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Hydroclimatic risk to economic growth in Sub-Saharan Africa

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ABSTRACT

In order to plan strategies for adaptation to climate change, the current effects of climate on economic growth needs to be understood. This study reviews evidence of climate effects on economic growth and presents original analysis of the effect in Sub-Saharan Africa (SSA). Case studies from the literature demonstrate that historically, climate has had significant and negative effects on household income, agricultural productivity and economic growth in SSA. This study focuses on the effects hydroclimatic variability on economic growth in the countries of SSA. We utilize a new national level precipitation statistic that incorporates spatial and temporal variability within each country. Country level economic growth statistics are analyzed with cross-country and panel regressions. Persistent negative precipitation anomalies (drought) are found to be the most significant climate influence on economic growth. This result is consistent across all model specifications and across several measures of welfare and economic activity. Temperature and precipitation variability show significant effects in some cases. Results imply the consideration of hydroclimatic risks, namely drought, may be the priority concern for adaptation to a changing climate for Sub-Saharan Africa. This conclusion is contrary to the focus of many climate change impact assessments that focus on temperature increases as the primary concern.

1. Introduction

The effects of climate change on future economic growth is a growing concern of policy makers as the scientific evidence of anthropogenic climate changes increase. The Fourth Assessment Report of the IPCC (2007) describes a strong consensus that anthropogenic changes to the climate are occurring, largely as a result of emissions of greenhouse gases such as carbon dioxide. Furthermore, the Working Group Two Report (*Impacts, Adaptation and Vulnerability*) describes a litany of harmful impacts that changes in climate may have on ecosystems, infrastructure, agriculture, water resources and other climate dependent sectors. The estimated negative potential consequences of climate change are sizeable.

There have been several efforts that assess the impact of climate change on global economic growth and of specific regions and countries (e.g., Nordhaus, 2006; Tol, 2002; Nordhaus and Boyer, 2000). Most of these efforts focus on changes in temperature when evaluating the impact of climate change. This is logical, since projections in temperature are uniformly positive in sign. Precipitation changes remain difficult to project as many models disagree on the sign of change in any particular location (IPCC, 2007). In addition, while there is growing evidence of the effect of climate variability on economic development, projections of higher order statistics of rainfall are even less certain than projections of means (IPCC, 2007). Nonetheless, there is some indication, both in theory and in the observed record, that precipitation variability will increase as a consequence of an acceleration of the hydrologic cycle.

When considering changes to the allocation of scarce resources for the purpose of adaptation to climate change, it is important that the most significant climate risks to economic growth are identified and considered. This is especially true in developing countries, where resources are scarce and the greatest impacts of climate change are expected. The relative importance of changes to particular aspects of climate is likely a function of the sensitivity of a country's economy to climate. Several factors, such as the importance of agriculture to an economy, the status of infrastructure and insurance systems and prevailing climate conditions to which society is accustomed, influence this sensitivity. At higher latitudes where most developed countries are located, precipitation is relatively constant and relatively plentiful, whereas temperature varies widely through the course of the year, from the cold of winter to the heat of summer. Furthermore, on average, countries at higher latitudes are wealthier, have diversified economies that are less dependent on agriculture and have infrastructure, financial instruments and markets that mitigate the effects of variable rainfall. Temperature variability remains the primary residual climate risk and as a result industrialized economies may be most sensitive to temperature changes.

For countries at lower latitudes and with less diversified economies, precipitation changes may be as important or more important than changes in temperature. At lower latitudes, the variability of rainfall is much greater than temperature variability. While the greatest temperature variations occur in the course of a day, rainfall varies from dry seasons where no rainfall occurs for months to wet seasons when rainfall may be daily and torrential. In addition, interannual variability of rainfall, such as droughts and fluvial seasons associated with the El Nino/Southern Oscillation (ENSO), are most pronounced within the tropics (Ropelewski and Halpert, 1987; 1989). Tropical countries are on average less wealthy, more dependent on agriculture, face a more challenging baseline climate in terms of rainfall variability, have less developed infrastructure, and lack financial instruments such as insurance and markets to mitigate these effects (Brown and Lall, 2006). In addition, Sub-Saharan Africa carries a disease burden that is exacerbated by epidemic outbreaks of malaria linked to climate variability (Sachs and Malaney, 2002).

High levels of hydroclimatic variability, as characterized by floods and drought or simply extended dry and wet seasons, are a likely impediment to development. Floods destroy infrastructure, disrupt transportation and economic flows of goods and services and can lead to contaminated water supplies and the outbreak of waterborne disease epidemics. Droughts have been identified as the world's most expensive disaster (FEMA, 1995), destroying the economic livelihood and food source for those dependent on the agricultural sector or their own food production. The effect of these hydrologic variability impacts can be devastating in any country, but especially in those with enhanced vulnerability due to high dependence on agriculture and low infrastructure inventory (World Bank, 2004; Grey and Sadoff, 2006).

The rural poor of SSA are affected by climate. They typically depend on agriculture for livelihood and sustenance, are unprotected against climate-related diseases, lack secure access to water and food, and are vulnerable to hydrometeorological hazards. Climate variability is arguably the dominant source of consumption risk in smallholder rainfed agriculture in the dryer environments of much of sub-Saharan Africa (Walker and Ryan, 1990; Rosenzweig and Binswanger, 1993; Dercon, 2002; Zimmerman and Carter, 2003). Climate contributes to price variability in regions where markets and transportation infrastructure are poorly developed (Zimmerman and Carter, 2003). Since the relatively poor have less capacity to buffer against climate risk through own assets or financial markets, they tend to experience disproportionate livelihood risk in the face of climate variations.

In the current paper, we investigate climate effects on economic growth in Sub-Saharan Africa to inform adaptation policy making. Given the differential climate changes that countries face and their differing capacity to manage those challenges, the current analysis is seen as necessary for adaptation planning to be informed by an understanding of how economies are affected by climate. In the next section, previous studies of climate change impacts on economic growth are reviewed with emphasis on their relevance to SSA. Then, the current vulnerabilities of SSA economies are investigated using an econometric analysis of national level economic growth and climate data. Finally, adaptation planning is discussed in view of the findings presented in the previous sections.

2. Review of literature on climate impacts on economic growth in SSA

In this section we explore the existing literature that addresses the effects of climate on economic growth in SSA. The studies may be generally divided into case studies, panel studies, cross-country analyses and climate change studies and include surveys and econometric analysis. The sense of the literature varies with the scale of the study. In general, case studies find climate to be a dominant and negative effect on economic growth in SSA. The few panel studies that investigate climate and economic growth support the views of case studies. Cross-country analyses tend to focus on global datasets and highlight the role of institutions in addition to, or in opposition to, the effect of climate, although climate is poorly instrumented in most studies.

Several studies have investigated the effects of climate on economic growth in individual countries or at the household scale. Some general conclusions may be drawn. The findings of these studies support the hypothesis that climate variability has a significant effect on economic progress in the locations studied. In general, the results provide evidence that rainfall variability contributes to reduced economic productivity and increased poverty. Rural households have limited means for managing covariant risks[1] such as those associated with climate variability. In addition, rainfall variability contributes to risk aversion in farmers that leading to investments that are less profitable than would be the case in the absence of this climate-induced risk aversion. The sum of the studies paints hydroclimatic variability as a major source of risk that remains unsuccessfully mitigated.

[1] Covariant risk refers to risks resulting from events that affect a large number of people in the same location at the same time, such as droughts, and so are difficult to insure against locally.

In a study of six villages in India, Rosenzweig and Binswanger (1993) used panel data over about 10 years to investigate household wealth, weather risk as measured by monsoon onset date, and the composition and profitability of agricultural investments. The authors find that farmers' investment portfolios are influenced by their risk aversion, wealth and rainfall variability, resulting in less profitable investments. The authors find that farmers are often successful in compensating for idiosyncratic risks, but are less successful managing covariant risk, such as due to rainfall variability that affects an entire village. This unmanaged climate risk contributes to lower incomes and greater income inequality.

Dercon (2001) studied data from six villages in Ethiopia between 1989 and 1995, finding the occurrence of rainfall shocks had large negative effects on income growth and were the primary reason households fell into poverty. The analysis found that growth was reduced by one fifth and that there would be 15% less poverty in these villages (as measured in the study) without rainfall shocks. A study of farm household vulnerability and climate adaptation in Cameroon (Molua, 2002) found rainfall variability to be a major cause of income fluctuation and that farmers were actively changing farming practices to adapt to perceived changes in climate and climate information, although the climate information was often provided from nonscientific sources. Christiansen et al. (2002) summarized a variety of studies from SSA, concluding drought had a major negative effect on household income and that the capacity of households to manage covariant risk was very limited. Access to infrastructure and urban markets were identified as important contributors to the income of rural households, as was political stability.

At the national level, the evidence indicates hydroclimatic hazards produce observable effects on national economic growth statistics. Several single country studies have shown that rainfall extremes have major impacts on economic development (World Bank, 2004; Grey and Sadoff, 2006). A study of hydrologic effects on the Ethiopian economy found that the occurrence of droughts and floods reduced economic growth by more than one third (Grey and Sadoff, 2006). Kenya suffered annual damages of 10 – 16% of GDP due to flooding associated with El Niño in 1997-1998 and La Niña drought in 1998-2000. These damages extended beyond agriculture, with 88% of flood losses incurred by the transport sector, while hydropower losses and industrial production totalled 84% of the drought losses (World Bank, 2004). In addition, a study of the economy wide impact of drought on 6 SSA countries found significant impacts and that vulnerability was related to the complexity of a country's economy (Benson and Clay, 1998). Surprisingly, the findings suggested that a country may become more sensitive to drought as it develops from a low level of development. It may be that the poorest economies are influenced by the risk aversion and low levels of investment that characterize poor households (Rosenzweig and Binswanger, 1993) and trapped in a low level equilibrium that appears as insensitivity to rainfall fluctuations.

The findings in these various studies provide compelling evidence that hydroclimatic variability has a significant effect on households in SSA, especially the rural poor, and on some countries. Does this translate into a significant drag on the national economies of SSA? The question remains unanswered and has rarely been addressed. Despite the evidence from household and village studies, few studies have considered the effects of hydroclimatic variability on national level economic development. Yet is has important implications for the approaches adopted as adaptation to climate change.

A large number of cross-country regression analyses have investigated the role of geography in the economic development of the nations of the world (e.g. Sachs, 2001; Diamond, 1997; Easterly and Levine, 2003; Rodrik et al., 2004)). In general, the cross-country results indicate that institutions and geography are important determinants of current economic levels, but the results for SSA are diminished by the co-occurrence of both poor institutions and substantial geographic challenges. Climate variability is not explicitly considered in these studies although it is identified as one source of the "geography effect." Several recent studies have focused on the climate effect. Nordhaus (2006) used a global subnational economic output database to explore spatial relationships between climate and output, finding that climate was a "significant handicap," representing 20% of the difference with industrialized countries in economic output. Typical of studies that consider climate, mean temperature and precipitation were used as the climate variables, omitting the very real differences in variability that affect the tropics disproportionately.

Some studies have examined the effects of climate variability. In a cross-country regression analysis, Brown and Lall (2006) found that the coefficient of rainfall variability was more strongly associated (inversely) with per capita GDP than mean precipitation or temperature. Mendelsohn et al. (2004) compared farm income in Brazil and the US and found that locations with adverse climates have lower per capita incomes and concluded that "adverse climates contribute to rural poverty."

The question of climate variability versus climate means was explored by Mendelsohn et al. (2005), in a study of climate effects on India, Brazil and Africa. The authors compare the relative effects of climate means (average conditions) versus climate variability of both soil moisture (effectively a proxy for rainfall) and temperature on farm income using a ricardian analysis. The findings show that the most significant climate effects depend on the nation considered. In the US, the mean climate was more important than climate variability and temperature was more important than precipitation for explaining farm income. In Brazil, climate variability was more significant than climate means, and precipitation was more important than temperature. In India, mean climate and precipitation were the more significant predictors of farm income. The results are likely indicative of the differential capacity to manage different climate risks. The results also serve as a cautionary note for studies that project economic effects of climate change with changes to the mean of single climate variables.

In a study that is similar in approach to this study, Barrios et al. (2008) investigated the effect of rainfall changes on agricultural production in SSA countries in comparison to other non-SSA poor countries. The authors conclude that the decades long drought affecting the Sahel since the 1960's accounts for the gap between agricultural production in SSA and the rest of the world. As we have seen with other studies, the role of rainfall variability in deterring agricultural investment is highlighted.

The results of several studies of the effects of climate change on global economic growth remain inconclusive. As reported in Nordhaus (2006), estimates range from -0.2 to -0.4% for 2.5C warming (Nordhaus and Boyer, 2000), to a neutral effect (Mendelsohn, Dinar and Williams, unpublished report) to +2.3% per 1C of warming (Tol, 2002). Using a disaggregated snapshot of global economic output, Nordhaus (2006) uses the spatial relationship between climate (temperature and precipitation means) and economic output to estimate climate change effects to be up to -1 to -3% of output.

However, the effects of climate change are likely to be difficult to generalize since countries have radically different vulnerabilities to climate and capacities to cope with climate anomalies. Developing countries, and those of Sub-Saharan Africa, may be presumed to have very different responses to a changing climate than developed countries. As Nordhaus (2006) states, most impact studies have focused on developed countries and extrapolated to other regions. While there is substantial literature addressing the effects of climate variability on households, there is little analysis of the economic effects at the country scale.

We attempt to address this gap by investigating the effect of hydroclimatic variability on the economic growth and welfare outcomes of countries of SSA using regression analysis. The study builds on the work of Barrios et al. (2008) by introducing an index of rainfall extremes and by considering welfare indicators and GDP growth in addition to agricultural production.

3 Empirical Methods

3.1 Data

Data has been collected from a variety of sources and falls into two categories: (1) livelihood measures, and (2) climate data. These measures are described in detail below.

Livelihood measures[2]

Per capita economic growth or agricultural production are commonly considered in national scale studies. We expand the analysis by including industrial value added to GDP and poverty headcount ratios at $1 and $2 a day (PPP) (% of population). Panel data is available from1961-2005 for all data sets except industrial value added.

Climate data[3]

All precipitation and temperature data are extracted from the New et al. (2000) gridded 0.5 degree dataset. Annual average temperature and precipitation are spatially averaged over the domain of each country. Data is available for 1901 to 2003. In addition to the spatially averaged national values, we employ an alternative approach to creating a national level precipitation statistic that preserves more of the spatial and temporal information that is available in the climate data. In order to preserve more sub-annual

[2] Source: World Development Indicators (WDI), World Bank

[3] Sources: Dartmouth Flood Observatory, Active Archive of Large Floods from 1975-present (2007); NOAA NCEP Merged Analysis; Brown and Lall (2006); Brown, Meeks, Hunu (forthcoming)

temporal signal, we use a weighted anomaly standardized precipitation (WASP) index in place of an annual average (Lyon and Barnston, 2006). The WASP calculates deviations in monthly precipitation from their long term mean and then sums those anomalies weighted by the average contribution of each month to the annual total, according to the following formula:

$$S_N = \sum_{t=1}^{N}\left(\frac{P_i - \overline{P_i}}{\sigma_i}\right)\frac{\overline{P_i}}{\overline{P_A}} \qquad (1)$$

In (1) P_i and $\overline{P_A}$ are the observed precipitation in the *i*th month and the long term average precipitation for the *i*th month, σ_i is the standard deviation of monthly precipitation for the *i*th month and P_A is the mean annual precipitation. The number of months over which the index is calculated is indicated by N. We use $N = 12$ to capture annual precipitation anomalies. The WASP is designed such that rainfall anomalies are measured relative to the typical rainfall for a given month. The result is well correlated with drought indices, such as the Palmer Drought Severity Index. In addition, we choose the ending month over which to calculate the WASP index based on the seasonality of rainfall. Otherwise, an annual value of rainfall based on the calendar year will split a single rainy season (and growing season) between two years for much of Africa where the rainy season occurs during boreal winter (Nov to Mar).

In order to preserve the spatial signal of precipitation variability, we calculate the WASP at the grid cell level using a 0.5 degree resolution dataset (New et al., 2000). Following Lyon and Barnston (2006), we set thresholds at -2, -1, +1, +2 values of WASP and calculate the percentage of grid cells within a country exceeding each threshold. We consider the area exceeding the negative thresholds as representing areas of severe drought, moderate drought, and consider the positive thresholds are representative of moderate and severe flooding. We label negatives anomalies of the WASP as drought as they are well correlated with other measures of drought, such as the Palmer Drought Severity Index. Although it may be intuitively appealing to consider strong positive anomalies to be incidences of flooding, because the WASP is based on monthly values and floods operate on much shorter timescales (days to week), it is unlikely to be representative of flood occurrences. The flood risk that a country faces likely has a significant effect on economic growth. However, there is no objective, quantitative data set of flood occurrence or risk for SSA. Inclusion of such data would undoubtedly improve this study.

The use of the rainfall index has several possible advantages. The ability to separate anomalous low rainfall from high rainfall is expected to be a significant advantage over a single precipitation series, as the responses to positive and negative anomalies are unlikely to be symmetric. Also, the response to the magnitude of the rainfall anomaly is likely nonlinear, making a threshold approach more appropriate. For example, there is likely little or no effect due to small aberrations in rainfall, while large anomalies likely have very large effects. We calculate the WASP to capture the complete annual cycle of rainfall, not constrained by the annual Jan – Dec value. Studies that use annual values of precipitation from Jan – Dec overlook the fact that the rainy season in much of southern Africa occurs over the end of the calendar year, and thus aggregate rainfall from two separate growing seasons into a single value that is not representative of either growing season. Perhaps most significantly, the use of the area exceeding the thresholds preserves the spatial variability of rainfall across a country. Spatial averaging of precipitation may result in extremes in one location balancing extremes of the opposite sign in another location. With the WASP index, the area of a country that is in drought is preserved regardless if another region is in a state of above average rainfall. This is expected to be especially advantageous in large countries or in those that cross climate regions.

3.1 Cross-country regressions

In acknowledgement of the problems associated with comparing across countries, cross-country regressions are used here primarily to establish that a substantial relationship exists in our data between climate variability and a variety of our livelihood indicators. This relationship is also generally supported by some of the literature discussed above.

For the purposes of this paper we focus on five primary livelihood indicators as our outcome variables: (1) GDP growth, (2) agricultural GDP value added, (3) industrial GDP value added, (4) poverty headcount under $1/day, and (5) poverty headcount under $2 per day.

Our general cross-country specification is:

$$Y_i = \beta X_i + \mu V_i + \varepsilon_i$$

where Y_i is country *i*'s livelihood measures, X_i is a vector of a country's climate variables, as described above in the data section, V_i is a vector of control variables, and ε is the error term.

3.2 Fixed effects and random effects regressions (Panel data)

We employ both fixed effects[4] and random effects[5] identification strategies using panel data for years 1975 - 2003. These results are more robust than cross-country regressions and are the primary evidence underpinning the conclusions of this analysis. The specifications for these regressions are shown below.

3.2.1 Fixed effects:

Using fixed effects with the repeated observations for each country, we control for the time-invariant and unobserved characteristics that are correlated with both the dependent and independent variables. In these regressions, such time-invariant characteristics include, for example, the geographical characteristics of a country (exclusive of climate variables).

[4] **Fixed effects regression:** Fixed effects regression uses panel data, in which there are observations from two or more time periods for each entity, to control for omitted variables that vary across entities but not over time.

[5] **Random effects regression:** Random effects regression also uses panel data to control for omitted variables, but, unlike fixed effects, it permits the estimation of time invariant characteristics. To do so, random effects regression requires stricter conditions than fixed effects regressions, such as that individual entity effects are uncorrelated with the regressors.

We begin with a basic fixed effects regression using the panel data for all forty-two SSA countries included in our sample.

$$Y_{it} = \beta X_{it} + \alpha_i + \varepsilon_{it} \qquad \textit{i= 1,.. , 42 and t= 1, …, T}$$

where Y_{it} represents a livelihood measure of country *i* at time t, X_{it} represents climate measures for country *i* at time t, α_i represents the sum of all time-invariant aspects of country *i*, and ε_{it} represents time-variant factors, which are typically not known by the countries before the time period occurs, for example, the amount of rainfall that will occur in that year. We also add controls for other variables, such as mean annual temperature. The identifying assumption is that the effect of the time-invariant country characteristics does not change over time.

If we could observe all of the time-invariant country characteristics, then we could use a single cross-section regression of the livelihood indicators on the climate variables. But in such situations, we often cannot observe all of the relevant time-invariant country characteristics, and therefore cross-sectional estimates can be inconsistent. The benefit of using fixed effects instead of cross-country regressions is that we control for the possibility that the hydroclimatic variability might depend (at least to some extent) on the time-invariant characteristics, which would therefore make the variables correlated.

Also, we run these fixed effects regressions with standard errors that are both clustered and non-clustered at the country-level. Clustering the standard errors at the country-level allows for potential correlation between observations for any given country at different times. Without clustering the standard errors, we may be overstating the relationship, and the significance of such a relationship, between variables included in the analysis.

3.2.2 Random effects:

In addition to the regressions specified above, we run separate regressions using a random effects identification strategy, which avoids some of the weaknesses of the fixed effects approach (such as the inability to estimate the effects of time-invariant characteristics). Also, a fixed effects approach can result in imprecise estimates when there is insufficient variance in independent variables over time (although this is unlikely to be the case for climate variables). A random effects strategy, however, requires several stronger assumptions than fixed effects; in particular, the individual country effects must be uncorrelated with the climate variability and both α_i and ε_{it} must be normally distributed.

3.2.3 Hausman Test

Given the different assumptions required for the fixed and random effects regressions, we must establish which identification strategy most accurately fits the panel data used here. Therefore, we perform a Hausman Test to determine whether the random or fixed effects approach is the most appropriate for each of the different specifications. The test does so by providing a test of the assumptions required for random effects approach to be valid. By using random effects with these data, we obtain estimators with smaller variances, which are therefore more precise if the assumption hold. The outcome of these tests provides the basis for our decision to use fixed effects in some regressions and random effects in others. The outcomes of the Hausman Tests are presented in the results section below.

4 Results and Analysis

4.1 Cross-country regressions

The cross-country regressions provide general patterns in the relationships between our five primary livelihood indicators (GDP per capita growth, Agricultural GDP Value Added, Industrial GDP Value Added, poverty headcount of people living under $1 per day, and poverty headcount of people living under $2 per day) and the climate variables, which are later supported with the panel regression results. In cross-country regressions, average values over the years 1962 – 2003 for each of the variables were used except in the case of Industrial GDP Value Added (1999 – 2003). The results of these regressions are shown in tables 3 through 12.

First, we review results for the regressions with GDP per capita growth as the outcome variable (Table 1). The results are generally consistent with previous studies that indicate precipitation and temperature have moderate effects. Temperature tends to have a negative and statistically significant (at the 99% level) relationship with GDP growth when precipitation data is not included. When considered together, neither precipitation or temperature is significant. This is likely due to the negative correlation between temperature and precipitation between much of SSA. A previous study indicated that precipitation variability was more important than mean precipitation in cross-country regressions on per capita GDP using a global dataset (Brown and Lall, 2006). Here the dataset is limited to the countries of SSA, partially controlling for region wide effects. Also, here the WASP variables are introduced as better measures of precipitation variability that is likely to impact economic growth, i.e., climate extremes such as droughts and floods, than the instrument used for climate variability in the previous study, which was the coefficient of variation of monthly and annual precipitation.

The results for the WASP(-1) and WASP(-2) variables stand in contrast to the moderate effects of precipitation and temperature. The effect of drought risk, as represented by the average WASP index, is negative and statistically significant at the 95% (WASP(-2)) or 99% (WASP(-1)) level with and without a control for temperature. As further results will show, this result is robust and consistent across model specifications.

The results for GDP per capita growth and spatially averaged precipitation and the two flood variables, moderate and severe positive WASP values, are not statistically significant in any of the regressions performed with GDP per capita growth as the dependent variable. The coefficients on the positive WASP variables are positive in some regressions and negative and others. This is most likely a signal that the positive WASP variables do not represent a pure flood effect, but rather are conflating the positive effect of strong rains with the negative effect of floods. This provides an indication that additional work is required to refine the flood data to distinguish these two effects.

The regressions with Agricultural GDP Value Added as the dependent variable display many of the same overall patterns as the per capita GDP regressions (Table 2). This is consistent with expectations as many of the Sub-Saharan countries included in this analysis are heavily dependent on agriculture as a main contributor to GDP. Drought coefficients are negative and statistically significant at the 99% confidence level, with and without temperature controls. Precipitation is not statistically significant, while the WASP(+) indices have statistically significant (95%) coefficients, again indicating positive rainfall anomalies as measured over longer time periods (months) are advantageous to agriculture and not representative of flood effects.

Interestingly, industrial GDP is also significantly affected by hydroclimate (Table 3). Results indicate strong negative relationships between industrial value added and moderate and severe drought (both statistically significant). The drought effect may be due both to reduced hydroelectricity, which is a major energy source in many SSA countries, and the upstream effects of poor agricultural production. Industrial GDP value added is also positively associated with precipitation (statistically significant), another indicator of the effect of hydroelectricity production or perhaps agricultural inputs. There is a significant negative effect with temperature without including precipitation in the model, but it does not hold when precipitation is included.

Finally, regressions were performed using poverty headcounts below both one and two dollars a day as an alternative to GDP as a measure of economic progress (Table 5). The directions of the relationships, as seen through the signs of the coefficients, are similar to the GDP statistics. The only relationship, however, that is statistically significant is WASP(-2), severe drought. Severe drought, as instrumented by WASP(-2), is associated with an increase in the number of people living under one dollar per day (at the 99% significance level).

The results of the cross-country regression analysis provide general evidence that mean values of precipitation and temperature are relatively poor indicators of climate effects on economic growth in SSA in comparison to the WASP variables which are indicators of climate extremes. The next analysis uses panel data of the same datasets to control for all the factors of individual country that do not change with time significantly with time. This presents a more robust estimate of climate effects than cross-country analysis which does not control for these time-invariant factors.

4.3 Fixed effects and random effects regressions

Fixed effects and random effects regressions use annual values for all variables during the period 1975 – 2003. In this way, the year to year changes or variability in climate variables is investigated in terms of year to year responses in economic growth. Fixed effects regressions permit us to control for the unobserved time-invariant country characteristics and are therefore more conservative estimates than the basic cross-country regressions. We report fixed effects results with clustered and non-clustered standard errors at the country level. In general the results are consistent with the cross-country regressions in terms of the significant independent variables and the sign of the regression coefficients. In many cases the statistical significance of some variables is reduced, an indication of the more rigorous test of association through these specifications. We interpret this as a sign of robustness in the results for those variables that retain significance. That is the case for the drought indices, indicating that drought is the most influential climate effect on economic growth in SSA as measured in this study.

The results of the Hausman Tests performed for this analysis indicate that fixed effects identification strategy is generally most appropriate for the basic regressions with just the precipitation and temperature variables. This result indicates that the assumption required for random effects are not upheld with these data.

In the case of the regressions including the WASP variables, a random effects approach is more appropriate for most of the specifications and thus the assumption that the individual country and the climate variability are orthogonal to one another is upheld. Due to the results of the Hausman Testwe report the fixed effects results for the basic regressions and the random effects results for most of the calculations performed with the WASP variables. For the few specifications with the WASP variables that do not uphold the assumptions of orthogonality, we use the fixed effects identification strategy. In all cases, the most telling results related to the effect of drought are consistently significant across model specification.

The panel regressions with per capita GDP growth as the dependent variable find moderate drought (WASP(-1)) to be negatively associated at the 99% confidence level, both with and without temperature controls (Table 6). These results are consistent with the cross-country regressions. Severe drought and precipitation also have significant, though weaker, effects, while temperature is only significant when precipitation is not included. In the case of agricultural value added, the results are similar (Table 7). Moderate and severe drought have significantly negative effects. In addition, the WASP(+1) coefficient is significant and positive, indicating a positive benefit to above average rains.

In the case of poverty count, drought was again the only significant climate variable (Table 8). The WASP(-1) and WASP(-2) variables were both significant at the 95% confidence level for an increasing effect on number of people living on less than $1/day. There were no significant results at the $2/day threshold (Table 9). There are no fixed effects results for industrial GDP value added to report due to data limitations.

As expected the results from the fixed effects regressions with clustered standard errors are more conservative than the results without clustering. For this reason, the method including clustered standard errors is the preferred fixed effects specification and are the results reported here.

5 Discussion

Understanding the current impact of climate on economic growth is critical to estimating the effects of climate change on growth, and for the planning of adaptation strategies. Developing countries are of concern because they are likely to suffer the most harmful effects of a changing climate and have the least capacity to manage those effects. In this study we examined the historical effect of climate on economic growth in Sub-Saharan Africa using cross-country and panel regression analysis. We focused specifically on the effects of hydroclimatic variability relative to temperature and employed a precipitation-based index that captures subnational spatial aspects and distinguished between small and large rainfall anomalies using a threshold.

The most striking result from all analyses is the consistent negative effect of persistent dry conditions, i.e., drought, on economic growth. For both panel regressions, with fixed effects and randomized effects, and cross-country regressions, the WASP(-1) index coefficient is negative and statistically significant at the 99% confidence interval for the dependent variables per capita GDP and per capita Agricultural Value Added. For poverty, the WASP(-2) index (severe drought) is significant at the 99% confidence interval across all model specifications, while WASP(-1) is significant for the random effects panel regression. The results for Industrial Value Added are similar but slightly less significant in the cross-country regression. Interestingly, the results are stronger at a 1 year lag, which may indicate a delay caused by the propagation of the drought effect through agriculture to the secondary industries relying on agricultural inputs.

Another interesting result from the study is the limited significance of temperature in any of the regressions. Although temperature is often used in climate change impact assessments, it may not be indicative of the most important climate effects on economic growth. These results indicate that drought may be of greater concern. Temperature and precipitation are strongly and negatively correlated on an interannual basis in much of Africa; it may be that temperature effects cited elsewhere are associated with the occurrence of drought. The focus on temperature changes in economic evaluations of climate change impacts may be due to the reduced uncertainty in the direction of temperature projections, and the greater impact that temperature changes may have relative to precipitation in developed countries, where most methodologies are developed (Nordhaus, 2006).

Although we attempted to address hydroclimatic risk in this study, it is clear that the WASP index is effective at representing drought (as indicated by a high correlation with the Palmer Drought Severity Index) and its effects (based on the results of this study) but is not representative of flood events or their impacts. The evidence from case studies implies that flood risk is likely to be an important concern for economic growth, but the authors are unaware of a suitably quantitative dataset of historical flood risk for SSA.

The evidence of the literature from household to village scales presents hydroclimatic variability as a major impediment to agricultural productivity in SSA. This study provides evidence that the effects penetrate to the level of national economies. The hydroclimate of SSA is the most variable in the world, with seasonal dry periods and wet periods, interannual variability related to ENSO, and decadal scale variability related to low frequency ocean circulation patterns (Giannini et al., 2007). While climate change remains a concern, economic growth in the present depends on the ability to manage the effects of hydroclimatic variability.

Society's ability to manage climate variability can be improved. We propose that improving the ability of economies to manage their current climate challenges is the foundation of adaptation. By successfully managing current climate risks, economic growth is engendered and countries should be in a better position to manage future climate challenges.

One state of hydroclimatic extreme, drought, is identified as the primary concern. However, as noted, the effects of flood remain largely unexamined except in case studies. Rural populations dependent on rainfed agriculture, who make up 93% of the population of SSA, remain immensely vulnerable to drought. The cumulative negative effects of drought and other traps lead to a poverty trap of highly vulnerable, low productivity subsistence level agriculture. In this study, severe drought was strongly associated (99% CI) with increasing poverty counts, results that are consistent with those of Dercon (2001) which found rainfall shocks were the primary reason households fell into poverty. While there is no single solution, a portfolio of interventions may reduce the large uninsured risk that currently hinders the progress of farmers on the path to economic development. Some of the most promising, underutilized opportunities include: improved climate information systems, diversification of crops and livelihoods, better water management including on-farm and community level storage, financial risk transfers such as index insurance, improved market access through market development, transportation and storage, and finally, protection from hydrometeorological hazards.

In addition, SSA, on average, has a small fraction of the infrastructure of developed countries, and a small fraction of infrastructure relative to the hydrometeolorogic risks experienced (Grey and Sadoff, 2007). Developed countries have invested heavily in infrastructure to reduce their exposure to hydroclimatic risks. Roads provide access to markets, access to jobs and increase the flexibility of an economy. Water storage reduces hydrologic variability and provides protection from floods. Further investment in infrastructure and in technologies that provide infrastructure services are likely needed to reduce the effects of hydroclimatic risk on economic growth in SSA.

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Cross-country Regression Results

Table 1:

[illegible]

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
Precip	[illegible]		[illegible]												
	([illegible])		([illegible])												
Temp		[illegible]***	[illegible]												
		([illegible])	([illegible])												
WASP+ med				[illegible]	[illegible]			[illegible]	[illegible]						
				([illegible])	([illegible])			([illegible])	([illegible])						
WASP- med						[illegible]***	[illegible]***	[illegible]***	[illegible]***						
						([illegible])	([illegible])	([illegible])	([illegible])						
WASP+ sev										[illegible]	[illegible]			[illegible]	[illegible]
										([illegible])	([illegible])			([illegible])	([illegible])
WASP- sev												[illegible]***	[illegible]***	[illegible]***	[illegible]***
												([illegible])	([illegible])	([illegible])	([illegible])
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
R-sqd	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

[illegible]

Table 2:

Dependent variable: Ag GDP Value Added, Cross-Country

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
Precip	[illegible]		[illegible]												
	([illegible])		([illegible])												
Temp		[illegible]***	[illegible]***												
		([illegible])	([illegible])												
WASF+ mod				[illegible]**	[illegible]***			[illegible]	[illegible]						
				([illegible])	([illegible])			([illegible])	([illegible])						
WASF- mod						[illegible]***	[illegible]***	[illegible]***	[illegible]***						
						([illegible])	([illegible])	([illegible])	([illegible])						
WASF+ sev										[illegible]	[illegible]*			[illegible]	[illegible]*
										([illegible])	([illegible])			([illegible])	([illegible])
WASF- sev												[illegible]	[illegible]	[illegible]	[illegible]
												([illegible])	([illegible])	([illegible])	([illegible])
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	775	1326	679	1278	1278	1280	1280	1261	1261	1297	1297	1215	1215	1215	1215

Notes: Robust standard errors are in parentheses. Temperature controls are the average annual temperature. Significance is designated by: * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3:

Dependent variable: Ind_GDP_Value added, logged

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
Precip	0.012***		0.014**												
	(0.004)		(0.006)												
Temp		-0.577***	-0.93**												
		(0.067)	(0.407)												
WASP + mod				0.043	2.213			-0.895	0.000***						
				(0.104)	(2.398)			(9.276)	(0.000)						
WASP - mod						-16.60***	-21.628***	-17.205**	0.000***						
						(5.900)	(6.203)	(6.854)	(0.000)						
WASP + sev										0.000***	20.16			-12.512	-13.126
										(0.000)	(24.388)			(30.920)	(30.915)
WASP - sev												-12.582**	-21.451***	-16.120**	-23.051***
												(6.094)	(6.844)	(8.282)	(8.910)
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	136	35	34	33	33	33	33	32	32	34	34	32	32	32	32

Notes: Robust standard errors are in parentheses. Temperature controls are the average annual temperature. Significance is designated by: * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4:

Dependent variable: Poverty headcount 1, cross country

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
Precip	[illegible]		[illegible]												
	([illegible])		([illegible])												
Temp		[illegible]	[illegible]												
		([illegible])	([illegible])												
WASF + mod				[illegible]	[illegible]			[illegible]	[illegible]						
				([illegible])	([illegible])			([illegible])	([illegible])						
WASF - mod						[illegible]	[illegible]	[illegible]	[illegible]						
						([illegible])	([illegible])	([illegible])	([illegible])						
WASF + sev										[illegible]	[illegible]			[illegible]	[illegible]
										([illegible])	([illegible])			([illegible])	([illegible])
WASF - sev												[illegible]***	[illegible]***	[illegible]***	[illegible]***
												([illegible])	([illegible])	([illegible])	([illegible])
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	57	59	57	54	54	55	55	52	52	57	57	57	57	57	57

Notes: Robust standard errors are in parentheses. Temperature controls are the average annual temperature. Significance is designated by: * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5:

Dependent variable: Poverty Headcount 2, cross country

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
Precip	-0.001		-0.011												
	([illegible])		([illegible])												
Temp		0.515*	[illegible]												
		(0.279)	(0.272)												
WASP + med				17.175	16.651			12.37	17.451						
				(10.104)	(11.434)			(11.781)	(11.761)						
WASP - med						-3.401	5.215	1.006	4.514						
						(5.592)	(9.566)	(8.616)	(9.452)						
WASP + mv										-11.984	-18.369			-8.097	-1.247
										(34.275)	(32.898)			(34.990)	(32.718)
WASP - mv												15.382***	22.004***	14.857***	22.638***
												(3.487)	(5.281)	(3.587)	(5.460)
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	67	59	57	54	54	55	55	52	52	57	57	57	57	57	57

Notes: Robust standard errors are in parentheses. Temperature controls are the average annual temperature. Significance is designated by: * significant at 10%; ** significant at 5%; *** significant at 1%

Fixed Effects and Random Effects Results

Table 6:

Dependent Variable: GDP per capita growth, continued

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
	FE	FE	FE	RE	RE	RE	FE	FE	RE	RE	FE	FE	RE	RE	RE
Precip	0.000		0.000***												
	(0.000)		(0.000)												
Temp		-0.012**	0.001												
		(0.005)	(0.001)												
WASP + med				0.013	0.013			-0.006	-0.007						
				(0.012)	(0.012)			(0.011)	(0.011)						
WASP - med						-0.044***	-0.047***	-0.045***	-0.046***						
						(0.009)	(0.009)	(0.010)	(0.010)						
WASP + sev										0.011	0.009			0.009	0.007
										(0.020)	(0.018)			(0.020)	(0.020)
WASP - sev												[illegible]**	[illegible]**	[illegible]**	[illegible]**
												([illegible])	([illegible])	([illegible])	([illegible])
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	[illegible]	[illegible]	712	1912	1913	1904	1904	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
# GCodes	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Notes: Robust standard errors are in parentheses. Temperature controls are the average annual temperature. Significance is designated by: * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7:

Dependent Variable: Ag_GDP_added, With Clustered SE's

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
	FE	[illegible]	FE	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	RE
Precip	0		-0.001												
	([illegible])		([illegible])												
Temp		-2.332	[illegible]												
		([illegible])	([illegible])												
WASP + mod				5.19[illegible]***	[illegible]***			2.94[illegible]**	[illegible]**						
				([illegible])	([illegible])			([illegible])	([illegible])						
WASP - mod						[illegible]***	[illegible]***	[illegible]***	[illegible]***						
						([illegible])	([illegible])	([illegible])	([illegible])						
WASP + sev										[illegible]*	[illegible]			[illegible]	5.79
										([illegible])	([illegible])			([illegible])	([illegible])
WASP - sev												[illegible]***	[illegible]***	[illegible]***	[illegible]***
												([illegible])	([illegible])	([illegible])	([illegible])
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	775	1328	679	1278	1278	1280	1280	1261	1261	1287	1322	1215	1215	1215	1215
# CCode	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Notes: Robust standard errors are in parentheses. Temperature controls are the average annual temperature. Significance is designated by: * significant at 10%; ** significant at 5%; *** significant at 1%

Table 8:

Dependent variable: Poverty headcount, Clustered SE's

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
	FE	FE	FE	RE	FE	RE	FE	RE	FE	RE	FE	RE	RE	FE	FE
Precip	-0.013		-0.014												
	(0.012)		(0.012)												
Temp		4.865	2.161												
		(4.258)	(4.884)												
WASP + mod				9.525	8.978			11.563	10.871						
				(8.178)	(8.317)			(7.916)	(7.867)						
WASP - mod						9.35*	10.068*	11.813***	11.709***						
						(5.534)	(5.213)	(5.445)	(5.471)						
WASP + sev										-3.064	-3.919			0.312	1.409
										(21.194)	(21.140)			(18.980)	(21.354)
WASP - sev												21.675**	22.334**	21.57**	11.628*
												(9.097)	(9.472)	(9.724)	(10.894)
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	57	59	47	54	54	55	48	42	42	57	57	57	47	57	57
# CCode	24	25	23	23	23	23	23	22	22	24	24	24	24	24	24

Notes: Robust standard errors are in parentheses. Temperature controls are the average annual temperature. Significance is designated by: * significant at 10%; ** significant at 5%; *** significant at 1%

Table 9:

Dependent variable: Poverty headcount 2, Clustered 91's

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)	(xv)
	FE	FE	FE	RE	FE	RE	FE	RE	FE	RE	FE	RE	RE	FE	RE
Precip	-0.097		-0.016												
	(0.616)		(0.600)												
Temp		1.967	1.181												
		(2.484)	(1.834)												
WASP + mod				6.75	4.161			5.906	4.341						
				(5.190)	(6.590)			(6.681)	(6.701)						
WASP - mod						0.819	1.496	1.580	2.167						
						(5.499)	(4.535)	(4.795)	(4.351)						
WASP + sev										-1.440	-0.710			-1.459	-0.727
										(14.374)	(18.991)			(16.521)	(18.798)
WASP - sev												[illegible]	[illegible]	[illegible]	[illegible]
												(5.060)	(5.125)	(5.097)	(5.151)
Temp controls	NA	NA	NA	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs	67	69	47	64	64	55	40	42	42	57	57	57	47	57	57
# CCode	24	25	23	23	23	23	23	22	22	24	24	24	24	24	24

Notes: Robust standard errors are in parentheses. Temperature controls are the average annual temperature. Significance is designated by: * significant at 10%; ** significant at 5%; *** significant at 1%