

Food security in Southern Madagascar informed by satellite-based remote sensing data

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ABSTRACT

Recurrent droughts and food shortages in southern Madagascar highlight the need for real-time food security monitoring. Since 2018, monthly surveys of 602 households have documented dietary responses to food shocks. We assess whether remotely sensed vegetation conditions capture temporal variation in food consumption using the Normalized Difference Vegetation Index (NDVI). NDVI does not predict standard food security indices, including the Reduced Coping Strategies Index, Household Dietary Diversity Score, Food Consumption Score, or Household Hunger Scale. Instead, NDVI is strongly associated with the leading empirically derived dietary pattern identified through principal component analysis of reported food consumption. This pattern, Dietary Component 1 (DC1), reflects substitution from staple or aid-supported foods toward lower-preference fallback foods during periods of food stress. At the commune level, DC1 explains an average of 43% of dietary variability. DC1 is also well predicted by NDVI: linear models using commune-averaged NDVI explain 32–58% of DC1 variability, increasing to 38–70% when accounting for seasonality, with NDVI remaining a significant predictor. Higher-order dietary components show no association with NDVI. These results demonstrate that satellite-derived NDVI captures primary dietary shifts and can support improved food security monitoring systems.

Introduction

According to the United Nations, approximately 1.7 million people in Madagascar are currently facing acute food insecurity, many of whom rely on emergency food sources to survive^{1,2}. Southern Madagascar is the most severely affected region^{3,4}, and is currently experiencing heightened food insecurity due to prolonged drought⁵. Mirroring broader patterns across sub-Saharan Africa, smallholder farmers—who make up the majority of agricultural producers—are disproportionately vulnerable to weather and climate shocks^{6,7}. Even modest disruptions to rainfall or yields can significantly affect both household income and food access^{8,9}. A recent World Food Program assessment identified food aid as the primary buffer preventing widespread famine in the region¹⁰. These urgent needs highlight the importance of spatially and temporally precise tools for monitoring food security.

New digital tools are enabling more rapid collection of household food security data in low-income regions, supporting near real-time monitoring^{11,12}. Existing surveys typically fall into two distinct categories. Rapid assessment surveys, such as the Standardized Monitoring and Assessment of Relief and Transitions (SMART or SMART+) and related initiatives, are designed for early warning and emergency response, but typically rely on single or repeated cross-sectional samples rather than tracking the same households over time^{12,13}. As a result, they provide limited insight into the dynamics of household behavior and adaptations or resilience to shocks.

This gap between high-frequency monitoring and longitudinal analysis has limited the ability to study how households respond to environmental variability in real time. The Measurement Indicators for Resilience Analysis (MIRA) dataset addresses this limitation by combining high-frequency data collection with a panel structure, enabling both early warning applications and analysis of intra-annual dietary dynamics. MIRA has been implemented by Catholic Relief Services and collaborators in multiple countries, including southern Madagascar¹⁴.

MIRA is a panel survey conducted monthly through in-person interviews with the same households using a computer-assisted platform. The survey captures detailed information on dietary intake, income sources, and shocks to food access. Given that over 83% of Madagascar's population is engaged in smallholder agriculture¹⁵, these data are essential for understanding the impacts of climate variability on household food systems and for informing response efforts at the subnational level.

Satellite observations offer a promising complement to household data for monitoring food security¹⁶. In southern Madagascar, for example, the Pearson correlation between remotely sensed soil moisture and rice production ranges from 0.67

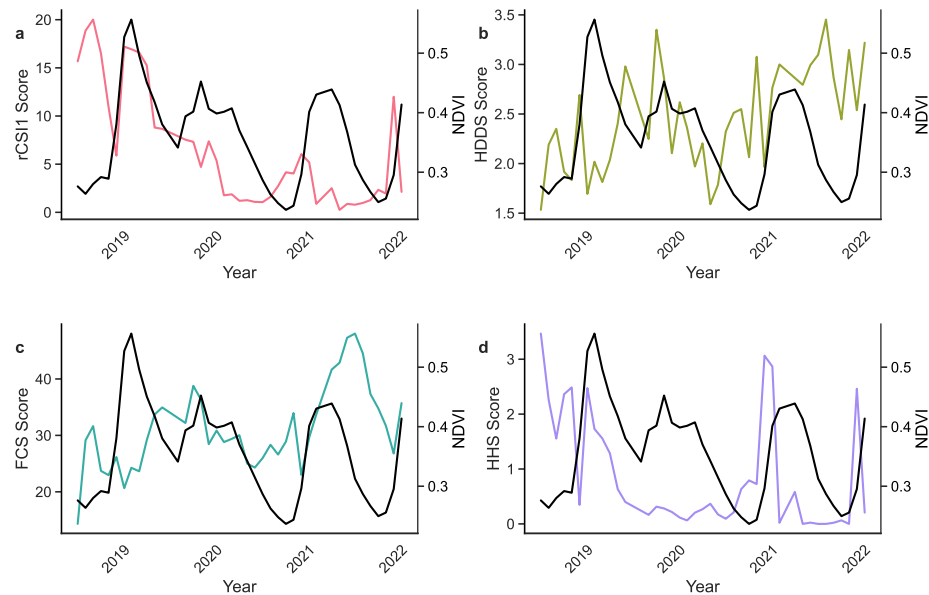


Figure 1. Standard food security indices. Monthly average values of four food security metrics captured in the MIRA dataset for the Marolinta Commune: panel (a): Reduced Coping Strategies Index (rCSI), panel (b): Household Dietary Diversity Score (HDDS), panel (c): Food Consumption Score (FCS), and panel (d): Household Hunger Scale (HHS). Each panel shows mean values aggregated at the commune level for Marolinta. NDVI trends are overlaid in black lines on a secondary y-axis for comparison.

to 0.95 across administrative districts¹⁷. Other studies demonstrate the ability to nowcast standard food security indices across multiple countries in sub-Saharan Africa using satellite data¹⁸, and even to predict specific elements of food security variability up to 30 days in advance¹⁹.

In this study, we assess whether satellite-based NDVI can aid in predicting variation in household dietary patterns as monitored by high-frequency MIRA data. Traditional food security indicators exhibit weak correspondence with environmental variables. But when we apply a dimensionality reduction technique to isolate dominant modes of dietary variation, we find that the first principal component—termed Dietary Component 1 (DC1)—captures variation in household consumption and is significantly associated with NDVI patterns. This approach offers a pathway for integrating remote sensing with household-level dietary data to improve subnational food security monitoring.

Observability of food consumption indices using remote sensing

Existing indices: We begin by evaluating whether NDVI is associated with any of four commonly-used food security indices using a simple linear model estimated independently for each commune. The indices considered include the Reduced Coping Strategies Index (rCSI), Household Dietary Diversity Score (HDDS), Food Consumption Score (FCS), and Household Hunger Score (HHS). In all cases, we find no statistically significant relationship (Fig. 1).

One explanation for this lack of correspondence is that the MIRA survey captures dietary shifts driven by food substitution—particularly when staple foods become scarce. For example, consumption of maize, sorghum, and red cactus tends to increase as consumption of cassava root and sweet potatoes declines (Fig. 2). Standard indices based on food group categorization fail to capture this dynamic. HDDS, for instance, measures dietary diversity by counting distinct food groups consumed, but it does not register substitutions within the same group, such as replacing sweet potatoes with cassava. Similarly, FCS weights the frequency of consumption across food groups²⁰, but because both cassava and sweet potatoes fall within the same starch category, variation in their relative consumption is not reflected in the index.

We observe similar substitution patterns across administrative communes in our study (Fig. 2), suggesting the potential utility of a new food security index that better captures dominant substitution dynamics, as opposed to relying on linear combinations of consumed foods indicated by traditional indices.

Self-defined index of food consumption: An alternative way to explore food substitution patterns within the MIRA data is to examine the correlation among all 34 of the foods reported (Fig. 4). For each commune we observe strong correlations between foods like maize, millet, rice, beans, cowpeas and melons. Other foods that are known to be eaten in times of scarcity,

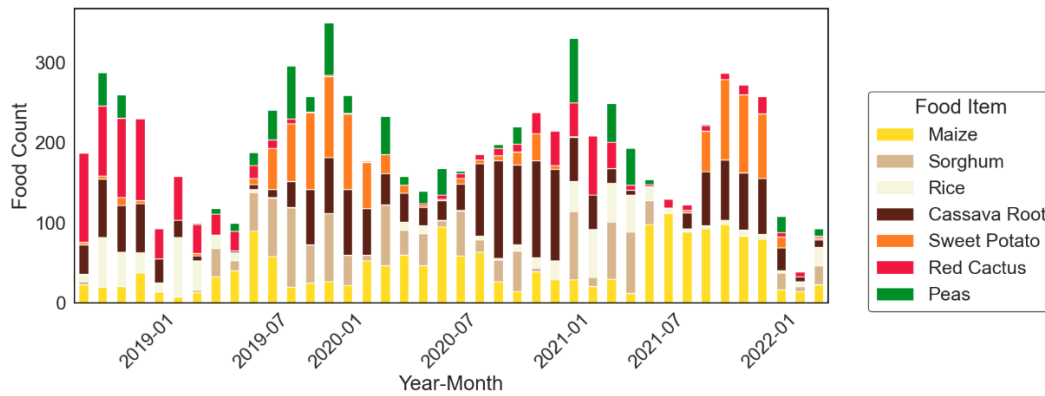


Figure 2. Surveyed food consumption data. Frequency of consumption of common foods in households in the Marolinta Commune between August 2018 to February 2022.

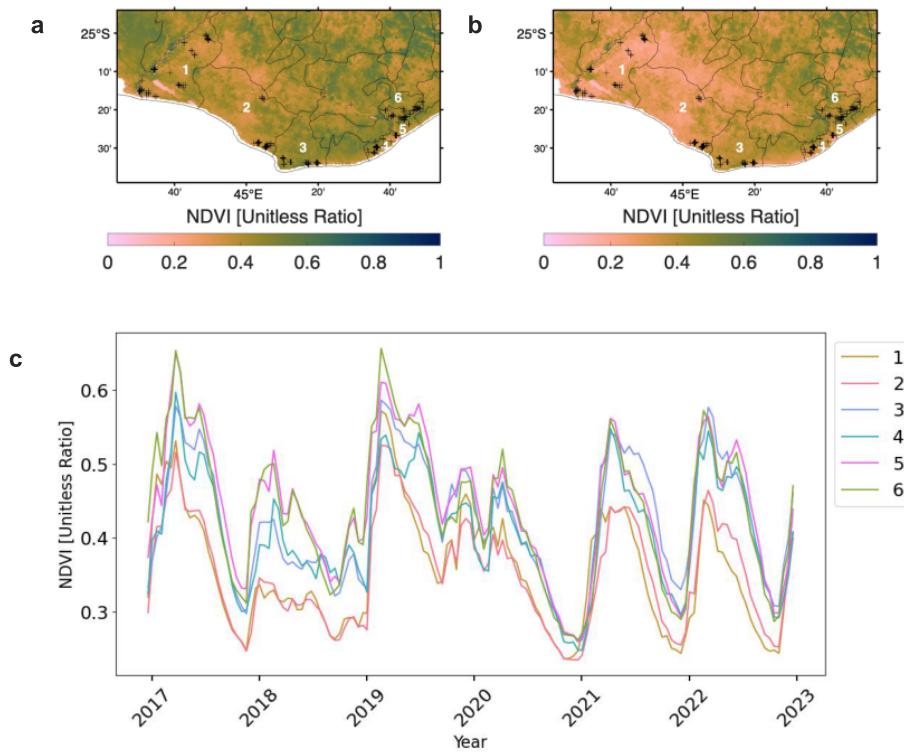


Figure 3. Remotely sensed NDVI. Panels (a) and (b): spatial distribution of NDVI and related features. Panel (a) displays the average NDVI from 2000–2017, representing pre-drought conditions. Panel (b) shows the average NDVI in 2018, marking the onset of the drought in southern Madagascar. MIRA survey households are marked with black crosses. Communes are labeled as follows: (1) Marolinta, (2) Tranovaho, (3) Morovato, (4) Anjampaly, (5) Antaritarika, (6) Imongy. Panel (c): seasonal variability in NDVI over time.

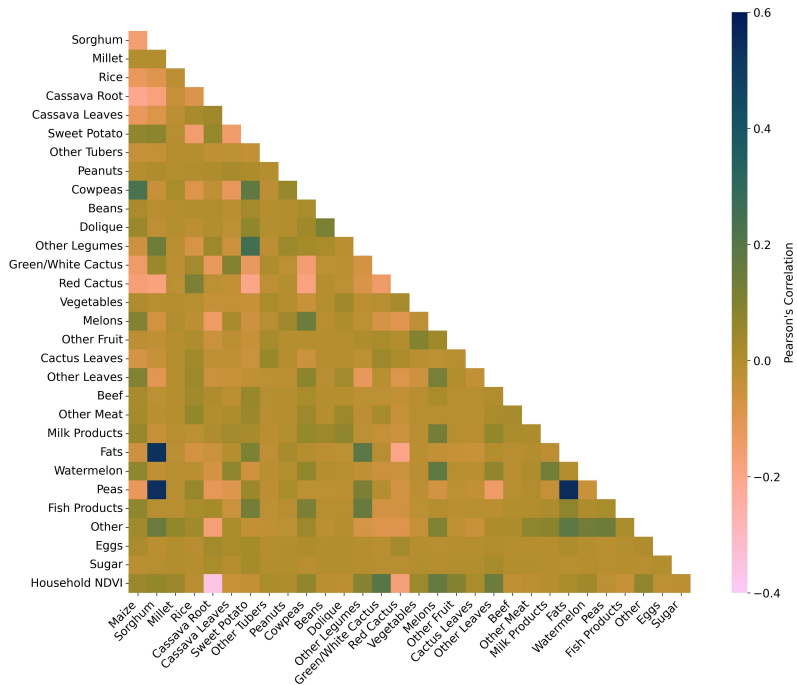


Figure 4. Heatmap of Pearson correlation coefficients. Correlations are between monthly consumption levels of different food groups in the Marolinta commune. Blue indicates strong positive correlations, while red indicates negative correlations.

namely red cactus and cassava root, are negatively correlated with many of these staple foods. The disappearance of staple foods from the diet and their substitution with red cactus and cassava root is observed consistently across communes, and suggests that the latter are emergency foods when staple foods are scarce. NDVI is negatively correlated with red cactus and cassava root consumption in each commune (Supplementary Fig. 2), consistent with the interpretation that these foods are consumed more frequently when crop production is limited.

To reduce the dimensionality of household dietary data and identify dominant modes of covariability, we apply principal component analysis (PCA) via singular value decomposition (SVD) to a matrix of foods consumed across months. Prior to analysis, we exclude households with more than 30% missing responses. Remaining missing values are imputed using the column mean, after which the data are column-centered. Meat and dairy items are also excluded, as they are not directly observable via NDVI and together account for less than 1% of total dietary intake among surveyed households. PCA of the resulting food consumption matrix—comprising 21,153 household-month pairs across 22 food items—yields a first principal component that explains 17.7% of the total variance across all communes. For a random matrix of comparable dimension, the leading principal component would be expected to explain only about 5% of the variance²¹. We interpret this leading component, hereafter referred to as Dietary Component 1 (DC1), as a proxy for food security: positive DC1 values correspond to food-secure conditions, and negative values to food insecurity. Maize, sorghum, and peas load strongly and positively on DC1, while cassava root and red cactus load strongly and negatively, indicating that DC1 captures a contrast between staple or aid-supported foods and less preferred or emergency foods (Fig. 5).

To assess whether the magnitude of variance explained by DC1 could arise from sampling variability, we conducted a Monte Carlo experiment in which the dietary matrix was replaced by white noise. Across 500 trials, the leading principal component of the null matrices explained a mean of 4.8% of the variance (95% range: 4.77–4.85%), far below the observed value of 17.7%. Consistent with this result, North’s rule of thumb²² indicates that DC1 is statistically distinct from higher-order components: the separation between the first and second eigenvalues (0.049) is approximately twenty times larger than the estimated sampling uncertainty of the leading eigenvalue (~ 0.002).

Supporting the interpretation of positive values of DC1 as indicating receipt of food aid, household consumption of sorghum, as well as peas, closely tracks self-reported receipt of food aid, with Pearson correlations of 0.71 and 0.80, respectively. Aid delivery increased sharply in early 2019, during which reported consumption of sorghum and peas rose from under 20% to over 40–50%, then stabilized by 2020. This expansion coincided with a decline in the consumption of locally grown cassava and red cactus (Fig. 2).

To explore temporal variability, we project DC1 onto the MIRA data aggregated at the commune level, yielding PC1_c,

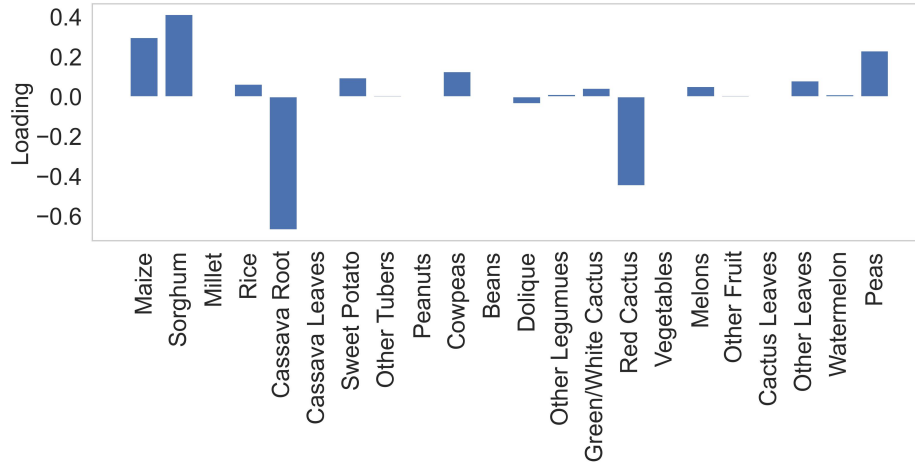


Figure 5. Dietary Component 1. Loadings for the first principal component across the 22 different foods.

where the subscript, c , indicates which of the six communes that we consider. MIRA responses are first averaged by month within each commune, such that $PC1_c$ is also defined at monthly resolution. Because MIRA surveys are conducted on varying days throughout each month, this averaging helps to reduce noise and clarify the underlying signal. Survey dates are approximately uniformly distributed across each month, so averaging does not introduce bias related to temporal leads or lags. The resulting $PC1_c$ time series typically shows a seasonal peak in April–May and a decline from August through November (Fig. 6). Interannual variability is also evident, with a notably suppressed peak in 2020 corresponding to a period of unusually low NDVI in the wake of the 2018 drought.

Observability of the leading Dietary Component: We explore the extent to which $PC1$ can be predicted using NDVI by way of a simple linear model,

$$PC1_c = \beta_1 \cdot NDVI_c + \beta_0 + \varepsilon. \quad (1)$$

$NDVI_c$ is computed as the average over each commune and is averaged to same monthly resolution as $PC1$ (Fig. 3). The ε term is residual noise that is assumed Gaussian. $PC1$ is significantly ($p < 0.01$) predicted by NDVI for each commune with Pearson’s R^2 cross-correlations ranging from 0.32–0.57. These strong and repeated correlations indicate that the changes in monthly household diet captured in $PC1$ are observable in satellite measured NDVI.

Model Name	NDVI Coeff.	Lower Bound	Upper Bound	P-Value	R^2	Adj. R^2	AIC	BIC
Marolinta	2.389	1.465	3.312	$p < 0.001$	0.413	0.397	0.75	4.18
with FE	1.292	−0.166	2.749	$p = 0.080$	0.582	0.403	8.77	31.04
Tranovaho	2.895	2.110	3.680	$p < 0.001$	0.575	0.564	−18.36	−14.84
with FE	2.382	1.253	3.511	$p < 0.001$	0.697	0.576	−10.98	11.92
Morovato	2.321	1.256	3.385	$p < 0.001$	0.321	0.305	18.99	22.51
with FE	2.491	0.941	4.040	$p = 0.003$	0.426	0.196	33.80	56.70
Anjampaly	3.215	2.249	4.182	$p < 0.001$	0.524	0.512	1.98	5.51
with FE	2.528	1.008	4.048	$p = 0.002$	0.609	0.453	15.47	38.36
Antaritarika	2.992	1.695	4.288	$p < 0.001$	0.346	0.330	41.50	45.03
with FE	2.454	0.393	4.516	$p = 0.021$	0.375	0.125	61.54	84.44
Imongy	3.146	1.952	4.340	$p < 0.001$	0.409	0.394	38.87	42.39
with FE	2.900	0.936	4.864	$p = 0.005$	0.440	0.216	58.51	81.40

Table 1. Regression results including only NDVI as a predictor and including monthly fixed effects by commune. Commune locations are shown in Fig. 3.

We further explore the relationship between NDVI and $PC1$ after controlling for seasonality,

$$PC1_c = \beta_1 \cdot NDVI_c + \beta_0 + u_{\text{month}} + \varepsilon. \quad (2)$$

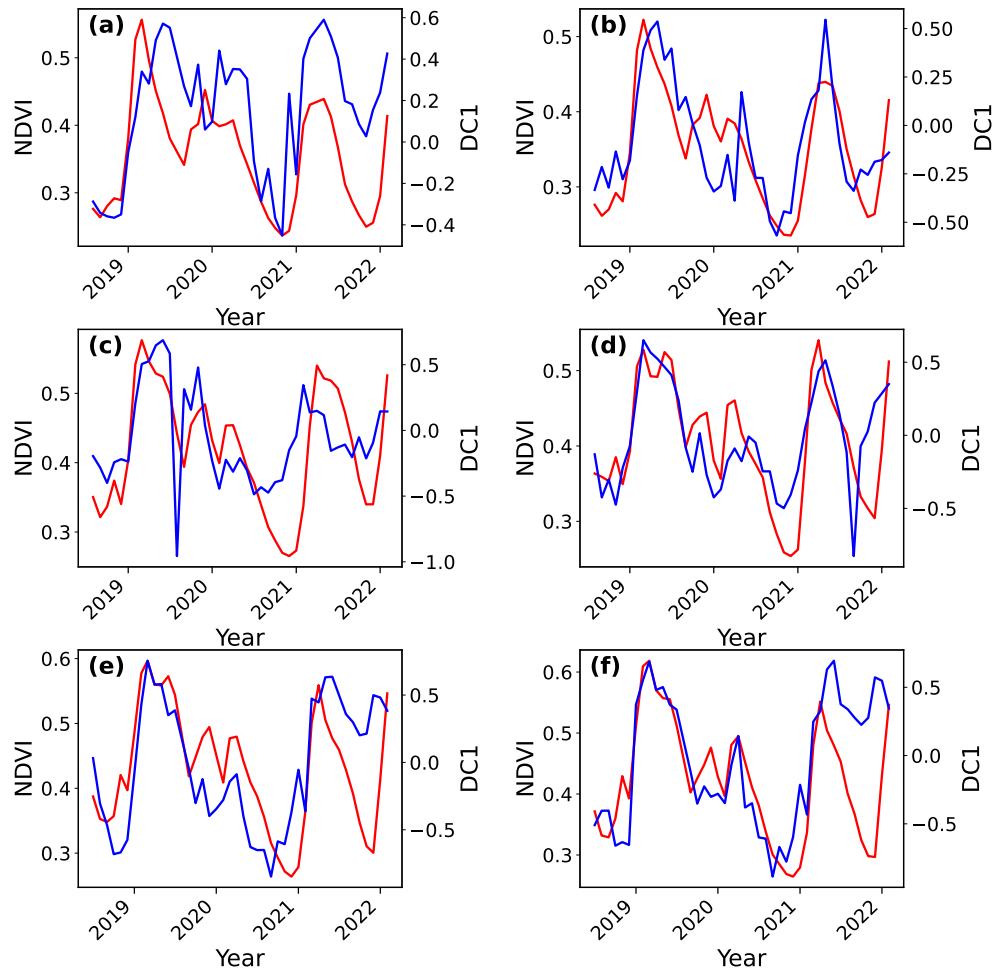


Figure 6. Comparison of NDVI and DC1. Each panel corresponds to one of the six subnational communes represented in the MIRA dataset: (a) Marolinta, (b) Tranovaho, (c) Morovato, (d) Anjampaly, (e) Antaritarika, and (f) Imongy. For each commune, the plot compares NASA MODIS 16-day Normalized Difference Vegetation Index (NDVI; red) to the first principal component derived from food consumption data (DC1; blue).

where u_{month} is a monthly fixed effect. Integrating the PC1 vector into a mixed effects model allows us to account for seasonal variation that may arise from processes causally linked to both NDVI and food consumption — such as seasonal fishery, herding activity, or seasonality in import or export activity. After controlling for seasonality, a significant positive relationship remains between NDVI and the projection of DC1 onto different food consumption across each commune. Notably, NDVI explains a greater proportion of the variance within each commune than the seasonal effects.

Results and Discussion

By applying principal component analysis to monthly food consumption data, we isolate a dominant axis of dietary variability, Dietary Component 1 (DC1), which reflects transitions from typical diets to emergency coping foods such as red cactus and cassava. Our findings demonstrate that satellite-derived vegetation indices, specifically NDVI, capture variation in DC1 projections, referred to as PC1, across smallholder farming communities in southern Madagascar. Depending on the modeling approach, NDVI explains between 32% and 58% of dietary variation at the commune level.

This work contributes to a growing body of research leveraging remote sensing to monitor food security in data-scarce regions. NDVI has been widely used as a proxy for agricultural productivity and environmental stress^{16,17} as well as an indicator of food security²³. Household dietary outcomes have also been studied in depth²⁴. It has been unclear, however, whether satellite monitoring strategies can directly inform dietary outcomes. Our analysis helps bridge this gap by demonstrating that variability in a leading component of consumption-based indicators derived from high-frequency household surveys is captured by models relying on NDVI.

Difference in the ability of NDVI to explain DC1 variability across communes is partially interpretable. Alignment is especially strong in arid communes like Tranovaho and Marolinta, where persistent vegetation stress is tightly coupled to food access (see Table 1). In contrast, the lower model fit in Morovato may be explained by fish consumption accounting for more than 10% of the diet. Furthermore, fishery resources can help offset economic shocks associated with drought²⁵.

We additionally evaluate the Enhanced Vegetation Index (EVI) alongside NDVI. EVI was developed to address known limitations of NDVI, including improved atmospheric correction and decreasing saturation in areas of dense vegetation²⁶. Despite these advantages, NDVI and EVI are expected to perform similarly in this context, as the two indices are highly correlated (Pearson's $r=0.96$) and exhibit comparable seasonal patterns (Supplementary Fig. 7). However, NDVI remains a slightly better predictor overall in that it achieves higher R^2 and adjusted R^2 values for every commune both using OLS and fixed-effects models (Supplementary Table 2).

The MIRA questionnaire's inclusion of food sourcing data—distinguishing between homegrown, purchased, foraged, gifted, and aid-supplied foods—adds critical context. During the 2019–2020 drought, many households shifted from homegrown to purchased staples, a coping strategy not directly observable in NDVI. Because households report whether they received food assistance each month, we can also infer which foods are predominantly distributed as aid by examining correlations between food consumption and reported aid receipt over time (Supplementary Fig. 3 & 4). Sorghum, peas, and millet show the strongest positive correlations with aid receipt at 0.80, 0.71, and 0.63, respectively. In contrast, red cactus and cassava root are negatively correlated with aid, consistent with their being primarily sourced from home production or purchase (Supplementary Fig. 5). Among the foods loading on DC1, maize and cassava root are largely homegrown or purchased, whereas sorghum and peas are predominantly received as aid. Consequently, DC1 captures substitution from home-produced or purchased maize and aid-supplied sorghum toward cassava and cactus. Cassava and cactus, which are drought resilient²⁷ and tend to be harvested in the lean season²⁸, become more prominent after shocks.

Further analyses subsetting the data indicate that NDVI's predictive power weakens following the onset of the 2018 drought. This decoupling appears linked to increased reliance on markets and expansion of food aid, both of which decouple vegetation condition and diet, and are manifest in less consumption of fallback foods like red cactus (see Fig. 2). NDVI appears best suited for informing on diet in autarchic food production systems. This non-stationarity in the relationship between NDVI and food consumption patterns underscores the need to calibrate remotely sensed indicators with routinely-collected survey data in order to monitor changes in coping strategies.

Although our results highlight the promise of NDVI as a scalable, low-cost proxy for diet monitoring, they also reveal its limitations. NDVI alone cannot fully explain dietary shifts mediated by markets, aid, or social safety nets²⁹. The World Food Summit defines four areas of food security: physical availability, economic and physical access, food utilization, and stability^{30–32}. Food insecurity occurs when one or more of these conditions are lacking. Long-standing food indices typically relate to one or two of these dimensions^{20,33,34}. Here, NDVI reflects only the availability dimension of food security and cannot capture access, utilization, or stability, all of which are heavily mediated by markets and institutions. Notably, when the relationship between NDVI and DC1 deteriorates towards the end of 2019, households shift from foods that are normally homegrown to ones purchased at market (Supplementary Fig. 9).

We have shown traditional indices of dietary intake that provide some insight into food security are not observable in NDVI in Southern Madagascar (Supplementary Table 3), but another component of dietary variability that is captured by

DC1 is interpretable relative to NDVI. DC1 should not be interpreted as a comprehensive food security index, but rather as a behavioral indicator of dietary adaptation under stress. Our findings suggest that only a subset of dietary variability — specifically substitution toward drought-resilient foods — is observable via NDVI. The facts that DC1 explains the greatest fraction of dietary intake variability and is significantly predictable using NDVI suggest the ability to gain insight into diet from remote sensing. Furthermore, because this component of variability indicates food substitution between more frequently consumed foods and those that are relied upon under emergency conditions, it supports the interpretation that these dietary changes are related to variations in food security.

Additional analyses of food substitution practices that also account for food price, infrastructure, policies, and conflict are also warranted. Furthermore, because key foods loading on DC1 are distributed through food assistance, the component partly reflects the structure of aid delivery systems. In settings with different or absent aid, the interpretation of DC1 may differ. Further analysis of DC1, or similarly derived indices, will be important for vetting the degree to which such patterns of food substitution bear a stable and interpretable relationship with food security in smallholder farming households. Integrating market connectivity, food aid presence, and climatic variables alongside DC1 would help disentangle environmental signals from market- and aid-mediated effects.

Lagged analyses provide no evidence of a time offset between NDVI and food consumption (Supplementary Table 1). DC1 achieves the highest correlation with NDVI across all communes when no lag is imposed, with the one exception being Marolinta where a zero and one-month lag give nearly equivalent correlation values. It might be expected for DC1 to lag behind NDVI because, for example, exposure to drought would only result in reduced production later in the growing season. Food storage would lead to further delays. We speculate that proactive responses to anticipated variations in crop productivity may account for the absence of an observed lag. Variations in market access, the monthly resolution of our analysis, or other data limitations could also contribute to this pattern, such that we do not rule out the presence of lagged, causally-related mechanisms.

We also examine higher-order components from the second and third principal modes of dietary variability, but they contribute little additional interpretive value. Alternative dimensionality reduction techniques, including both unrotated and varimax-rotated factor analysis, yielded similar contrasts between emergency and typical food items (Supplementary Fig. 8).

Our analysis spans just under four years, a period marked by persistent drought. Testing these relationships during more typical growing seasons or in other smallholder settings would help assess how generalizable they are. Recent funding changes have led to the shutdown of the MIRA program in southern Madagascar and elsewhere, however, curtailing access to high-resolution, ground-truth data. This unfortunate development makes the case all the more urgent for improving and expanding remotely sensed approaches to monitoring diet and food security—especially in hard-to-reach smallholder farming communities. While we ideally would predict newly collected survey data using NDVI and DC1 to test predictive skill, we are currently pursuing analysis of MIRA data from Ethiopia. Testing whether this new localized index of household diet variability is interpretable in the context of smallholder farming in another region and also observable in environmental data will give us more insight into the globalization of these results.

MIRA supports the calculation of standard food-security indices. In addition, we show that this dataset contains an empirical mode of dietary substitution, DC1, that covaries with NDVI. NDVI explains 32–58% of DC1 variability at the commune level. This connection between MIRA and NDVI suggests that satellite vegetation indices can play a useful role in monitoring components of dietary variability, though changes in supply chains, aid delivery, and other non-stationarities may alter that relationship over time.

Methods

MIRA Data: In 2018, Catholic Relief Services (CRS) launched the Measurement Indicators for Resilience Analysis (MIRA) survey to assess household resilience to food insecurity and agricultural shocks in southern Madagascar and to inform targeted relief efforts¹⁴. MIRA surveys 602 households each month, selected randomly from among the most vulnerable households in administrative communes targeted for food security interventions¹⁴.

Trained local enumerators administer the surveys on tablets, which include questions related to household food consumption, income sources, and exposure to shocks that may affect food access. In addition to enabling the computation of established food security indices—such as the Household Hunger Scale (HHS), Food Consumption Score (FCS), Household Dietary Diversity Score (HDDS), and the Reduced Coping Strategies Index (rCSI), MIRA offers detailed insights into specific food items consumed by each household.

For this study, we restrict our analysis to the 547 households with responses available for at least 70% of months between August 2018 and February 2022. Food consumption data are collected as binary responses (1 = consumed, 0 = not consumed) for each of 34 food items. To align with remotely sensed vegetation indices, we exclude non-crop related food items such as meat, eggs, and dairy. We focus instead on 22 crop-based or vegetation-derived food categories: maize, sorghum, millet, rice,

cassava root, sweet potato, other tubers, peas, peanuts, cowpeas, beans, dolique, other legumes, green or white cactus, red cactus, vegetables, melons, watermelon, other fruit, cassava leaves, cactus leaves, and other leaves.

The original plan was for MIRA to sample households across five study communes. However, we find that 41 households also fall within the defined boundaries of Imongy and, therefore, include this sixth commune. We also emphasize that the data are not fully representative at either the population or commune level.

At the start of the survey (August 2018), many households reported consuming foods with less nutritional and adverse health effects like red cactus and cassava^{35,36}. Moving into June of 2019, the data reflect the initiation of food aid delivery in the form of peas and sorghum. Concurrently, sweet potatoes, a drought-hardy and highly prevalent crop in the region, also emerge as a substitute for red cactus³⁷. Subsequent to late 2020, sweet potato consumption dwindles and there is a resumption of red cactus and cassava in the diet along with aid foods like sorghum. Red cactus and cassava are drought-hardy and the resumption of eating these foods is consistent with food insecurity caused by drought conditions.

Remotely Sensed Data: We used Normalized Difference Vegetation Index (NDVI) to characterize vegetation conditions and serve as a proxy for crop health. NDVI is a widely used satellite-derived index that quantifies vegetation greenness based on differences in surface reflectance in the red (0.4–0.7 μm) and near-infrared (0.7–1.1 μm) spectral bands^{26,38}. The observations we use come from the MODIS/Terra Vegetation Indices product MOD13Q1.061, which has a 16-day temporal resolution and 250 m spatial resolution^{38,39}.

An initial assessment of NDVI patterns reveals the severity of drought conditions in Southern Madagascar during the study period. As illustrated in Fig. 3, the onset of drought is associated with widespread suppression of NDVI values across the region. These low vegetation index values are consistent with reduced crop productivity and land cover degradation, providing environmental context for the food security patterns we analyze^{16,17}.

To construct an NDVI sample for each commune, we identify the NDVI grid cell corresponding to the location of each MIRA household within that commune and compute the average NDVI across these sampled grid cells. In some cases, a single grid box is sampled multiple times, and this can be thought of as a weighted average of NDVI according to household distribution. Because changes in NDVI are spatially homogeneous, the details of how NDVI within communes are averaged has little influence on the results. For example, averaging across the entire commune equally gives results that are qualitatively the same.

Over the course of the NDVI record (2000–2022) the westernmost communes, Marolinta and Tranovaho, averaged the lowest NDVI. In the year leading up to the 2018 drought, we see exceptionally dry conditions across the region and much lower maximum values of NDVI across months in all communes, with the highest fractional difference in NDVI in the westernmost communes. Between 2012–2017 the average seasonal cycle has an NDVI amplitude of 0.53, with green up occurring in March and drying onset occurring in August. Drought years between 2018–2022 feature 11% lower NDVI than between 2012–2017, with the largest percentage reductions occurring between August and November. NDVI among communes generally co-varies. The data reflects the fact that 2018 featured one of the worst droughts in the satellite record, matched only in amplitude by a 2016 drought.

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331 **Author contributions statement**

332 A.B. & P.H. conceived the models, analyzed the results, and wrote the initial draft. A.B. performed analyses. A.R. provided
333 expertise on remote sensing data. J.U. & C.G. provided expertise on the data and relevant insights on the study area. All authors
334 reviewed the manuscript.

335 **Competing interests**

336 The authors declare no competing interests.