Climate and Consumption: Evidence From Mali

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A large literature has estimated the effects of climate change on agricultural yields. That work assumes, but rarely tests, that changes in yields translate directly into changes in household wellbeing. Such assumptions elide the rather large literature on resilience to climate and other shocks. This work uses satellite derived yield data (GCVI) to analyze the relationship between agricultural productivity and household welfare, as measured by overall and food expenditure in the West African Sahel. 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 for two growing seasons per household. As expected, we find that changes in yields have a statistically significant effect on overall household expenditure as well as other expenditure categories (food, leisure, etc.) for rural dwellers. This effect for rural dwellers is, however, relatively muted to changes in the values of vegetation indices, with GCVI to expenditure elasticities in the range of 0.10. Such low expenditure elasticities for changes in yields indicates a large degree of resilience to climate-related variation in agricultural productivity by Malian rural households. We draw conclusions based on this work for policy makers and for researchers interested in using remote 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 is most likely to hit small-holder farmers in Sub-Saharan Africa particularly hard (Ortiz-Bobea et al. 2021; Liu et al. 2016). At the same time throughout Sub-Saharan Africa there is a notable lack of reliable agricultural yield data. There is also still much that we do not know about the welfare impacts of changes in agricultural output on those that rely at least in part on farming to make a living (Gassner et al. 2019).

We contribute to the literature by answering two questions: 1. Can we use vegetation indices as yields and if so, which ones? 2. Do increases in agricultural productivity increase household welfare for rural Malians, and if so, by how much?

First, we demonstrate the efficacy of employing remotely sensed agricultural data as a proxy for yields across much of Mali, a major agricultural producer in Sub-Saharan Africa and the 8th largest country by area on the continent. We provide comparisons across multiple popular vegetation indices, focusing in particular on the Green Chlorophyll Vegetation Index (GCVI) that has previously demonstrated potential to be effective in the smallholder farming settings common to Sub-Saharan Africa.

We then show that our remotely sensed yield proxies can be utilized to estimate the relationship between variation in agricultural output and variation in household welfare outcomes,in our case, expenditures. We employ a repeated cross-section of Malian household data covering the period 2011-2019, comprising households from nearly 600 of Mali's roughly 700 administrative communes. Our results show that while increases in yields are associated with increases in per-capita expenditures for rural households, the elasticity of consumption expenditure in our preferred vegetation index is noticeably less than one (roughly .1), suggesting a striking amount of resilience to variation in agricultural production among rural Malians.

Our findings are relevant for the study of climate change and its impacts on human welfare. The methodology we employ 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 we often lack in-field measures of agricultural production. Combined with household datasets, these methods can help researchers and policymakers better understand how climate-induced changes to agriculture will impact the welfare of households in a variety of contexts.

1.1 Agricultural Output and Household Welfare

The relationship between agricultural output and household well-being has been discussed for some time in the literature. Datt and Ravallion (1998) combined data from household surveys spanning 35 years in rural India, and found that growth in farm yields and real wages reduced absolute poverty with about the same elasticity. Janvry and Sadoulet (2010) analyzed the impact of increases in international food prices during the years 2006-2008 on households in Guatemala, and found that even with only modest price transmission of prices into the domestic Guatemalan market, farm households represented about two-thirds of all poor households losing from rising food prices. This was in-part due to the fact that many agricultural households were in fact net buyers of food. Indeed, a key issue in evaluating the impact of of agricultural yields on households is the fact that there is a large amount of heterogeneity in the needs, skills, and incentives of rural households (Mekonnen and Kassa 2019).Gassner et al. (2019) critiqued what they saw as the conflation of the goals of food security and poverty reduction in the debate over the use of agriculture for development. They argue that the two issues have very distinct target groups based on the the role of farming in individual and household income. In 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.

Gassner et al. (2019) pointed out that while there are a wide array of possible interventions that can help with food security, some of them do not have a strong impact on poverty levels. For example, in one of the communities in Kenya that was part of the Millenium Villages, agricultural interventions almost doubled farm income, but most of this increase went to valued home consumption (Wanjala and Muradian 2013). These interventions therefore contributed significantly to food security, but not to cash income which could be used for reinvesting. It is therefore possible that the changes in the yields that we proxy for in our study may primarily impact auto-consumption of food rather than non-food consumption. That being said, work by Tesfaye, Blalock, and Tirivayi (2020), found that conservation agriculture techniques that attempt to sustainably increase agricultural intensity produced statistically significant decreases in household poverty in Ethiopia. However they caution about drawing the conclusion that the techniques they analyzed would be useful in other contexts. We will continue to build upon the foundation laid by previous work by studying how changes in administrative unit (commune) level proxies for yields are related to changes in the value and composition of household expenditures.

1.2 Climate Change and Agricultural Yields

This paper builds on and contributes to the significant previous work into making sense of 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. We extend existing work by applying these techniques to a setting in which they have been underutilized. Mali, and other countries in Sub-Saharan Africa are also perhaps some of the regions for which these predictive techniques are most sorely needed, given concerns about the connection between climate change and agricultural production. The intense push to understand this relationship is driven by the importance of agricultural activities for both economic stability and food security. Global demand for food is expected to increase 60% by the middle of the twentieth century and this slowdown is predicted to be worse for warmer regions (Liu et al. 2016). Sub-Saharan Africa is still the most food-insecure region in the world, with around 230 million people being undernourished (Gassner et al. 2019). Zhao et al. (2017) investigated the impact of temperature yields on global production of wheat, maize, rice, and soybean using four independent estimates. They found that each degree-Celsius increase in mean temperatures reduced global yields of wheat by 6.0%, rice by 3.2%, maize by 7.4%, and soybean by 3.1%. This is particularly relevant to the Malian context, as wheat, rice, and maize comprise a major portion of the expenditures of Malian households in our study. Grains(maize, wheat, and sorghum) and rice together make-up roughly 53% of household per-capita half-year food expenditure for rural Malians.

In using vegetation indices as proxies for yields, we contribute by making use of a technique that may prove incredibly useful in predicting and analyzing the impacts of changes in climate on crop performance, in a region where their use may be crucial to counteracting the potentially deleterious effects of climate change. 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 extremely 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 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 now apply the remote-sensing approach but with a chlorophyll-based measure that has been shown to correlate well with features that are predictive of crop yields in smallholder systems (Lambert et al. 2018; Lobell 2013).

1.3 Vegetation Indices as a Proxy For Agricultural Yields

This study will also contribute to the sizable literature on the predictive power of VIs for agricultural yields. We make use of the Green Chlorophyll Vegetation Index(GCVI) as our preferred yield proxy, and by conducting 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 popular vegetation index. NDVI has also been shown for some time, to have a strong relationship with plant photosynthetic capacity (Sellers 1985).

While NDVI has been the most commonly used vegetation index, the literature has shown that other indices may be better suited for predicting yields depending on factors such as the crop type, climate, and the characteristics being analyzed. With our study we will take inspiration from 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. They found 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 destructive 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 may be better able to capture nutrient deficiencies in plants (Burke and Lobell 2017).

There have been a wide variety of studies using NDVI in yield prediction in diverse settings. The NDVI-based model developed by Becker-Reshef et al. (2010) for forecasting winter wheat yields, makes use of a combination of remote sensing and official data. The model relates the values of the yields, the seasonal peak NDVI which they obtain from the Moderate Resolution Imaging Spectro-radiometer (MODIS) satellite system, and the maximum winter wheat percentage per corresponding administrative units of a country. The model was first tested in Kansas, and then applied to Ukraine. Panek and Gozdowski (2021) similarly used MODIS derived NDVI in studying yields, but analyzed a wider range of crops (all cereals, wheat, and barley) at the country level, for 20 European nations. In their analysis, they regressed yields on both raw NDVI values as well as cumulative NDVI (cNDVI). For some countries they found strong relationships between NDVI in early Spring, and the grain yield of cereals 4 months later. They also found that cNDVI, or the averaged NDVI directly proportional to it, were the most stable predictors of of grain yields. At the same time, they found very weak relationships between NDVI and yields for France and Belgium. Other works, such as those by He et al. (2018) and Mkhabela et al. (2011) have demonstrated the usefulness of NDVI for estimating crop yields in settings such as Montana, the Canadian Prairie, respectively.

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 Dataportrait* (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 according to research by Giller et al. (2021). They have found that in general, farms tend to be larger in drier agroecological zones, such as those in Mali. This trend is supported by findings from Harris, Oduol, and Hughes (2021) who found 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) also stated 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. In recent years, studies such as those conducted by 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, and as 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, though the Sentinel-2 system holds great potential for future work.

1.4 Climate Change and Household Welfare

With this work we also will speak into the literature that is attempting to examine the relationship between ACC and changes in the welfare of households in developing country contexts. With ACC 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% of those of the rest of the world Gassner et al. (2019), there is a pressing need to improve agricultural output and the level of human development.

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.

However other work has shown that agricultural interventions that increase yields, may improve food security without providing significant cash-income to help households move out of poverty (Wanjala and Muradian 2013). However, 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 attempts to complement studies such as these by giving insights into how variation in yields across geography and time in Mali are related to changes in consumption patterns. Given ever-improving knowledge about the impacts of ACC on climate change, our findings can 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 ACC.

2 Background, Context, and Data

Mali is a landlocked nation in West Africa, with a population of roughly 22.5 million as of 2022 (*World Bank* 2022). It is the 8th largest country in Africa by area at roughly 1.2 million square miles (*World Bank* 2022) with approximately 65% of that area being covered by desert. According to The World Bank, around 5.3% of Mali's land is arable *USAID* (2022). Mali has a low-income economy that is heavily dependent on agriculture, which makes up approximately 38% of national GDP (*World Bank* 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, cereal,peanuts, tobacco, and rice (*International Trade Administration* 2022). The country is divided into 704 administrative communes, and it is at the commune level that we will calculate vegetation indices.

Table 1: Descriptive Statistics- Rural Households(OECD Equivalence Scale-CFA Francs)

Statistic	N	Mean	St. Dev.
Grain Consumption	44,612	29,582.990	27,082.630
Grain Auto-Consumption	44,612	13,580.710	15,303.620
Grain Gift Consumption	44,612	744.281	5,831.944
Purchased Grain Consumption	44,612	15,257.990	24,207.640
Rice Consumption	44,612	13,937.540	18,377.530
Meat Consumption	44,612	3,291.810	9,521.759
Clothing Consumption	44,612	2,790.031	3,301.570
Housing Consumption	44,612	348.210	1,072.010
Education	44,612	90.485	3,049.437

2.1 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. This survey conducted by "L'Institut National de la Statistique" (INSTAT), the Malian National Statistics Institute. Each year, the survey interviews roughly 6000 thousand 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 measures. 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.

For our proxies of agricultural yields, we make use of the Landsat and MODIS sensors. Our preferred proxy for yields is GCVI, but we also run regressions with NDVI and 2 other vegetation indices. Calculation of GCVI is based on reflection in in the Near Infrared(NIR), and green wavelength spectrums. NDVI is based on the NIR and red wavelengths. The formula for GCVI is the following:

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

Where NIR is the amount of light reflected in Near-Infrared spectrum, and Green is the amount of light reflected in the green spectrum. and 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 these two indices across communes of Mali in the images below. In Figure 2 we can also observe that there is sizable variation in GCVI across years in the fertile southern regions of Mali.

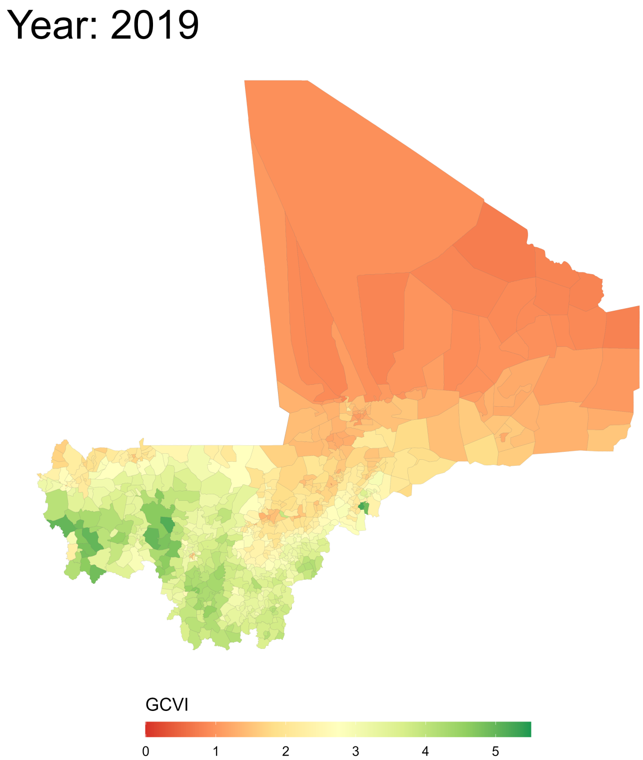

Figure 1: GCVI Across Mali for the 2019 Growing Season

While the sensors we use may differ in spatial resolution, we find considerable correlation between our calculated indices, as can be viewed in Figure 3. As we 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 and the red and NIR based indices NDVI and EVI having a coefficient of 0.99.

Across Years Standard Deviation of Averaged Maximum Commune-Level GCVI

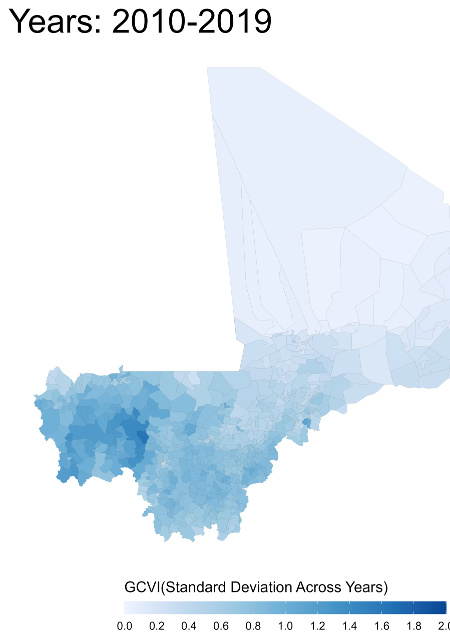

Figure 2

In order to verify the validity of our use of vegetation indices as proxies for agricultural output, we make use of yield data from World Bank Living Standard and Measurement Survey(LSMS) studies of yields across Mali in 2014 and 2017 (*Enquête Agricole de Conjoncture Intégrée aux Conditions de Vie des Ménages 2014* 2016; Tiberti, Ponzini, and Djima 2019). This data 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, and then relate them to the NDVI value for the grappe in that particular year. We estimate the relationship using the following specification:

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

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.

Our results in Table 2 demonstrate that there is a strong parabolic relationship between NDVI and yields for the included crops. Therefore, we employ a 2nd degree polynomial in the baseline specification of our study. 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 results show a strong correlation between the indices (.71) across our study period.

Table 2: Log Yields(Kg/Ha) of Millet, Maize and Sorghum and Log Maximum Seasonal NDVI 2014 and 2017

	Log Yields(Kg/Ha)
Log of Max NDVI	33.806^{***}
	(2.047)
Square of Log Max NDVI	-18.561^{***}
	(2.047)
Observations	6,915
R^2	0.049
Note:	*p<0.1; **p<0.05; ***p<0.01

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). We obtain an administrative shapefile of Mali's communes from the Global Administrative Areas (GADM) database.

Correlation Between Vegetation Indices

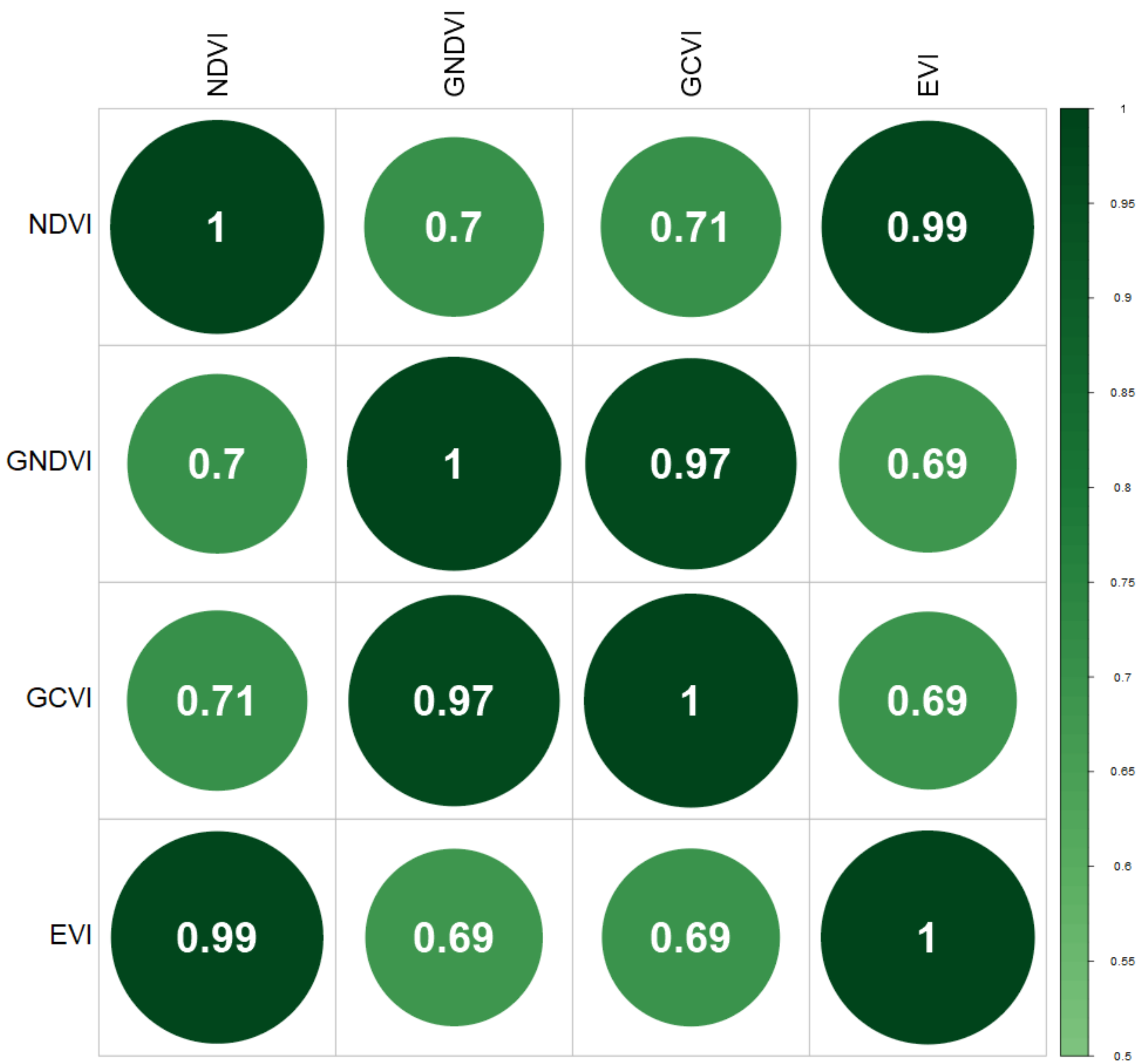

Figure 3

3 Empirical Approach

In calculating the commune-level value of GCVI for a particular growing season, we partially borrow from the approach of Becker-Reshef et al. (2010) in which they calculated an averaged maximum NDVI for counties in Kansas, and use peak-season averaged maximum GCVI but with adjustments. 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.

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. 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 every commune in Mali for almost every growing season from 2010-2019. For the year 2010 we were not able to obtain 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. Given that we still have data for the vast majority of communes in 2010, and the missing commune GCVI values are primarily limited to 2010, we are confident that our results are not impacted in a significant way.

We can then relate commune level GCVI values with household 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 quality 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 is felt and influences income, home consumption, and expenditure. 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. Average expenditure for the first half of the year is then regressed on the commune-level average of maximum GCVI for the growing season.

Our main empirical specification is given by the following:

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

.

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 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). We use the IHS Transformation in order to address 0 values for expenditure that are quite common for non-food items in this dataset.

Our identification strategy relies on variation geographically in the levels of GCVI across communes for a particular growing season, as well as variation in GCVI for communes between different growing seasons. Our 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.

4 Results

We observe a striking level of resilience in the expenditures of Malian households in response to changes in Averaged Maximum GCVI across years and communes. There is a significant amount of heterogeneity in our results depending on the type of good being consumed, and whether the household is urban or rural. In **??** we show the regression results for our three general categories of "Total Consumption", "Total Food Consumption" and "Total Non-Food Consumption", for our full sample of urban and rural households. There is a small but statistically significant and positive relationship between the averaged maximum of commune-level GCVI and the IHS transformation of total consumption. This effect seems to entirely come through non-food consumption, for which the coefficient on the mean of maximum GCVI is positive and statistically significant. The coefficient for total food consumption is positive but not statistically significant.

Relationship Between GCVI And Per-Capita Expenditure for Urban And Rural Households

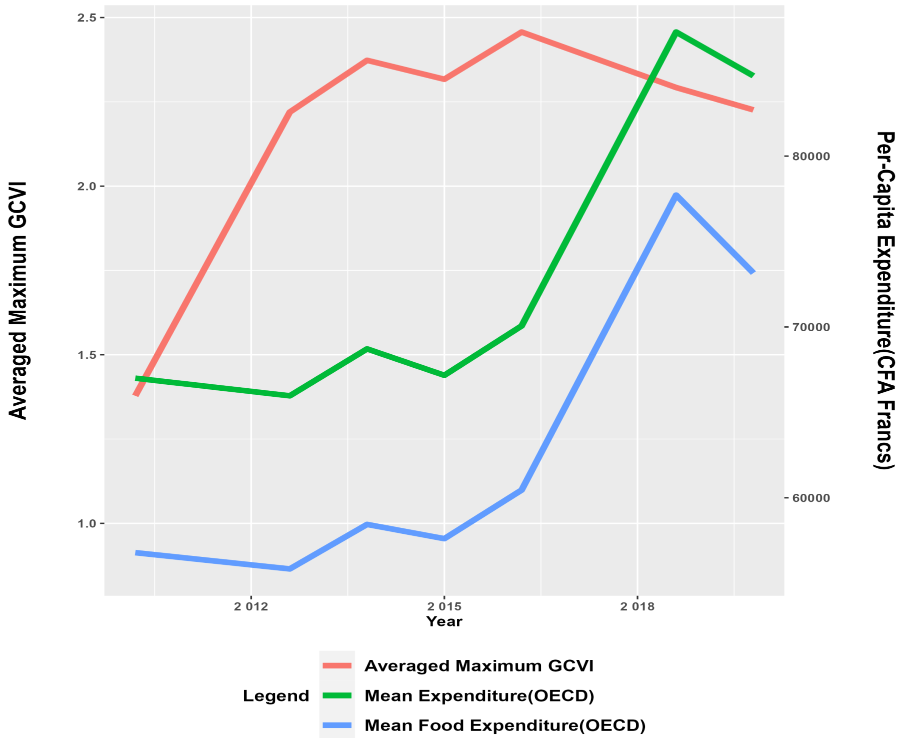

Figure 4

Table 3: Relationship Between GCVI and Averaged Half-Year General Expenditure for Urban and Rural Households- OECD Equivalence Scale

	(1) IHS Total Expenditure	(2) IHS Total Food Expenditure	(3) IHS Total Non-Food Expenditure
Log of Averaged Maximum GCVI	0.084***	0.067***	0.295***
	(0.020)	(0.019)	(0.048)
Square of Log Averaged Max GCVI	−0.046***	−0.048***	−0.062*
	(0.016)	(0.016)	(0.035)
Observations	75,472	75,472	75,472
R^2	0.871	0.848	0.884
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes
Controls	No	No	No
Mean of outcomes	11.719	11.568	9.447
Mean of GCVI mean	0.654	0.654	0.654
SD of GCVI mean	0.500	0.500	0.500
Note:			*p<0.1; **p<0.05; ***p<0.01

When we limit our regression to the same categories of consumption for only rural households, we find a noticeably stronger relationship between changes in GCVI and changes in the big three categories of consumption. In Table 3 we can see positive and statistically significant coefficients on the mean of maximum GCVI for each type of expenditure. As with the previous full-sample regressions, we see that the increase in total expenditure is primarily driven by the change in non-food expenditure. The fact that we see far more significant results for rural households as opposed to urban ones also lends support to our argument that our measures of GCVI are proxying for changes in agricultural yields.

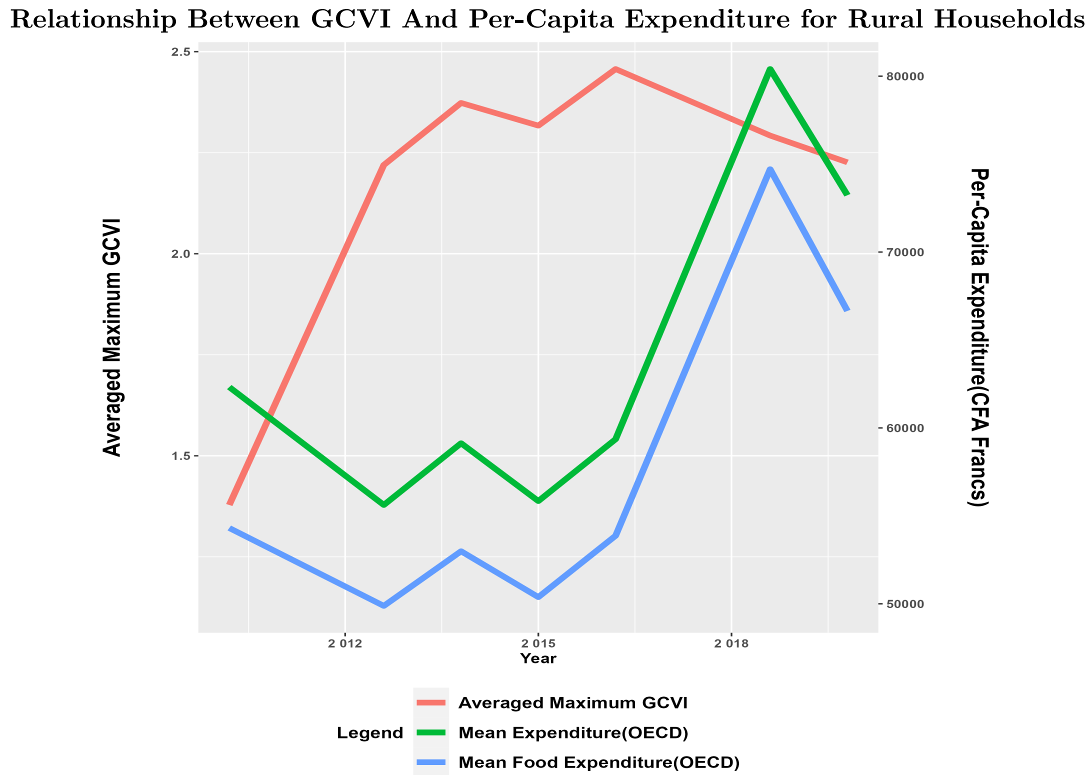

Figure 5

Table 4: Relationship Between GCVI and Averaged Half-Year General Expenditure for Rural Households-OECD Equivalence Scale

	(1) IHS Total Expenditure	(2) IHS Total Food Expenditure	(3) IHS Total Non-Food Expenditure
Log of Averaged Maximum GCVI	0.100***	0.089***	0.340***
	(0.022)	(0.023)	(0.048)
Square of Log Averaged Max GCVI	−0.041***	−0.043**	−0.071**
	(0.016)	(0.017)	(0.032)
Observations	40,786	40,786	40,786
R^2	0.858	0.848	0.821
Note:			*p<0.1; **p<0.05; ***p<0.01

When we break down rural food expenditure into some of its components, we see that increases in the commune-level mean of maximum GCVI are associated with statistically significant increases in spending on meats in Table 5, which can be interpreted as a shift towards luxury consumption. While there is no statistically significant change in total grain or rice consumption, once again, when analyzing their components we see that there is significant shifting of expenditures. In Table 9 we can see that the expenditure values of self-produced grains that rural households consume decrease markedly in averaged maximum GCVI. Conversely, there are statistically significant increases in expenditures on purchased grains in column 2, and the expenditure values of grains received as gifts in column 3. We observe the same dynamics in expenditures on rice in columns 4-6. The negative coefficient on averaged maximum GCVI for auto-consumption of rice is almost twice that of the coefficient in column 1. The coefficient on GCVI for purchased rice expenditure in column 5 is roughly the same as the coefficient for column 2.

Table 5: Relationship Between GCVI and Averaged Half-Year Food Expenditure for Rural Households-OECD Equivalence Scale

	(1) IHS Total Food	(2) IHS Grain	(3) IHS Rice	(4) IHS Meat	(5) IHS Peanut Oil
Log of Averaged Maximum GCVI	0.089***	0.132**	−0.040	0.447**	−1.074***
	(0.023)	(0.053)	(0.160)	(0.194)	(0.178)
Square of Log Averaged Max GCVI	−0.043**	−0.074*	0.073	−0.103	0.273**
	(0.017)	(0.039)	(0.108)	(0.145)	(0.124)
Observations	40,786	40,786	40,786	40,786	40,786
R^2	0.848	0.739	0.738	0.744	0.791
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Mean of outcomes	11.472	10.705	8.693	5.348	6.547
Mean of GCVI mean	0.792	0.792	0.792	0.792	0.792
SD of GCVI mean	0.500	0.500	0.500	0.500	0.500
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6: Relationship Between GCVI and Averaged Half-Year Food Expenditure for Rural Households-OECD Equivalence Scale

	(1) IHS Grain (auto)	(2) IHS Grain (buy)	(3) IHS Grain (gift)	(4) IHS Rice (auto)	(5) IHS Rice (buy)	(6) IHS Rice (gift)
Log of Averaged Maximum GCVI	−0.927***	0.962***	0.621***	−1.039***	0.608**	0.345***
	(0.250)	(0.230)	(0.139)	(0.311)	(0.304)	(0.103)
Square of Log Averaged Max GCVI	0.127	−0.391**	−0.232***	−0.245	−0.130	−0.146**
	(0.170)	(0.156)	(0.082)	(0.213)	(0.197)	(0.062)
Observations	40,786	40,786	40,786	40,786	40,786	40,786
R^2	0.784	0.722	0.670	0.765	0.744	0.604
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No
Mean of outcomes	7.959	7.994	0.651	2.897	6.884	0.268
Mean of GCVI mean	0.792	0.792	0.792	0.792	0.792	0.792
SD of GCVI mean	0.500	0.500	0.500	0.500	0.500	0.500
Note:						*p<0.1; **p<0.05; ***p<0.01

The dynamics for non-food consumption also present with interesting effects due to changes in GCVI. In Table 7 there is evidence that while per-capita total non-food expenditure is increasing in the average maximum of GCVI, the signs and magnitudes of the coefficients vary considerably, with the coefficient going from

−0.063 for per-capita spending on alcohol, to 1.139 for per-capita expenditure on clothing, with only the clothing coefficient being significant out of those two.

Table 7: Relationship Between GCVI and Averaged Half-Year Food Expenditure for Rural Households-OECD Equivalence Scale

	(1) IHS Total Non-Food	(2) IHS Alcohol	(3) IHS Health	(4) IHS Clothing	(5) IHS Housing
Log of Averaged Maximum GCVI	0.340***	−0.063	−0.056	1.139***	−0.094
	(0.048)	(0.156)	(0.125)	(0.108)	(0.130)
Square of Log Averaged Max GCVI	−0.071**	−0.113	0.185**	−0.372***	−0.126
	(0.032)	(0.099)	(0.085)	(0.075)	(0.095)
Observations	40,786	40,786	40,786	40,786	40,786
R^2	0.821	0.801	0.728	0.699	0.880
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Mean of outcomes	9.068	2.249	5.951	7.998	3.674
Mean of GCVI mean	0.792	0.792	0.792	0.792	0.792
SD of GCVI mean	0.500	0.500	0.500	0.500	0.500
Note:					*p<0.1; **p<0.05; ***p<0.01

We do find a statistically significant relationship between changes in the mean of maximum GCVI and changes in per-capita expenditure on schooling for rural households, though the coefficient is negative as can be seen in column 1 of Table 8. We see statistically significant increases in per-capita spending on communication services as well as other non-food goods.

Table 8: Relationship Between GCVI and Averaged Half-Year Non-Food Expenditure for Rural Households-OECD Equivalence Scale

	(1) IHS Education	(2) IHS Communication	(3) IHS Transportation	(4) IHS Restaurants	(5) IHS Other Non-Food Expenditure
Log of Averaged Maximum GCVI	−0.758***	0.332***	−0.060	−0.207***	0.710***
	(0.120)	(0.095)	(0.137)	(0.057)	(0.116)
Square of Log Averaged Max GCVI	0.540***	−0.148**	0.059	0.147**	−0.127
	(0.088)	(0.062)	(0.090)	(0.058)	(0.079)
Observations	40,786	40,786	40,786	40,786	40,786
R^2	0.762	0.827	0.843	0.842	0.845
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Mean of outcomes	1.312	5.588	4.836	0.526	4.423
Mean of GCVI mean	0.792	0.792	0.792	0.792	0.792
SD of GCVI mean	0.500	0.500	0.500	0.500	0.500
Note:					*p<0.1; **p<0.05; ***p<0.01

Although throughout our regressions there is meaningful heterogeneity in coefficient magnitudes and signs for different goods, they do not demonstrate massive swings in per-capita expenditure levels nor in the components of per-capita expenditure for rural households. We do see evidence of shifts towards more per-capita expenditure on “luxury” food items such as meats, as well as decreases in the expenditure value of auto consumption, when GCVI increases.

4.1 Urban Household Per-Capita Expenditure

We expected to find that urban household expenditure would be less elastic with respect to changes in averaged maximum GCVI, as it is reasonable to believe that less households in urban regions rely on agricultural activities for income or auto-consumption.

Relationship Between GCVI And Per-Capita Expenditure for Urban Households

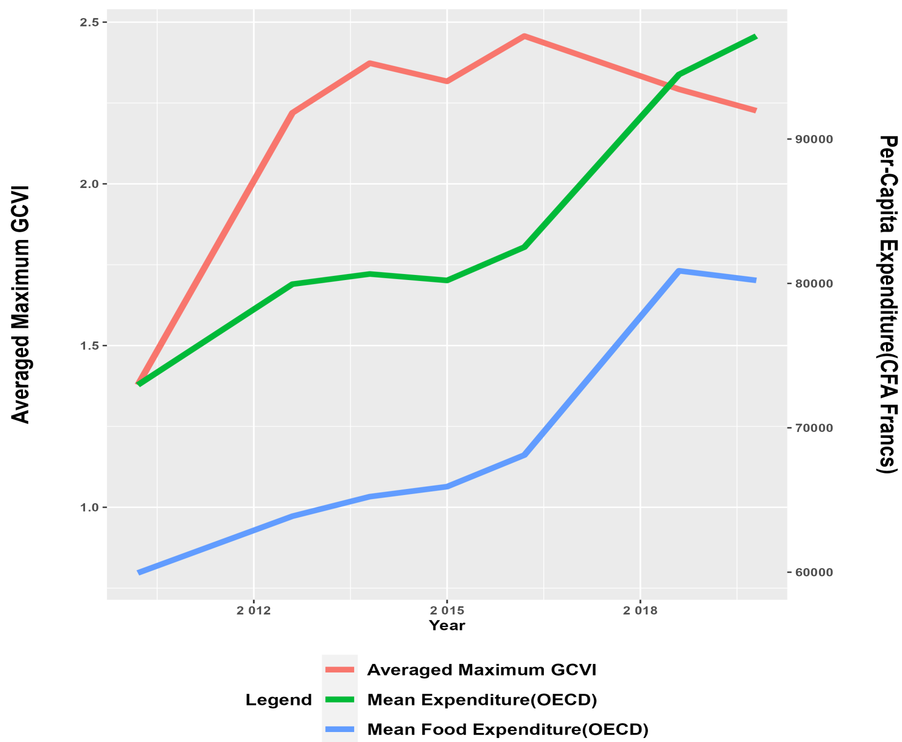

Figure 6

Our results for the urban segment of our sample are in line with our 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 slightly less than that of the rural sample Table 9. 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 had been statistically significant at the 5% level for our rural sample. As in the case of rural households, there is a statistically significant and negative relationship between averaged maximum GCVI and per-capita spending on Peanut Oil.

Table 9: Relationship Between GCVI and Averaged Half-Year General Expenditure for Urban Households-OECD Equivalence Scale

	(1) IHS Total Expenditure	(2) IHS Total Food Expenditure	(3) IHS Total Non-Food Expenditure
Log of Averaged Maximum GCVI	0.075**	0.052*	0.260***
	(0.034)	(0.030)	(0.083)
Square of Log Averaged Max GCVI	−0.067**	−0.073***	−0.069
	(0.028)	(0.026)	(0.066)
Observations	34,686	34,686	34,686
R^2	0.866	0.835	0.896
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes
Controls	No	No	No
Mean of outcomes	11.880	11.681	9.893
Mean of GCVI mean	0.493	0.493	0.493
SD of GCVI mean	0.450	0.450	0.450
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Relationship Between GCVI and Averaged Half-Year Food Expenditure for Urban Households-OECD Equivalence Scale

	(1) IHS Total Food	(2) IHS Grain	(3) IHS Rice	(4) IHS Meat	(5) IHS Peanut Oil
Log of Averaged Maximum GCVI	0.052*	0.172	0.086	0.437*	−0.402**
	(0.030)	(0.161)	(0.185)	(0.256)	(0.163)
Square of Log Averaged Max GCVI	−0.073***	−0.188*	−0.032	−0.278	0.072
	(0.026)	(0.103)	(0.136)	(0.212)	(0.106)
Observations	34,686	34,686	34,686	34,686	34,686
R^2	0.835	0.771	0.761	0.850	0.840
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Mean of outcomes	11.681	10.463	9.787	6.603	8.175
Mean of GCVI mean	0.493	0.493	0.493	0.493	0.493
SD of GCVI mean	0.450	0.450	0.450	0.450	0.450
Note:					*p<0.1; **p<0.05; ***p<0.01

Regarding 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.

Table 11: Relationship Between GCVI and Averaged Half-Year Non-Food Expenditure for Urban Households-OECD Equivalence Scale

	(1) IHS Total Non-Food	(2) IHS Alcohol	(3) IHS Health	(4) IHS Clothing	(5) IHS Housing
Log of Averaged Maximum GCVI	0.260***	−0.145	0.303	1.414***	−0.419***
	(0.083)	(0.169)	(0.195)	(0.325)	(0.157)
Square of Log Averaged Max GCVI	−0.069	0.029	0.041	−0.582**	0.109
	(0.066)	(0.150)	(0.145)	(0.246)	(0.117)
Observations	34,686	34,686	34,686	34,686	34,686
R^2	0.896	0.819	0.718	0.754	0.908
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Mean of outcomes	9.893	1.918	6.276	8.606	7.447
Mean of GCVI mean	0.493	0.493	0.493	0.493	0.493
SD of GCVI mean	0.450	0.450	0.450	0.450	0.450

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: Relationship Between GCVI and Averaged Half-Year Non-Food Expenditure for Urban Households-OECD Equivalence Scale

	(1) IHS Education	(2) IHS Communication	(3) IHS Transportation	(4) IHS Restaurants	(5) IHS Other Non-Food Expenditure
Log of Averaged Maximum GCVI	−0.971**	−0.318	0.102	−0.121	0.387**
	(0.424)	(0.196)	(0.127)	(0.076)	(0.172)
Square of Log Averaged Max GCVI	0.358	0.239*	0.091	0.118	−0.079
	(0.310)	(0.133)	(0.104)	(0.104)	(0.111)
Observations	34,686	34,686	34,686	34,686	34,686
R^2	0.810	0.869	0.898	0.835	0.886
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Mean of outcomes	2.395	6.993	5.865	0.586	5.541
Mean of GCVI mean	0.493	0.493	0.493	0.493	0.493
SD of GCVI mean	0.450	0.450	0.450	0.450	0.450

Note: *p<0.1; **p<0.05; ***p<0.01

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 agricultural activities are still taking place in communes classified as urban.

4.2 Robustness Checks

One potential threat to the quality of our estimates is mismeasurement of yields due to our using GCVI. We therefore conduct a series of robustness checks using the commune-level averaged maximum of 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, and this is what we observe. For the big three categories of general expenditure, the coefficients on the average of maximum of NDVI are positive and statistically significant. Viewing these results in Table 3, we can see that the signs on the coefficients are the same as in Table 13, however in the case of NDVI, the coefficients are significant for per-capita food expenditure which was not the case for GCVI. Similarly to GCVI, the strongest effect by far is for per-capita non-food expenditure in column 3.

Table 13: Relationship Between NDVI and Half-Year Expenditure for All Households- OECD Equivalence Scale

	(1) IHS Total Consumption	(2) IHS Total Food Consumption	(3) IHS Total Non-Food Consumption
Log Averaged Maximum NDVI	0.699***	0.683***	0.940***
	(0.132)	(0.137)	(0.302)
Square of Log Averaged Max NDVI	0.216***	0.226***	0.041
	(0.059)	(0.056)	(0.168)
Observations	75,678	75,678	75,678
R^2	0.871	0.848	0.882
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes
Controls	No	No	No
Mean of outcomes	11.719	11.568	9.446
Mean of NDVI mean	-0.744	-0.744	-0.744
SD of NDVI mean	0.416	0.416	0.416
Note:			*p<0.1; **p<0.05; ***p<0.01

When we focus on just rural households, for the big three expenditure categories, the coefficients on the mean of max NDVI are all positive and statistically significant, like in our original regressions. There are also interesting results when we look at the elements of food expenditure. We observe that the coefficient on NDVI for per-capita grain and rice expenditure is positive and statistically significant, but do not observe this for per-capita meat expenditure as in the GCVI regressions in Table 4.

Table 14: Relationship Between NDVI and Half-Year Food Expenditure for Rural Households- OECD Equivalence Scale

	(1) IHS Total expenditure	(2) IHS Total Food expenditure	(3) IHS Total Non-Food expenditure
Log Averaged Maximum NDVI	0.731***	0.731***	0.925***
	(0.154)	(0.166)	(0.266)
Square of Log Averaged Max NDVI	0.252***	0.268***	0.029
	(0.075)	(0.081)	(0.148)
Observations	40,912	40,912	40,912
R^2	0.857	0.847	0.819
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes
Controls	No	No	No
Mean of outcomes	11.583	11.473	9.068
Mean of NDVI mean	-0.622	-0.622	-0.622
SD of NDVI mean	0.378	0.378	0.378
Note:			*p<0.1; **p<0.05; ***p<0.01

We also see similar expenditure dynamics play out in Table 16 as with the breakdowns of spending on grain and rice. The coefficients on NDVI for autoconsumption 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.

Table 15: Relationship Between NDVI and Half-Year Food Expenditure for Rural Households- OECD Equivalence Scale

	(1) IHS Total Food	(2) IHS Grain	(3) IHS Rice	(4) IHS Meat	(5) IHS Peanut Oil
Log Averaged Maximum NDVI	0.731***	1.050***	1.635*	0.339	−3.425***
	(0.166)	(0.338)	(0.893)	(1.381)	(0.960)
Square of Log Averaged Max NDVI	0.268***	0.359**	0.413	−0.230	−1.308***
	(0.081)	(0.164)	(0.371)	(0.753)	(0.445)
Observations	40,912	40,912	40,912	40,912	40,912
R^2	0.847	0.737	0.737	0.744	0.789
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Mean of outcomes	11.473	10.706	8.693	5.357	6.552
Mean of NDVI mean	-0.622	-0.622	-0.622	-0.622	-0.622
SD of NDVI mean	0.378	0.378	0.378	0.378	0.378
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 16: Relationship Between NDVI and Half-Year Expenditure for Rural Households(Continued)- OECD Equivalence Scale

	(1) IHS Grain (auto)	(2) IHS Grain (buy)	(3) IHS Grain (gift)	(4) IHS Rice (auto)	(5) IHS Rice (buy)	(6) IHS Rice (gift)
Log Averaged Maximum NDVI	-9.514^{***}	2.830^{**}	-0.405	-9.693^{***}	3.058^{**}	0.248
	(2.159)	(1.175)	(0.773)	(2.006)	(1.258)	(0.531)
Square of Log Averaged Max NDVI	-3.398^{***}	0.142	-0.361	-3.562^{***}	0.409	0.070
	(1.218)	(0.558)	(0.510)	(1.213)	(0.691)	(0.380)
Observations	40,912	40,912	40,912	40,912	40,912	40,912
R^2	0.784	0.722	0.667	0.764	0.744	0.602
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No
Mean of outcomes	7.953	7.999	0.650	2.891	6.889	0.267
Mean of NDVI mean	-0.622	-0.622	-0.622	-0.622	-0.622	-0.622
SD of NDVI mean	0.378	0.378	0.378	0.378	0.378	0.378

Note: *p<0.1; **p<0.05; ***p<0.01

We also see in columns 3 and 6 that unlike in our GCVI regressions, NDVI increases are not associated with statistically significant increases in gifts of grain or rice, though the coefficients are positive. In Non-Food Consumption we see similar trends with NDVI as to those with GCVI. The coefficients on regressions of per-capita clothing and housing expenditures in columns 4 and 5 of Table 17, respectively, are both statistically significant. The signs are positive for clothing and negative and for housing as with the GCVI regressions. We do not observe a positive coefficient for averaged maximum GCVI for the per-capita health expenditure as in the GCVI regressions.

Table 17: Relationship Between NDVI and Half-Year Non-Food Expendituee for Rural Households(Continued)- OECD Equivalence Scale

	(1) IHS Total Non-Food	(2) IHS Alcohol	(3) IHS Health	(4) IHS Clothing	(5) IHS Housing
Log Averaged Maximum NDVI	0.925^{***}	-1.410^{*}	0.856	3.780^{***}	-2.948^{***}
	(0.266)	(0.851)	(0.799)	(0.653)	(0.882)
Square of Log Averaged Max NDVI	0.029	-1.167^{***}	0.703^{*}	0.602	-0.918^{**}
	(0.148)	(0.396)	(0.367)	(0.387)	(0.452)
Observations	40,912	40,912	40,912	40,912	40,912
R^2	0.819	0.799	0.727	0.695	0.878
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Mean of outcomes	9.068	2.252	5.953	7.998	3.678
Mean of NDVI mean	-0.622	-0.622	-0.622	-0.622	-0.622
SD of NDVI mean	0.378	0.378	0.378	0.378	0.378

Note: *p<0.1; **p<0.05; ***p<0.01

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.

5 Conclusion

In this work we have made use of vegetation indices as a proxy for yields in order to analyze the relationship between agricultural output and household expenditures in Mali. Our findings show a positive relationship between our preferred index, GCVI, and overall per-capita expenditure. 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 also see generally stronger effects for rural households as opposed to households from urban regions.

In terms of food consumption for rural households, with increases in GCVI we see evidence of shifts towards spending on "luxury" goods such as meat and rice. 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. For urban households generally these effects are far more muted, with no statistically significant change in total grain, rice, or meat consumption. Most of the increase in overall per-capita expenditure for rural and urban households associated with increases in averaged maximum GCVI comes through non-food expenditure, with rural households increasing spending on communication, health and clothing and urban households on health and transportation. Of particular interest was the lack of a statistically significant effect of our yield proxy on education investments for rural households, and the negative impact it had for urban households.

Generally our results demonstrate a high level of household resilience among rural Malian households in the face of changes in agricultural output. This finding calls into question the often assumed one-to-one correlation between ACC and household well-being. Specifically, this resilience of rural households suggest the need for more in depth work on the types of resilience and whether they are productive or not. In this paper we have also 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. 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, and on the welfare of households that rely on these activities.

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