Climate and Consumption: Using Vegetation Indices to Link Climate and Household Welfare in Mali

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Abstract

A large literature has estimated the effects of climate change on agricultural yields, but rarely tests whether changes in yields translate directly into changes in household welfare. Such assumptions elide the rather large literature on resilience to climate and other shocks. This work demonstrates how satellite derived yield data (GCVI) can analyze the relationship between agricultural productivity and household welfare. We use remotely-sensed vegetation indices as a proxy for crop yields as well as a granular household level dataset from 85% of Mali's administrative communes between 2011 and 2019. Calculating commune-level indices for each growing season, we are then able to estimate their effects on household level expenditures. We find that changes in yields have a statistically significant effect on overall household expenditure as well as other expenditure categories (food, leisure, etc.). This effect is, however, relatively muted, with GCVI to expenditure elasticities in the range of 0.03 - 0.45. Such low expenditure elasticities for changes in yields indicates a large degree of climate resilience. Having demonstrated the use of vegetation indices in measuring household welfare, we then demonstrate their superiority to nightlight measures as proxies for household welfare in rural areas of Africa. We draw conclusions for policy makers and for researchers interested in using remotely sensed data for climate change and resilience research.

1 Introduction

The literature has established that shifts in climate can result in changes in agricultural yields, and that such variation will most negatively effect small-holder farmers in Sub-Saharan Africa (Ortiz-Bobea et al. 2021; Liu et al. 2016). Recent reviews suggest that we still have much to learn about the welfare impacts of changes in agricultural output on those that rely on farming to make a living (Gassner et al. 2019). While a large literature has also shown the importance of agricultural productivity in the economies of Sub-Saharan Africa (Dercon and Gollin 2014), there is a notable lack of reliable agricultural yield data across the continent (Carter et al. 2017). The imperative of increasing African household resilience to climate change along with inadequate yield data, poses a quandary for researchers. While some recent work has shown the potential of remote sensing of vegetation to provide a usable proxy for agricultural yields (Lobell et al. 2019) at a small local scale, we do not yet know if they can relate household resilience to agricultural yield shocks. Similarly, how do vegetation indices compare to another commonly used remote sensing measure of welfare in Africa, nightlight data?

This work tests the efficacy of employing remotely sensed agricultural data as a proxy for yields across Mali, and tests how yields relate to household consumption and resilience. We provide comparisons across multiple popular vegetation indices, focusing on the Green Chlorophyll Vegetation Index (GCVI). We then show that remotely sensed yield proxies can be used to estimate the relationship between agricultural output and rural household expenditures. We employ a repeated cross-section of Malian household data covering the period 2011-2019, comprising rural households from nearly 600 of Mali's 704 administrative communes. We then test whether nightlight data, VIIR, which has commonly been used to measure incomes in difficult to measure areas, is correlated with our yield measures or with rural Malian household expenditures.

Our results show first that remotely sensed vegetation indices provide good proxies for agricultural yields and that differences between indices are relatively minor. Then our key regression results relating vegetation indices to household expenditures show remarkable levels of resilience among Malian households to yield shocks. They demonstrate that while increases in yields are associated with increases in per-capita expenditures for rural households, the elasticity of overall consumption expenditure in our preferred vegetation index is noticeably less than one (roughly 0.03). We demonstrate effects of vegetation index measures of yields on both food and non-food expenditures, with non-food being more elastic, driven primarily by discretionary goods such as clothes and communications (cellphone minutes). Our results are robust to alternative specifications of the vegetation indices and expenditures. Finally, our tests of whether VIIR nightlights data are correlated with vegetation indices or expenditures find low correlations of VIIR with vegetation indices and negative or zero correlations with most expenditure categories.

Our findings are relevant for the study of climate change and its impacts on human welfare. The methodology we demonstrate has the potential to provide new insights about climate-induced changes in agricultural output in Sub-

Saharan Africa and other parts of the world where there is a lack in-field measures of agricultural production. Specifically, the remotely sensed indices can provide better coverage of yields and estimates of incomes than can be done with available field data. Combined with household datasets, these remotely sensed products can help researchers and policymakers better understand how climate-induced changes to agriculture will impact the welfare of households in a variety of contexts. Our work also adds to a literature seeking to measure economic growth in poorly measured areas and highlights the need for caution in interpreting nightlight data as a measure of welfare in rural Africa.

1.1 Agricultural Output and Household Welfare

The relationship between agricultural output and household welfare has long been a staple of the development literature. The literature has established that shifts in climate can result in changes in agricultural yields, and that such variation is most likely to hit small-holder farmers in Sub-Saharan Africa particularly hard (Ortiz-Bobea et al. 2021; Liu et al. 2016). However, what is still not well understood is the extent to which changes in agricultural output affect the welfare of those who rely on farming to make a living (Gassner et al. 2019). Furthermore, the impact of climatic changes on crop production are likely to vary considerably from one region to the next. For example Ortiz-Bobea et al. (2021) demonstrate that while Anthropogenic Climate Change (ACC) has reduced overall global agricultural productivity since 1961, the effects have been far worse for warmer regions such as Sub-Saharan Africa (SSA).

A large related literature has developed measuring the resilience of various people to climate change (see e.g. Felbermayr et al. (2022)). Recent developments in this literature (Barrett et al. 2021; Upton, Constenla-Villoslada, and Barrett 2022) have found little consensus on the best measures of resilience, nor consistent definitions of what resilience would mean. In that context measuring household expenditure, as we do here, has emerged as a reasonable default option for measuring household resilience. Some studies such as Macours, Premand, and Vakis (2022) show that diversification of economic activities within the household can reduce vulnerability to climate risk, while others such as Premand and Stoeffler (2022) have shown how cash transfers can mitigate the effects of climate shocks. Similarly, a study of smallholder farmers in rural Ethiopia, Mekonnen and Kassa (2019) found that their "Adaptive Capacity" was positively correlated with their total income from farm and non-farm activities. While there is evidence of adaptation and resilience at the individual level in some African contexts, work by Baarsch et al. (2020) raises questions about African countries' ability to mitigate climate change under most future climate scenarios. Our work, focusing on households in a single Sahelian country, can add to our understanding of the degree of resilience to changes in agricultural yields.

This work also contributes to a literature on how to measure development and income in far flung places, especially the African continent. A recent work by Angrist, Goldberg, and Jolliffe (2021) highlights the methodological difficulties in measuring economic growth in developing countries. That work finds that measuring development or income in rural areas of developing countries is particularly fraught. Recent work by Mellon (2024) demonstrates that the commonly used rainfall IV for income is unlikely to be a good measure in most places. Similarly a large literature has emerged using remotely sensed nightlights to measure incomes across the world (see reviews in Gibson et al. (2021) and Levin et al. (2020)). Bluhm and Krause (2022) show that luminosity measures can be used as a reliable proxy for economic activity in urban areas of Sub-Saharan Africa. While night lights shows some promise for urban areas, much of the literature has found it wanting in measuring economic outcomes in rural areas (Gibson et al. 2021). In contrast, the GCVI measures of agricultural yields studied in this work provide a measure that is correlated with household expenditures for rural areas that are dependent on agricultural production for their livelihoods.

1.2 Climate Change and Agricultural Yields

This work also builds on and contributes to the significant previous work studying the relationship between changes in climate, and changes in agricultural output. First, we base our Vegetation Index (VI) proxies of agricultural yields on established work in the literature that use VIs to predict crop production. The continent-wide coverage of the vegetation indices can help expand the reach of studies of climate and yields, which have often contented themselves to countrywide measures (Schlenker and Lobell 2010) or areas of well measured yields such as experiment stations (see e.g., Lobell et al. (2011)). A large variety of other work has used rainfall as a proxy for yields and therefore income. Mellon (2024) provides a thorough and convincing critique of the uses of rainfall as a proxy for income. A key issue is that there is not a one-to-one correspondence between rainfall and yields and sometimes even a negative one. The remotely sensed vegetation indices used in our work provide an alternative.[1]

Studies such as those by Becker-Reshef et al. (2010) and Panek and Gozdowski (2021) have already demonstrated the ability of some remotely sensed VI data to be used for predicting Winter Wheat yields in Kansas and Ukraine, and cereals, wheat, and barley in Europe, respectively. Even as these techniques have become popular in the industrialized world, there still remains a lack of work using remote sensing to evaluate crop performance in many developing countries, including much of Sub-Saharan Africa (Burke and Lobell 2017). In many industrialized countries, agricultural lands are characterized by large field sizes that can easily be analyzed, along with reliable ground measures that can evaluate satellite derived data (Burke and Lobell 2017; Farmaha et al. 2016; Lobell 2013). On the other hand, smallholder agricultural systems are more difficult to analyze because of a lack of ground data, as well as difficulty in accurately characterizing field sizes (Burke and Lobell 2017). This is particularly problematic for Sub-Saharan Africa, where around 80% of the farmers are smallholders (Ameyaw and Nyamu 2016). We apply the remote-sensing approach with a chlorophyll-based measure that has been shown to correlate well with features that are predictive of crop yields in smallholder systems such as those in Mali (Lambert et al. 2018; Lobell 2013).

1.3 Vegetation Indices as a Proxy For Agricultural Yields

This study also contributes to the sizable literature on the predictive power of VIs for agricultural yields (Lobell et al. 2019). We make use of the Green Chlorophyll Vegetation Index(GCVI) as our preferred yield proxy, and conduct

1. While rainfall has an advantage of being purely exogenous to human effort, the vegetation indices do include human efforts in their measure of yields. As such they are better to measure yields, though not recommended if one wants a purely exogenous instrument as is often the case with research using rainfall.

robustness checks with three other indexes: The Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI), and the Green Normalized Difference Vegetation Index (GNDVI). GCVI, developed by Gitelson, Gritz, and Merzlyak (2003) is a measure of leaf chlorophyll concentration, which is strongly related to plant photosynthetic capacity, and therefore productivity Bausch, Halvorson, and Cipra (2008). NDVI, which measures the greenness of a particular region, is the most frequently used vegetation index in the economics literature. NDVI has been shown to have a strong relationship with plant photosynthetic capacity (Sellers 1985).

While NDVI has been the most commonly used vegetation index, we follow Burke and Lobell (2017) and use GCVI as our preferred index for predicting yields. Burke and Lobell (2017) studied the effectiveness of various VIs in predicting yields in western Kenya finding that GCVI significantly outperformed NDVI and EVI in predicting maize yields. One potential reason for this given by the authors, is that while GCVI relies on reflectance in the Near-Infrared and Green Wavelengths, NDVI and EVI incorporate reflection from the red wavelengths, and reflectance at green wavelengths is known to be more responsive than red wavelength reflection to changes in leaf chlorophyll concentration. Lambert et al. (2018) made use of GCVI when categorizing croplands in Mali, and found that the Leaf Area Index (LAI) was the strongest predictor of smallholder yields in Mali's cotton belt. According to Viña et al. (2011), chlorophyll based measures are the most strongly correlated with LAI (a strong predictor of photosynthetic activity), and suggested that in some circumstances, GCVI may be a better estimate of the photosynthetic component of LAI (the most relevant component for agricultural productivity) than other methods. Wahab, Hall, and Jirström (2018) studied the predictive power of drone calculated GNDVI to predict maize yields in Ghana, finding that GNDVI better predicted yields ($r = .393$) than in-field measures ($r = 0.259$). GNDVI is a modified version of NDVI that is more sensitive to chlorophyll concentration (Bausch, Halvorson, and Cipra 2008), and is effective capturing nutrient deficiencies in plants (Burke and Lobell 2017).

1.4 Climate Change and Household Welfare

This work also contributes to the literature examining the relationship between climate change and changes in the welfare of households in developing country contexts. With climate change expected to most negatively impact warmer climates, particularly Sub-Saharan Africa (Liu et al. 2016), this is a very pressing concern. In Sub-Saharan Africa, where cereal yields are already 47% below those of those of the rest of the world Gassner et al. (2019), there is a pressing need to improve agricultural output and household welfare.

Our work relates changes in yield proxies in communes across the country of Mali to household level expenditures over the course of nearly a decade. The intensity of changes in the level, and composition of expenditure give a picture of the extent to the resilience and adaptability of households to yearly changes in both agricultural conditions. Another study conducted within this area was that by Tesfaye, Blalock, and Tirivayi (2020), which investigated the impact of "Climate-Smart" innovations for farming on rural poverty in Ethiopia. They found that conservation agriculture interventions with minimum tillage and cereal-legume associations reduced poverty and improved climate-risk management.

Other work has shown that agricultural interventions that increase yields, may improve food security even without providing significant cash-income to help households move out of poverty (Wanjala and Muradian 2013), suggesting a need to consider own consumption of agricultural products. Work by Lunduka et al. (2017), showed that adoption of drought resistant maize in South Africa improved both yields and income for farmers that adopted the drought-resistant varieties. Our study complements studies such as these by showing how variation in yields across geography and time in Mali are related to changes in household consumption patterns. Our findings also contribute to understanding the degree of adaptation and resilience that already exists in the Malian context, and in so doing, begin to determine the amount that will be necessary given the progression of climate change.

2 Context and Data

Mali is a low-income economy in West Africa that is heavily dependent on agriculture, which makes up approximately 38% of national GDP (*World Bank* 2022), while 5.3% of Mali's land is arable *USAID* (2022). The GDP per-capita as of 2022 is $833 (*World Bank* 2022) with around 80% of the population making a living based off of agriculture (*International Trade Administration* 2022), the overwhelming majority of this being done via smallholder farms (Giller et al. 2021). The fertile lands of Mali lie within an arid agro-ecological zone (Giller et al. 2021), with agricultural activities are heavily based around the Niger River in the south of the country and the surrounding fertile land (*USAID* 2022). Mali's main crops are cotton, corn, millet, sorghum, tobacco, and rice (*International Trade Administration* 2022). The country is divided into 704 administrative communes.

2.1 Data

2.1.1 Household expenditure data

In our study, the source of the household data that we use is the "L'Enquete Modulaire et Permanente Aupres Des Menages" (EMOP) or "The Modular and Permanent Study of Households" dataset for the years 2011, 2013-16, and 2018-2019, conducted by "L'Institut National de la Statistique" (INSTAT), the Malian National Statistics Institute. Each year, the survey interviews roughly 6,000 households who are visited once per-quarter. Households are asked for detailed breakdowns of their food and non-food expenditure, while also being asked questions on the demographic makeup of the household such as the age and gender of household members. This dataset gives us access to household expenditure and demographic information throughout each year, across Mali. In our dataset we have households from 596 of Mali's 704 communes, including observations from communes affected by violence.[2]

2. INSTAT employs outside consultants, locally based enumerators, who can access communes outside of government control so that they are able to collect data in places that rebel groups control. Note that there was no data collection in 2012 because of a Coup d'Etat, but other years data was collected even during violence and political unrest through the use of local enumerators.

2.1.2 Vegetation Index Data

For our proxies of agricultural yields, we make use of the Landsat and MODIS sensors to provide Vegetation Indices(VI). In this study we use VIs across much of Mali and during a period spanning almost a decade. Within the literature, work using VIs to predict yields in smallholder systems has been hampered by a a lack of high resolution imagery up until fairly recently. Burke and Lobell (2017) explained that because of the small size of smallholder fields in Sub-Saharan Africa, as well as irregular boundaries, sensor systems such as Landsat, which operates at a relatively high resolution of 30m, have difficulty obtaining accurate crop information. *Familiy Farming Knowledge Platform: Smallholders Data-portrait* (2017) found across a sample of 7 African countries that the average field size was roughly 2 hectares, however this masked significant heterogeneity. Carletto, Gourlay, and Winters (2015) found in a survey of 4 African countries (Malawi, Uganda, Tanzania, and Niger) that around 25% of fields were less than 0.5 acre in size, and more than 50% were less than 1 acre, and more than 80% less than 2 acre.

We benefit from the fact that on average, Malian fields tend to be larger than in many other countries in Sub-Saharan Africa (Giller et al. 2021). Similar findings from Harris, Oduol, and Hughes (2021) show in a sample of 6 African countries that median farm sizes ranged from 0.63 hectares in Ethiopia to 7 hectares in Mali, with a mean of 9.15. Giller et al. (2021) found that in the Cotton Basin of Mali, the median amount of cultivated land per household was 10 hectares. Lobell (2013) found that the spatial resolution of (30m x 30m) used by the Landsat sensor is sufficient to delineate individual fields that are roughly 1ha in size or greater.[3]

Table 1: Summary Statistics on Per-Capita Annual Expenditures for Malian Households (CFA Francs)

Consumption Type	N	Mean	St. Dev
Total Consumption	40,786	125,622.200	105,497.600
Total Food Consumption	40,786	113,078.600	96,934.800
Total Non-Food Consumption	40,786	12,543.610	17,680.180
Grain Consumption	40,786	30,519.200	29,946.660
Grain Auto-Consumption	40,786	19,354.760	22,156.040
Grain Gift Consumption	40,786	853.391	6,164.517
Purchased Grain Consumption	40,786	10,311.050	21,654.650
Rice Consumption	40,786	27,280.480	34,960.610
Meat Consumption	40,786	6,624.260	15,978.760
Clothing	40,786	5,618.586	7,049.144
Housing	40,786	742.681	2,311.587
Education	40,786	170.401	3,700.361
Communication	40,786	951.578	1,979.805

Our preferred proxy for yields is GCVI, but we also run regressions with NDVI as a robustness checks. Calculation of GCVI is based on reflection in in the Near Infrared (NIR), and green wavelength spectrums, while NDVI is based on the NIR and red wavelengths. The formula for GCVI is the following:

3. In recent years, studies such as Azzari, Jain, and Lobell (2017), Lobell et al. (2015) and Lobell et al. (2019) have proposed methods for yield prediction based on the Sentinel-2 sensor that produce images at a resolution of (10m x 10m). The Sentinel-2 system's first available images are in 2017, since our study period for collecting VIs begins in 2010 and ends in 2019, we have opted to use the Landsat system for all years of our project.

$$GCVI = (NIR/Green) - 1, \tag{1}$$

where NIR is the amount of light reflected in Near-Infrared spectrum, and Green is the amount of light reflected in the green spectrum. The formula for NDVI is given by:

$$NDVI = (NIR - Red)/(NIR + Red), \tag{2}$$

where Red is the amount of light reflected in the red spectrum. NDVI ranges between -1 and 1, with negative values indicating clouds and water, values near 0 indicating bare soil, values from 0.1-0.5 indicating sparse vegetation, and values of 0.6 and higher indicating dense vegetation. GCVI is not standardized and so there is no consistent interpretation of obtained values, though our calculations range from slightly above 0 to roughly 5.2. We can view the distribution of values for GCVI across communes of Mali in the images below. In order to calculate the values of the vegetation indices for each commune, we overlay the satellite images with an administrative shapefile of Mali's communes that we obtain from the Global Administrative Areas (GADM) database.

In calculating the commune-level value of GCVI for a particular growing season, we follow the approach of Becker-Reshef et al. (2010). We set the growing season as lasting from May 1st to October 1st of each year and then using GEE and the administrative shapefile of Malian communes, we obtain images in between those dates in 16 day intervals for every commune in Mali from the Landsat sensor. For each pixel in a particular commune, we take the maximum value of GCVI from images taken during the growing season. Then, within each commune, we take the mean of the maximum values of GCVI across all pixels to obtain a Mean of the Maximum GCVI for a particular commune for the growing season. This gives us a measure of GCVI for almost every Malian commune for every growing season from 2010 to 2019.[4]

4. Unlike Becker-Reshef et al. (2010), who predict yields of a specific crop, wheat, we do not weight pixels according to a crop filter. We also do not adjust our maximum GCVI values by subtracting the average of the minimum 5th percentile values of GCVI, as they did. We do apply cloud masks to our images in order to remove pixels that have particularly heavy cloud cover, as the presence of clouds can result in erroneous calculations of a VI. Once this procedure is finished we have a dataset of Averaged Maximum GCVI values. For the year 2010 we were lack Averaged Maximum GCVI values for 40 communes. This may have been a result of gaps in Landsat coverage, or a particularly rainy season causing thick cloud cover, which then resulted in pixels being removed by our cloud mask. We also had two communes without GCVI values for 2011. Tests show no bias due to the missing commune GCVI values in 2010 and 2011.

Figure 1: GCVI Across Mali for the 2019 Growing Season

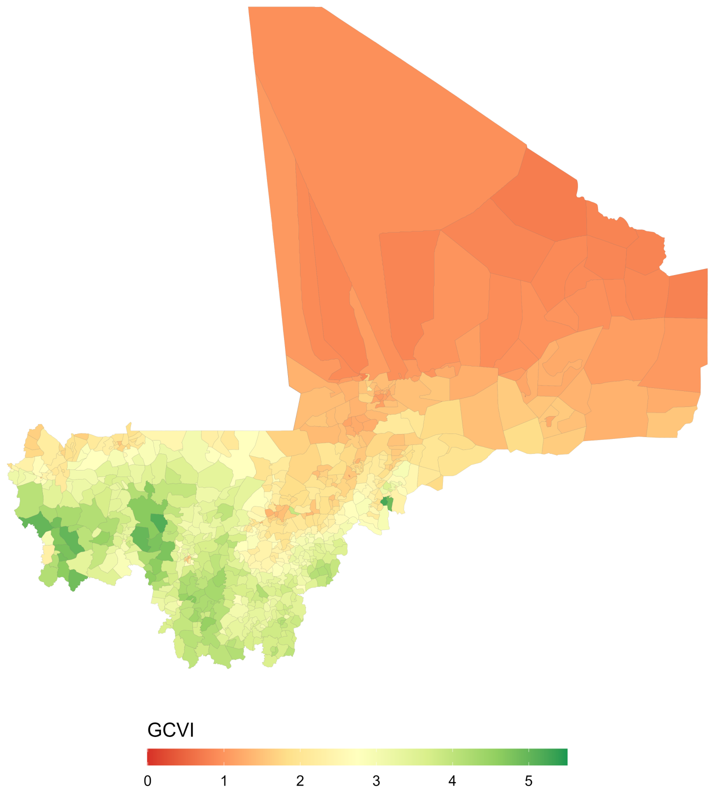


Figure 2: Across Years Standard Deviation of Averaged Maximum Commune-Level GCVI (2010-2019)

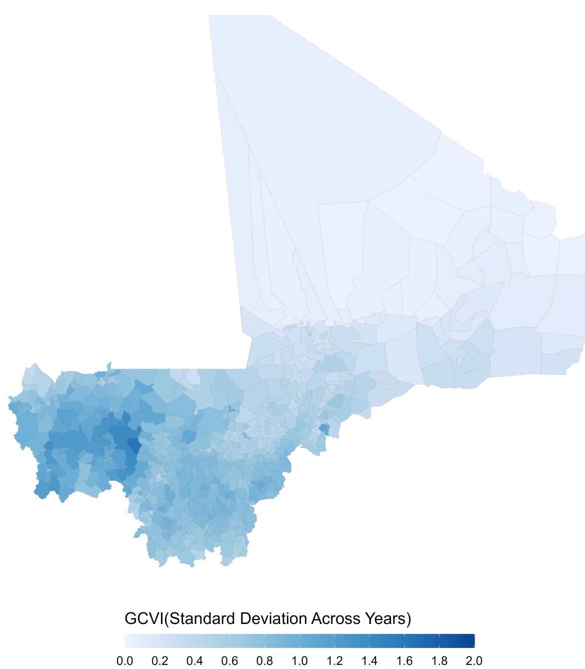


Figure 3

Figure 1 demonstrates sizable variation in GCVI across communes within our example year, 2019, in the fertile southern regions of Mali. This area is where the majority of the population lives and the majority of agricultural production takes place. That variation is confirmed in Figure 2 which shows the standard deviation of GCVI across mali's 704 communes across the years in our study. The relatively high variation in GCVI suggests its suitability to measuring yields, which also exhibit high year to year variation in the Sahel. Table 2 shows the commune level GCVI summary statistics, showing mean, standard deviation, and median.

Table 2: Commune-level GCVI Summary Statistics (2010-2019)

Statistic	Value
Mean of Averaged Maximum GCVI Across Years 2010-2019	2.162
Standard Deviation of Averaged Maximum GCVI Across Years 2010-2019	1.002
Median of Averaged Maximum GCVI Across Years 2010-2019	1.986
Number of Observations	7,040

2.2 Do vegetation indices measure yields?

In order to verify the validity of our use of vegetation indices as proxies for agricultural output, we test for the correlation of vegetative indices with field measured yields in Mali. To do so, we make use of yield data from World Bank Living Standard and Measurement Survey (LSMS) data in Mali from 2014 and 2017 (*Enquête Agricole de Conjoncture Intégrée aux Conditions de Vie des Ménages 2014* 2016; Tiberti, Ponzini, and Djima 2019). These data include farmer reported yield data and also includes the maximal seasonal NDVI for each enumeration area, or "grappe", for which there are over 900. For each household we aggregate the yields for millet, sorghum, and maize as our yield measure. We then regress that yield on the NDVI value for the grappe reported by LSMS in that particular year.[5] We estimate the relationship using the following 2nd degree polynomial specification as follows:[6]

$$log(Y_{igt}) = \alpha V_{gt} + \gamma (V_{gt})^2 + \varepsilon_{igt}, \tag{3}$$

where Y_{igt} represents yields in kilograms-per-hectare (kg/ha) i in an enumeration area g in year$t$, M_{gt} maximum GCVI in enumeration area g during the growing season of year t, and ε_{igt} is an error term for the enumeration area.

The results shown in Table 3 demonstrate that there is a strong relationship between NDVI and crop yields for the LSMS data. This result demonstrates a countrywide analogue to the results in Lobell et al. (2019) which shows similarly strong correlations of satellite and ground based crop yield measurement for a 400 sq km area of Eastern Uganda. This strong effect of NDVI on yields in the Mali LSMS data also demonstrates a strong parabolic relationship. There-

5. The LSMS data collection procedure included pulling NDVI estimates, but did not include the corresponding GCVI estimates, which is our preferred measure. As shown in the appendix there is a high correlation between them, so we think this provides a reasonable test for our purposes.

6. Tests with linear models, higher level polynomials, and log-log specifications fit the data less well than this specification.

fore, in implementing our expenditure estimation, we specify a model with a 2nd degree polynomial of GCVI. We make use of GCVI in the main specification for our study because it has been found to be more accurate in small-holder farming systems, but our data show a strong correlation between NDVI and GCVI (.71) across our study period.

Table 3: Yields(Kg/Ha) of Millet, Maize and Sorghum and Log Seasonal NDVI 2014 and 2017

	Dependent variable:
	Log Yields (Kg/Ha)
Log of NDVI	23.724***
	(1.741)
Square of Log NDVI	−12.306***
	(1.741)
Observations	4,678
R^2	0.048
Adjusted R^2	0.048

Notes: Millet, Sorghum, and Maize are the principal consumption crops grown in Mali. In this regression, we use the log of the maximum annual NDVI for a particular district.

3 Empirical Approach

Our empirical approach relates commune level GCVI values with household expenditure outcomes. Given that the growing season begins in May, and ends in October, it is reasonable to expect that household expenditure in the first half of the year is impacted by the quantity of the previous growing season's harvest. We are able to observe household consumption in all 4 quarters of the year, and therefore are able to observe how expenditure may change as the outcome of the current-year growing season influences expenditures and home consumption. This allows us to treat our data as a panel in which we have two observations for each household. We average expenditure for the first two quarters of the year, and do the same for the last two quarters to create two half-year average expenditure values per household.[7] Average expenditure for the first half of the year is then regressed on the commune-level average of maximum GCVI for the previous growing season, while expenditure for the second half of the year is regressed on that year's growing season.

Our main empirical specification is given by the following equation:

$$IHS(Y_{ijht}) = \alpha log(M_{jt}) + \gamma(log(M_{jt}))^2 + \lambda_h + \phi_t + \mu_i + \varepsilon_{ijht}, \quad (4)$$

.

where Y_{ijty} is the Inverse Hyperbolic Sine (IHS) Transformation of per-capita average quarterly expenditure of a household i in a commune j in half-year h in year t, M_{jt} is within-commune averaged maximum GCVI in commune j during

7. Results are robust to using each quarter, but the half year averaging allows us more non-zero observations for less frequently purchased goods.

the growing season of year t , μ_i is a household fixed-effect, λ_h is a half-year fixed-effect, ϕ_t is a year fixed effect, and ε_{ijht} is a commune-level clustered standard error. For calculating per-capita expenditure we use the OECD-Modified Scale (Hagenaars, Zaidi, and Vos 1994), which adjusts household size on an adult equivalent basis. Although our main expenditure measures are well above zero, we use the IHS Transformation in order to address zero values for expenditure that are quite common for non-food items in this dataset. We choose the same functional form for the dependent variables across all models for consistency.[8]

Our identification strategy relies on geographic variation in the levels of GCVI across communes for a particular growing season, as well as variation in GCVI for communes between different years. The key assumption is that conditional on household, year, and half-year fixed effects, commune-level averaged maximum GCVI is not correlated with the error terms. In other words, our assumption is that unexplained household differences in expenditures are unrelated to the commune level measured vegetation indices.

4 Results

The main results in Table 4 demonstrate a significant relationship between expenditures of rural Malian households due to changes in averaged maximum GCVI across years and communes.[9] Both the linear and quadratic terms are significant in all three regressions and suggest an inverted U-shape in which expenditures are increasing at mean GCVI (2.16) and beyond one standard deviation in a positive direction. The effects on total expenditures and food expenditures are similar, while those on non-food expenditures are more than twice the level of the others. This suggests increments of income from higher yields being spent on non-food items as opposed to food expenditures, in a manner consistent with Engle curves. The coefficients and implied elasticities on total, food, and non-food expenditure in Table 4 show remarkable levels of resilience of Malian rural households to changes in agricultural yields. In contrast to the general expectation that agricultural yields might share a one-to-one elasticity with consumption, these estimates suggest that on average the elasticity between yields and overall per-capita expenditure is roughly 0.04. The elasticities do differ for expenditure sub-categories, with the elasticity for food expenditure being lower at 0.02, and the expenditure for non-food consumption a much higher 0.23. [10] All of these elasticities suggest that the broad categories are normal goods with increases in agricultural yields increasing their purchases.

8. The results for non-zero dependent variables are essentially unchanged if we instead use the logarithm of the dependent variable. They are, however, sensitive to this choice for expenditures with large numbers of zero values.

9. The appendix shows these results for urban households as a robustness/placebo check. Results are significantly muted for urban residents who are less likely to depend on agriculture, despite a substantial number of urban residents reporting consumption of home produced food products.

10. Following the spirit of the derivations in Bellemare and Wichman (2020), elasticities for the functional form in equation (4) are given by the expression:

$$\epsilon_{yx} = \left(\frac{\sqrt{y^2+1}}{y}\right)\left(\hat{\alpha} + 2\hat{\gamma} ln(x)\right).$$

Table 4: Relationship Between GCVI and Per-Capita General Expenditure - Rural Households

	(1) Total Expenditure	(2) Total Food Expenditure	(3) Total Non-Food Expenditure
Log GCVI	0.100***	0.089***	0.340***
	(0.022)	(0.023)	(0.048)
Square of Log GCVI	−0.041***	−0.043**	−0.071**
	(0.016)	(0.017)	(0.032)
Year FE	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes

When we break down rural food expenditure into some of its components, in Table 5, we see that increases in the commune-level mean of maximum GCVI are associated with statistically significant increases in spending on meats but not grain or rice. This suggests a shift towards luxury and more nutritious consumption, consistent with Bennett's law. There being no statistically significant change in total grain or rice consumption, is also suggestive of the resilience levels we see in which changes in yields may be accounted for by changes in net grain storage or Engle curve effects in which consumption of the staple grain stays constant. To test how yields effect own consumption, purchases, and gift receipts, we then divide the expenditures on grain (millet, sorghum, and maize) and rice into "auto" (own consumption produced by the household), purchased, and gifted.[11] Table 6 shows that the expenditure values of self-produced grains and rice decrease with averaged maximum GCVI, suggesting increased market sales. Conversely, there are statistically significant increases in expenditures on purchased and gifted grains and rice. These effects may be due to households diversifying their types of carbohydrate consumption, substituting purchased higher quality grains, while selling their own grain on the market.[12]

11. The survey procedure valued self-produced and gifted agricultural products at the local market price, such that they should be equivalent to purchases. The "gift" measure only accounts for gifts received, not gifts given out, nor net gifts.

12. We are unable to measure price effects, which may also lead to these differential effects. But in order for price effects to cause this pattern, we would have to see differential effects on prices for own produced and market purchased grains or rice, which we think is unlikely to have happened.

Table 5: Relationship Between GCVI and Per-Capita Food Expenditure
by Food Category

	(1) Total Food	(2) Grain	(3) Rice	(4) Meat
Log GCVI	0.089***	−0.083	−0.039	0.447**
	(0.023)	(0.125)	(0.160)	(0.194)
Square of Log GCVI	−0.043**	0.053	0.073	−0.103
	(0.017)	(0.089)	(0.108)	(0.145)
Year FE	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. GCVI is calculated based on the averaged maximum seasonal GCVI across pixels within a commune.

Table 6: Relationship Between GCVI and Per-Capita Grain and Rice Expenditure
by Expenditure Types

	(1) Grain (auto)	(2) Grain (buy)	(3) Grain (gift)	(4) Rice (auto)	(5) Rice (buy)	(6) Rice (gift)
Log GCVI	−1.090***	1.468***	0.419***	−1.039***	0.608**	0.345***
	(0.209)	(0.314)	(0.093)	(0.311)	(0.304)	(0.103)
Square of Log GCVI	0.450***	−0.638***	−0.125**	−0.245	−0.130	−0.146**
	(0.149)	(0.205)	(0.056)	(0.213)	(0.197)	(0.062)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. GCVI is calculated based on the averaged maximum seasonal GCVI across pixels within a commune.

In Table 7 and Table 8 we show expenditures on non-food sub-categories. While per-capita total non-food expenditure is increasing in the average maximum of GCVI, the signs and magnitudes of the coefficients across sub-categories vary considerably. In Table 7 we see only clothing expenditures significantly changing due to changes in GCVI. We see a strong positive elasticity of clothing expenditures to higher yields (0.57 at mean GCVI), as would be expected of a normal consumption good. Other expenditure types alcohol, health and housing show no effect of higher yields.[13] In Table 8 we see strong positive effects of GCVI on communication expenditures (cellphone and internet minutes) and on the residual other non-food categories.[14] In contrast, education and restaurant expenditures go down with higher levels of GCVI. While the restaurant expenditures drop could be due to higher own production of food, we do not have a

13. Mali is a more than 90% Muslim country, so it is consistent to see no effects on alcohol.
14. Communication expenditures are the least likely of the measures we have to change due to localized inflation. Cellphone minute costs are decided nationally and so expenditures would only go up when the quantity of minutes went up.

good explanation of lower education expenditures.[15] Overall, the non-food expenditure results are strongly suggestive of GCVI being related to rural incomes, Malian households being resilient to yield shocks, and rural households spending more on normal goods when GCVI is higher.

Table 7: Relationship Between GCVI and Per-Capita Non-Food Expenditure Categories I

	(1) Total Non-Food	(2) Alcohol	(3) Health	(4) Clothing	(5) Housing
Log GCVI	0.340***	−0.063	−0.054	1.139***	−0.094
	(0.048)	(0.156)	(0.125)	(0.108)	(0.130)
Square of Log GCVI	−0.071**	−0.113	0.183**	−0.372***	−0.126
	(0.032)	(0.099)	(0.085)	(0.075)	(0.095)
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. GCVI is calculated based on the averaged maximum seasonal GCVI across pixels within a commune.

Table 8: Relationship Between GCVI and Per-Capita Non-Food Expenditure Categories II

	(1) Education	(2) Communication	(3) Transportation	(4) Restaurants	(5) Other Non-Food Expenditure
Log GCVI	−0.743***	0.332***	−0.060	−0.207***	0.704***
	(0.120)	(0.095)	(0.137)	(0.057)	(0.116)
Square of Log GCVI	0.528***	−0.148**	0.059	0.147**	−0.127
	(0.087)	(0.062)	(0.090)	(0.058)	(0.079)
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. GCVI is calculated based on the averaged maximum seasonal GCVI across pixels within a commune.

4.1 Robustness Checks

One potential threat to the quality of our estimates is mis-measurement of yields due to using GCVI rather than NDVI. We therefore conduct a series of robustness checks using the commune-level averaged maximum NDVI. Because the range of NDVI values is smaller than that of GCVI, we would expect the magnitudes of the coefficients to be larger in the NDVI regressions than in those for GCVI if they capture similar changes in vegetation health across Mali. For

15. It is possible that education expenditures are mis-measured or measured on the wrong timescale due to their being more like durable goods. One pays once a year for education, which might lead to spurious correlations with yields.

the big three categories of general expenditure in Table 9, the coefficients on the average of maximum of NDVI are positive and statistically significant, even while they are larger in magnitude than in Table 4. Similar to GCVI, the strongest effect by far is for per-capita non-food expenditure in column 3. When we calculate elasticities of expenditure to yields, we find larger implied elasticities than for GCVI of 0.44 for all expenditures, 0.42 for food, and 0.89 for non-food. These still show the remarkable levels of resilience of Malian households in which a 1% change in yields produces a less than 1% change in expenditures.

Table 9: Relationship Between NDVI and Per-Capita Expenditure - Rural Households

	(1) Total	(2) Total Food	(3) Total Non-Food
Log of NDVI	0.731***	0.731***	0.925***
	(0.154)	(0.166)	(0.267)
Square of Log NDVI	0.252***	0.268***	0.029
	(0.075)	(0.081)	(0.148)
Observations	40,898	40,898	40,898
R^2	0.857	0.847	0.819
Year FE	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. NDVI is calculated based on the averaged maximum seasonal NDVI across pixels within a commune.

We also test estimates for the break down of food expenditures by type and of non-food expenditure by type using NDVI as our variable of interest. These are shown in appendix A3. The results there are broadly similar to the results with GCVI, with some differences in emphasis. Among food types, rice expenditures increase, while there is no statistically significant effect on meat expenditures. We also see similar expenditure dynamics play out in Table 22 as with the breakdowns of spending on grain and rice shown above. The coefficients on NDVI for auto-consumption of grain and rice are both negative and statistically significant, while the coefficients in the regression on purchased grain and rice are both statistically significant and positive.

In Non-Food Consumption we see similar trends with NDVI as to those with GCVI. The coefficient on regressions of per-capita clothing expenditures in columns 4 of Table 23 is statistically significant and positive. The sign is negative and statistically significant for housing in contrast to the GCVI regressions. In general, we find that in terms of statistical significance, and the signs of coefficients that regressions of per-capita expenditure on average maximum NDVI are similar to those for our GCVI regressions.

4.2 Comparisons to Night Lights

In order to test how GCVI compares as a correlate of household expenditure in rural Africa to the commonly used nighttime light emissions measures (henceforth "night lights"), we replace GCVI with night light measures from the same communes in our regressions of household expenditures. There is an extensive literature that exploits remotely sensed measures of nightlight intensity as proxies for outcomes such as GDP, household welfare, and overall economic development (Gibson et al. 2021; Gibson, Olivia, and Boe-Gibson 2020; Ivan et al. 2020). That literature, however, raises some questions as to whether night lights are effective in measuring incomes in rural areas particularly in Africa.

To measure night lights, we use the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) dataset for this analysis because it has been shown to significantly outperform the other major source of nightlight data, the Defense Meteorological Satellite Program (DMSP). At the same time, Gibson et al. (2021) showed that data from VIIRS performed relatively poorly in rural areas with lower population densities, the same types of locales which we focus on for our study. We obtain our VIIRS data from the Google Earth Engine.[16] From VIIRS, a we produce a quarterly composite image for each commune during each year. This composite provides the average radiance observed from each pixel.[17] Following the methodology of Ivan et al. (2020), we then take the sum of each pixel in each commune for a particular quarter of the year to get the total commune radiance for that quarter. We then take the logarithm of the sum of quarterly night lights, to produce a measure akin to our vegetation indices.

The summary statistics for VIIRS night lights in Mali are presented in table Table 10 along with the correlation between nightlights and GCVI. The VIIRS data show a high standard deviation, driven by differences between urban areas, such as the capital Bamako, and desert areas with no population and functionally no lights. In addition the median is much lower than the average. The VIIRS data shows a very low negative correlation with GCVI of 0.07, although that correlation is statistically different from zero.

In general, the VIIRS data demonstrate very little variation in night lights across Mali outside of the major urban center of Bamako as we can see in Figure 4, which maps the standard deviation of VIIRS across the country. This low variation in rural Mali is in line with the findings of papers such as those by Gibson et al. (2021) and Gibson, Olivia, and Boe-Gibson (2020). Keola, Anderson, and Hall (2015) argue that nighttime lights are not a good predictor of growth of agricultural value-added. They found that the elasticity of nighttime lights on GDP was negative for countries with an agricultural share between 20% and 40%, with an insignificant relationship for countries with an agricultural share of GDP above 50%. This further suggests that nighttime lights may not be effective proxies of economic activity in rural regions, which we also observe in our own results. Figure 5 shows that there is an overall negative correlation between semesterly nightlights and GCVI. A visual inspection of the relationship also shows little consistent correlation

16. There are two versions of the VIIRS dataset available, one dataset which removes data contaminated by stray light which came online in 2012, and another that corrects for stray light, which came online in 2014. We use the first dataset since it better covers the years of our study.

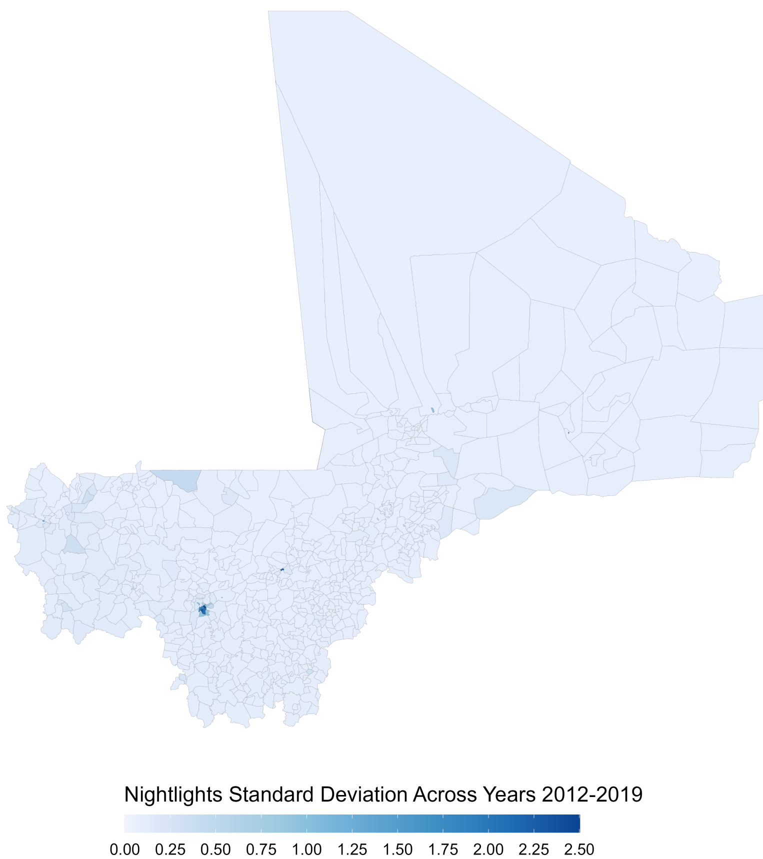
17. Radiance is measured in nanoWatts per centimeter squared per steradian.

between these two measures.

Table 10: Summary Statistics For VIIRS Night Light Radiance Data in Mali

Statistic	Value
Average of The Sum of Quarterly Radiance 2012-2019	266.88
Standard Deviation of The Sum of Quarterly Radiance 2012-2019	1858.71
Median of The Sum of Quarterly Radiance 2012-2019	56.01
Number of Observations (Quarterly)	21824
Correlation Between Semesterly Nightlight Radiance and GCVI	-0.07
t-Statistic	-7.0152

Figure 4: Across Years Standard Deviation of Average Commune-Level Nightlight Radiance



Correlation Between Log Sum of Night Lights and Log GCVI

Figure 5

4.3 Regression results using VIIRS

Night lights perform significantly differently than GCVI and NDVI when we use it as a right hand side variable in our regressions of household expenditure in Mali. In Table 11, the coefficient on the log of the sum of night lights is insignificant for total, food, and non-food expenditures, though the coefficient on the quadratic is statistically significant and negative in the non-food expenditure regression. In addition the coefficients are very small relative to those of the vegetation indices, which suggests no economically significant relationship between VIIRS and any of our household expenditure measures for rural Mali.[18]

In Table 12 and Table 13 we break down food expenditure categories as we did for GCVI and find similarly small or insignificant effects as the main VIIRS regression. As with the overall expenditure results, the coefficients are much closer to zero than in the regressions for either of the vegetation indices.

18. We find similarly small and insignificant coefficients if we run these regressions using urban households and urban commune average VIIRS values. Results available from the authors on request.

Table 11: Relationship Between Radiance and Per-Capita General Expenditure - Rural Households

	(1) Total Expenditure	(2) Total Food Expenditure	(3) Total Non-Food Expenditure
Log Radiance	0.004	0.008	0.042*
	(0.015)	(0.018)	(0.024)
Square of Log Radiance	−0.005**	−0.004	−0.017***
	(0.002)	(0.002)	(0.003)
Observations	62,502	62,502	62,502
R^2	0.590	0.572	0.605
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Notes: Radiance is measured in nanoWatts per square centimeter per steradian ($nW/(cm^2\text{-}sr)$). Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales.

Table 12: Relationship Between Radiance and Per-Capita Food Expenditure by Food Category

	(1) Total Food	(2) Grain	(3) Rice	(4) Meat
Log Radiance	0.008	0.078	0.098	0.094
	(0.018)	(0.081)	(0.104)	(0.103)
Square of Log Radiance	−0.004	−0.004	−0.006	−0.026**
	(0.002)	(0.009)	(0.014)	(0.013)
Observations	62,502	62,502	62,502	62,502
R^2	0.572	0.575	0.571	0.572
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Notes: Radiance is measured in nanoWatts per square centimeter per steradian ($nW/(cm^2\text{-}sr)$). Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales.

Table 13: Relationship Between Radiance and Per-Capita Food Expenditure by Expenditure Types

	(1) Grain (auto)	(2) Grain (buy)	(3) Grain (gift)	(4) Rice (auto)	(5) Rice (buy)	(6) Rice (gift)
Log Radiance	0.065	0.174	−0.042	−0.256**	0.063	−0.021
	(0.117)	(0.132)	(0.037)	(0.113)	(0.116)	(0.028)
Square of Log Radiance	0.010	−0.026	0.012**	0.028*	−0.006	0.003
	(0.016)	(0.018)	(0.005)	(0.015)	(0.016)	(0.003)
Observations	62,502	62,502	62,502	62,502	62,502	62,502
R^2	0.690	0.571	0.491	0.620	0.587	0.397
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Radiance is measured in nanoWatts per square centimeter per steradian ($nW/(cm^2\text{-}sr)$). Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales.

When we move to non-food expenditure for rural households in Table 14 and Table 15, we do observe a few more plausible correlations of expenditures with the night light measure. The regressions in Table 14 show statistically significant and positive effects for health and clothing expenditures. Such effects would be consistent with places with more markets and health centers, that likely have more lights, having higher expenditures on these categories. One might expect similar effects in communication, transportation, restaurant expenditures, but Table 15 shows that there is no such significant relationship. We do find a negative coefficient on education that mirrors the one found for GCVI, although it is only significant at the 10% level. Overall, although the non-food consumption coefficients look more plausible, the correlation between night lights and household expenditure in rural Mali is not a strong one.

Table 14: Relationship Between Radiance and Per-Capita Non-Food Expenditure Categories I

	(1) Total Non-Food	(2) Alcohol	(3) Health	(4) Clothing	(5) Housing
Log Radiance	0.042*	0.010	0.186**	0.260***	−0.048
	(0.024)	(0.066)	(0.074)	(0.072)	(0.067)
Square of Log Radiance	−0.017***	−0.008	−0.041***	−0.055***	−0.001
	(0.003)	(0.009)	(0.010)	(0.010)	(0.008)
Observations	62,502	62,502	62,502	62,502	62,502
R^2	0.605	0.661	0.547	0.483	0.796
Year FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes

Notes: Radiance is measured in nanoWatts per square centimeter per steradian ($nW/(cm^2\text{-}sr)$). Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales.

Table 15: Relationship Between Radiance and Per-Capita Non-Food Expenditure Categories II

	(1) Education	(2) Communication	(3) Transportation	(4) Restaurants	(5) Other Non-Food Expenditure
Log Radiance	-0.143^{*}	0.028	0.073	-0.027	-0.050
	(0.080)	(0.056)	(0.065)	(0.033)	(0.056)
Square of Log Radiance	0.018^{*}	-0.0001	-0.025^{***}	0.003	0.005
	(0.010)	(0.007)	(0.009)	(0.004)	(0.007)
Observations	62,502	62,502	62,502	62,502	62,502
R^2	0.553	0.661	0.708	0.751	0.746
Year FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes

Notes: Radiance is measured in nanoWatts per square centimeter per steradian ($nW/(cm^2\text{-}sr)$). Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales.

5 Conclusion

This work has demonstrated the use of vegetation indices as a proxy for yields across an African country in order to analyze the relationship between agricultural output and household expenditures. Our findings show a strong positive relationship between vegetation indices, including our preferred index, GCVI, and overall per-capita expenditure in rural Mali. The results we find show a strong level of resilience of Malian households to changes in agricultural yields, as proxied by either GCVI or NDVI. The effects we found are primarily driven by changes in expenditures on non-food items, though there are noticeable changes in the composition of food expenditure. We see stronger effects for rural households compared to urban households, suggesting these results are indeed related to agricultural yields.

In terms of specific types of food consumption for rural households with increases in GCVI, we see evidence of shifts towards spending on "luxury" foods such as meat and rice, consistent with Bennett's law. We also observe declines in the expenditure value of consumption of self-produced grains and increases in expenditure on purchased grains and rice, as well as the expenditure value of grain and rice gifts received by households. A good part of the increase in overall per-capita expenditure for rural households associated with increases in GCVI comes through non-food expenditure, particularly increases in spending on communication and clothing. Overall, our results demonstrate a high level of household resilience among rural Malian households in the face of changes in agricultural output. This resilience of rural households suggests the need for more in depth work on the types of resilience and whether the resilience efforts are sustainable.

When we try to substitute the vegetation indices with night light data, which is often used as a proxy for income, we do not find sensible results. We find the VIIRS night light measure poorly and negatively correlated with our measure of yield, GCVI, and almost unrelated to most household expenditure, either in aggregate or by category. This suggests that, at least for rural Africa, researchers should use caution in using night light data as a proxy for income or expenditure.

We have demonstrated the potential efficacy of remotely sensed vegetation indices as proxies for yields in the absence of reliable in-field measures. Furthermore, we have also shown that these yield proxies can then be utilized to quantify changes in household consumption expenditures resulting from variation in agricultural output, and thereby be used for climate resilience measurement. The methodologies and techniques we used here have the potential to be of great use in work to understand the impacts of Anthropogenic Climate Change on agricultural activities in parts of the world with poorly measured yields, and on the welfare of households that rely on these activities.

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Appendix

A1: Vegetation Indices

There are a number of different vegetation indices used in specific contexts or for certain kinds of plants. We examine how the values of for several of theses indices compare in the Malian setting. In addition to the GCVI and NDVI which are the indices we use in our expenditure regressions, we also employ consider the Green Normal Differenced Vegetation Index (GNDVI), as well as the Enhanced Vegetation Index (EVI).

For GCVI and GNDVI, we use the Landsat sensor, and for NDVI and EVI we use the MODIS sensors. MODIS operates at a (250m x 250m) spatial resolution and a 16-day temporal resolution. The system provides built-in functions for calculating NDVI and EVI, but lacks the sensors to calculate GCVI and GNDVI. For Landsat, we use the Landsat 7 between 2010 and 2012, and Landsat 8 between 2013 and 2018, as Landsat 8 did not come online until 2013. We calculate the indices using Google Earth Engine (GEE). While the sensors we use may differ in spatial resolution, we find considerable correlation between the various available vegetation indices, as can be viewed in the appendix Figure 7. That figure shows the correlation across GCVI, GNDVI, NDVI, and EVI. As expected, correlations are strongest between indices that are based on reflection in the same wavelengths, with the green and NIR indices GCVI and GNDVI having a correlation coefficient of 0.97. The red and NIR based indices, NDVI and EVI, share a coefficient of 0.99.

Figure 6: Correlation Between Vegetation Indices

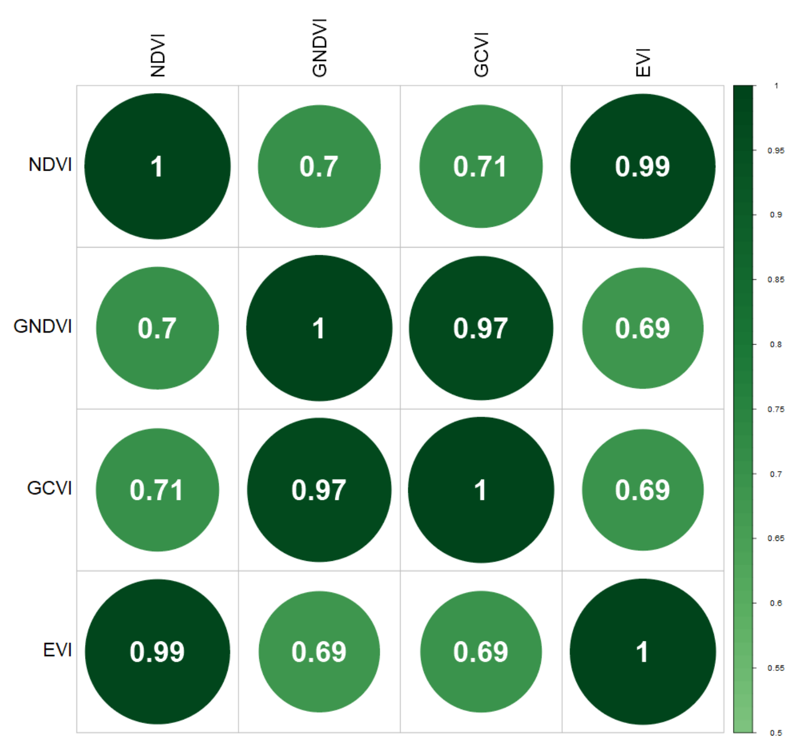

Figure 7

Correlations dip noticeably when comparing those indexes that do not rely on the same wavelengths, such as GCVI and NDVI, which share a correlation of .71. However, the indexes broadly follow similar patterns.

A2: Urban Households Regressions

We expect to find that urban household expenditure would be less elastic with respect to changes in averaged maximum GCVI, since fewer households in urban regions rely on agricultural activities for income or auto-consumption. As such, these urban regressions can be seen as either a placebo test or as a robustness check. Our results for households in urban communes are in line with expectations. For per-capita total expenditure, and per-capita food expenditure, the coefficients on the mean of maximum GCVI are positive but statistically insignificant. The coefficient for the regression of per-capita non-food expenditure on GCVI is positive and statistically significant, with the magnitude less than that of the rural sample Table 18. The regressions for per-capita expenditure of grain and rice both yield statistically insignificant coefficients, a sharp contrast with our findings for rural households. The coefficient is positive and statistically significant at the 10% level for per-capita meat expenditure. This value is statistically significant at the 5% level for our rural sample.

With respect to non-food expenditure for urban households, we see some adjustments that are similar to those of rural households, and also some that differ. Increases in average maximum GCVI are associated with statistically significant increases in per-capita expenditure on clothing and health similarly to rural households, as well as a decrease in per-capita expenditure on housing. Other results are insignificant.

Table 16: Relationship Between GCVI and Per-Capita General Expenditure - Urban

	(1) Total Expenditure	(2) Total Food Expenditure	(3) Total Non-Food Expenditure
Log GCVI	0.075**	0.052*	0.260***
	(0.034)	(0.030)	(0.083)
Square of Log GCVI	−0.067**	−0.073***	−0.069
	(0.028)	(0.026)	(0.066)
Year FE	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. NDVI is calculated based on the averaged maximum seasonal NDVI across pixels within a commune.

Table 17: Relationship Between GCVI and Per-Capita Food Expenditure
by Food Category - Urban Households

	(1) Total Food	(2) Grain	(3) Rice	(4) Meat
Log GCVI	0.052*	−0.271	0.086	0.437*
	(0.030)	(0.381)	(0.185)	(0.256)
Square of Log GCVI	−0.073***	0.245	−0.032	−0.278
	(0.026)	(0.303)	(0.136)	(0.212)
Year FE	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. GCVI is calculated based on the averaged maximum seasonal GCVI across pixels within a commune.

Table 18: Relationship Between GCVI and Per-Capita Non-Food Expenditure Categories I - Urban Households

	(1) Total Non-Food	(2) Alcohol	(3) Health	(4) Clothing	(5) Housing
Log GCVI	0.260***	−0.145	0.303	1.414***	−0.419***
	(0.083)	(0.169)	(0.195)	(0.325)	(0.157)
Square of Log GCVI	−0.069	0.029	0.041	−0.582**	0.109
	(0.066)	(0.150)	(0.145)	(0.246)	(0.117)
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. GCVI is calculated based on the averaged maximum seasonal GCVI across pixels within a commune.

Table 19: Relationship Between GCVI and Per-Capita Non-Food Expenditure Categories II - Urban Households

	(1) Education	(2) Communication	(3) Transportation	(4) Restaurants	(5) Other Non-Food Expenditure
Log GCVI	−0.971**	−0.318	0.102	−0.121	0.386**
	(0.425)	(0.196)	(0.127)	(0.076)	(0.172)
Square of Log GCVI	0.370	0.239*	0.091	0.118	−0.078
	(0.310)	(0.133)	(0.104)	(0.104)	(0.112)
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. GCVI is calculated based on the averaged maximum seasonal GCVI across pixels within a commune.

For urban households, we find a statistically significant decrease in per-capita expenditure on education as GCVI increases, which appears counter-intuitive. The strongest effect of our proxy for yields on education is seen in the segment of our sample that is least directly dependent on agricultural activities for income, which may suggest a price or crowding out effect. It is also not immediately obvious why the effect of improved yields on education expenditures would be negative. One possibility for why the effects of higher yields reduces education expenditure may be that improved yields lead households to substitute away from investing in the education of their children, and towards having their children assist in agricultural activities. It is also likely that some agricultural activities are still taking place in communes classified as urban.

A3: Additional NDVI Data and Regressions

In this section we show summary statistics for NDVI and additional regressions using NDVI instead of GCVI, that mirror the regression tables in the main text.

Table 20: Commune-level NDVI Summary Statistics (2010-2019)

Statistic	Value
Mean of Averaged Maximum NDVI Across Years 2010-2019	0.570
Standard Deviation of Averaged Maximum NDVI Across Years 2010-2019	0.169
Median of Averaged Maximum NDVI Across Years 2010-2019	0.606
Number of Observations	7,040

Table 21: Relationship Between NDVI and Per-Capita Expenditure - Rural Households

	(1) Total Food	(2) Grain	(3) Rice	(4) Meat
Log of NDVI	0.731***	0.670	1.635*	0.339
	(0.166)	(0.711)	(0.893)	(1.382)
Square of Log NDVI	0.268***	0.433	0.413	−0.231
	(0.081)	(0.411)	(0.371)	(0.753)
Observations	40,898	40,898	40,898	40,898
R^2	0.847	0.750	0.737	0.744
Year FE	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. NDVI is calculated based on the averaged maximum seasonal NDVI across pixels within a commune.

Table 22: Relationship Between NDVI and Per-Capita Food Expenditure Categories I

	(1) Grain (auto)	(2) Grain (buy)	(3) Grain (gift)	(4) Rice (auto)	(5) Rice (buy)	(6) Rice (gift)
Log of NDVI	-5.386^{***}	7.323^{***}	-0.998^{*}	-9.696^{***}	3.058^{**}	0.248
	(1.725)	(1.778)	(0.576)	(2.007)	(1.258)	(0.531)
Square of Log NDVI	-1.049	2.083^{**}	-0.698^{*}	-3.563^{***}	0.410	0.070
	(0.705)	(0.842)	(0.356)	(1.213)	(0.691)	(0.380)
Observations	40,898	40,898	40,898	40,898	40,898	40,898
R^2	0.836	0.731	0.675	0.763	0.744	0.602
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. NDVI is calculated based on the averaged maximum seasonal NDVI across pixels within a commune.

Table 23: Relationship Between NDVI and Per-Capita Non-Food Expenditure Categories I

	(1) Total Non-Food	(2) Alcohol	(3) Health	(4) Clothing	(5) Housing
Log of NDVI	0.925^{***}	-1.413^{*}	0.857	3.780^{***}	-2.945^{***}
	(0.267)	(0.851)	(0.799)	(0.653)	(0.883)
Square of Log NDVI	0.029	-1.167^{***}	0.702^{*}	0.602	-0.916^{**}
	(0.148)	(0.396)	(0.367)	(0.387)	(0.452)
Observations	40,898	40,898	40,898	40,898	40,898
R^2	0.819	0.799	0.727	0.695	0.878
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. NDVI is calculated based on the averaged maximum seasonal NDVI across pixels within a commune.

Table 24: Relationship Between NDVI and Per-Capita Non-Food Expenditure Categories II

	(1) Education	(2) Communication	(3) Transportation	(4) Restaurants	(5) Other Non-Food Expenditure
Log of NDVI	-1.483^{**}	-0.416	0.543	0.841^{*}	2.955^{***}
	(0.742)	(0.535)	(0.787)	(0.432)	(0.739)
Square of Log NDVI	-0.438	-0.444^{*}	0.140	0.425^{**}	0.570
	(0.331)	(0.260)	(0.462)	(0.209)	(0.368)
Observations	40,898	40,898	40,898	40,898	40,898
R^2	0.762	0.826	0.842	0.842	0.844
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are the inverse hyperbolic sine (IHS) transformation of all expenditures, food expenditures, and non-food expenditures. All regressions have household fixed effects, year and half year fixed effects. Standard errors are clustered at the commune level. Per-capita expenditure outcome values for each semester/half-year are the average of the values within each quarter of a half-year, with household size determined based on OECD equivalence scales. NDVI is calculated based on the averaged maximum seasonal NDVI across pixels within a commune.