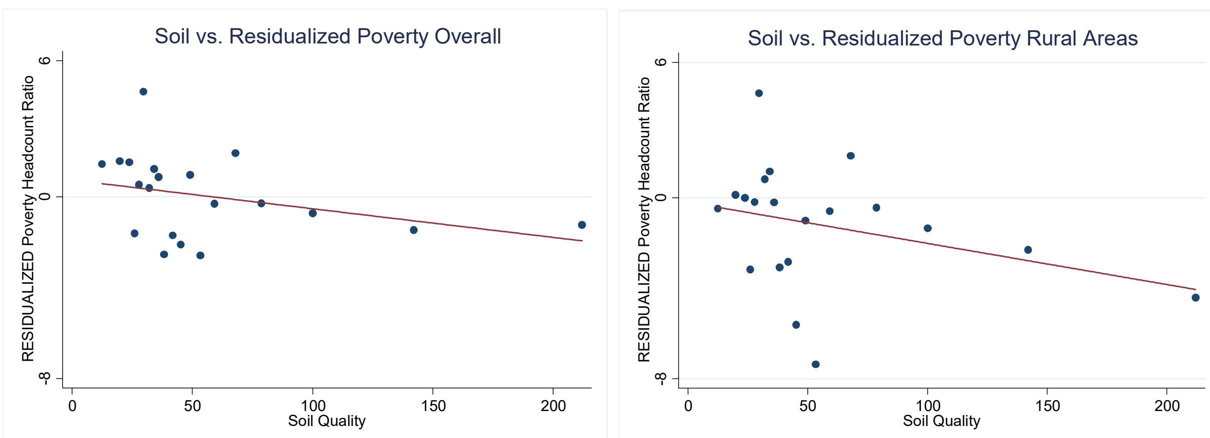
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficients of the other control variables are in line with the effects suggested by the literature. Note however that all effects other than those of environmental quality are not 'exogenized,' meaning they may not be interpreted as causal. That said, important lessons can be drawn from correlations as well. For example, road density, our proxy for infrastructural development, is an important and strong predictor of poverty reduction. This is a long established and well-known effect in development economics. For an overview of possible theoretical channels see for instance Brenneman & Kerf (2002). Urbanization (as measured by the growing area of cities), another variable that is consistently correlated with poverty reduction in the development economics literature (Rakodi, 2014), does not show consistently significant correlations with poverty reduction. Ruggedness in turn is statistically positively related to poverty rates, suggesting that rougher terrains make it harder to escape poverty. The direction of control variable coefficients is generally in line with the literature, which gives confidence in the quality of the data and empirical approach.[12]

b. Cross-sectional findings

There is a negative relationship between poverty and soil quality. This means the better the soil quality, the lower the poverty rates (see figure 2). The correlations after controlling for fixed effects point in the direction of poverty being a problem in regions with low soil quality. This relationship is even stronger when we look at the rural subset of our data. Due to the unavailability of time-variant soil fertility and subnational GDP measures, we use a cross-sectional model specification.

Figure 2: Poverty and Soil Quality



Note: Each dot represents an equally sized bin of observations (grouped over the x-axis). Within these bins, the average of the x- and y-variable is computed and used in a scatterplot. The residuals from a regression of poverty headcount ratio on country fixed effects are on the y-axis. Top soil carbon content is on the x-axis. Left panel is overall sample, right panel is areas with high dependence on agriculture.

This inverse correlation of soil fertility and poverty (as shown in figure 2 and the OLS specification in table 3) is also significant in the specifications that isolate the effects of poverty (see specification 3). An increase in top soil carbon content of 10 percent reduces the poverty headcount ratio by around 2 percentage points in the global and the rural samples. Rural Sub-Saharan African areas are particularly poverty-reducing as a consequence of soil quality improving: a 10 percent increase is soil fertility is linked to a

[12] It is also worth noting that the results of the first-stage regressions in the appendix are broadly in line with what we would expect from a theoretical point of view. For instance, a higher forest share is significantly correlated with higher NPP/NDVI levels, whereas a higher grassland share is connected to a lower biomass level. Similar observations can be made with respect to the cross-sectional first-stage regressions.

roughly 9 percentage points reduction in poverty rates. The positive soil fertility effects on poverty reduction are in line with the agricultural literature that connects farm income and soil erosion, see for example Hazarika and Honda (2001).

Aside from land use, we also control for soil type, which is a very important control measure in the cross section, as it allows us, along with land use, to isolate the intensive margin changes, and control for poverty reduction effects due to changes in land use.

Table 3: Dependent Variable - Poverty Headcount Ratio

VARIABLES	(1) OLS	(2) IV	(3) IV - no outlier	(4) IV - SSA	(5) IV- rural	(6) IV- rural SSA
Top Soil Carbon	-4.634***	-0.920	-23.46**	4.116	-21.27***	-93.74**
	(1.092)	(5.718)	(11.41)	(13.08)	(6.944)	(39.28)
Precipitation	0.761					
	(1.244)					
Ruggedness	0.375	0.615	-1.016	-1.745	-0.449	-2.325
	(0.399)	(0.547)	(1.094)	(1.976)	(0.668)	(2.915)
Road Density	-3.247***	-3.190***	-3.453***	-1.769	-2.249*	-0.698
	(0.752)	(0.749)	(0.942)	(3.417)	(1.353)	(6.701)
Share Cropland	5.335*	5.762**	0.502	12.55	-7.192	-41.08
	(3.169)	(2.870)	(4.270)	(8.749)	(6.062)	(25.89)
Share Urban	-5.325	-4.374	-14.48	-1,219***	-36.89**	-269.1
	(7.556)	(7.178)	(9.897)	(227.2)	(17.74)	(274.4)
Share Grassland	1.271	2.226	-16.56*	8.183	7.265	-37.47
	(4.475)	(4.341)	(9.805)	(18.57)	(9.766)	(32.39)
Share Forest	4.408	3.738	4.530	-2.272	-11.09	-43.33**
	(3.250)	(3.625)	(4.783)	(8.170)	(7.012)	(20.90)
Population	-1.235**	-1.314***	-1.157*	-2.472	-0.439	-5.638
	(0.489)	(0.466)	(0.621)	(2.495)	(0.722)	(3.762)
soil_type = 2, Andisol	5.178**	3.188	14.30*			
	(2.461)	(4.040)	(7.359)			
soil_type = 3, Ardisol	-0.561	-0.234	-7.278*	10.19		
	(2.351)	(2.459)	(4.367)	(7.561)		
soil_type = 4, Entisol	0.555	0.474	0.740	3.855		3.411
	(1.749)	(1.658)	(2.431)	(4.268)		(4.020)
soil_type = 5, Gelisol	-5.893*	-7.451**	-1.303			
	(3.128)	(3.706)	(5.060)			
soil_type = 6, Histosol	4.658**	0.729	24.53**			
	(2.311)	(6.567)	(12.31)			
soil_type = 7, Inceptisol	-1.272	-1.966	3.569	-8.919		16.14*
	(1.170)	(1.583)	(3.168)	(7.673)		(8.951)
soil_type = 8, Mollisol	1.011	0.450	-0.406			
	(1.131)	(1.175)	(1.549)			
soil_type = 9, Oxisol	-6.385**	-6.398**	-5.728	-3.552		48.02**
	(2.907)	(2.784)	(4.342)	(7.083)		(19.63)
soil_type = 10, Rock	3.414	2.975	10.50**			
	(3.195)	(3.057)	(4.527)			
soil_type = 11, Sand	2.961	3.428	-5.060	10.78**		
	(6.370)	(5.782)	(9.317)	(4.916)		
soil_type = 12, Spodosol	-2.232	-4.123	6.588			
	(1.826)	(3.456)	(6.506)			
soil_type = 13, Ultisol	1.342	1.315	2.058	0.986		23.20***
	(1.902)	(1.825)	(2.551)	(4.467)		(6.570)
soil_type = 14, Vertisol	2.128	1.440	-1.785	-4.657		35.69**
	(2.754)	(2.908)	(3.911)	(11.76)		(17.23)
Constant	65.17***	53.55**	147.0***	107.5	132.6***	501.4***
	(10.48)	(23.31)	(47.92)	(78.21)	(28.55)	(153.1)

Observations	932	932	577	127	475	64
R-squared	0.767	0.765	0.660	0.577	0.762	0.600
Country FE	YES	YES	YES	NO	YES	NO

The soil-GDP elasticities are much less consistently significant (see table 4) than the soil-poverty elasticities. Higher soil quality does not contribute to higher GDP per capita. However, caution is warranted in interpreting these findings, because while the existence of a positive effect, as shown in the poverty example, is a good indication that there are indeed significant relationships, the absence of such may also be due to poor data quality[13] and a small sample size and resulting low powered analysis.

Table 4: Dependent Variable – GDP per capita

VARIABLES	(1) OLS	(2) IV	(3) IV - no outlier	(4) IV - SSA	(5) IV- rural	(6) IV- rural SSA
Top Soil Carbon	0.141**	-0.267	-0.576	0.512	0.568*	0.576
	(0.0616)	(0.239)	(0.637)	(0.514)	(0.320)	(0.519)
Precipitation	-0.104					
	(0.0644)					
Ruggedness	-0.0820***	-0.112***	-0.146**	-0.124**	-0.0345	-0.151***
	(0.0181)	(0.0280)	(0.0727)	(0.0582)	(0.0324)	(0.0578)
Road Density	0.0775*	0.0744*	0.0493	0.0536	0.181***	-0.252**
	(0.0413)	(0.0424)	(0.0616)	(0.223)	(0.0651)	(0.0988)
Share Cropland	-0.696***	-0.811***	-0.877**	0.258	-0.132	0.405
	(0.164)	(0.158)	(0.387)	(0.467)	(0.229)	(0.479)
Share Urban	1.408***	1.197***	0.989	14.04**	2.774***	11.89***
	(0.383)	(0.373)	(0.656)	(6.756)	(0.536)	(3.838)
Share Grassland	-0.458*	-0.549**	-1.129	-0.0681	-0.350	0.371
	(0.268)	(0.264)	(0.757)	(1.565)	(0.417)	(0.831)
Share Forest	-0.317*	-0.266	-0.312	0.581	0.340	0.687*
	(0.170)	(0.189)	(0.242)	(0.512)	(0.244)	(0.399)
Population	-0.934***	-0.922***	-0.904***	-1.162***	-0.929***	-0.835***
	(0.0239)	(0.0253)	(0.0348)	(0.139)	(0.0361)	(0.0870)
soil_type = 2, Andisol	-0.189**	0.0211	0.254		-0.440**	
	(0.0911)	(0.152)	(0.366)		(0.175)	
soil_type = 3, Ardisol	-0.103	-0.199	-0.243		0.538***	
	(0.143)	(0.166)	(0.250)		(0.185)	
soil_type = 4, Entisol	-0.0632	-0.0453	-0.126	-0.0233	-0.0866	-0.272***
	(0.0727)	(0.0761)	(0.114)	(0.112)	(0.0816)	(0.0645)
soil_type = 5, Gelisol	0.750***	0.910***	0.977***			
	(0.190)	(0.204)	(0.294)			
soil_type = 6, Histosol	0.958***	1.373***	1.674***		0.621**	
	(0.127)	(0.276)	(0.624)		(0.298)	
soil_type = 7, Inceptisol	0.0135	0.0905	0.212	0.0423	-0.174**	
	(0.0577)	(0.0776)	(0.193)	(0.417)	(0.0697)	
soil_type = 8, Mollisol	0.0204	0.0940	0.0785		-0.0179	
	(0.0529)	(0.0666)	(0.0824)		(0.0699)	
soil_type = 9, Oxisol	0.369***	0.345***	0.317*	-0.303	0.134	-0.183
	(0.128)	(0.131)	(0.180)	(0.237)	(0.145)	(0.317)
soil_type = 10, Rock	-0.243	-0.240	-0.384		-1.247***	
	(0.310)	(0.320)	(0.383)		(0.135)	
soil_type = 11, Sand	-0.224	-0.271	-0.448	-0.161	0.0726	

[13] Finding significant effects despite noisy data is not the epistemological equivalent to not finding significant effects with noisy data.

	(0.137)	(0.179)	(0.321)	(0.270)	(0.172)	
soil_type = 12, Spodosol	0.200*	0.395**	0.764**		-0.00456	
	(0.111)	(0.155)	(0.301)		(0.173)	
soil_type = 13, Ultisol	0.0905	0.0799	0.117	-0.0599	0.0488	-0.0875
	(0.0819)	(0.0783)	(0.108)	(0.125)	(0.0819)	(0.129)
soil_type = 14, Vertisol	0.126	0.129	0.119		0.139	
	(0.115)	(0.119)	(0.200)		(0.125)	
Constant	10.53***	8.818***	10.17***	8.959***	4.060***	4.588
	(0.506)	(1.076)	(2.965)	(3.369)	(1.409)	(3.301)
Observations	635	635	419	46	338	32
R-squared	0.964	0.960	0.942	0.836	0.978	0.915
Country FE	YES	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Aside from the positive effects of environmental quality on poverty reduction, and effect of the intensive margin, there are also interesting associations displayed by measures of the extensive margin such as land use changes. Infrastructure (road density) development shows significant positive relationships with GDP per capita and significant negative relationships with poverty ratios in the panel estimation and the cross-sectional specifications.

Not in line with our expectations, crop land expansion is not positively associated with poverty reduction, quite to the contrary (in both the panel and the cross-sectional OLS specifications). The direction of the effects may be an indication that it has not been the poor who have been benefitting from land conversion (such as forest-to-crop conversion) in the overall sample. In fact, poverty rates might increase after areas are converted into cropland according to our results. However, much more research into the reasons for this unexpected positive correlation between poverty rates and cropland is necessary.

Urbanization (urban expansion) is significantly linked to increasing GDP per capita, and has in fact the largest coefficient among any land use change measures, by a large margin, attesting to the powerful links between urbanization and economic development. However, the effects on poverty rates are not significant. This is a puzzling observation. As we had mentioned before, only environmental quality is ‘exogenized’ and therefore all other relationships can be interpreted merely as correlative. That said, the absence of a correlation between urbanization and poverty, especially despite such strong and significant relationships with GDP per capita, suggests that urbanization is not an inclusive demographic process. On the other hand, the Stable Unit Treatment Variable Assumption (SUTVA) may be violated, meaning that it could be that those in rural areas with the most talent moved to the cities (in other provinces), contributing to economic growth there, but being absent from contributing to the economic development process in the rural origin provinces, which would have helped to reduce poverty (and not sent back home enough remittances to counteract that demographic effect).

The relative strength of the effects of the different explanatory variables on poverty need to be assessed with caution, as it is hard to grasp at what expense each of these changes happen. For example, looking at the original OLS specification reveals that although a 10 percent change in NPP is associated with a 0.4 percentage point change in poverty rates, a 1 percent change in road density only leads to a 0.3 percentage point change in poverty rates. This could indicate that improving environmental quality has larger ties to poverty reduction than improvements of road density. However, the relative costs for pursuing one over the other are not part of the modeling, and this specification does not provide causal identification. Additional research efforts to compare the relative effects of urbanization, infrastructure development, and in-situ development of environmental quality in rural areas are needed.

4. Conclusion and Discussion

As expected, we find evidence that building roads is associated with reductions in poverty rates, as many studies have shown before (see e.g. Jacoby, 2000; Gibson and Rozelle 2003; Mu and van de Walle 2007; Jacoby and Minten, 2009; Khandker et al., 2009). What has not been shown conclusively so far however is whether in-situ improvements of environmental quality significantly reduce poverty. Several authors have suggested that they do not. Okwi et al. (2007), for example conclude that if all of Kenya's soil was raised to its highest quality, an only 1 percentage point reduction in poverty rates would ensue. Wantchekon and Stanig (2015) go even farther and conclude that in Sub-Sharan Africa good soil may be a hindrance for poverty reduction.

We find that environmental quality is indeed important for poverty reduction. Using the unbalanced panel data from the Hidden Dimensions data set, we find that as environmental quality increases, the speed of poverty reduction accelerates. Using instrumental variable regressions and exploiting the exogenous time variations in annual rainfall, we find that increasing environmental quality causes significant accelerations in poverty reduction rates, particularly in rural areas and in Sub-Saharan Africa.

Our analysis does not specifically address any mechanism through which environmental quality helps reduce poverty, which is a major research question that has yet to be tackled (see Andam et al., 2010). Agricultural productivity and higher environmental services are most likely to be the channels through which the poverty reduction effect operates. More research on this issue is required in the future, such as disentangling the different channels of irrigation schemes,[14] the importance of the primary sector, and the effect of high initial poverty rates.

We find a similar pattern in a cross-sectional setting. Soil quality has significant and sizeable effects on poverty rates and on GDP per capita. We think that the underlying mechanism is that as environmental quality increases, agricultural and environmental output increase as well. This might be especially relevant for low income households that draw a larger share of their income from natural resources and the environment (Wunder, 2015).

Landscape restoration can reduce degradation and positively contribute to increasing environmental quality (and therefore also poverty reduction). In the Inner Mongolia region of China, Mu et al. (2013) examined NPP changes from 2001 to 2009 and found NPP increased by 21 percent. Of this increase, 80 percent of the NPP change was due to human activity – notably landscape restoration programs (returning cropland to grassland, converting desert to grassland, and better grazing management). These results

[14] The coefficients for Sub-Saharan Africa are usually larger than for the full sample specifications. An interesting idea to pursue for further research would therefore be to explore the mechanisms that lead to this result. It is hard to establish whether the effects are larger in SSA because of the extreme poverty in the region or lower irrigation. The irrigation channel could be instrumentalized using available subnational irrigation data sets, see for instance the AQUASTAT data set (Siebert et al., 2005). However, data quality is low especially in Southern and East Africa. For example, the highest indicated data quality in AQUASTAT is measured in North America with 1.03, whereas it is just 3.85 in Southern Africa (the worst measured quality is 4.00). As this means that the geospatial data in these regions rely on highly modeled estimates, we did not pursue this idea in this paper.

suggest that human activities – and landscape restoration specifically – can have a larger impact on NPP changes than climate. Similar results have been found in the Qinghai-Tibet Plateau (Chen et al., 2014; Cai et al., 2015), and elsewhere in China (Xiao et al., 2015). A cross-country comparison of China, Mongolia, Uzbekistan, and Pakistan finds climate influences to be stronger than human influences in explaining NPP changes, but nonetheless concludes that improvements were largely determined by landscape restoration programs (Yang et al., 2016).

In conclusion, we find that the environment does matter for poverty reduction. The greener the vegetation and the richer the soil, the faster the poverty reduction, particularly so in Sub-Saharan Africa and rural areas. Moreover, we find that the effects of environmental quality on poverty are stronger than its effects on average income, suggesting that the poor benefit disproportionately more from environmental quality. Lastly, we find that although urbanization has highly significant and sizeable correlations with GDP per capita, it is not significantly correlated with poverty reduction.

REFERENCES

Ahmed, S. A., Diffenbaugh, N. S., Hertel, T. W., Lobell, D. B., Ramankutty, N., Rios, A. R., & Rowhani, P. (2011). Climate volatility and poverty vulnerability in Tanzania. Global Environmental Change, 21(1), 46-55.

Alix-Garcia, J. M., Sims, K. R., & Yañez-Pagans, P. (2015). Only one tree from each seed? Environmental effectiveness and poverty alleviation in Mexico's Payments for Ecosystem Services Program. American Economic Journal: Economic Policy, 7(4), 1-40.

Amaral, S., Câmara, G., Monteiro, A. M. V., Quintanilha, J. A., & Elvidge, C. D. (2005). Estimating population and energy consumption in Brazilian Amazonia using DMSP night-time satellite data. Computers, Environment and Urban Systems, 29(2), 179-195.

Angelsen, A., & Wunder, S. (2003). Exploring the forest—poverty link. *CIFOR occasional paper*, *40*, 1-20.

Barbier, E.B. 2010. "Poverty, development and environment." Environment and Development Economics 15 (Special issue 06): 635-660.

Barbier, E. B., & Hochard, J. P. (2016). Does land degradation increase poverty in developing countries?. PloS one, 11(5), e0152973.

Brenneman, A., & Kerf, M. (2002). Infrastructure & Poverty Linkages. A Literature Review'', The World Bank, Washington, DC.

Buringh, P. (1984). Organic carbon in soils of the world. In The role of terrestrial vegetation in the global carbon cycle: Measurement by remote sensing (Vol. 23, pp. 91-109). Wiley, New York.

Cabral, Joseph François. 2014. Rainfall and Economic Growth and Poverty: Evidence from Senegal and Burkina Faso. AGRODEP Working Paper 0008. Washington, DC: International Food Policy Research Institute.

CIESIN - Columbia University. 2016. Gridded Population of the World, Version 4 (GPWv4): Administrative Unit Center Points with Population Estimates. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC).http://dx.doi.org/10.7927/H4F47M2C.

Conley, T.G (1999). GMM estimation with cross sectional dependence. Journal of Econometrics, Volume 92, Issue 1, 1-45.

Davidson, R. and MacKinnon, J.G., 2004. Econometric theory and methods (Vol. 5). New York: Oxford University Press.

Dean Yang, HwaJung Choi; Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines, The World Bank Economic Review, Volume 21, Issue 2, 1 January 2007, Pages 219–248, https://doi.org/10.1093/wber/lhm003

Dinar, A., Hassan, R., Mendelsohn, R., & Benhin, J. (2012). Climate change and agriculture in Africa: impact assessment and adaptation strategies. Routledge.

Duraiappah, A. K. (1996). Poverty and environmental degradation: A literature review and analysis (No. 8). Iied.

Durán Zuazo, V.H., Rodríguez Pleguezuelo C.R. (2008) Soil-erosion and runoff prevention by plant covers. A review, Agron. Sustain. Dev. 28, 65–86.

Ephraim Nkonya, Nicolas Gerber, Philipp Baumgartner, Joachim von Braun, Alex De Pinto, Valerie Graw, Edward Kato, Julia Kloos, and Teresa Walter. 2011. "The Economics of Land Degradation." Peter Lang Internationaler Verlag der Wissenschaften, 2011.

Gennaioli, N., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2012). Human capital and regional development. The Quarterly journal of economics, 128(1), 105-164.

Guyer, J. I., & Belinga, S. M. E. (1995). Wealth in people as wealth in knowledge: Accumulation and composition in Equatorial Africa. The Journal of African History, 36(1), 91-120.

Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: effect on plant growth and development. Weather and climate extremes, 10, 4-10.

Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., Ort, D., ... & Wolfe, D. (2011). Climate impacts on agriculture: implications for crop production. Agronomy journal, 103(2), 351-370.

Helen Suich, Caroline Howe, Georgina Mace, (2015). Ecosystem services and poverty alleviation: A review of the empirical links. Ecosystem Services (12): 137 – 147.

Jacoby, H. 2000. "Access to markets and the benefits of rural roads." Economic Journal 465:713-737.

Jacoby, H. and Minten, B. 2009. "On Measuring the benefits of lower transport costs." Journal of Development Economics, 89:28-38.

Kirschbaum, M. U. (2000). Will changes in soil organic carbon act as a positive or negative feedback on global warming?. Biogeochemistry, 48(1), 21-51.

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. science, 304(5677), 1623-1627.

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. Science, 333(6042), 616-620.

Louwagie G., Gay S.H., Burrell A. (2009) Addressing soil degradation in EU agriculture: relevant processes, practices and policies, Report on the project 'Sustainable Agriculture and Soil Conservation (SoCo)', JRC Scientific and Technical Reports, ISSN 1018 5593, 209 p.

Miguel, E. (2005). Poverty and Witch Killing. The Review of Economic Studies, 72(4), 1153-1172. Retrieved from http://www.jstor.org/stable/3700704

Miguel, E., Satyanath, S., & Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. Journal of political Economy, 112(4), 725-753.

Mueller, Lothar, et al. "Assessing the productivity function of soils. A review." Agronomy for Sustainable Development 30.3 (2010): 601-614.

NCAR (2017). "The Climate Data Guide: CRU TS Gridded precipitation and other meteorological variables since 1901 ." Retrieved from https://climatedataguide.ucar.edu/climate-data/cru-ts-gridded-precipitation-and-other-meteorological-variables-1901.

Nunn, N., and D. Puga. 2012. "Ruggedness: The Blessing of Bad Geography in Africa." Review of Economics and Statistics 94(1): 20-36.

Olinto, P., Beegle, K., Sobrado, C., & Uematsu, H. (2013). The state of the poor: Where are the poor, where is extreme poverty harder to end, and what is the current profile of the world's poor. Economic Premise, 125(2).

Okwi, Paul O., Godfrey Ndeng'e, Patti Kristjanson, Mike Arunga, An Notenbaert, Abisalom Omolo, Norbert Henninger, Todd Benson, Patrick Kariuki, and John Owuor. 2007. "Spatial determinants of poverty in rural Kenya." Proceedings of the National Academy of Sciences of the USA (PNAS) 104 (43):16769-16774.

Paaijmans, K. P., Blanford, S., Bell, A. S., Blanford, J. I., Read, A. F., & Thomas, M. B. (2010). Influence of climate on malaria transmission depends on daily temperature variation. Proceedings of the National Academy of Sciences, 107(34), 15135-15139.

Paxson, C. (1992). Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand. The American Economic Review, 82(1), 15-33. Retrieved from http://www.jstor.org/stable/2117600

Paxson, C. H. (1992). Using weather variability to estimate the response of savings to transitory income in Thailand. The American Economic Review, 15-33.

Pritchett, Lant and Kenny, Charles, Promoting Millennium Development Ideals: The Risks of Defining Development Down (August 14, 2013). Center for Global Development Working Paper No. 338. Available at SSRN: https://ssrn.com/abstract=2364643 or http://dx.doi.org/10.2139/ssrn.2364643

R. Hiederer, M. Kochy 2012. Global Soil Organic Carbon Estimates and the Harmonized World Soil Database. EUR Scientific and Technical Research series; ISSN 1831-9424 (online), ISSN 1018-5593 (print), ISBN 978-92-79-23108-7, doi:10.2788/1326

Rustad, L. E. J. L., Campbell, J., Marion, G., Norby, R., Mitchell, M., Hartley, A., ... & Gurevitch, J. (2001). A meta-analysis of the response of soil respiration, net nitrogen mineralization, and aboveground plant growth to experimental ecosystem warming. Oecologia, 126(4), 543-562.

S. Siebert, P. Döll, J. Hoogeveen, J. M. Faures, K. Frenken, S. Feick (2005). Development and validation of the global map of irrigation areas. Hydrology & Earth System Sciences Discussions, 2(4), doi: http://dx.doi.org/http://hal.archives-ouvertes.fr/docs/00/29/86/82/PDF/hessd-2-1299-2005.pdf.

Sandker, M., Ruiz-Perez, M., & Campbell, B. M. (2012). Trade-offs between biodiversity conservation and economic development in five tropical forest landscapes. Environmental management, 50(4), 633-644.

Sedda, L., Tatem, A. J., Morley, D. W., Atkinson, P. M., Wardrop, N. A., Pezzulo, C., ... & Rogers, D. J. (2015). Poverty, health and satellite-derived vegetation indices: their inter-spatial relationship in West Africa. International health, 7(2), 99-106.

Showers, K. B. (2006). A history of African soil: Perceptions, use and abuse. Soils and Societies: Perspectives from environmental history, 118-176.

Thornley, J. H. M., & Cannell, M. G. R. (2001). Soil carbon storage response to temperature: an hypothesis. Annals of Botany, 87(5), 591-598.

Wantchekon, Leonarf and Stanig, Piero (2015). The curse of good soil? Land fertility, roads and rural poverty in Africa. Working Paper Princeton University.

Western, D., & Dunne, T. (1979). Environmental aspects of settlement site decisions among pastoral Maasai. Human ecology, 7(1), 75-98.

Wong M.T.F., Asseng S. (2006) Determining the causes of spatial and temporal variability of wheat yields at sub-field scale using a new method of upscaling a crop model, Plant Soil 283, 203–215.

World Bank. 2016. Poverty and Shared Prosperity 2016: Taking on Inequality. Washington, DC: World Bank. doi:10.1596/978-1-4648-0958-3. License: Creative Commons Attribution CC BY 3.0 IGO

You, Liangzhi & Ringler, Claudia & Nelson, Gerald & Wood-Sichra, Ulrike & Robertson, Richard & Wood, Stanley & Guo, Zhe & Zhu, Tingju & Sun, Yan, 2010. "What is the irrigation potential for Africa?," IFPRI discussion papers 993, International Food Policy Research Institute (IFPRI).

Krishna, A., Lumonya, D., Markiewicz, M., Mugumya, F., Kafuko, A., & Wegoye, J. (2006). Escaping poverty and becoming poor in 36 villages of Central and Western Uganda. The Journal of Development Studies, 42(2), 346-370.

Carter, M. R., & Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. The Journal of Development Studies, 42(2), 178-199.

Barrett, C. B., & Swallow, B. M. (2006). Fractal poverty traps. World development, 34(1), 1-15.

Barrett, C. B., & Bevis, L. E. (2015). The self-reinforcing feedback between low soil fertility and chronic poverty. Nature Geoscience, 8(12), 907.

Barrett, C. B., & Bevis, L. E. (2015). The micronutrient deficiencies challenge in African Food Systems. The fight against hunger and malnutrition: the role of food, agriculture, and targeted policies, 61-88.

Eswaran, H., Almaraz, R., van den Berg, E., & Reich, P. (1997). An assessment of the soil resources of Africa in relation to productivity. Geoderma, 77(1), 1-18.

Garrity, D. P., Akinnifesi, F. K., Ajayi, O. C., Weldesemayat, S. G., Mowo, J. G., Kalinganire, A., ... & Bayala, J. (2010). Evergreen Agriculture: a robust approach to sustainable food security in Africa. Food security, 2(3), 197-214.

Ayongwa, G. C., Stomph, T. J., Belder, P., Leffelaar, P. A., & Kuyper, T. W. (2011). Organic matter and seed survival of Striga hermonthica–mechanisms for seed depletion in the soil. Crop Protection, 30(12), 1594-1600.

Yamano, T., & Kijima, Y. (2010). The associations of soil fertility and market access with household income: Evidence from rural Uganda. Food Policy, 35(1), 51-59.

Alkire, S., Roche, J. M., Ballon, P., Foster, J., Santos, M. E., & Seth, S. (2015). Multidimensional poverty measurement and analysis. Oxford University Press, USA.

Greene, W. H. (2003). Econometric analysis. Pearson Education India.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT press.

J.D. Angrist and J.S. Pischke, Mastering ‘Metrics: The Path from Cause to Effect, Princeton UniversityPress, 2015 (MM).

Vlam, M., Baker, P. J., Bunyavejchewin, S., & Zuidema, P. A. (2014). Temperature and rainfall strongly drive temporal growth variation in Asian tropical forest trees. Oecologia, 174(4), 1449-1461.

Schippers, P., Sterck, F., Vlam, M., & Zuidema, P. A. (2015). Tree growth variation in the tropical forest: understanding effects of temperature, rainfall and CO2. Global change biology, 21(7), 2749-2761.

Kang G. Z., Li G. Z., Liu G. Q., Xu W., Peng X. Q., Wang C. Y., et al. (2013). Exogenous salicylic acid enhances wheat drought tolerance by influence on the expression of genes related to ascorbate-glutathione cycle. Biol. Plant 57 718–724 10.1007/s10535-013-0335-z

Liu, Y., Y. Zhou, W. Ju, S. Wang, X. Wu, M. He, and G. Zhu (2014), Impacts of droughts on carbon sequestration by China's terrestrial ecosystems from 2000 to 2011, Biogeosciences, 11(10), 2583–2599

Yan, H., Wang, S. Q., Lu, H. Q., Yu, Q., Zhu, Z. C., Myneni, R. B., ... & Shugart, H. H. (2014). Development of a remotely sensing seasonal vegetation‐based Palmer drought severity index and its application of global drought monitoring over 1982–2011. Journal of Geophysical Research: Atmospheres, 119(15), 9419-9440.

Angulo-Martínez, M., & Beguería, S. (2009). Estimating rainfall erosivity from daily precipitation records: A comparison among methods using data from the Ebro Basin (NE Spain). Journal of Hydrology, 379(1-2), 111-121.

Hernando, D., & Romana, M. G. (2015). Estimating the rainfall erosivity factor from monthly precipitation data in the Madrid Region (Spain). Journal of Hydrology and Hydromechanics, 63(1), 55-62.

Angima, S. D., Stott, D. E., O’neill, M. K., Ong, C. K., & Weesies, G. A. (2003). Soil erosion prediction using RUSLE for central Kenyan highland conditions. Agriculture, ecosystems & environment, 97(1-3), 295-308.

Fu, B. J., Zhao, W. W., Chen, L. D., Zhang, Q. J., Lü, Y. H., Gulinck, H., & Poesen, J. (2005). Assessment of soil erosion at large watershed scale using RUSLE and GIS: a case study in the Loess Plateau of China. Land degradation & development, 16(1), 73-85.

Lufafa, A., Tenywa, M. M., Isabirye, M., Majaliwa, M. J. G., & Woomer, P. L. (2003). Prediction of soil erosion in a Lake Victoria basin catchment using a GIS-based Universal Soil Loss model. Agricultural systems, 76(3), 883-894.

Sarsons, H. (2015). Rainfall and conflict: A cautionary tale. Journal of development Economics, 115, 62-72.

Gibson, J., & Rozelle, S. (2003). Poverty and access to roads in Papua New Guinea. Economic development and cultural change, 52(1), 159-185.

Mu, R., & Van de Walle, D. (2011). Rural roads and local market development in Vietnam. The Journal of Development Studies, 47(5), 709-734.

Khandker, S. R., Bakht, Z., & Koolwal, G. B. (2009). The poverty impact of rural roads: Evidence from Bangladesh. Economic Development and Cultural Change, 57(4), 685-722.

Nemani, R. R., Keeling, C. D., Hashimoto, H., Jolly, W. M., Piper, S. C., Tucker, C. J., ... & Running, S. W. (2003). Climate-driven increases in global terrestrial net primary production from 1982 to 1999. science, 300(5625), 1560-1563.

Ainsworth, E. A., Yendrek, C. R., Sitch, S., Collins, W. J., & Emberson, L. D. (2012). The effects of tropospheric ozone on net primary productivity and implications for climate change. Annual review of plant biology, 63, 637-661.

Wunder, S. (2015). Revisiting the concept of payments for environmental services. Ecological Economics, 117, 234-243.

Mu, S., Yang, H., Li, J., Chen, Y., Gang, C., Zhou, W., & Ju, W. (2013). Spatio-temporal dynamics of vegetation coverage and its relationship with climate factors in Inner Mongolia, China. Journal of Geographical Sciences, 23(2), 231-246.

Chen, B., Zhang, X., Tao, J., Wu, J., Wang, J., Shi, P., ... & Yu, C. (2014). The impact of climate change and anthropogenic activities on alpine grassland over the Qinghai-Tibet Plateau. Agricultural and Forest Meteorology, 189, 11-18.

Cai, H., Yang, X., & Xu, X. (2015). Human-induced grassland degradation/restoration in the central Tibetan Plateau: The effects of ecological protection and restoration projects. Ecological Engineering, 83, 112-119.

Yang, Y., Wang, Z., Li, J., Gang, C., Zhang, Y., Zhang, Y., ... & Qi, J. (2016). Comparative assessment of grassland degradation dynamics in response to climate variation and human activities in China, Mongolia, Pakistan and Uzbekistan from 2000 to 2013. Journal of Arid Environments, 135, 164-172.

Xiao, J., Zhou, Y., & Zhang, L. (2015). Contributions of natural and human factors to increases in vegetation productivity in China. Ecosphere, 6(11), 1-20.

Andam, K. S., Ferraro, P. J., Sims, K. R., Healy, A., & Holland, M. B. (2010). Protected areas reduced poverty in Costa Rica and Thailand. Proceedings of the National Academy of Sciences, 107(22), 9996-10001.

Phillips, L. B., Hansen, A. J., & Flather, C. H. (2008). Evaluating the species energy relationship with the newest measures of ecosystem energy: NDVI versus MODIS primary production. Remote Sensing of Environment, 112(12), 4381-4392.

Hazarika, Manzul & Kiyoshi, Honda. (2001). Estimation of soil erosion using Remote Sensing and GIS, its valuation and economic implications on agricultural production.

Table 2: Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) p10	(6) p25	(7) p75	(8) p90	(9) max
Poverty Headcount Ratio	3,303	33.28	19.13	0.400	9.900	17.10	46.97	59.80	93.60
Share Cropland	3,303	0.354	0.250	0	0.0545	0.157	0.538	0.734	0.967
Share Forest	3,303	0.370	0.263	0	0.0127	0.127	0.572	0.734	0.977
Share Grassland	3,303	0.0683	0.125	0	0	0.000500	0.0672	0.223	0.863
Share Urban	3,303	0.0269	0.0998	0	0.000358	0.00143	0.0134	0.0376	0.955
Top Soil Carbon	3,297	64.87	51.76	7.998	25.42	31.77	74.58	142.4	318.1
Precipitation	2,802	4.557	0.837	-0.261	3.518	4.036	5.193	5.459	6.464
NDVI	3,279	-0.677	0.444	-3.611	-1.251	-0.765	-0.393	-0.319	-0.229
NPP	3,225	0.494	0.786	-5.081	-0.453	0.167	1.047	1.263	1.669
Road Density	3,295	2.832	1.156	-2.316	1.532	2.145	3.584	4.151	6.548
Ruggedness	3,299	11.38	1.249	3.158	9.782	10.65	12.30	12.64	13.71
GDP per capita	2,287	-5.427	1.807	-11.52	-7.686	-6.572	-4.222	-3.391	4.860
Population	3,290	13.56	1.574	4.706	11.56	12.54	14.51	15.34	19.14

Table 3:Poverty observations per country and year

ISO3 country code	year															
	1996	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
afg									34				34			
arm														11		
aut													9			
bgd		7					7					7				
bgr												28	28			
bih						3			3				3			
blr														6	6	
bol													9			
bra		27										27				
btn														18		
chl		14						16			16		14			
cmr			10						10							
cod							8									
col				22	22	22	22			22	22	22	22	22		
cri												1	1	1	1	
dnk													5			
dom		32	32	32	32	32	32	32	32	32	32	32	32			
ecu									15	15	17	17	17	17	17	
est						15							15			
geo													10	7		
gin									8					8		
gtm								22					22			
hti														10		
hun													20	20		
idn				30	30	30	31	33	33	33	33	33	33	33	33	
ind						31						36	35			
irq									18					18		
jor												12				
kaz															14	
kgz											9		9	9	9	
lao				18						18					17	
lbn							6									
lbr									15							
lva													5	5		
mar			13						13							
mda													33			
mex										32		32		32		
mne													20	20		
moz	11				11					11						
nga						37						37				
nld													12			
npl												5				
pan										9	9	9	12	12	12	
pse					2		2	2			2	2	2			
rou												42	42			
rus				1									83	84		
sdn											15					
sle					3								3			
slv							14	14	14	14	14	14	14	14		
ssd											10					
svk													8			
svn												12	12			
swe													21			
syr									14							
tgo								5					5			
tjk											5					
tls									13							13
tun		21					21					21				
ven				24	24	24	24	24	24	24	24	24	24	24	24	
vnm												65		65		
yem							20									
zmb								9				9				

Table 4: The effect of vegetation vigor (NPP) on poverty rates; cross-province regressions with latest year available

VARIABLES	(1) OLS	(2) IV	(3) IV - no outlier	(4) IV - SSA	(5) IV- rural	(6) IV- SSA & rural
NPP	-4.649***	-1.429	-3.356	-9.238**	-3.198	-5.005
	(1.256)	(2.829)	(2.074)	(4.047)	(2.189)	(3.534)
Precipitation	1.556					
	(1.585)					
Ruggedness	1.289***	1.024**	1.526***	-0.154	1.971***	2.960
	(0.384)	(0.409)	(0.417)	(2.068)	(0.495)	(2.619)
Road Density	-2.913***	-3.192***	-2.605***	-3.156	-3.587***	-5.548*
	(0.754)	(0.746)	(0.788)	(3.022)	(1.226)	(2.872)
Share Cropland	7.363**	6.274*	8.800***	19.35*	1.810	11.92
	(3.190)	(3.498)	(3.355)	(10.35)	(5.631)	(13.31)
Share Urban	-0.869	-2.008	-0.433	-890.7***	-16.00	-668.1***
	(7.452)	(7.874)	(7.605)	(209.0)	(12.58)	(184.1)
Share Grassland	1.469	1.374	4.220	-50.86	15.04*	-21.93
	(4.709)	(4.592)	(5.581)	(33.02)	(8.783)	(28.55)
Share Forest	9.125**	5.577	9.670**	12.48	-2.842	-5.104
	(3.565)	(5.190)	(4.859)	(12.42)	(7.299)	(15.27)
Population	-1.243**	-1.228**	-1.421**	-10.34***	-0.945	-8.481***
	(0.500)	(0.480)	(0.572)	(1.612)	(0.620)	(2.968)
soil_type = 2, Andisol	2.618	2.685				
	(2.351)	(2.256)				
soil_type = 3, Ardisol	-2.122	-0.963				
	(2.593)	(3.011)				
soil_type = 4, Entisol	-0.698	-0.167				
	(1.780)	(1.829)				
soil_type = 5, Gelisol	-8.182**	-8.218***				
	(3.288)	(3.139)				
soil_type = 6, Histosol	1.538	0.814				
	(2.009)	(2.112)				
soil_type = 7, Inceptisol	-2.189*	-2.152*				
	(1.174)	(1.119)				
soil_type = 8, Mollisol	0.433	0.458				
	(1.122)	(1.080)				
soil_type = 9, Oxisol	-5.027	-5.394*				
	(3.100)	(3.092)				
soil_type = 10, Rock	1.715	1.956				
	(3.241)	(3.151)				
soil_type = 11, Sand	0.294	2.399				
	(6.737)	(6.414)				
soil_type = 12, Spodosol	-5.241***	-4.839***				
	(1.824)	(1.719)				
soil_type = 13, Ultisol	1.928	1.559				
	(1.869)	(1.886)				
soil_type = 14, Vertisol	1.783	1.698				
	(2.754)	(2.585)				
Constant	30.64**	43.72***	33.47***	210.1***	39.25***	174.0***
	(12.34)	(10.67)	(10.62)	(27.77)	(13.18)	(52.06)
Observations	892	892	560	109	464	60
R-squared	0.782	0.779	0.748	0.567	0.811	0.658
Country FE	YES	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: The effect of vegetation vigor (NPP) on GDP per capita; cross-province regression with latest year available

VARIABLES	(1) OLS	(2) IV	(3) IV - no outlier	(4) IV - SSA	(5) IV- rural	(6) IV- SSA & rural
NPP	0.0179	0.0843	0.0307	0.0648	0.211**	0.372***
	(0.0557)	(0.0871)	(0.102)	(0.137)	(0.104)	(0.115)
Precipitation	-0.0820					
	(0.0730)					
Ruggedness	-0.0934***	-0.0914***	-0.0880***	-0.164***	-0.0908***	-0.183***
	(0.0189)	(0.0182)	(0.0183)	(0.0501)	(0.0197)	(0.0459)
Road Density	0.0747*	-0.00280	-0.0371	-0.0518	0.183***	-0.220***
	(0.0442)	(0.0448)	(0.0536)	(0.131)	(0.0647)	(0.0635)
Share Cropland	-0.723***	-0.862***	-0.868***	-0.0470	-0.307	-0.250
	(0.164)	(0.152)	(0.184)	(0.352)	(0.210)	(0.247)
Share Urban	1.339***	1.257***	1.173***	16.86***	1.880***	11.67***
	(0.378)	(0.358)	(0.366)	(4.957)	(0.593)	(2.866)
Share Grassland	-0.467*	-0.538*	-0.935**	1.649	-0.651	6.521***
	(0.270)	(0.282)	(0.377)	(2.655)	(0.427)	(2.209)
Share Forest	-0.305*	-0.652***	-0.720***	0.243	-0.130	-0.259
	(0.177)	(0.213)	(0.230)	(0.395)	(0.292)	(0.358)
Population	-0.931***	-0.939***	-0.938***	-1.254***	-0.914***	-0.984***
	(0.0241)	(0.0244)	(0.0286)	(0.143)	(0.0351)	(0.0785)
soil_type = 2, Andisol	-0.113					
	(0.0837)					
soil_type = 3, Ardisol	-0.127					
	(0.146)					
soil_type = 4, Entisol	-0.0446					
	(0.0757)					
soil_type = 5, Gelisol	0.809***					
	(0.188)					
soil_type = 6, Histosol	1.102***					
	(0.122)					
soil_type = 7, Inceptisol	0.0429					
	(0.0601)					
soil_type = 8, Mollisol	0.0440					
	(0.0517)					
soil_type = 9, Oxisol	0.364***					
	(0.131)					
soil_type = 10, Rock	-0.239					
	(0.316)					
soil_type = 11, Sand	-0.228					
	(0.152)					
soil_type = 12, Spodosol	0.275***					
	(0.100)					
soil_type = 13, Ultisol	0.0868					
	(0.0815)					
soil_type = 14, Vertisol	0.130					
	(0.118)					
Constant	11.09***	8.258***	8.330***	12.94***	6.688***	9.678***
	(0.538)	(0.400)	(0.463)	(1.908)	(0.512)	(1.136)
Observations	634	634	419	45	337	31
R-squared	0.964	0.960	0.952	0.837	0.976	0.922
Country FE	YES	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: The effect of vegetation vigor (NDVI) on poverty rates; cross-province regression with latest year available

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OLS	IV	IV - no outlier	IV - SSA	IV- rural	IV- SSA & rural
NDVI	-1.235	-2.382	-8.822	-4.358	-19.72**	-16.04
	(2.570)	(3.683)	(5.553)	(7.245)	(7.963)	(14.48)
Precipitation	0.0999					
	(1.418)					
Ruggedness	0.690*	0.756**	1.133***	-1.801	1.739***	2.347
	(0.391)	(0.363)	(0.427)	(1.702)	(0.486)	(2.148)
Road Density	-3.124***	-2.365***	-2.458***	-4.170	-2.463**	-5.409**
	(0.790)	(0.722)	(0.858)	(2.904)	(1.246)	(2.560)
Share Cropland	6.433*	7.978**	10.38**	13.51	4.992	8.261
	(3.493)	(3.656)	(4.468)	(8.549)	(6.481)	(12.06)
Share Urban	-4.255	-4.946	-4.092	-1,075***	-20.30	-700.4***
	(7.613)	(6.613)	(6.995)	(163.3)	(12.55)	(200.1)
Share Grassland	2.503	3.630	2.364	3.674	15.33*	-0.440
	(4.638)	(4.081)	(5.859)	(23.21)	(9.068)	(25.17)
Share Forest	4.418	5.773	10.06*	-1.746	8.583	-7.747
	(3.735)	(4.886)	(5.709)	(9.850)	(9.557)	(16.79)
Population	-1.328***	-1.262***	-1.462**	-7.126***	-1.369**	-7.675***
	(0.496)	(0.465)	(0.583)	(1.376)	(0.652)	(1.888)
soil_type = 2, Andisol	2.570					
	(2.406)					
soil_type = 3, Ardisol	-0.300					
	(2.443)					
soil_type = 4, Entisol	0.404					
	(1.765)					
soil_type = 5, Gelisol	-8.090**					
	(3.348)					
soil_type = 6, Histosol	-0.101					
	(2.031)					
soil_type = 7, Inceptisol	-2.181*					
	(1.184)					
soil_type = 8, Mollisol	0.234					
	(1.135)					
soil_type = 9, Oxisol	-6.439**					
	(2.938)					
soil_type = 10, Rock	2.437					
	(3.385)					
soil_type = 11, Sand	3.336					
	(5.895)					
soil_type = 12, Spodosol	-4.646**					
	(1.803)					
soil_type = 13, Ultisol	1.368					
	(1.919)					
soil_type = 14, Vertisol	1.238					
	(2.791)					
Constant	46.83***	41.99***	27.03*	193.3***	20.70	161.3***
	(12.93)	(12.03)	(14.79)	(28.57)	(18.99)	(38.67)
Observations	932	932	577	127	475	64
R-squared	0.763	0.756	0.723	0.508	0.790	0.662
Country FE	YES	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: The effect of vegetation vigor (NDVI) on GDP per capita; cross-province regression with latest year available

VARIABLES	(1) OLS	(2) IV	(3) IV - no outlier	(4) IV - SSA	(5) IV- rural	(6) IV- SSA & rural
NDVI	-0.150	0.0200	-0.358	0.364	0.915***	2.935**
	(0.140)	(0.178)	(0.258)	(0.609)	(0.286)	(1.247)
Precipitation	-0.0242					
	(0.0682)					
Ruggedness	-0.0915***	-0.0855***	-0.0864***	-0.135**	-0.0966***	-0.0482
	(0.0186)	(0.0172)	(0.0186)	(0.0636)	(0.0186)	(0.0963)
Road Density	0.0846*	0.00702	-0.00691	-0.0500	0.197***	-0.0363
	(0.0434)	(0.0436)	(0.0520)	(0.144)	(0.0645)	(0.150)
Share Cropland	-0.686***	-0.822***	-0.744***	-0.0475	-0.587**	-0.473
	(0.166)	(0.182)	(0.203)	(0.357)	(0.249)	(0.383)
Share Urban	1.295***	1.300***	1.071***	15.91***	1.725***	1.698
	(0.394)	(0.359)	(0.383)	(5.646)	(0.613)	(6.541)
Share Grassland	-0.458*	-0.544*	-1.052***	0.439	-0.873**	7.301**
	(0.267)	(0.293)	(0.360)	(2.134)	(0.404)	(3.455)
Share Forest	-0.207	-0.507**	-0.410	0.119	-0.588	-1.538*
	(0.192)	(0.240)	(0.259)	(0.493)	(0.378)	(0.932)
Population	-0.929***	-0.940***	-0.940***	-1.229***	-0.905***	-0.850***
	(0.0241)	(0.0243)	(0.0283)	(0.148)	(0.0358)	(0.124)
soil_type = 2, Andisol	-0.135					
	(0.0852)					
soil_type = 3, Ardisol	-0.156					
	(0.146)					
soil_type = 4, Entisol	-0.0631					
	(0.0755)					
soil_type = 5, Gelisol	0.774***					
	(0.189)					
soil_type = 6, Histosol	1.111***					
	(0.122)					
soil_type = 7, Inceptisol	0.0280					
	(0.0622)					
soil_type = 8, Mollisol	0.0386					
	(0.0513)					
soil_type = 9, Oxisol	0.351***					
	(0.130)					
soil_type = 10, Rock	-0.276					
	(0.321)					
soil_type = 11, Sand	-0.261*					
	(0.157)					
soil_type = 12, Spodosol	0.255**					
	(0.0998)					
soil_type = 13, Ultisol	0.0902					
	(0.0815)					
soil_type = 14, Vertisol	0.117					
	(0.119)					
Constant	10.62***	8.179***	7.929***	12.59***	7.445***	8.587***
	(0.596)	(0.462)	(0.528)	(1.935)	(0.615)	(1.945)
Observations	635	635	419	46	338	32
R-squared	0.964	0.960	0.951	0.824	0.976	0.824
Country FE	YES	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Panel Specification - Dependent Variable: Poverty Headcount Ratio

VARIABLES	(1) OLS	(2) OLS - SSA	(3) OLS - rural	(4) IV	(5) IV - No Outliers	(6) IV - rural	(7) IV - SSA
NDVI	0.495	1.249	0.738	-2.173	-2.143	-26.79***	-10.64
	(2.693)	(2.640)	(2.706)	(4.140)	(6.230)	(8.430)	(8.236)
NDVI * SSA		-16.40**					
		(6.998)					
Precipitation	-0.708	-0.283	-0.761				
	(1.372)	(1.397)	(1.374)				
Share Cropland	7.332**	6.383*	4.340	8.384**	9.280*	11.94*	15.91*
	(3.597)	(3.562)	(4.175)	(4.201)	(5.397)	(6.281)	(9.664)
Share Urban	-1.123	-1.613	-1.838	-1.859	1.132	-29.09***	-1,125***
	(7.471)	(7.458)	(7.388)	(6.959)	(6.828)	(10.21)	(199.4)
Share Grassland	-1.492	-2.022	-1.601	-1.437	-2.702	19.62*	-4.649
	(5.375)	(5.361)	(5.403)	(5.184)	(5.837)	(10.17)	(24.63)
Share Forest	-0.629	-1.037	-1.037	0.805	0.116	10.98	5.955
	(4.222)	(4.185)	(4.246)	(5.131)	(6.308)	(9.038)	(11.58)
Population	-1.829***	-1.818***	-1.829***	-1.842***	-2.016***	-1.410**	-6.414***
	(0.572)	(0.573)	(0.572)	(0.552)	(0.625)	(0.592)	(1.236)
Ruggedness	1.194***	1.130***	1.185***	1.223***	1.322***	2.578***	-2.131
	(0.423)	(0.425)	(0.423)	(0.414)	(0.448)	(0.513)	(1.863)
Road Density	-2.988***	-2.899***	-2.949***	-2.887***	-3.033***	-4.200***	0.240
	(0.865)	(0.871)	(0.866)	(0.820)	(0.952)	(1.383)	(2.433)
NDVI * Rural			-2.228*				
			(1.348)				
Constant	69.52***	70.78***	70.20***	42.53***	50.12***	-16.00	162.7***
	(12.38)	(12.38)	(12.41)	(15.01)	(17.32)	(19.63)	(27.30)
Observations	2,790	2,790	2,790	2,790	1,495	1,377	207
R-squared	0.732	0.734	0.733	0.732	0.753	0.792	0.427
Country FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Country trend	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: First Stage Results Soil fertility - Poverty

VARIABLES	(1) IV	(2) IV - no outlier	(3) IV - SSA	(4) IV- rural	(5) IV- rural SSA
Ruggedness	-7.036***	-7.030***	-1.832	-8.571***	-1.744
	(1.530)	(1.928)	(1.660)	(1.866)	(1.601)
Road Density	-4.161	-3.144	-5.542**	-1.355	-1.468
	(3.405)	(4.407)	(2.327)	(3.830)	(3.170)
Share Cropland	-32.38***	-40.90***	-23.07***	-31.15	-22.39*
	(10.01)	(14.00)	(8.455)	(20.92)	(11.42)
Share Urban	-55.67***	-74.76***	39.33	-56.25	60.32
	(21.41)	(24.62)	(128.9)	(42.50)	(172.8)
Share Grassland	-42.58***	-70.55***	-22.44	-13.98	-8.908
	(13.54)	(18.90)	(15.10)	(32.23)	(17.47)
Share Forest	-14.15	-26.45	-19.23**	-22.98	-18.66
	(12.15)	(17.00)	(8.992)	(23.63)	(15.25)
Population	1.593	2.186	0.206	1.681	3.109*
	(1.401)	(1.844)	(1.269)	(1.538)	(1.600)
soil_type = 2, Andisol	70.65***	69.87***		37.76***	
	(12.40)	(14.01)		(13.31)	
soil_type = 3, Ardisol	-7.353	-8.765	11.15*	-2.085	
	(6.014)	(10.47)	(5.861)	(6.615)	
soil_type = 4, Entisol	5.701	9.284	8.656***	14.61**	2.609
	(4.906)	(6.756)	(2.872)	(6.619)	(2.714)
soil_type = 5, Gelisol	16.20	12.70			
	(16.46)	(19.00)			
soil_type = 6, Histosol	209.3***	205.5***		200.9***	
	(9.470)	(11.34)		(9.921)	
soil_type = 7, Inceptisol	11.07**	14.12**	10.30**	-0.0353	2.831
	(4.407)	(6.595)	(4.899)	(3.631)	(9.004)
soil_type = 8, Mollisol	9.482*	-2.786		8.553*	
	(4.933)	(7.718)		(4.408)	
soil_type = 9, Oxisol	-12.27*	-11.16	13.96***	2.074	8.746**
	(6.470)	(9.106)	(3.770)	(7.191)	(4.062)
soil_type = 10, Rock	4.242	16.00**		5.038	
	(5.515)	(7.551)		(6.117)	
soil_type = 11, Sand	-0.448	-5.904	8.277*	-5.808	
	(5.150)	(8.851)	(4.429)	(5.218)	
soil_type = 12, Spodosol	37.57***	41.71*		21.70	
	(13.52)	(22.33)		(28.30)	
soil_type = 13, Ultisol	-7.246	-7.278	2.738	-1.990	4.315
	(5.169)	(6.779)	(2.503)	(5.804)	(2.767)
soil_type = 14, Vertisol	8.029	-4.090	36.17***	9.445*	25.23***
	(6.029)	(13.44)	(5.498)	(5.468)	(6.671)
Precipitation	12.06***	7.857	5.669***	10.38**	2.943
	(3.124)	(6.527)	(1.845)	(4.652)	(4.038)
Constant	71.50**	84.42*	48.98*	75.18	16.48
	(30.72)	(50.49)	(27.25)	(49.67)	(26.72)
Observations	932	577	127	475	64
R-squared	0.624	0.625	0.564	0.674	0.697
Country FE	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: First Stage Results Soil fertility - GDP

VARIABLES	(1) IV	(2) IV - no outlier	(3) IV - SSA	(4) IV- rural	(5) IV- rural SSA
Ruggedness	-7.464***	-8.103***	0.992	-9.422***	0.510
	(1.903)	(2.473)	(2.638)	(2.354)	
Road Density	-5.389	-3.581	-1.688	0.394	-7.569
	(4.602)	(5.722)	(9.120)	(5.118)	
Share Cropland	-50.30***	-65.41***	-12.36	-59.19	-21.93
	(16.64)	(22.69)	(18.39)	(38.76)	
Share Urban	-79.18***	-100.9***	175.4	-98.87*	171.2
	(26.09)	(31.24)	(272.0)	(59.17)	
Share Grassland	-55.20**	-112.8***	54.88	-23.58	54.27
	(21.71)	(36.72)	(49.54)	(53.83)	
Share Forest	-27.73	-47.70*	-17.53	-45.24	-31.42
	(18.64)	(25.98)	(26.17)	(41.83)	
Population	1.870	2.364	-2.744	1.756	-4.056
	(1.762)	(2.214)	(4.188)	(1.892)	
soil_type = 2, Andisol	71.27***	72.23***		37.88***	
	(13.06)	(14.86)		(14.31)	
soil_type = 3, Ardisol	-17.00*	-5.790		-1.667	
	(9.919)	(12.07)		(7.681)	
soil_type = 4, Entisol	8.729	2.186	2.737	15.75*	2.074
	(7.157)	(9.237)	(4.133)	(9.477)	
soil_type = 5, Gelisol	8.096	2.391			
	(18.74)	(23.21)			
soil_type = 6, Histosol	207.0***	201.1***		195.8***	
	(10.82)	(13.13)		(12.75)	
soil_type = 7, Inceptisol	11.52**	15.74*	22.73	-2.278	
	(5.251)	(8.239)	(15.32)	(5.193)	
soil_type = 8, Mollisol	11.85**	-0.611		9.914*	
	(5.932)	(8.822)		(5.142)	
soil_type = 9, Oxisol	-23.59**	-17.29	5.891	3.722	17.25
	(10.17)	(12.41)	(15.96)	(9.620)	
soil_type = 10, Rock	-9.013	5.943		-12.52	
	(13.72)	(13.26)		(9.289)	
soil_type = 11, Sand	1.744	-11.87	7.731	-9.617	
	(7.640)	(11.84)	(11.83)	(8.042)	
soil_type = 12, Spodosol	34.28**	35.53		21.56	
	(13.74)	(23.13)		(28.86)	
soil_type = 13, Ultisol	-8.859	-5.629	2.769	-0.503	5.909
	(5.739)	(7.448)	(5.546)	(5.902)	
soil_type = 14, Vertisol	-0.0960	-3.142		4.169	
	(8.963)	(14.85)		(6.178)	
Precipitation	16.49***	5.295	12.01	10.06	9.152
	(5.992)	(10.46)	(9.503)	(7.666)	
Constant	78.16	141.2*	14.67	116.9	72.60
	(49.20)	(84.03)	(84.98)	(78.23)	
Observations	635	419	46	338	32
R-squared	0.588	0.591	0.719	0.675	0.838
Country FE	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: First Stage Results NPP – Poverty

VARIABLES	(1) IV	(2) IV - no outlier	(3) IV - SSA	(4) IV- rural	(5) IV- SSA & rural
Ruggedness	0.0823***	0.0688***	0.165*	0.0705***	0.303**
	(0.0162)	(0.0184)	(0.0900)	(0.0203)	(0.133)
Road Density	0.0867***	0.0968**	-0.0564	-0.0361	-0.455**
	(0.0328)	(0.0395)	(0.127)	(0.0657)	(0.203)
Share Cropland	0.338**	-0.0289	0.248	0.334	0.537
	(0.153)	(0.169)	(0.731)	(0.367)	(0.697)
Share Urban	0.354	0.0129	15.07*	1.331**	16.55
	(0.366)	(0.413)	(8.323)	(0.624)	(11.13)
Share Grassland	0.0295	-0.157	-4.319*	0.0795	-5.781**
	(0.273)	(0.408)	(2.203)	(0.690)	(2.685)
Share Forest	1.102***	0.820***	0.876	1.307***	0.522
	(0.136)	(0.158)	(0.770)	(0.370)	(0.865)
Population	-0.00480	0.0105	-0.216***	-0.0363*	-0.174
	(0.0142)	(0.0147)	(0.0663)	(0.0216)	(0.144)
Precipitation	0.483***	0.607***	0.904***	0.715***	1.264***
	(0.0562)	(0.0914)	(0.197)	(0.141)	(0.313)
soil_type = 2, Andisol	-0.0209	0.0133		0.0804	
	(0.0621)	(0.0702)		(0.102)	
soil_type = 3, Ardisol	-0.360***	-0.370**		-0.504	
	(0.118)	(0.180)		(0.496)	
soil_type = 4, Entisol	-0.165**	-0.183**	-0.0980	-0.133	-0.259
	(0.0684)	(0.0894)	(0.162)	(0.119)	(0.230)
soil_type = 5, Gelisol	0.0114	-0.0112			
	(0.113)	(0.119)			
soil_type = 6, Histosol	0.225***	0.160**		0.249*	
	(0.0726)	(0.0779)		(0.130)	
soil_type = 7, Inceptisol	-0.0116	0.00836	0.320	-0.0541	0.455
	(0.0382)	(0.0511)	(0.258)	(0.0566)	(0.315)
soil_type = 8, Mollisol	-0.00755	0.0360		0.0681	
	(0.0441)	(0.0596)		(0.0597)	
soil_type = 9, Oxisol	0.114	0.00786	0.419**	0.131	0.400
	(0.0928)	(0.121)	(0.168)	(0.141)	(0.310)
soil_type = 10, Rock	-0.0747	0.00843		0.0265	
	(0.120)	(0.132)		(0.116)	
soil_type = 11, Sand	-0.654***	-0.610***	-0.0596	-0.575***	
	(0.203)	(0.224)	(0.228)	(0.179)	
soil_type = 12, Spodosol	-0.125*	-0.0325		-0.122	
	(0.0741)	(0.110)		(0.0889)	
soil_type = 13, Ultisol	0.115*	0.0691	0.161	0.0747	0.111
	(0.0615)	(0.0754)	(0.147)	(0.0846)	(0.207)
soil_type = 14, Vertisol	0.0265	-0.137	0.270	0.174	-0.135
	(0.121)	(0.119)	(0.538)	(0.151)	(0.856)
Constant	-4.514***	-4.874***	-3.491**	-5.030***	-5.787**
	(0.496)	(0.777)	(1.449)	(1.079)	(2.569)
Observations	892	560	109	464	60
R-squared	0.886	0.877	0.884	0.862	0.941
Country FE	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: First Stage Results NPP - GDP

VARIABLES	(1) IV	(2) IV - no outlier	(3) IV - SSA	(4) IV- rural	(5) IV- SSA & rural
Ruggedness	0.0544***	0.0465***	0.0150	0.0416**	0.151
	(0.0138)	(0.0150)	(0.0956)	(0.0178)	(0.213)
Road Density	0.136***	0.130***	-0.143	-0.0175	-0.210
	(0.0318)	(0.0349)	(0.209)	(0.0532)	(0.490)
Share Cropland	-0.107	-0.392**	0.322	-0.726***	0.604
	(0.148)	(0.195)	(0.473)	(0.269)	(0.973)
Share Urban	-0.271	-0.544	7.172	0.187	9.215
	(0.398)	(0.434)	(7.546)	(0.453)	(13.80)
Share Grassland	-0.294	-0.755**	-13.41***	-0.787	-13.43**
	(0.204)	(0.317)	(2.976)	(0.603)	(5.879)
Share Forest	0.868***	0.582***	0.478	0.450	0.222
	(0.138)	(0.184)	(0.623)	(0.275)	(1.686)
Population	0.00445	0.0157	-0.265	-0.0125	-0.0676
	(0.0131)	(0.0141)	(0.172)	(0.0194)	(0.579)
Precipitation	0.548***	0.590***	1.138***	0.803***	1.471*
	(0.0499)	(0.0795)	(0.307)	(0.119)	(0.821)
soil_type = 2, Andisol	-0.0489	0.00683		0.0546	
	(0.0643)	(0.0691)		(0.103)	
soil_type = 3, Ardisol	-0.438***	-0.426**		0.150	
	(0.111)	(0.170)		(0.197)	
soil_type = 4, Entisol	-0.145*	-0.135	-0.171	-0.0984	-0.350
	(0.0767)	(0.0940)	(0.170)	(0.136)	(0.328)
soil_type = 5, Gelisol	0.00161	-0.0884			
	(0.113)	(0.123)			
soil_type = 6, Histosol	0.0860	0.0584		0.0412	
	(0.0684)	(0.0739)		(0.104)	
soil_type = 7, Inceptisol	-0.0489	-0.0245	-0.629	-0.125**	
	(0.0357)	(0.0442)	(0.380)	(0.0565)	
soil_type = 8, Mollisol	0.0562	0.0531		0.135**	
	(0.0440)	(0.0645)		(0.0643)	
soil_type = 9, Oxisol	0.0124	-0.106	-0.299	0.0429	-0.547
	(0.0922)	(0.0998)	(0.186)	(0.153)	(0.509)
soil_type = 10, Rock	-0.0233	-0.107		-0.267***	
	(0.153)	(0.196)		(0.100)	
soil_type = 11, Sand	-0.673***	-0.674***	-0.221	-0.588***	
	(0.205)	(0.236)	(0.301)	(0.169)	
soil_type = 12, Spodosol	-0.190**	-0.128		-0.121	
	(0.0737)	(0.119)		(0.0908)	
soil_type = 13, Ultisol	0.0701	0.0674	-0.271	0.0483	-0.308
	(0.0600)	(0.0680)	(0.163)	(0.0801)	(0.380)
soil_type = 14, Vertisol	-0.151	-0.143		-0.0166	
	(0.100)	(0.128)		(0.120)	
Constant	-3.542***	-3.538***	-1.630	-3.416***	-7.533
	(0.349)	(0.509)	(2.816)	(0.671)	(8.464)
Observations	634	419	45	337	31
R-squared	0.867	0.852	0.949	0.845	0.968
Country FE	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: First Stage Results NDVI - Poverty

VARIABLES	(1) IV	(2) IV - no outlier	(3) IV - SSA	(4) IV- rural	(5) IV- SSA & rural
Ruggedness	0.0127**	0.0153**	0.00636	0.0228***	0.0246
	(0.00637)	(0.00746)	(0.0179)	(0.00675)	(0.0284)
Road Density	0.0424***	0.0338**	-0.0267	0.0141	-0.0107
	(0.0124)	(0.0134)	(0.0354)	(0.0245)	(0.0367)
Share Cropland	0.458***	0.365***	0.0169	0.411***	0.111
	(0.0565)	(0.0724)	(0.112)	(0.100)	(0.189)
Share Urban	-0.0945	-0.0942	1.167	0.305*	4.146
	(0.121)	(0.143)	(2.202)	(0.165)	(2.867)
Share Grassland	0.0326	-0.157	-1.128***	0.0573	-1.367***
	(0.0917)	(0.121)	(0.206)	(0.161)	(0.321)
Share Forest	0.686***	0.551***	0.294**	0.807***	0.417*
	(0.0636)	(0.0777)	(0.112)	(0.126)	(0.221)
Population	0.00487	-0.00549	-0.0317*	-0.0126	-0.00187
	(0.00814)	(0.00821)	(0.0180)	(0.00798)	(0.0272)
Precipitation	0.234***	0.213***	0.352***	0.213***	0.218***
	(0.0222)	(0.0314)	(0.0307)	(0.0406)	(0.0680)
soil_type = 2, Andisol	-0.102**	-0.0767**		-0.124***	
	(0.0441)	(0.0357)		(0.0475)	
soil_type = 3, Ardisol	-0.119***	-0.0813	-0.269***	-0.0341	
	(0.0444)	(0.0604)	(0.0974)	(0.111)	
soil_type = 4, Entisol	-0.0396*	-0.0453	-0.0252	0.0199	-0.0680
	(0.0239)	(0.0294)	(0.0311)	(0.0320)	(0.0482)
soil_type = 5, Gelisol	-0.205**	-0.255***			
	(0.0925)	(0.0880)			
soil_type = 6, Histosol	0.116***	0.105***		0.202***	
	(0.0270)	(0.0304)		(0.0349)	
soil_type = 7, Inceptisol	-0.0351**	-0.0259	-0.0521	-0.00962	-0.00719
	(0.0171)	(0.0244)	(0.0958)	(0.0230)	(0.0833)
soil_type = 8, Mollisol	-0.0624***	-0.0177		-0.0163	
	(0.0173)	(0.0221)		(0.0180)	
soil_type = 9, Oxisol	-0.0309	-0.0523	0.0208	0.0206	0.0317
	(0.0307)	(0.0352)	(0.0372)	(0.0568)	(0.0729)
soil_type = 10, Rock	-0.347***	-0.254***		-0.130*	
	(0.0801)	(0.0811)		(0.0706)	
soil_type = 11, Sand	-0.168**	-0.181**	0.0147	-0.218***	
	(0.0681)	(0.0764)	(0.0525)	(0.0462)	
soil_type = 12, Spodosol	-0.0443*	-0.0842***		0.0711*	
	(0.0263)	(0.0309)		(0.0398)	
soil_type = 13, Ultisol	0.0482**	0.0353	-0.0537	0.0493*	0.0149
	(0.0219)	(0.0243)	(0.0354)	(0.0299)	(0.0664)
soil_type = 14, Vertisol	-0.0260	-0.0660*	0.0445	-0.00831	-0.264***
	(0.0331)	(0.0395)	(0.0720)	(0.0449)	(0.0763)
Constant	-2.982***	-2.800***	-1.970***	-2.609***	-2.011***
	(0.167)	(0.205)	(0.328)	(0.235)	(0.634)
Observations	932	577	127	475	64
R-squared	0.930	0.934	0.946	0.915	0.942
Country FE	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: First Stage Results NDVI - GDP

VARIABLES	(1) IV	(2) IV - no outlier	(3) IV - SSA	(4) IV- rural	(5) IV- SSA & rural
Ruggedness	0.00477	0.00736	-0.0144	0.0193***	-0.0152
	(0.00721)	(0.00881)	(0.0244)	(0.00711)	(0.0670)
Road Density	0.0544***	0.0448***	-0.0983*	-0.0291	-0.0940
	(0.0149)	(0.0153)	(0.0559)	(0.0197)	(0.143)
Share Cropland	0.326***	0.130*	0.110	0.103	0.135
	(0.0704)	(0.0776)	(0.168)	(0.123)	(0.426)
Share Urban	-0.267*	-0.390**	5.183*	0.270	4.990
	(0.137)	(0.154)	(2.945)	(0.174)	(5.582)
Share Grassland	0.206**	-0.231*	-1.781***	0.0724	-1.925
	(0.0983)	(0.133)	(0.577)	(0.166)	(1.322)
Share Forest	0.620***	0.372***	0.329*	0.478***	0.417
	(0.0790)	(0.0855)	(0.176)	(0.130)	(0.580)
Population	0.00413	-0.00354	-0.0835*	-0.00613	-0.0523
	(0.00780)	(0.00875)	(0.0481)	(0.00746)	(0.165)
Precipitation	0.294***	0.266***	0.252**	0.289***	0.201
	(0.0295)	(0.0347)	(0.107)	(0.0340)	(0.312)
soil_type = 2, Andisol	-0.125***	-0.0941***		-0.113***	
	(0.0444)	(0.0357)		(0.0422)	
soil_type = 3, Ardisol	-0.137**	0.0329		0.259***	
	(0.0674)	(0.0856)		(0.0590)	
soil_type = 4, Entisol	-0.0402	-0.0692**	-0.0231	-0.0143	-0.0450
	(0.0294)	(0.0350)	(0.0493)	(0.0340)	(0.118)
soil_type = 5, Gelisol	-0.205**	-0.297***			
	(0.0933)	(0.0838)			
soil_type = 6, Histosol	0.0678**	0.0328		0.145***	
	(0.0314)	(0.0330)		(0.0378)	
soil_type = 7, Inceptisol	-0.0800***	-0.0811***	-0.325**	-0.0692***	
	(0.0189)	(0.0257)	(0.134)	(0.0237)	
soil_type = 8, Mollisol	-0.0480**	-0.00225		-0.00904	
	(0.0189)	(0.0224)		(0.0193)	
soil_type = 9, Oxisol	-0.0634	-0.0991**	-0.117*	-0.0340	-0.0857
	(0.0408)	(0.0419)	(0.0603)	(0.0517)	(0.233)
soil_type = 10, Rock	-0.229**	-0.157		-0.165*	
	(0.113)	(0.123)		(0.0973)	
soil_type = 11, Sand	-0.138**	-0.165**	-0.0425	-0.174***	
	(0.0667)	(0.0671)	(0.0807)	(0.0493)	
soil_type = 12, Spodosol	-0.0828***	-0.152***		0.0423	
	(0.0264)	(0.0373)		(0.0321)	
soil_type = 13, Ultisol	0.0225	0.00983	-0.0379	0.0133	-0.0213
	(0.0232)	(0.0245)	(0.0656)	(0.0267)	(0.156)
soil_type = 14, Vertisol	-0.0614	-0.0570		-0.00554	
	(0.0394)	(0.0385)		(0.0426)	
Constant	-2.679***	-2.206***	-0.508	-2.188***	-0.776
	(0.208)	(0.249)	(0.772)	(0.234)	(2.827)
Observations	635	419	46	338	32
R-squared	0.897	0.891	0.939	0.896	0.936
Country FE	YES	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: First Stage Results Panel NDVI

VARIABLES	(1) IV	(2) IV - No Outliers	(3) IV - rural	(4) IV - SSA
Share Cropland	0.394***	0.325***	0.355*	0.131
	(0.0597)	(0.102)	(0.197)	(0.106)
Share Urban	-0.276**	-0.358**	0.155	0.149
	(0.122)	(0.165)	(0.297)	(2.091)
Share Grassland	0.0205	-0.0299	0.240	-1.158***
	(0.113)	(0.183)	(0.305)	(0.197)
Share Forest	0.537***	0.440***	0.641***	0.411***
	(0.0708)	(0.116)	(0.219)	(0.114)
Population	-0.00483	-0.00503	-0.0196	-0.0243*
	(0.00793)	(0.0118)	(0.0128)	(0.0136)
Ruggedness	0.0109	0.00547	0.0232*	0.00911
	(0.00900)	(0.0145)	(0.0136)	(0.0157)
Road Density	0.0380*	0.0271	0.00436	-0.0100
	(0.0194)	(0.0288)	(0.0337)	(0.0277)
Precipitation	0.265***	0.239***	0.223***	0.312***
	(0.0297)	(0.0614)	(0.0546)	(0.0301)
Constant	-3.184***	-2.882***	-2.615***	-2.097***
	(0.203)	(0.371)	(0.358)	(0.283)
Observations	2,790	1,495	1,377	207
R-squared	0.916	0.917	0.918	0.911
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country trend	YES	YES	YES	YES

Table 16: First Stage Results Panel NPP

VARIABLES	(1) IV	(2) IV - No outliers	(3) IV - rural	(4) IV - SSA
Share Cropland	0.361**	0.125	0.155	0.273
	(0.149)	(0.269)	(0.534)	(0.498)
Share Urban	-0.232	-0.540	0.584	12.62**
	(0.379)	(0.523)	(0.859)	(5.750)
Share Grassland	0.0350	-0.157	-0.128	-6.057***
	(0.248)	(0.498)	(0.848)	(2.010)
Share Forest	0.967***	0.737**	0.941*	0.858
	(0.155)	(0.293)	(0.528)	(0.538)
Population	-0.00780	0.00354	-0.0358	-0.210***
	(0.0149)	(0.0241)	(0.0292)	(0.0514)
Ruggedness	0.103***	0.0869**	0.0934***	0.104*
	(0.0187)	(0.0339)	(0.0327)	(0.0548)
Road Density	0.0584	0.0454	0.00493	-0.0908
	(0.0513)	(0.0847)	(0.0807)	(0.0798)
Precipitation	0.474***	0.460***	0.595***	0.746***
	(0.0508)	(0.0891)	(0.160)	(0.0971)
Constant	-4.397***	-4.297***	-3.952***	-2.020**
	(0.460)	(0.978)	(0.963)	(0.969)
Observations	2,736	1,478	1,360	189
R-squared	0.877	0.868	0.873	0.839
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country trend	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1