IGC

Global warming and vulnerability to food insecurity in Mozambique: Local adaptation will matter

Paulo Santos and Reiss McLeod

- This policy brief presents findings from a study of climate-related food insecurity in Mozambique, using 2012 data from the Ministry of Agriculture and Rural Development.
- More than half of the Mozambican households surveyed by the Inquerito Agricola Integrado 2012 (IAI2012) were food insecure, as revealed by an inadequate or poor diet.
- Using machine learning methods, we characterise the heterogeneous relation between local environment, including weather (temperature and rainfall) in 2012, and food security.
- We identify 11 clusters that reflect local environmental conditions, with temperature at the start of the main agricultural production season being the most important determinant of cluster membership.
- The relation between food security and temperature is U-shaped.
- Future research should explore the set of adaptation strategies that is feasible at the local level, given this existing relation.

POLICY BRIEF MOZ-22195

AUGUST 2024

This project was funded by IGC Mozambique

theigc.org

DIRECTED BY

FUNDED BY

Mozambique is considered highly vulnerable to climate change given its geographical location, its long coastline, and the importance of the area close to (or below) mean sea level. Global warming may impact the welfare of rural populations through rising sea levels and the increase in the intensity and frequency of natural hazards, including droughts, floods and cyclones. While these shocks have deservedly received much attention, changes in average temperature may also lead to other slow-moving impacts via changes in the profitability and risk of current agricultural production.

In our analysis, we measure the effects of global warming on food security, using microeconomic data on diet quality collected as part of the Inquerito Agricola Integrado – 2012 (IAI2012) (see Box 1) and modelling the relation between this indicator and local environmental characteristics (see Box 2), using regression forests and associated surrogate models (see Santos et al, (2023) for a detailed discussion of the methodology used here).

A heterogeneous relation between local environment and food security

The statistical relation between diet quality and local environmental conditions is presented in Figure 2. The surrogate model created 11 groups (corresponding to the final leaf nodes), characterised in terms of differences in expected food consumption score (our outcome of interest) and its set of predictors, selected among a larger set that includes both natural capital and climatic variables. Figure 3 shows the distribution of these groups across the territory, with purple colours showing lower predicted food consumption scores (higher food insecurity) and green to yellow colours showing higher food consumption scores. There are some geographic groupings of the different cohorts. For the most part, households in the higher groups (higher FCS) are located in the centre-west of the country, and households in lower groups (lower FCS) are located in the centre-east of the country.

A U-shaped relation between temperature and diet quality

On the basis of the relatively high predictive power of this statistic model, we make three central observations:

- First, the regression tree succeeds in creating groups with meaningful differences in consumption: the expected food security in the most deprived cluster is 31, which is 14 points below the cluster with the highest expected food consumption score.
- Second, the temperature seems to matter most among the weather conditions, both in terms of the average monthly temperature at the

start of the planting season and the variance of the average monthly temperature in the planting season. Higher average monthly temperatures in the planting season and less variance in average monthly temperatures in the planting season (lower risk) are linked to higher expected food consumption scores. However, and importantly, this relation is nonlinear: households living in areas with unusually high average temperatures at the start of the planting season (>29C) are much better off (in terms of average diet quality) than 90% of the rural households in the country.

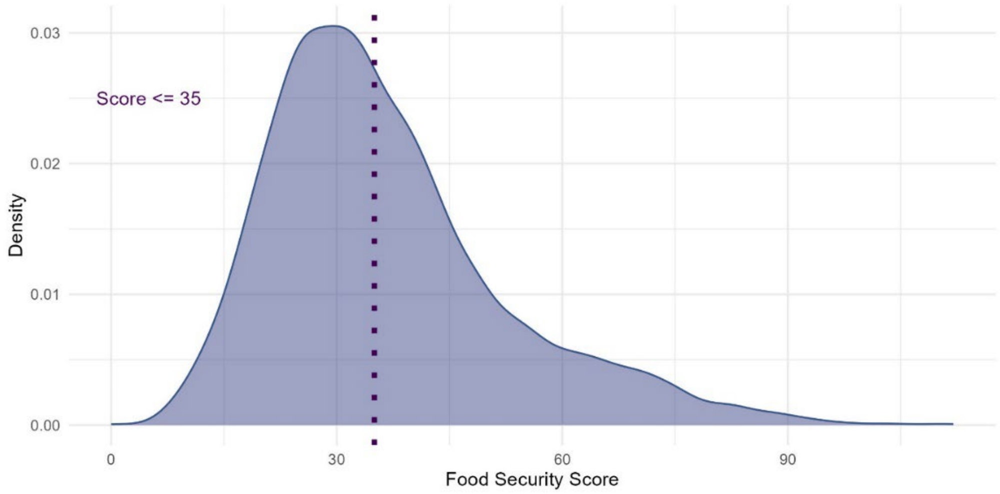
- Third, households in different cohorts do not seem substantively different in terms of demographic characteristics, including dependency ratio and, to a lesser degree, the number of adults (as a proxy for access to labour). However, they do seem to make different use of migration as a livelihood strategy, which differs significantly between cohorts and seems mostly associated with lower average FCS, suggesting its use as a coping strategy.
- Finally, households in different clusters differ in their use of land, most significantly in the importance of the area devoted to pasture. These differences are not mimicked in the importance of ownership of cattle: the data suggests that some of the better-off cohorts associated with higher temperatures at the start of the production season (>29C) may be better characterised by intensive cattle production, given their large ownership of cattle (>5 animals) and almost no land devoted to pasture or fallow.

BOX 1: Food Consumption Score

The Food Consumption Score (FCS) represents the frequency of food consumption across different food groups, including starches, pulses, vegetables, fruit, meat, dairy, fats and sugar, in the 7 days prior to the survey (World Food Programme, 2024). Respondents are asked to recall the number of days they consumed different foods, from a list of 14 food items, with each item in the list corresponding to a food group. The crosswalk between items and food group is used to identify the number of days a food was eaten from each food group, with the maximum value for any food group capped at 7. The number of days each food group (Staples - St, Pulses - P, Vegetables - V, Fruits - Fr, Meat - M, Dairy – D, Fats – Fa, Sugars - Su) is consumed is weighted by their nutritional content leading to the food consumption score.

We define a household as food insecure if its FCS is less than or equal to 35, the threshold above which a diet can be considered adequate. Figure 1 presents the distribution of the FCS in our sample: worryingly, and by this measure, approximately 55% of the households are food insecure.

FIGURE 1: Food security in the IAI2012



BOX 2: Characterising local environment

We characterise the environmental conditions affecting households surveyed in IAI2012 using different spatial datasets with global coverage. We start by creating buffer zones with a radius of 5000 metres centred on household locations, as provided by IAI2012, and calculate the mean of each variable within this buffer area for each spatial dataset. In most cases, this process is performed using Google Earth Engine (GEE), and the results are exported for further analysis in R (see methods section). When data is missing for a household, we replace the missing data with the sample mean.

We characterise a household's natural capital as the set of physical characteristics of the terrain, including elevation, slope and ruggedness, and soil properties (such as soil pH and soil carbon).

We create historical climatic variables using ERA5 (European Centre for Medium-Range Weather Forecasts Reanalysis Atmosphere 5th generation) daily data (Copernicus Climate Change Service, 2023) and create future climatic variables using Coupled Model Intercomparison Project climate projection data (Copernicus Climate Change Service, 2021). These historical climatic variables are processed using GEE, while future climate variables are processed using R.

ERA5 is the fifth generation ECMWF atmospheric reanalysis of the global climate. Reanalysis combines model data with observations from across the world into a globally complete and consistent dataset. ERA5 DAILY provides aggregated values for each day for seven ERA5 climate reanalysis parameters: 2m air temperature, 2m dewpoint temperature, total precipitation, mean sea level pressure, surface pressure, 10m u-component of wind and 10m v-component of wind, and the data is available from 1979 to three months from real-time. We use data on 2m air temperature (presented as daily averages) and total precipitation (presented as daily sums) in our analysis.

BOX 3: Characterising global warming

CMIP (Coupled Model Intercomparison Project) climate projection data provides daily projections on several climatic variables for 2015 to 2100. We use data for SSP1-2.6, SSP2-4.5 and SSP5-8.5, where SSP1, SSP 2 and SSP5 refer to shared socioeconomic pathways 1, 2, and 5, respectively, and Representative Concentration Pathways (RCPs) 2.6, 4.5, and 8.5 refer to levels of radiative forcing in watts per square metre (W/m2) by 2100. Generally, positive radiative forcing leads to warming of the Earth's surface and atmosphere because more energy is being retained in the Earth system. SSP1-2.6 is often considered a stringent mitigation scenario where strong efforts are made to reduce greenhouse gas emissions, while SSP5-8.5 is characterised by high greenhouse gas emissions, particularly carbon dioxide, resulting from continued fossil fuel use and limited mitigation efforts, and SSP2-4.5 is considered the middle of the road (Gidden et al., 2019).

We select three different scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) to quantify the sensitivity of vulnerability to food insecurity and compute all variables, except hot days and wet days for 3 different years (2050, 2070 and 2090) across these three different scenarios (SSP1-2.6, 2-4.5 and 5-8.5). We select these three scenarios because they contrast in terms of their levels of radiative forcing and their coupled social scenarios.

FIGURE 2: Predicting the food consumption score as a function of local environmental characteristics

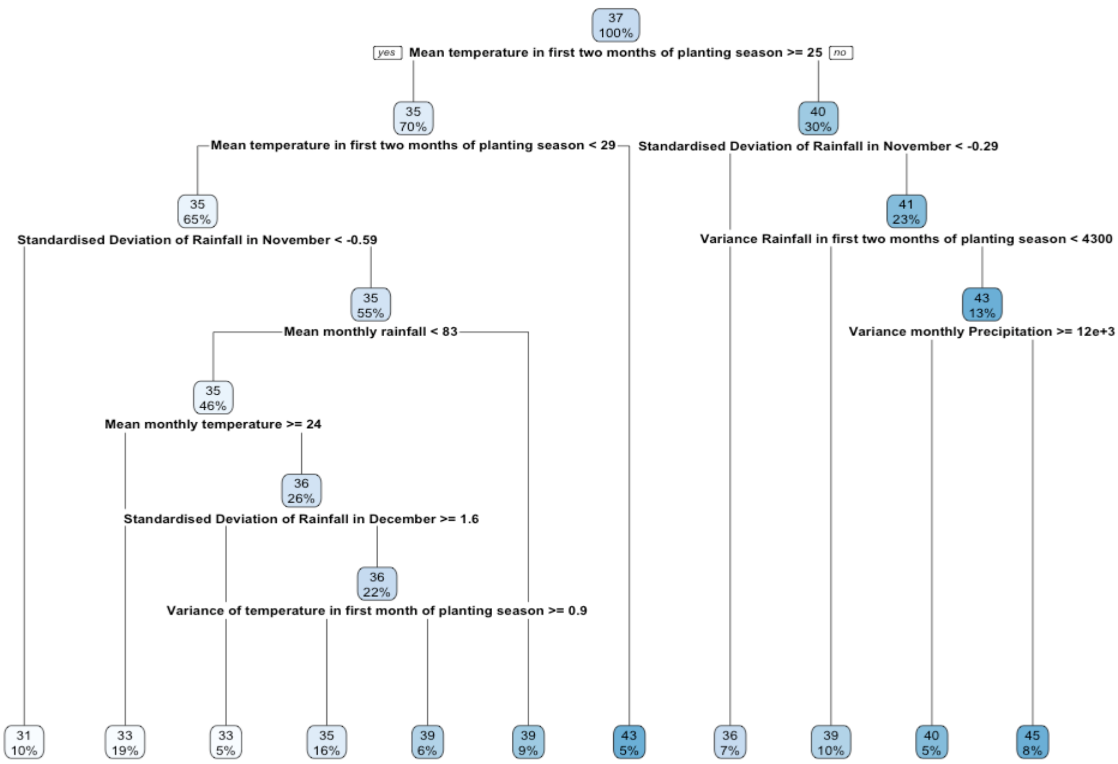
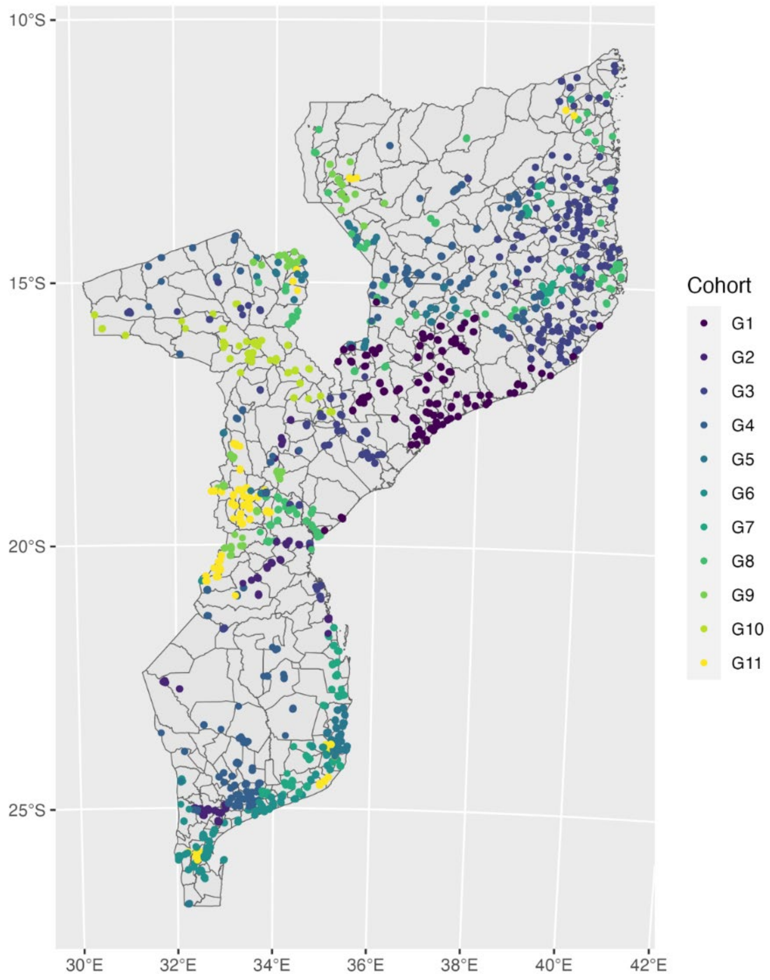


FIGURE 3: Food security clusters and their distribution in the territory



How this shapes the impact of global warming and creates a policy space for adaptation

Predicting the impacts of different climate scenarios (characterised in Box 3) on future food insecurity is a relatively straightforward exercise: it requires substituting our climatic variables with the respective values under different scenarios (see Box 3) and using the decision tree (Figure 2) to determine their (potentially new) group.

The association between different production strategies and local environmental conditions suggests different adaptation strategies to global warming. We consider two such cases: first, when the set of livelihood strategies adopted by households in the warmest locations is not present (and, consequently, the negative relation between temperature at the start of the main agricultural season and diet quality is monotonic), which we label as "adaptation: restricted" in the table below; and when those activities are feasible (and the relation between temperature and diet quality is nonlinear, as presented in Figure 2), which we label below as "adaptation: unrestricted."

The implications of these simulations, presented in Table 1, are as follows:

- Firstly, if the set of livelihood activities currently practised by households in warmer locations (>29C) is not available, the dismal levels of household food security in rural Mozambique observed in the IAI2012 are expected to remain unchanged. However, their variability is expected to be smaller.
- Secondly, if adaptation is unrestricted, changes associated with global warming would lead to improvements in diet quality and associated reduction in food insecurity.

Both scenarios are likely extreme, but they illustrate one simple point: even in the absence of technological change, creating conditions to adapt to global warming that address the heterogeneity of local conditions is central to minimising the impact of global warming on the welfare of households living in rural Mozambique.

TABLE 1: Simulating the effect of global warming on food consumption score under different adaptation possibilities

Scenario	Adaptation: restricted			Adaptation: unrestricted		
	2050	2070	2090	2050	2070	2090
SSP 1-2.6	34.52 (4.47)	38.24 (2.58)	36.57 (3.73)	35.64 (4.91)	41.73 (1.75)	41.36 (2.47)
SSP 2-4.5	37.97 (2.70)	37.16 (3.63)	38.96 (1.74)	41.29 (2.60)	41.87 (1.66)	40.83 (1.87)
SSP 5-8.5	34.52 (4.18)	34.93 (3.86)	36.29 (3.81)	41.81 (1.71)	42.67 (0.98)	42.67 (0.98)

References

Copernicus Climate Change Service (2021). ‘CMIP6 predictions underpinning the C3S decadal prediction prototypes’. ECMWF. https://doi.org/10.24381/CDS.C866074C.

Copernicus Climate Change Service (2023). ‘Complete ERA5 global atmospheric reanalysis’. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://doi.org/10.24381/CDS.143582CF.

Gidden, M.J., Riahi, K., Smith, S.J., Fujimori, S., Luderer, G., Kriegler, E., van Vuuren, D.P., van den Berg, M., Feng, L., Klein, D., Calvin, K., Doelman, J.C., Frank, S., Fricko, O., Harmsen, M., Hasegawa, T., Havlik, P., Hilaire, J., Hoesly, R., ...Takahashi, K. (2019). Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century. *Geoscientific Model Development*, *12*(4), 1443–1475. https://doi.org/10.5194/gmd-12-1443-2019.

Santos, P., McLeod, R., Meyer, S., Le, H.C., & Rakhmadi, M.F. (2023). *Vulnerability in the Anthropocene: a prospective analysis of the need for social protection*. Australian Centre for International Agricultural Research. https://www.aciar.gov.au/publication/TR102-vulnerability

World Food Programme (2024, December 2). *Food Consumption Score*. https://resources.vam.wfp.org/data-analysis/quantitative/food-security/food-consumption-score