Unveiling Hidden Drivers: A Latent Variable Approach to Food Security Dynamics in Africa

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Motivation

- Global progress on food security has stalled, with **hunger and malnutrition remaining persistently high** (FAO, IFAD, et al. 2024).
- **Sub-Saharan Africa faces the highest burden**, often exacerbated by compounding shocks such as conflicts, climate-related disasters, and economic instability (Barrett 2021; FAO, IFAD, et al. 2021).
- Climate-related shocks disproportionately affect agriculture in developing countries (Mendelsohn, 2008), undermining **food availability**, and also compromise **food access** through their impact on incomes and markets (Myers et al., 2017; IPCC, 2023), by increasing price volatility and reducing households' purchasing power.

Limitations of Existing Research

- Focus mostly on food availability and caloric intake, neglecting dietary quality, diversity, and intra-household distribution (Costlow et al., 2025).
- Limited longitudinal and high-frequency data, challenging assessment of temporal dynamics (Hangoma et al., 2024).
- Global metrics often miss local context, seasonality, and cultural dimensions (Izraelov and Silber, 2019).
- Potential endogeneity and omitted-variable bias that limit the credibility of causal inference (Ahmadzai et al., 2025).

A **latent variable framework** can directly address these limitations by capturing food insecurity as a **multidimensional, unobservable construct** and accounting for **dynamic transitions** between food security states.

Research aim

This study aims to examine the dynamics of household food insecurity in low-income countries, focusing on how **dietary diversity evolves** and how households in sub-Saharan Africa move between more and less secure states in response to climate shocks.

Innovative contribution

By modelling transitions across **unobservable states of food security**, our findings move beyond static measures and capture the **persistence and mobility** of households in response to climate shocks, offering deeper insight into the mechanisms that shape vulnerability and resilience.

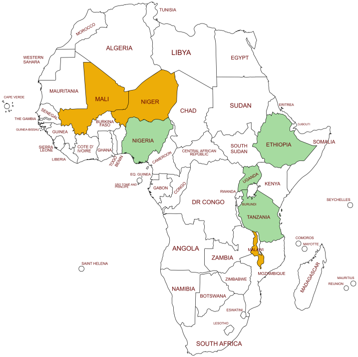
Latent class model and food security literature

While latent variable models are widely used across various fields, their application to the study of food security and its dimensions has been relatively scarce.

- Consumers' food choice (Alemu and Olsen, 2019). Analysis of consumer preferences for insect-based foods in Kenya
- Food access (Bartolucci and Farcomeni 2022). Cluster and profiling areas according to their food access
- Food insecurity (Waqo et al., 2025). Analysis of the evolution of household food insecurity status in Ethiopia during the COVID-19 pandemic

Our study extends this approach by **considering multiple countries** and examining how **household food insecurity evolves in response to climate shocks**.

Our sample - Living Standards Measurement Study (1/3)



The countries highlighted in green represent those included in our sample: Ethiopia, Nigeria, Tanzania, and Uganda.

Waves by country and survey years

Waves	Country	Survey year
1	Ethiopia	2010/2011
	Nigeria	2010/2011
	Tanzania	2010/2011
	Uganda	2010/2011
2	Ethiopia	2012/2013
	Nigeria	2012/2013
	Tanzania	2012/2013
	Uganda	2011/2012
3	Ethiopia	2014/2015
	Nigeria	2015/2016
	Tanzania	2014/2015
	Uganda	2015/2016
4	Ethiopia	2017/2018
	Nigeria	2018/2019
	Tanzania	2019/2021
	Uganda	2018/2020

Total sample composed of 25,502 observations.

Our sample - Living Standards Measurement Study (2/3)

We rely on the **Household Dietary Diversity Score (HDDS)** as the primary measure of food security (**outcome**)

The HDDS is positively associated with both the quality and quantity of food intake (e.g. Swindale and Bilinsky, 2006), reflecting greater access to a diverse range of nutrients and, consequently, improved household food security.

- The HDDS indicator is calculated using twelve food groups. Each group is assigned a score of 1 if it was consumed in the previous 24 hours, or 0 if it was not.
- Following Vaitla et al. (2017) and extending their approach, we recoded the continuous HDDS variable into a categorical response variable with values ranging from 0 to 3:

  HDDS 0-3: scarce variety diet (0);

  HDDS 4-6: middle-scarce variety diet (1);

  HDDS 7-9: middle-plentiful variety diet (2);

  HDDS 10-12: plentiful variety diet (3).

Our sample - Living Standards Measurement Study (3/3)

Covariates

- Age: age of household head in years (continuous)
- Female: values equal to 1 if household head is a female, 0 otherwise (dichotomous)
- Drought: values equal to 1 if household was affected by drought shock, 0 otherwise (dichotomous)
- Distance: distance in Km from an urban centre with more than 20,000 inhabitants (UN-Habitat, 2018) (continuous)

Model (1/3)

- We implement an Hidden Markov Model (HMM)
- An HMM is used to analyze sequential data by inferring a sequence of unobservable (hidden) states from a sequence of observable outputs
- HMM in our case:
  - *Hidden states:* the unobservable states of the system, representing household food security in Africa.
  - *Observable outcome:* data that can be directly measured, such as the HDDS.
  - *Initial state distribution:* the probability of starting in each possible hidden state.
  - *Transition probability:* the probability of moving from one hidden state to another.

Model (2/3)

Initial probabilities can be written as:

$$log \frac{P(U^{(1)} = u | X^{(1)} = x)}{P(U^{(1)} = 1 | X^{(1)} = x)} = log \frac{\pi_{u|x}}{\pi_{1|x}} = \beta_{0u} + x^{\top} \beta_{1u}$$

where:

- β_{0u} is the intercept for latent state u (baseline log-odds of being in u versus 1 when x = 0)
- $x^{\top} \beta_{1u}$ is the contribution of covariates to the log-odds of being in state u versus state 1

Model (3/3)

Transition probabilities can be expressed as:

$$log \frac{P(U^{(t)} = u | U^{(t-1)} = \bar{u}, X^{(t)} = x)}{P(U^{(t)} = \bar{u} | U^{(t-1)} = \bar{u}, X^{(t)} = x)} = \gamma_{0\bar{u}u} + x^\top(\gamma_{1u} - \gamma_{1\bar{u}})$$

where:

- $\gamma_{0\bar{u}u}$ represents the intercept for the transition from the baseline state $\bar{u}$ to the outcome state u when all covariates are equal to zero;
- $x^\top(\gamma_{1u} - \gamma_{1\bar{u}})$ captures the relative effect of the covariates on the probability of moving to u versus remaining in $\bar{u}$ (difference-logit parametrization; Bartolucci, 2017).

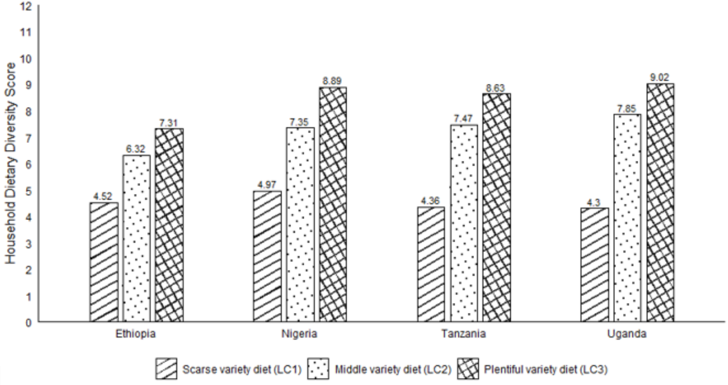
Selection of latent states according to BIC criterion

k	Log Likelihood	AIC	BIC
1	-57184.26	114374.50	114398.90
2	-27272.90	54579.79	54717.98
3	-27135.93	54337.85	**54606.10**
4	-27079.28	54260.56	54675.13
5	-27049.63	54241.25	54818.39

Based on these findings, we use three latent states which we define:

- Scarce variety diet (LC1) $\rightarrow$ food insecure
- Middle variety diet (LC2) $\rightarrow$ somewhat secure
- Plentiful variety diet (LC3) $\rightarrow$ food secure

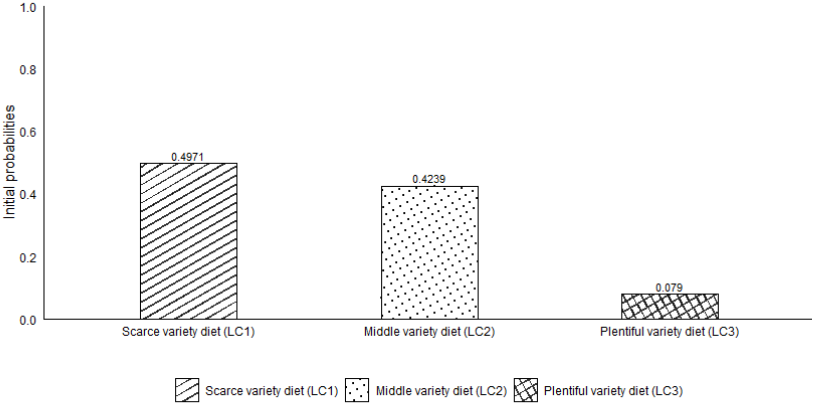
Average HDDS by Country and Latent Class



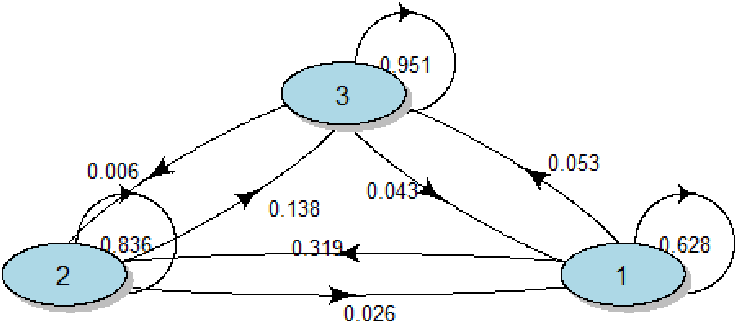
Conditional Response Probabilities

Variety diet	Scarce (LC1)	Middle (LC2)	Plentiful (LC3)
HDDS Category			
Scarce dietary diversity (0)	0.1948	0.0002	0.0002
Middle-scarce dietary diversity (1)	0.6884	0.3666	0.1664
Middle-plentiful dietary diversity (2)	0.1167	0.5655	0.5617
Plentiful dietary diversity (3)	0.0001	0.0677	0.2717

- Conditional response probabilities are the probabilities of observing a given response conditional on the latent state at that time
- Approximately 88,0% of households assigned to scarce variety diet (LC1) report either scarce (19,5%) or middle-scarce (68,8%) dietary diversity
- By contrast, in plentiful variety diet (LC3), only 16,6% of respondents fall into the categories of scarce or middle-scarce dietary diversity



a) Initial probabilities



1 = scarce variety diet (LC1)
2 = middle variety diet (LC2)
3 = plentiful variety diet (LC3)

b) Transition probabilities

Parameters affecting transition probabilities

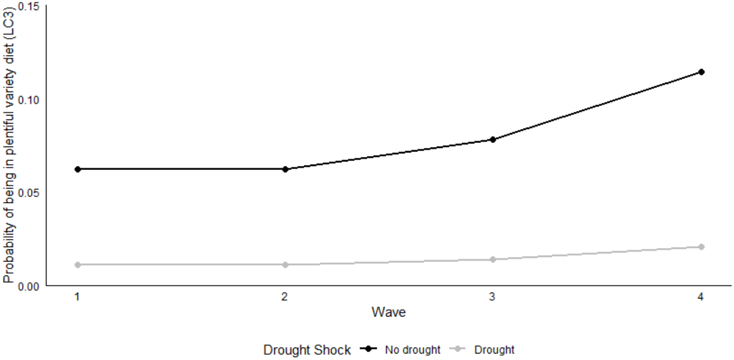
	Middle variety diet (LC2)			Plentiful variety diet (LC3)		
	Coefficient	Std.error	P-value	Coefficient	Std.error	P-value
Age	0.9990	0.0060	0.8676	**1.0135**	0.0061	0.0268
Drought	0.7972	0.2141	0.2952	**0.0214**	1.1485	0.0008
Female	**0.2805**	0.2128	0.0000	**0.4271**	0.2281	0.0002
Distance	1.0060	0.0045	0.1824	**0.8982**	0.0214	0.0000

Notes: coefficients written in bold are statistically significant. Coefficients are reported as odds-ratio.

The covariates affect the probabilities of moving to a situation of middle or plentiful variety diet (LC2 and LC3) rather than scarce food variety diet (LC1)

Impact of Drought on Initial Dietary Diversity

Likelihood of households being in the plentiful variety diet latent state (LC3) over time in response to drought shocks.



Findings in a nutshell

The results indicate that demographic characteristics and environmental conditions play a key role in shaping individuals' likelihood of moving towards a more diversified and plentiful diet (LC3).

- **Older individuals** show a higher probability of transitioning to a diet with plentiful variety (LC3), increasing by approximately 1.35% for each additional year of age
- **Being female** reduces the transition probability to the plentiful-variety diet (LC3) by about 57%.
- A **drought shock** has a detrimental effect on the transition probability from the scarce-variety diet (LC1) to the plentiful-variety diet (LC3), reducing it by about 98%
- The probability of transitioning to a state of plentiful dietary diversity tends to decrease by approximately 10% among **individuals living far from an urban centre**

Further improvements

- **Drought variable** is self-reported; a more objective measure could be obtained from the Standardized Precipitation Evapotranspiration Index (SPEI-crop).
- **Country-level analysis and heterogeneity**: country-specific economic structures, policy frameworks, and agro-ecological conditions may lead to different transition dynamics, offering more precise and context-sensitive insights.
- **Institutional quality** and climate shock diffusion: institutional quality may influence how climate shocks propagate and how effectively households cope. By incorporating governance indicators—such as government effectiveness or political stability—we aim to test whether stronger institutions mitigate the negative impact of climate shocks and enhance resilience.

Thank you for your attention!

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Descriptive statistics

	HDDS	Age	Drought	Sex	Distance
Panel A - Full sample					
Mean	1.58	47.10	0.16	0.22	34.25
Min	0.00	16.00	0.00	0.00	0.00
Max	3.00	75.00	1.00	1.00	208.20
Panel B - Ethiopia					
Mean	1.24	46.22	0.25	0.24	35.10
Min	0.00	17.00	0.00	0.00	0.00
Max	3.00	75.00	1.00	1.00	208.20
Panel C - Nigeria					
Mean	1.86	49.55	0.01	0.14	24.72
Min	0.00	16.00	0.00	0.00	0.06
Max	3.00	75.00	1.00	1.00	108.70
Panel D - Tanzania					
Mean	1.73	45.53	0.16	0.25	47.48
Min	0.00	17.00	0.00	0.00	0.50
Max	3.00	75.00	1.00	1.00	200.00
Panel E - Uganda					
Mean	1.80	47.05	0.36	0.36	24.17
Min	0.00	16.00	0.00	0.00	0.45
Max	3.00	75.00	1.00	1.00	101.23