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

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**Article**

**Keywords:**

**Posted Date:** August 20th, 2025

**DOI:** https://doi.org/10.21203/rs.3.rs-7265637/v1



**Additional Declarations:** There is **NO** Competing Interest.

# 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 underscore the need for real-time food security monitoring. Since 2018, a monthly survey of 602 households has tracked dietary coping strategies in response to food shocks. Here we assess whether remotely sensed observations of crop and pasturelands can track temporal variation in household food consumption. We use the Normalized Difference Vegetation Index (NDVI) in a linear mixed-effects framework to predict variability in dietary intake across administrative communes in southern Madagascar. NDVI does not predict standard food security indices but captures variation in a principal mode of monthly dietary intake, termed Dietary Component 1 (DC1). As the first principal component of food consumption, DC1 primarily reflects an anticorrelation between the consumption of maize and sorghum during times of food security and red cactus, along with lower-preference roots and tubers such as cassava, during times of food insecurity. When projected onto dietary patterns at the commune level, DC1 explains an average of 43% of the variance in monthly food consumption. Moreover, DC1 can be skillfully represented using NDVI. A linear model using commune-averaged NDVI explains between 32–58% of DC1 variability, whereas a mixed-effects model that includes monthly fixed effects to account for seasonality explains 38–70%, with NDVI remaining a highly significant predictor in all cases. No significant relationships are found with higher-order dietary components, and alternative approaches—such as rotated singular value decomposition or lagged predictors—do not improve performance. These findings demonstrate that satellite-based NDVI can effectively capture primary dietary shifts, supporting its integration into more detailed food security monitoring systems.

## Introduction

According to the United Nations, approximately 1.3 million people in Madagascar are currently facing acute food insecurity, many of whom rely on emergency food sources to survive[1]. Southern Madagascar is the most severely affected region[2,3], and is currently experiencing heightened food insecurity due to prolonged drought[4]. 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[5,6]. Even modest disruptions to rainfall or yields can significantly affect both household income and food access[7,8]. A recent World Food Program assessment identified food aid as the primary buffer preventing widespread famine in the region[9]. These urgent needs highlight the importance of spatially and temporally precise tools for monitoring food security.

Digitally collected household dietary surveys are transforming food security monitoring in low-income regions by enabling near real-time assessments[10]. Traditional census-based surveys—such as those used by FEWS NET, USAID, and WFP—are typically conducted at annual or multi-year intervals[11], limiting their ability to capture short-term shocks to food access. In contrast, digital tools developed in recent years have enabled much higher-frequency monitoring[12], providing a foundation for linking food insecurity to weather and climate variability and supporting timely interventions[13]. One such initiative, the Measurement Indicators for Resilience Analysis (MIRA), has been implemented by Catholic Relief Services (CRS) and Cornell University[14] in several countries, including southern Madagascar.

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 agriculture[15], 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 security[16]. In southern Madagascar, for example, the Pearson correlation between remotely sensed soil moisture and rice production ranges from 0.67 to 0.95 across administrative districts[17]. Other studies have demonstrated the ability to nowcast standard food security indices

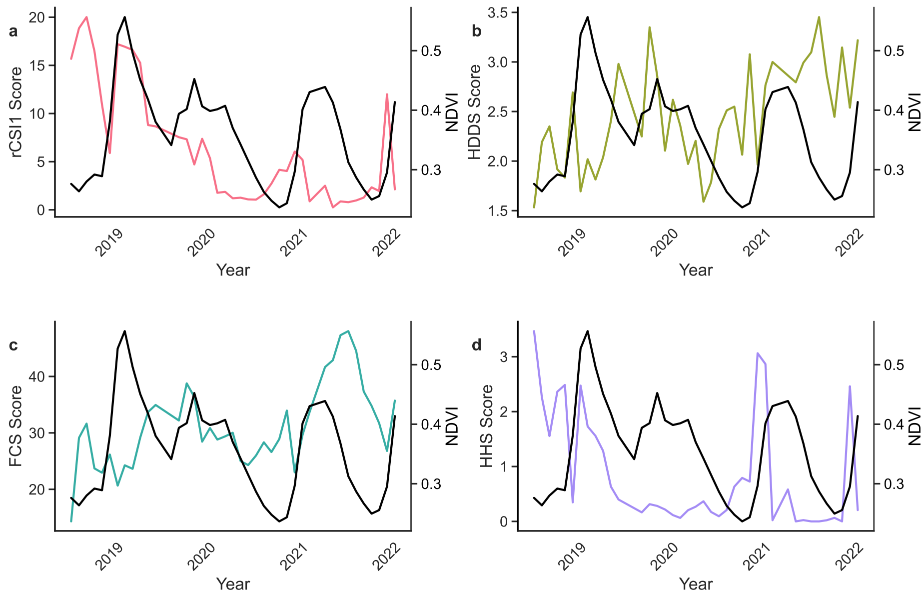


**Figure 1. Standard food security indices.** Monthly average values of four food security metrics captured in the MIRA dataset for the Marolinta Commune: Panel (a): Reduced Coping Strategies Index (rCSI), panel (b): Household Dietary Diversity Score (HDDS), panel (c): Food Consumption Score (FCS), and 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.

across multiple countries in sub-Saharan Africa using satellite data[18], and even to predict specific elements of food security variability up to 30 days in advance[19].

In this study, we assess whether satellite-based NDVI can predict variation in household dietary patterns using high-frequency MIRA data. Traditional food security indicators exhibit weak correspondence with environmental variables, so 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 meaningful variation in household consumption and is significantly associated with NDVI patterns. This approach offers a novel 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 relationships (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 may 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 groups[20], 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. 3), suggesting the potential utility of a food security index that captures dominant substitution dynamics rather than relying on categorical diversity.

**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, namely red cactus and cassava root, are negatively correlated with many of these staple foods. The disappearance of staple

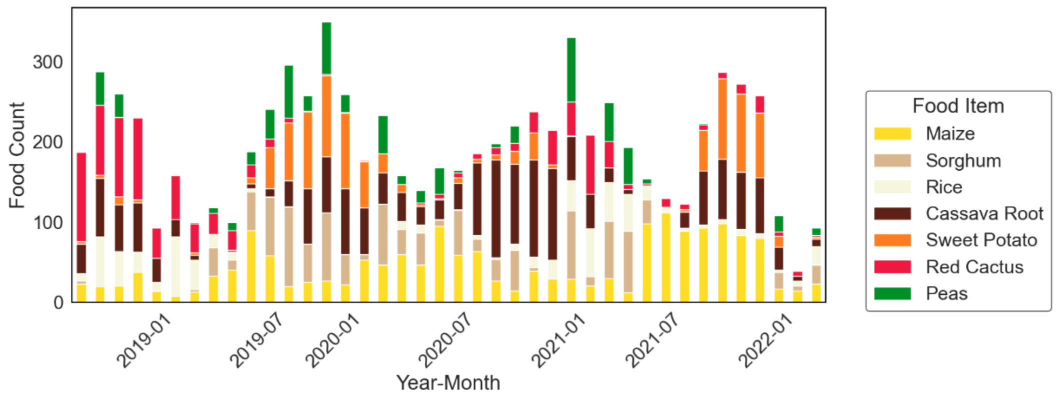


**Figure 2.** **Surveyed food consumption data.** Frequency of consumption of common foods in households in the Marolinta Commune between August 2018 to February 2022.

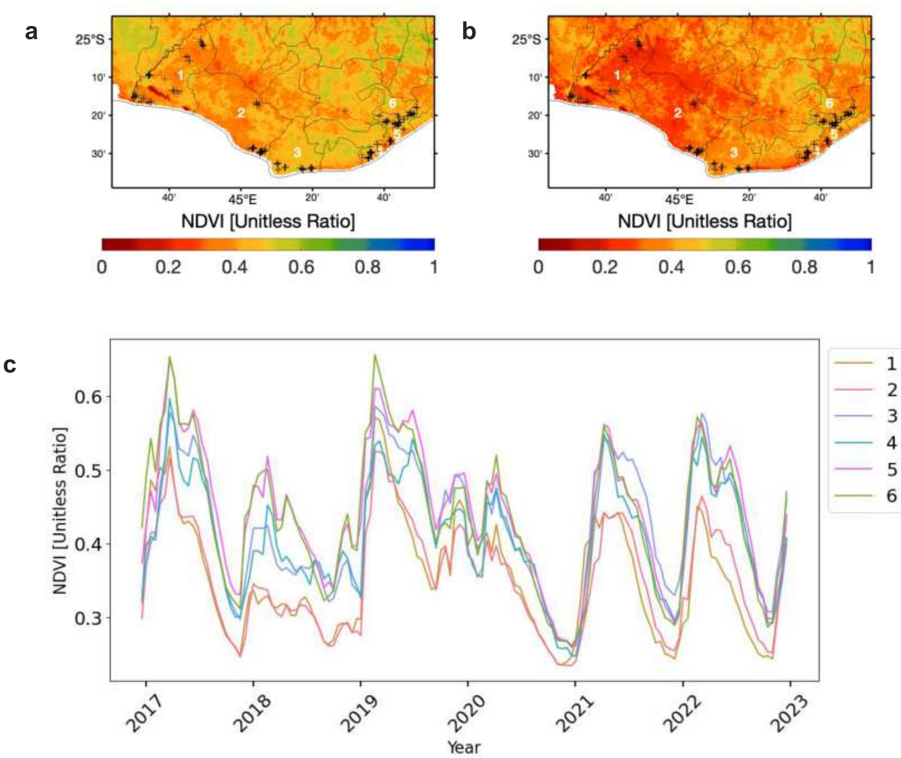


**Figure 3.** **Remotely sensed NDVI.** Panels (a) and (b): spatial distribution of NDVI and related features. Panel (a) displays the average NDVI from 2000–2017, representing pre-drought conditions. Panel (b) shows the average NDVI in 2018, marking the onset of the drought in southern Madagascar. MIRA 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.

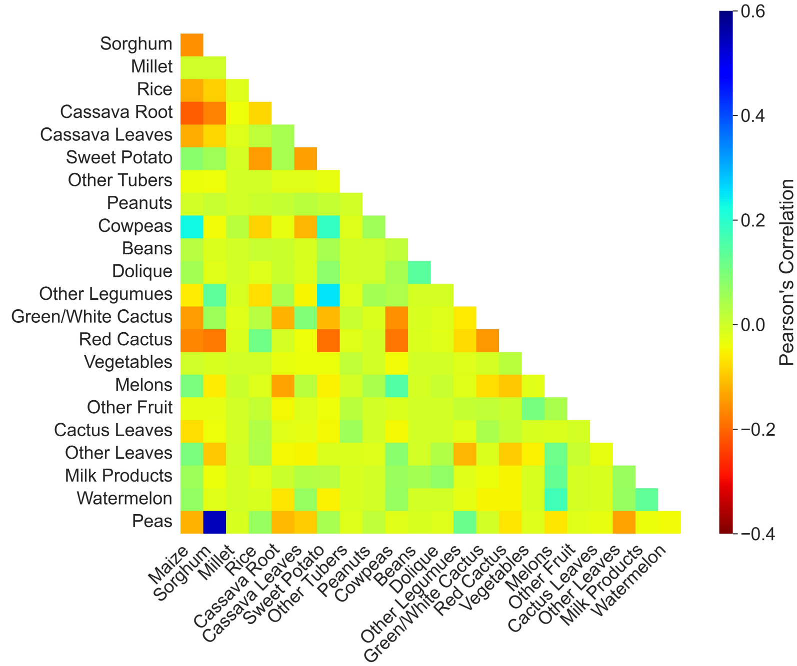


**Figure 4. Heatmap of Pearson correlation coefficients.** Correlations are between monthly consumption levels of different food groups in the Marolinta commune. Blue indicates strong positive correlations, while red indicates negative correlations.

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.

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. 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).

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 $\mathrm{PC1}_c$, where the subscript c = 1,...,6 denotes the six communes. MIRA responses are first averaged by month within each commune, such that $\mathrm{PC1}_c$ 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 $\mathrm{PC1}_c$ 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,

$$\mathrm{PC1}_c = \beta_1 \cdot \mathrm{NDVI}_c + \beta_0 + \varepsilon, \tag{1}$$

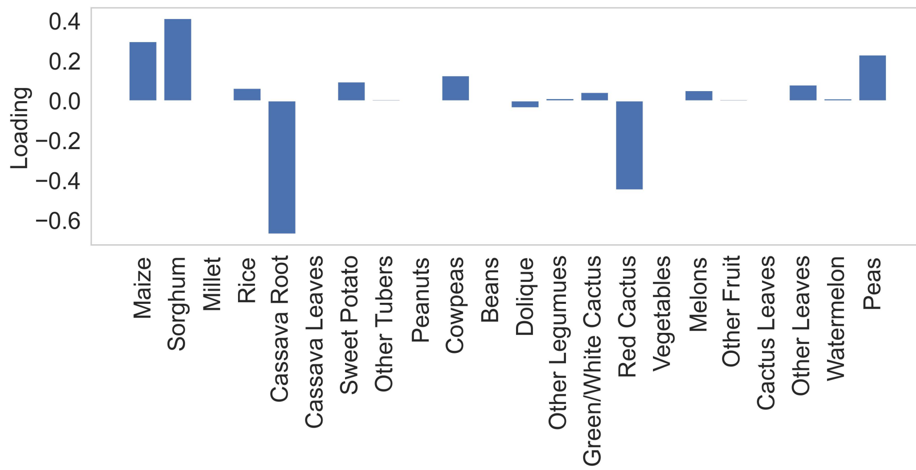


**Figure 5. Dietary Component 1.** Loadings for the first principal component across the 22 different foods.

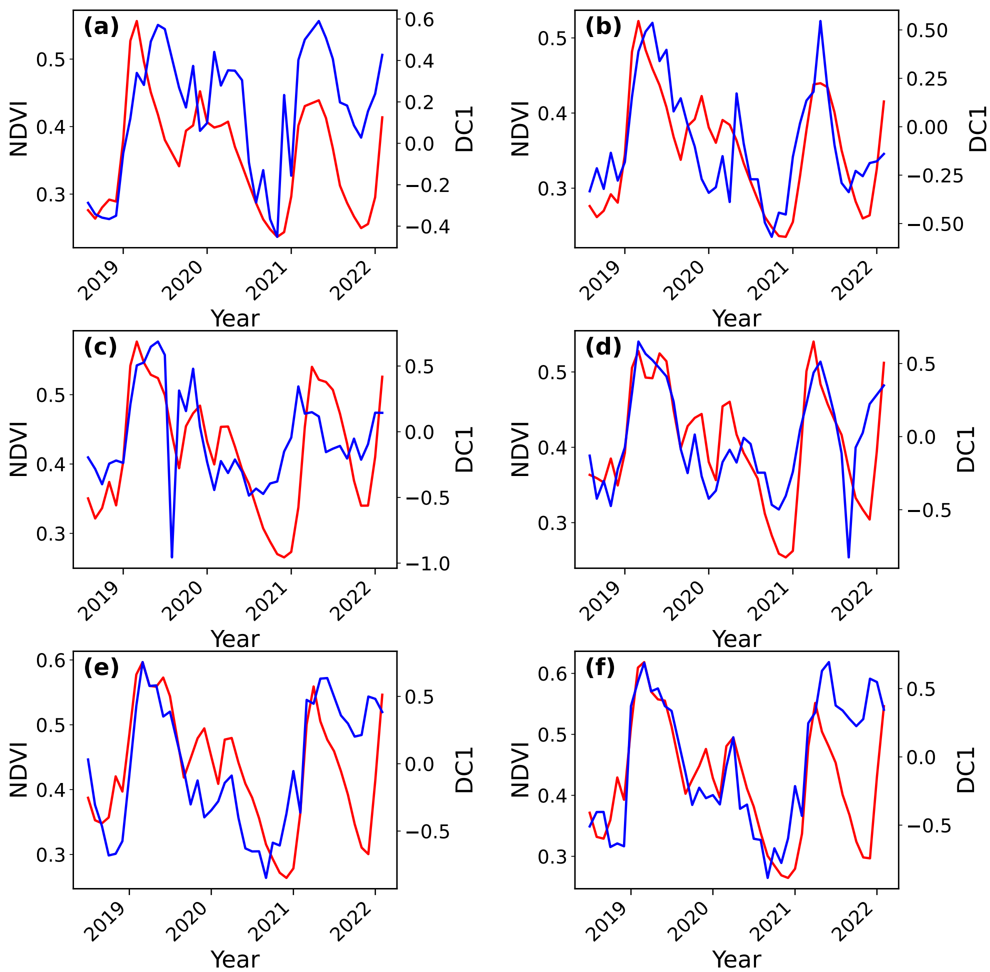


**Figure 6. Comparison of NDVI and DC1.** Each panel corresponds to one of the six subnational communes represented in the MIRA dataset: (a) Marolinta, (b) Tranavaho, (c) Marovato, (d)Anjampaly , (e) Antaritarika, and (f) Imongy. For each commune, the plot compares NASA MODIS 16-day Normalized Difference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

$\text{NDVI}_c$ is computed as the average over each commune and is averaged to same monthly resolution as PC1(Fig. 3). The $\varepsilon$ 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,

$$\text{PC1}_c = \beta_1 \cdot \text{NDVI}_c + \beta_0 + u_{\text{month}} + \varepsilon, \tag{2}$$

where $u_{\text{month}}$ 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.

## Discussion and Conclusion

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 PC1, across smallholder farming communities in southern Madagascar. Depending on the modeling approach, NDVI explains between 20% 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 security[21]. Household dietary outcomes have also been studied in depth[22]. It has been unclear, however, whether satellite monitoring strategies can directly inform regarding 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 PC1 variability across communes are 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 drought[23].

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.

Further analyses subsetting the data indicates 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 combine remotely sensed indicators with routinely-collected survey data in order to fully 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 nets[24]. Future work would benefit from integrating market connectivity, climatic variables, and food price data to refine the interpretation of environmental signals. Further, an assumption in our analysis is that key foods contributing to DC1 are homegrown and consumed shortly after harvest. Although we currently lack data on storage practices, lagged analyses provide no evidence of a consistent time offset between NDVI and food consumption.

We also examined higher-order components from the second and third principal modes of dietary variability, but they contributed 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.

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.

## 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 efforts[14]. MIRA surveys 602 households each month, selected randomly from among the most vulnerable households in administrative communes targeted for food security interventions[14].

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[25,26]. Moving into June of 2019, the data reflects 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 cactus [27]. 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[28,29]. 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[28,30].

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 Tranavaho, averaged the lowest NDVI. The year leading up to the 2018 drought we see exceptionally dry conditions across the region and a much lower max NDVI 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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## Acknowledgements

This research was supported by the United States Agency for International Development through funding to Catholic Relief Services. The MIRA program provided access to household survey data and logistical support.

## Author contributions statement

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

## Competing interests

the authors declare no competing interests.