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The impact of climate change on cropland productivity: evidence from satellite based products at the river basin scale in Africa

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Abstract We investigate the effect of climate change on crop productivity in Africa using satellite derived data on land use and net primary productivity (NPP) at a small river basin scale, distinguishing between the impact of local and upper-catchment weather. Regression results show that both of these are determining factors of local cropland productivity. These estimates are then combined with climate change predictions obtained from two general circulation models (GCMs) under two greenhouse gas emissions (GHG) assumptions to evaluate the impact of climate change by 2100. For some scenarios significant decreases are predicted over the northern and southern parts of Africa.

1 Introduction

It is well known that agriculture in Africa is particularly vulnerable to weather¹ (Rockström et al. 2004). For example, Barrios et al. (2008) estimated that African agricultural production has since the 1960s been 32 % lower than the rest of the developing world due to a lack of rainfall. Given that a majority of the African population relies mainly on agriculture for subsistence (Badiane and Delgado 1995), the impact of climate² change is arguably of major concern. The challenge is not only to determine the range of plausible climate change scenarios but also to accurately estimate the relationship between agricultural production and weather so that these scenarios will serve as an input in a predictive model.

Importantly, empirical studies of climate change impact on agricultural production for Africa have almost exclusively used administrative breakdowns, such as national or sub-

¹The term weather describes meteorological events over a short period of time.

²The term climate represents long term patterns of weather.

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national areas, as spatial unit of analysis, and then defined local weather as an input into agricultural production (e.g. Schlenker and Lobell 2010). Arguably, however, this oversimplifies the complex hydrological systems underlying plant growth, and ultimately agricultural production. More specifically, the hydrological cycle involves the continuous movement of water on, above, and below the surface of the Earth over time so that water available to plant growth may not only depend on current local weather and soil conditions but also their counterparts considerable distances away. Alternatively, upstream rainfall can contribute to downstream yields through rainfall runoff which can carry fertile topsoil to downstream areas and increase soil fertility. With these potential shortcomings in mind, one may ultimately be inclined to question predictions under different climate change scenarios based on estimates derived from administrative spatial units and local weather indicators.

In this paper, we attempt to address these weaknesses in a number of novel ways. Firstly, we use a hydrological spatial breakdown of the African continent into over 7,000 upstream/downstream river basins based on topographic elevation and river network data that is independent of any ‘administrative’ classification. This allows us to assess both local and upstream weather impacts on local agricultural productivity.

One problem with using such a fairly disaggregated spatial unit of analysis is that consistent agricultural data derived from the ground over time will not be available for the whole African continent. Our second contribution hence lies in using spatially detailed satellite derived information to identify cropland and changes in its productivity over time. Cropland productivity is proxied by satellite derived measures of net primary productivity (NPP) which represents the creation of new organic matter through the process of photosynthesis. Unlike yields, NPP provides a common metric of productivity among crops (Hicke et al. 2004), thereby facilitating comparisons and aggregation over all types. NPP represents therefore an appealing proxy of cropland productivity and is used in several studies (e.g. Lobell et al. 2002; Melillo et al. 1993).

A number of statistical studies have already considered the correlation between NPP and weather using either spatial data (e.g. Wang et al. 2008) or time series data (e.g. Gao et al. 2009). In contrast, we construct panel data considering both spatial and temporal relationships. We then use the estimates of our regression model in conjunction with two climate change scenarios to predict future changes in agricultural productivity in Africa.

The remainder of the paper is organized as follows. Section 2 details the data employed. The modeling framework and regression results are reported and discussed in section 3. Section 4 contains climate change impact predictions. Finally, concluding comments are presented in section 5.

2 Data

2.1 Spatial level of analysis

To delineate river basins within Africa we use the HYDRO1k dataset (USGS 2011) which provides drainage basin boundaries derived from river network and flow direction data. At its most disaggregated level, this involves dividing the African continent into 7131 hydrological basins, with an average area of 4,200 km². This spatial breakdown depicted by grey lines in Fig. 1 shows that basins vary greatly in shape and size. Many basins cross national borders, suggesting that to capture the role of water in agricultural productivity, an analysis at the river basin scale is preferable to that at administrative levels.

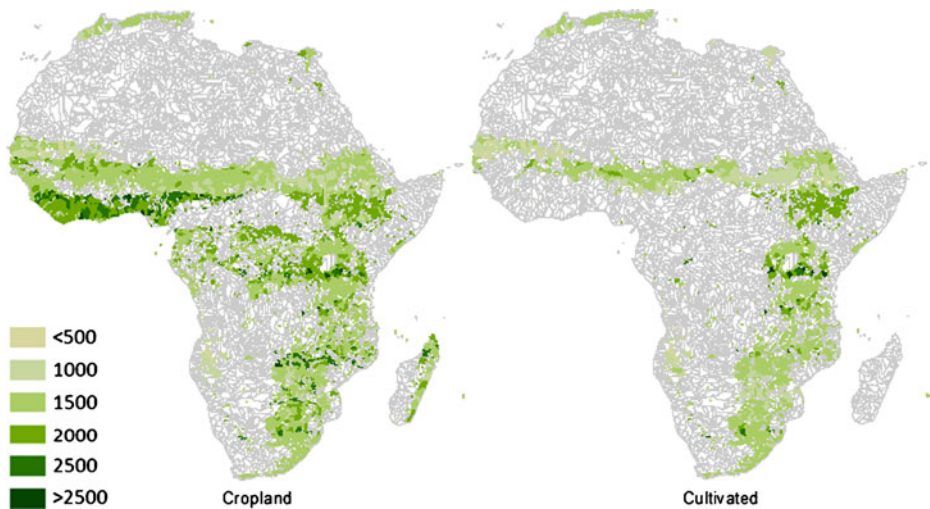


Fig. 1 NPP_{cropland} and $NPP_{\text{cultivated}}$ (in $\text{gC}/\text{m}^2/\text{year}$) in average over the period 1981–2000

2.2 Cropland productivity

To identify cropland and its productivity over time within river basins we use two satellite data sources. The Global Land Cover 2000 (GLC) dataset (GEM 2011) allows us to identify cropland locally within Africa. The dataset classifies global land cover into 22 categories at the 1 km resolution based on daily data acquired by the SPOT4 satellite during 2000. We used the land cover categories called ‘cultivated and managed area’, ‘mosaic of cropland/shrub or herbaceous cover’, and ‘mosaic of cropland/tree cover/other natural vegetation’ to identify cropland area. To identify cultivated cropland, we considered the ‘cultivated and managed area’ only. According to the GLC data, cropland is located in only 51 % of the river basins. As depicted in Fig. 1, most of the cropland is located in Sub-Saharan Africa (SSA). Cultivated areas occupy a noticeably smaller area of the continent.

To measure cropland productivity, we use NPP values derived from satellite images on spectral reflectance of terrestrial vegetation. In essence, NPP quantifies the conversion of atmospheric CO_2 into plant biomass and the resultant values can then serve as a proxy of cropland productivity.³ NPP data for Africa are obtained from the Global Production Efficiency Model (Glo-PEM) dataset (Prince and Small 2003). The data are available annually at the 8 km resolution for the period 1981 to 2000 and are given as grams of Carbon per m^2 ($\text{gC}/\text{m}^2/\text{year}$).

Satellite derived NPP data are not completely free of measurement error. For one, given the 1 km resolution of land use, one may only capture larger cropland areas, unless small farms are spatially agglomerated enough. Our results can thus generally only be interpreted in terms of larger cropland and possibly small but spatially agglomerated crops. Moreover, as this data is only available for 2000 we cannot identify and take account any changes in cropland area over our sample period. Whether this may result in an over- or under-estimation of cropland productivity will depend on what the prior or post cropland use of

³ The accuracy of NPP values derived from satellite data compared to NPP values derived from ground data has been investigated in numerous studies (e.g. Lobell et al. (2002)).

the area was. To roughly check how cropland may have changed over our sample period, we used data from FAOSTAT (2011) to calculate the share of cropland in total area by country in 1981 and 2000. Reassuringly, there appear to be small changes over time - cropland area represented 6 % of total area in 1981 and 7 % in 2000.

To also roughly verify that our NPP measure is related to standard agricultural data, we aggregated its value at the country level. We then regressed country level proxies of log of cropland production as well as its growth rate, both derived from FAOSTAT, on the logged values of this aggregate NPP measure from 1981 to 2000, controlling for year and country fixed effects. The estimated coefficients are 0.38 and 0.34 respectively, and significant at the 1 % level, hence providing evidence that these are indeed positively related.⁴ The R^2 of respectively 0.89 and 0.93 indicate that our proxy of cropland production explains around 90 % of NPP variations. NPP in cropland and cultivated areas are presented in Fig. 1.

2.3 Weather

To calculate annual river basin level weather, we use monthly data obtained from the CRU-TS 2.1 dataset (Mitchell and Jones 2005) at the $0.5 \times 0.5^\circ$ resolution globally over the period 1901–2002.

To identify periods of severe dryness or wetness, we calculate the standardized precipitation index (SPI) (McKee et al. 1993) which has been argued to be particularly good at capturing the cumulative effect of reduced rainfall over time in a chosen locality. Following McKee et al. (1993), a drought starts when $SPI \leq -2.00$ and ends when $SPI \geq 0$. Similarly, an extremely wet period starts when the $SPI \geq +2.00$ and ends when the $SPI \leq 0$.

We also consider reference evapotranspiration (ET) to represent the evaporative demand of the air within a basin. Following Hargreaves and Samani (1985), ET is calculated as:

$$ET = 0.0023 (T_{\text{avg}} + 17.8) (T_{\text{max}} - T_{\text{min}})^{0.5} R_a \quad (1)$$

where T_{avg} , T_{max} and T_{min} are mean, maximum and minimum temperatures, respectively. R_a is the extraterrestrial radiation calculated as a function of the latitude and time of the year (Allen et al. 1998; p45–47).

2.4 River flow

In order to calculate the river flow in each river basin, we employ the GeoSFM model, an hydrological model with particular relevance for Africa (Asante et al. 2007). More specifically, it simulates the dynamics of runoff processes using spatial information on river basin and network coverage, land cover type, soil characteristics, and daily precipitation and ET. To satisfy the model's requirements on soil characteristics we take data from the Digital Soil Map of the World (FAO 1995), which are given at a 1:5,000,000 scale. To generate approximate daily rainfall and temperature series from the monthly CRU-TS data we follow the procedure recommended by Schuol and Abbaspour (2007). Daily ET is then calculated as outlined above. Given that the river flow series generated from the GeoSFM model has been shown to be particularly suitable in describing river flow anomalies,⁵ we express the generated data in terms of standard deviation relative to the mean of the base period 1950–2006.

⁴ Corresponding standard errors are 0.085 and 0.091 respectively.

⁵ See Asante et al. (2008).

2.5 Climate change predictions

Climate change is predicted using coupled atmosphere–ocean general circulation models (AOGCM) representing climate states in response to greenhouse gases (GHG) concentrations. The choice of AOGCM used for this analysis is mainly guided by data availability. We consider the CSIRO2, HadCM3, CGCM2, ECHAM4 and PCM models as their outputs are freely available from IPCC (2000). A few studies compare the performance of these AOGCMs for Africa. For example, McHugh's (2005) find that ECHAM4 and HadCM3 are among the four most representative models for east Africa, while Liu et al. (2002) find that CSIRO2 and PCM are two of the five preferred models for the Saharan region. However, according to McAvaney et al. (2001), each model has its own strengths and weaknesses, so various ones should be used conjointly to obtain a wide range of results.

Alternative future GHG emissions scenarios proposed by the IPCC (2000) are considered and serve as inputs into the AOGCMs detailed above. Data are available for four scenarios, A1FI, A2, B1 and B2, each assuming different levels of anthropogenic GHG emissions driven by population growth, economic and social development, energy and technology, and agriculture.

As probabilities are not associated with each scenario, the combination of AOGCMs and scenarios produces 20 plausible futures, each with an equal likelihood of occurrence (Mitchell 2007). Out of the whole range of climate change impact considered possible in the future by the IPCC (2001), the 20 permutations of AOGCMs and scenarios presented above enable one to represent 93 % of the possible future climate change outcomes.

However, computational limitations in running the river flow model with our sample size restrict us to experimenting with only two sets of climate change predictions. Hence, we use outputs from the ECHAM4 and the PCM models, which predict the greatest and smallest warming for Africa, respectively combined with the A1FI and B2 scenarios, representing the widest range of GHG emissions.

Data are available globally at the $0.5 \times 0.5^\circ$ resolution from the TYN-SC 2.0 dataset (Mitchell et al. 2003). This dataset is especially suited to complement the CRU-TS dataset used in the regression analyses. Predicted values of weather variables are reported in Table 4 for the 2050s (averaged from 2041 to 2060) and for the 2090s (averaged from 2081 to 2100), where confidence intervals (CI) are calculated using standard errors based on the delta method. Accordingly, the greatest increases in precipitation and ET are predicted under the ECHAM4-A1FI scenario. Droughts are generally expected to decrease during the 21st century compared to the reference period, while wet spells are projected to increase under all scenarios.

3 Modeling framework and results

3.1 Regression specification

In this analysis, we consider a vector of various weather factors as determinants of cropland productivity at the river basin level. Our base regression specification is thus as follows:

$$\ln \text{NPP}_{bt} = \alpha + \beta X_{bt} + \lambda_t + \mu_b + \varepsilon_{bt} \quad (2)$$

where the subscripts b and t refer to basin and time units, X represents a vector of weather variables, α a constant, β the estimated coefficients (i.e., the marginal effects), λ time

varying factors affecting all river basins, μ the unobservable basin specific time invariant determinants, and ε a standard i.i.d. error term. The dependent variable is log-transformed to obtain semi-elasticities and control for outliers. In order to control for the time varying aspects affecting all basins, we include a set of year dummies ($=1$ for the year and $=0$ otherwise), while we use a fixed effects specification to take into account unobservable basin specific time invariant determinants. One may want to note that all time varying variables are yearly averages.

A number of reasons justify including time dummies in the regression analysis. For one, the quality of satellite pictures is likely to have changed over time and this may have introduced systematic measurement error across regions. Similarly, the quality of the CRU-TS data may have changed as the underlying grid cell data is derived from local weather stations, the number of which has changed over time. Finally, other factors may have changed over time, such as global agricultural policies and economic conditions that one would want to control for. As a matter of fact, a joint F-test of the null hypothesis that the time dummies were zero could be decisively rejected in all regressions, suggesting that these dummies capture important determinants of NPP.

Similarly, it may be important to control for other basin specific time invariant geographical features – such as soil type and quality – that determine NPP, but for which we have no information. An F-test of the basin specific fixed effects also indicates their importance in all specifications. The Moran's test results indicate that our cropland measure is serially and spatially correlated. We therefore implement the nonparametric covariance matrix estimator proposed by Driscoll and Kraay (1998).⁶

3.2 Regression results

We provide a base specification of Eq. (2) including river basin rainfall and ET in Table 1. The results meet a priori expectations, i.e., rainfall has a significant positive effect, while greater ET reduces cropland productivity. In order to allow for non-linear threshold effects at extreme levels of dryness and wetness we next include rainfall interacted with our DROUGHT and WET dummies. The estimated coefficient suggests that there is only an upper threshold effect.

Next, we allow weather in upstream basins to affect local cropland productivity by including the average rainfall and ET in the river basins immediately upstream.⁷ Accordingly, while ET upstream does not affect downstream cropland productivity, greater precipitation upstream positively increases downstream cropland productivity, although this effect is lower than for local rainfall. Moreover, there are no apparent non-linearities in the impact of upstream precipitation.

Precipitation upstream may also affect local cropland productivity via river flow, potentially derived from weather upstream. We thus include the constructed river flow anomalies. The coefficient suggests, however, that it has no direct linear effect on cropland productivity. We subsequently experimented with non-linearities by interacting RIVERFLOW with high and low river flow dummies defined respectively as $HIGH=1$ when $RIVERFLOW \geq 1$ and $LOW=1$ when $RIVERFLOW \leq -1$ ($HIGH$ and LOW are null otherwise). The positive and significant coefficient of $RIVERFLOW \times LOW$ suggests that greater flow contribute positively to cropland productivity up to a certain threshold.

⁶ We also confirmed our productivity series was stationary using a Hadri panel unit root test (Hadri 2000).

⁷ Our river basins have up to four upstream basins, and we use weather averaged over these. For those basins with no upstream basin we assume that the upstream variables take on the value of zero.

Table 1 Regression results: dependent variable log NPP_{cropland}

VARIABLES	Basin Model		Upstream Model		Riverflow Model		Upstream-Riverflow Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RAIN	8.19e-05*** (1.64e-05)	8.73e-05*** (1.62e-05)	7.43e-05*** (1.53e-05)	7.89e-05*** (1.53e-05)	8.05e-05*** (1.62e-05)	8.54e-05*** (1.63e-05)	7.34e-05*** (1.53e-05)	7.77e-05*** (1.53e-05)
ET	-0.0587*** (0.0137)	-0.0581*** (0.0136)	-0.0560*** (0.0136)	-0.0554*** (0.0136)	-0.0582*** (0.0136)	-0.0571*** (0.0135)	-0.0553*** (0.0134)	-0.0546*** (0.0134)
RAIN×DROUGHT		-1.92e-06 (3.51e-06)		-2.73e-06 (3.30e-06)		-1.19e-06 (3.33e-06)		-2.26e-06 (3.18e-06)
RAIN×WET		-1.42e-05*** (3.22e-06)		-1.23e-05*** (3.21e-06)		-1.40e-05*** (3.20e-06)		-1.22e-05*** (3.20e-06)
U_RAIN			1.21e-05*** (3.63e-06)	1.40e-05*** (3.05e-06)			1.14e-05*** (3.46e-06)	1.30e-05*** (2.97e-06)
U_ET			-0.00629 (0.00398)	-0.00606 (0.00399)			-0.00666 (0.00384)	-0.00558 (0.00364)
U_RAIN×U_DROUGHT				4.55e-06 (3.35e-06)				5.90e-06 (3.54e-06)
U_RAIN×U_WET				-8.04e-06 (4.92e-06)				-7.70e-06 (4.96e-06)
RIVERFLOW					0.00288 (0.00163)	0.00135 (0.00192)	0.00282 (0.00162)	-0.000107 (0.00192)
RIVERFLOW×HIGH						-0.000234 (0.00419)		0.00230 (0.00420)
RIVERFLOW×LOW						0.00915*** (0.00338)		0.00890*** (0.00334)
Observations	72220	72220	72220	72220	72220	72220	72220	72220
Basins	3611	3611	3611	3611	3611	3611	3611	3611

Table 1 (continued)

VARIABLES	Basin Model		Upstream Model		Riverflow Model		Upstream-Riverflow Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
F	3410 ^{***}	9090 ^{***}	37571 ^{***}	2.280e+07 ^{***}	2350 ^{***}	8346 ^{***}	42734 ^{***}	2.95e+07 ^{***}
R ² within	0.169	0.170	0.169	0.170	0.170	0.170	0.170	0.170
RMSE	0.829	0.828	0.830	0.828	0.829	0.827	0.830	0.828

(1) Results for each model are presented in two columns under each model name; (2) Only the results for the time and space variant explanatory variables are presented in this table; (3) R2 within represents the share of variability of the dependent variable within each group explained by the model; (4) Variable names preceded by 'U' indicates upstream variables, 'x' represent interaction terms; (5) Driscoll and Kraay standard errors in parenthesis; Significance levels: *** $p < 0.01$, ** $p < 0.05$; Constants and time dummies are included but the coefficients are not reported.

Table 2 Regression results: dependent variable log NPP_{cultivated}

VARIABLES	Basin Model		Upstream Model		Riverflow Model		Upstream–Riverflow Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RAIN	0.000112*** (2.27e-05)	0.000121*** (2.23e-05)	0.000105*** (2.16e-05)	0.000113*** (2.17e-05)	0.000111*** (2.24e-05)	0.000119*** (2.23e-05)	0.000104*** (2.15e-05)	0.000112*** (2.17e-05)
ET	−0.0766*** (0.0176)	−0.0755*** (0.0176)	−0.0737*** (0.0173)	−0.0727*** (0.0173)	−0.0761*** (0.0174)	−0.0745*** (0.0175)	−0.0730*** (0.0171)	−0.0719*** (0.0172)
RAIN×DROUGHT		−3.71e-06 (7.30e-06)		−4.18e-06 (6.95e-06)		−2.80e-06 (6.93e-06)		−3.48e-06 (6.66e-06)
RAIN×WET		−2.21e-05*** (4.56e-06)		−1.94e-05*** (4.89e-06)		−2.21e-05*** (4.57e-06)		−1.94e-05*** (4.90e-06)
U_RAIN			1.16e-05** (5.75e-06)	1.32e-05**** (4.83e-06)			1.09e-05 (5.65e-06)	1.23e-05** (4.80e-06)
U_ET			−0.00706 (0.00438)	−0.00687 (0.00434)			−0.00747 (0.00424)	−0.00627 (0.00393)
U_RAIN×U_DROUGHT				2.91e-06 (6.29e-06)				3.84e-06 (6.42e-06)
U_RAIN×U_WET				−1.18e-05 (6.36e-06)				−1.17e-05 (6.42e-06)
RIVERFLOW					0.00275 (0.00179)	−0.000227 (0.00255)	0.00270 (0.00179)	−0.00224 (0.00255)
RIVERFLOW×HIGH						0.00518 (0.00517)		0.00514 (0.00518)
RIVERFLOW×LOW						0.0112** (0.00486)		0.0109** (0.00482)
Observations	54520	54520	54520	54520	54520	54520	54520	54520
Basins	2726	2726	2726	2726	2726	2726	2726	2726

Table 2 (continued)

VARIABLES	Basin Model		Upstream Model		Riverflow Model		Upstream-Riverflow Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
F	3083 ^{***}	15360 ^{***}	183042 ^{***}	2.070e+07 ^{***}	2320 ^{***}	16707 ^{***}	169279 ^{***}	5.01e+07 ^{***}
R ² within	0.174	0.175	0.175	0.175	0.175	0.175	0.175	0.176
RMSE	0.876	0.874	0.503	0.502	0.876	0.874	0.503	0.502

See notes from Table 1.

Finally, we include all our local and upstream weather variables. Qualitatively, the results of the individual specifications are the same, with only some slight quantitative changes. One can thus conclude that while local weather matters for cropland productivity, upstream rainfall and river flow can also have an important impact and thus should not be neglected.

We also re-ran all specifications from Table 1 by considering NPP from areas defined explicitly as ‘cultivated and managed areas’. However, as reported in Table 2, this entails no qualitative changes in our results, although on many occasions, the resultant coefficient is higher than under the broader definition.

To assess the predictive performance of each model, we computed the root mean squared error (RMSE) over the calibration sample (Kennedy 2003) using the leave-one-out cross-validation method (Michaelson 1987). RMSEs are relatively similar amongst models for NPP_{cropland}. For NPP_{cultivated}, however, the RMSEs are the lowest for the Upstream and Upstream-Riverflow models, which indicates that they have the best predictive power.

Given the well-known spatial correlation of rainfall, cross-sectional correlation is of great concern when interpreting our results. To this end, we calculated standard errors which are robust to cross-sectional correlation. As a further robustness check, we estimate regressions including weather effects from neighboring, non-hydrologically related basins. As can be seen in Table 3, rainfall and ET from neighboring basins do not significantly influence NPP_{cropland} and NPP_{cultivated}, which show that upstream weather variables are not just capturing the spatial correlation of weather. Additionally, we estimate the regression using the ‘irrigated’ sub-sample of ‘cultivated and managed area’ defined in the GLC 2000 dataset, since irrigated land is likely to benefit the most from upstream weather. The results reported in Table 3 show that rainfall from upstream basins is still significant and that the coefficient for irrigated area is nearly four times larger than the coefficient estimated for cultivated areas. Overall, these robustness checks show that the results reported in Table 1 and Table 2 are indeed capturing an upstream weather effect and not just spatial correlation of weather.

As an alternative to rainfall and ET, we also experiment using water balance, WB, which is roughly calculated as precipitation minus annual ET, and represents the water available to the plant. Additionally, we use temperature instead of ET and include a rainfall squared term as is often done in the literature. These alternative weather effects are similar to those observed in Tables 1 and 2. However, their RMSEs show that these specifications have lower predictive powers. Finally, Table 3 shows that our results hold even when not including time dummies.

3.3 Economic significance

Conveniently, NPP can be roughly converted into kilocalories (kcal), and hence to its nutritional value. More specifically, we use the fact that 1gC is equal to about 9.33 kcal (Mackenzie et al. 2004), and the methodology of Imhoff and Bounoua (2006) to convert our NPP kilocalories into kilocalories of final agricultural production available for human consumption, which suggested a one to one ratio between these. Considering that each river basin in our sample has on average 1287gC/m²/year of NPP, a population of 180,000⁸ and that the average size of cropland within these is about 168 km², then the average in basins with cropland is 3290 kcal/pers/day. Within the context of Africa’s total population (about one billion), this figure falls to 2139 kcal/pers.

With this conversion factor in mind, we use our estimated significant coefficients on the rainfall related variables to assess the economic significance of a shortage in rainfall on food production. More specifically, we take the example of the low precipitation year of 1983

⁸ The local average population figure was estimated from the African Population database.

Table 3 Alternative regression results: dependent variable log NPP

VARIABLES	Neighboring basins		Irrigated land	Water Balance		Standard weather variables		No time dummies	
	NPP _{cropland} (1)	NPP _{cultivated} (2)	NPP _{irrigated} (3)	NPP _{cropland} (4)	NPP _{cultivated} (5)	NPP _{cropland} (6)	NPP _{cultivated} (7)	NPP _{cropland} (8)	NPP _{cultivated} (9)
RAIN	6.36e-05*** (1.34e-05)	8.98e-05*** (1.99e-05)	0.000148*** (4.46e-05)			0.000174*** (4.19e-05)	0.000223*** (5.44e-05)	0.000176*** (3.81e-05)	0.000216*** (4.68e-05)
ET	-0.0546*** (0.0147)	-0.0721*** (0.0184)	-0.0625 (0.0328)					-0.0278 (0.0253)	-0.0464* (0.0278)
U_RAIN	1.12e-05*** (3.33e-06)	1.05e-05** (5.34e-06)	4.22e-05*** (2.06e-05)			4.32e-05*** (1.34e-05)	3.57e-05** (1.51e-05)		
U_ET	-0.00645 (0.00390)	-0.00718 (0.00431)	-0.0619 (0.0368)						
NB_RAIN	1.73e-05 (9.97e-06)	2.39e-05 (1.52e-05)							
NB_ET	-0.000982 (0.00287)	-0.00102 (0.00279)							
WB				0.00714 (0.00395)	0.0148*** (0.00571)				
U_WB				0.0347*** (0.00499)	0.0411*** (0.00522)				
RAIN2						-3.97e-08*** (1.15e-08)	-5.20e-08*** (1.49e-08)		
U_RAIN2						-8.36e-09*** (3.00e-09)	-7.53e-09** (3.54e-09)		
TEMP						-0.0520*** (0.00955)	-0.0638*** (0.0119)		
U_TEMP						-0.00124	-0.00280		

Table 3 (continued)

VARIABLES	Neighboring basins		Irrigated land	Water Balance		Standard weather variables		No time dummies	
	NPP _{cropland} (1)	NPP _{cultivated} (2)	NPP _{irrigated} (3)	NPP _{cropland} (4)	NPP _{cultivated} (5)	NPP _{cropland} (6)	NPP _{cultivated} (7)	NPP _{cropland} (8)	NPP _{cultivated} (9)
Observations	72220	54520	8020	28080	20820	(0.00385)	(0.00380)	72220	54520
Basins	3611	2726	401	1404	1041	72220	54520	3611	2726
F	795026 ^{****}	5184244 ^{****}	297956 ^{**}	25 ^{***}	31 ^{***}	1527230 ^{***}	1.26e+07 ^{***}	39.13	35.22
R ² within	0.170	0.175	0.162	0.159	0.163	0.180	0.187	0.0320	0.0369
RMSE	0.829	0.502	1.429	0.816	0.503	0.484	0.530	0.450	0.492

See notes from Table 1.

relative to the high precipitation year of 1997 and compare the relative losses in calories. This entails using the mean difference in the value of NPP in levels (NPP averaged $1175\text{gC/m}^2/\text{year}$ in 1983 and $1384\text{gC/m}^2/\text{year}$ in 1997), and in the relevant rainfall variables between these 2 years, and their estimated coefficients to calculate the subsequent caloric impact of a shortage in rainfall. This calculation suggests that between these 2 years, there was a loss of $94\text{ kcal/m}^2/\text{year}$ in our river basins, which represents roughly $240\text{ kcal/person/day}$ less of food available for the basin population in 1983 due to shortages in precipitation. In this regard, current estimates set the poverty line at about $2,100\text{ kcal/day}$.⁹ One should note that this calculation implicitly assumes that any food produced would be available only to those living in the basins where there is cropland.

4 Climate change impact predictions

Average climate change impact predicted using the Upstream-Riverflow model under alternative scenarios are presented in Table 4. The table indicates a general decrease in NPP in both cropland and cultivated areas, with slightly larger effects on cultivated areas. By the 2090s, the largest decreases are predicted under ECHAM4-A1FI with an average of -5.3% and -7.9% in cropland and cultivated areas respectively. Under PCM-B2, the impact is less significant, with decreases ranging from -1.3% to $+0.9\%$ in cropland and cultivated areas respectively. CIs, represented in parenthesis in Table 4, show increasing uncertainty regarding climate change impacts toward the end of the 21st century. However, these CIs do not account for uncertainty related to climate change predictions.

Predicted changes in $\text{NPP}_{\text{cropland}}$ and $\text{NPP}_{\text{cultivated}}$, given in percentage change compared to the 1990s, are represented geographically in Fig. 2. Accordingly, the southern and northern parts of the continent will be the most affected, particularly in the Nile Delta, where decreases in NPP range between -30% and -50% under both scenarios. Some increases are predicted in the Sudano-Sahelian belt by the 2050s, but generally don't persist in the 2090s. In their literature review of climate change impacts on African agriculture, Roudier et al. (2011) find a median yield loss of 11% , while Müller et al. (2011) note a range of -100 to $+168\%$ relative to current production levels.

To estimate the individual daily caloric food availability under climate change scenarios, we incorporate the postulated changes in population size of each scenario into our calculation. However, due to lack of any priors, we assume that cropped land area remains constant. The results suggest that under the ECHAM4-A1FI scenario, calories produced will reduce by 717 kcal/pers/day , i.e., about one third of the poverty line. Despite the higher underlying population growth, the relatively moderate fall in NPP under the PCM-B2 scenario, in contrast, suggests a drop of 81 kcal/pers/day .

5 Conclusions

This study provides an analysis of crop productivity in Africa at a highly disaggregated spatial level which accounts for the impact of both local and upstream weather. The regression analysis not only reveals a significant effect of local rainfall within a basin, but

⁹ See Ravallion (1994).

Table 4 Observed and predicted changes in weather variables and NPP under two climate change scenarios

VARIABLES	Location	1990s	ECHAM-A1FI		PCM-B2	
			2050s	2090s	2050s	2090s
RAIN (mm)	cropland	856	965 [+109]	991 [+135]	952 [+96]	945 [+89]
	cultivated	750	849 [+99]	876 [+126]	835 [+85]	828 [+78]
ET (mm/day)	cropland	12.0	12.6 [+0.6]	13.4 [+1.4]	12.1 [+0.1]	12.1 [+0.1]
	cultivated	12.0	12.7 [+0.7]	13.5 [+1.5]	12.1 [+0.1]	12.2 [+0.2]
DROUGHT (%)	cropland	0.12	0.04 [−0.08]	0.11 [−0.01]	0.02 [−0.10]	0.05 [−0.07]
	cultivated	0.11	0.05 [−0.06]	0.12 [+0.01]	0.02 [−0.09]	0.06 [−0.05]
WET (%)	cropland	0.02	0.21 [+0.19]	0.39 [+0.37]	0.14 [+0.12]	0.18 [+0.16]
	cultivated	0.02	0.22 [+0.2]	0.38 [+0.36]	0.14 [+0.12]	0.18 [+0.16]
RIVERFLOW (std. dev. from mean)	cropland	−0.0061	0.129 [+0.14]	0.091 [+0.10]	0.166 [+0.17]	0.121 [+0.13]
	cultivated	−0.0064	0.125 [+0.13]	0.089 [+0.10]	0.165 [+0.17]	0.123 [+0.13]
NPP (gC/m ² /year)	cropland	1287	1271 (1214;1331) [−17]	1220 (1158; 1286) [−68]	1312 (1255;1372) [+24]	1305 (1248; 1365) [+17]
	cultivated	1187	1156 (1094;1223) [−31]	1093 (1025; 1166) [−94]	1207 (1145;1274) [+20]	1198 (1136; 1265) [+11]

Changes compared to the 1990s are presented in brackets; 90 % confidence intervals are presented in parentheses

also an impact arising from precipitation occurring upstream, both directly via upstream rainfall runoff and indirectly from river flow.

Using our estimated weather effects to predict possible future impacts under two alternative scenarios of climate change, we find that a general decrease in crop productivity for Africa, with largest decreases predicted under the scenario forecasting the largest change in climate. Rough calculations suggest a decrease in food availability between 81 kcal/person/day and 717 kcal/person/day. In terms of spatial distribution, decreases in NPP are more pronounced in the northern and southern parts of Africa, and especially in the Nile Delta region. One should note, however, that the accuracy of these predictions is subject to the uncertainties underlying climate modeling and future GHG emissions. Moreover, we are not able to take account of changes in cropland area neither in our underlying regressions analysis results nor under the two climatic change scenarios.

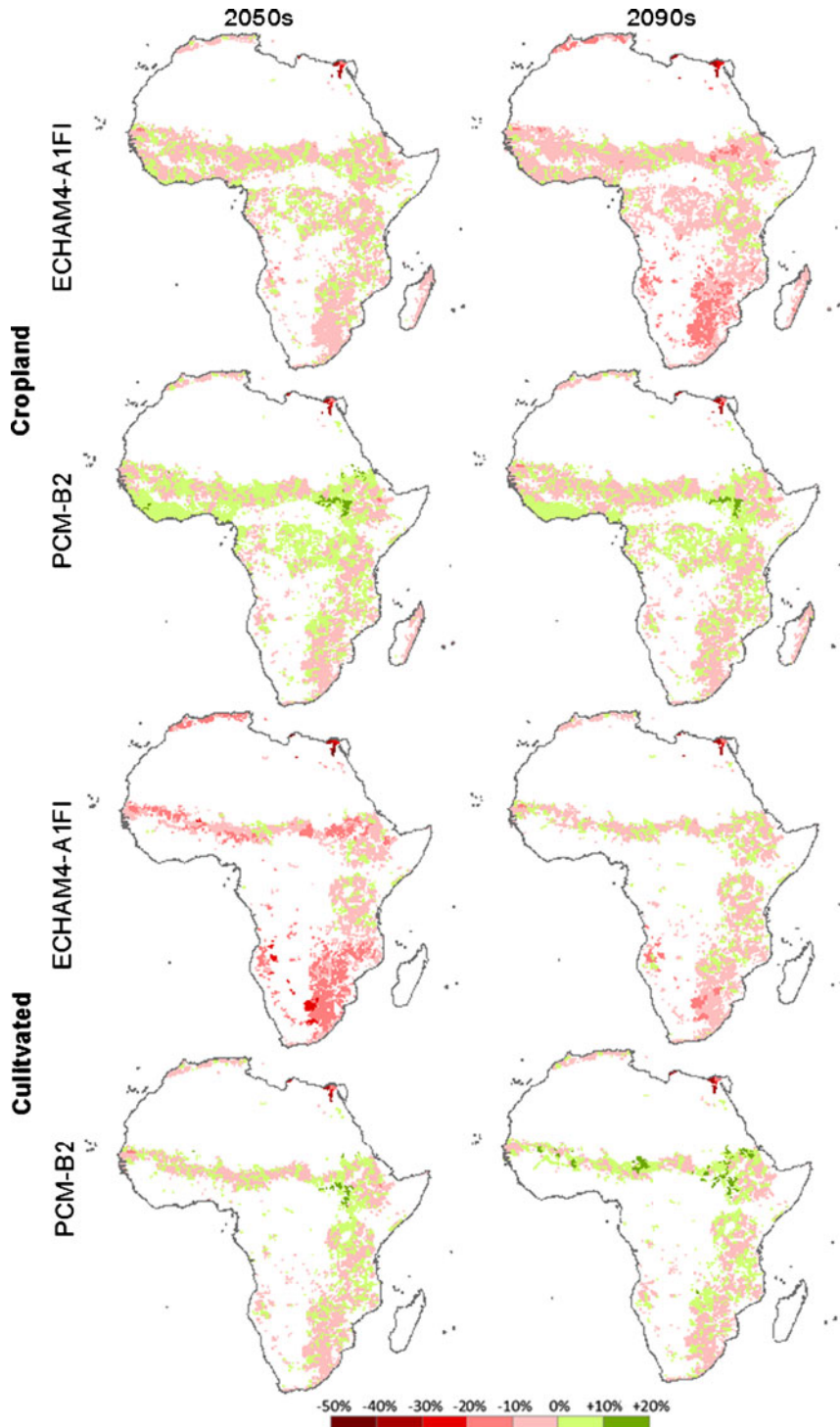


Fig. 2 Changes in $NPP_{cropland}$ and $NPP_{cultivated}$ (in percent compared to 1990s)

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