Supplementary Information:
Trajectories of Resilience to Acute Malnutrition in the Kenyan Drylands

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1 DATA SOURCES AND PROCESSING

1.1 Household Nutrition Surveys

We note three limitations of the NDMA Kenya nutrition data for our analysis. First, missing and incomplete information. Note that the NDMA has a total of 23 local county offices, yet we do not include Tharaka Nithi County for reasons of data unavailability. In addition, we drop 5,208 implausible MUAC observations, and 2,341 more as the age range is not between 6 and 59 months. For all data included, information is missing at random. In addition, our analysis is constrained by nutrition data availability due to COVID-19—in light of travel restrictions and government guidance on social distancing, NDMA suspended their data collection at the end of March 2020. Second, NDMA samples a small subset of all wards (on average a quarter of all wards in a given county), intended to constitute a representative sample for each county, and then, in turn, samples households to represent each ward. As a result, we cannot meaningfully analyze cross-sectional variation within counties, and since wards tend to be non-contiguous, we cannot account for potential spill-over effects between adjacent wards. And third, the main anthropometric measure used in this study is the MUAC.

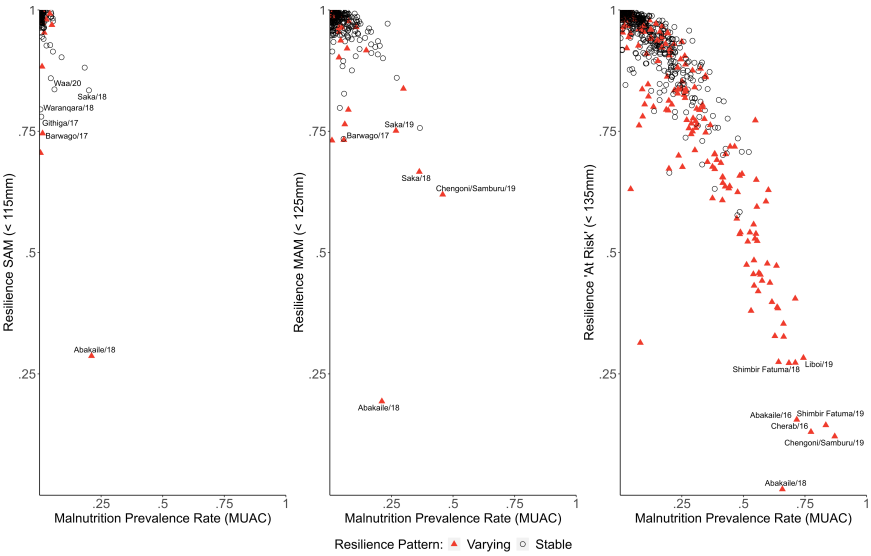

Figure 1. Scatterplots for resilience vs. malnutrition prevalence at the ward-year level, by normative threshold w. A ward is coded as stable across years when $\sigma_r \leq 0.1$, and varying otherwise.

1.2 Conflict Stressor Intensity

Based on the UCDP data, Kenya experienced 140 violent events with at least one fatality between 2016 and April 2020. As a robustness check, we draw on another leading dataset on conflict events, namely from the Armed Conflict Location & Event Data Project (Raleigh et al., 2010). The comparison of event counts per county is illustrated in Figure 2. Whereas UCDP restricts its domain to events which result in a fatality, ACLED also includes non-fatal events (e.g. injuries) and non-violent events (e.g. arrests, troop movements, demonstrations). Due to its broader inclusion criteria, ACLED captures more forms of violent events than UCDP-GED, some of which are unlikely to impact household food security or nutrition directly. We only include events coded as either "Battles", "Explosions/Remote violence", "Violence against civilians", and "Strategic developments", and further exclude one event where the government dismantled an Al Shabaab cell in a remote area of Lamu county with no casualties. The final ACLED data lists 595 conflict-related events for Kenya between 2016 and April 2020, with the vast majority (79%) coded as battles or violence against civilians. The results remain robust, regardless of the conflict event data used. Note that due to their heavy reliance on media reports, both UCDP-GED and ACLED suffer from reporting biases that negatively impact our ability to reliably measure conflict events that affect household resilience to malnutrition. Future studies could draw on data from local courts or conflict resolution institutions to account for this shortcoming.

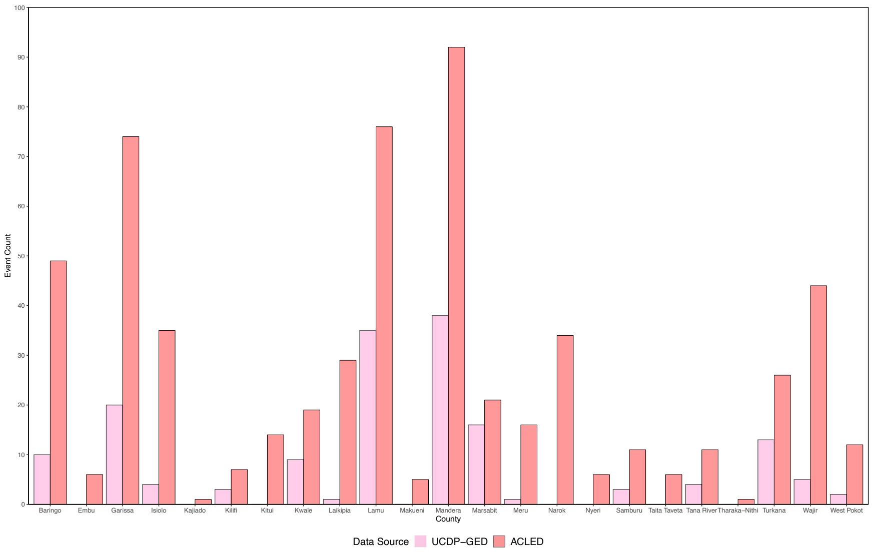

Figure 2. Observed conflict events in Kenyan counties in ACLED vs UCDP-GED dataset (2016–2020)

Table 1. Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
county (ADM1)								
climate stressor intensity	50,124	0.61	0.14	0	0.53	0.63	0.69	1
conflict stressor intensity	6,016	0.24	0.20	0	0.091	0.18	0.27	1
market stressor intensity	49,213	0.37	0.15	0	0.27	0.34	0.43	1
household								
months	54,839	6.06	3.44	1	3.00	6.00	9.00	12
resilience trajectory	54,839							
... chronic	22,019	39%						
... increase	31,243	57%						
... robust	1,111	3%						
... decrease	466	1%						
education	40,218							
... no	24,495	61%						
... yes	15,723	39%						
gender	54,643							
... female	12,402	23%						
... male	42,241	77%						
livelihood	54,839							
... other	24,993	46%						
... pastoralist	29,846	54%						
water source	48,116							
... safe	14,036	29%						
... unsafe	34,080	71%						

2 METHODOLOGY

2.1 Latent Class Mixed Model

Table 2. GRoLTS-Checklist (Van De Schoot et al., 2017)

no	item	y/n
1	Is the metric of time used in the statistical model reported?	y
2	Is information presented about the mean and variance of time within a wave?	y
3	Is the missing data mechanism reported?	y
4	Is information about the distribution of the observed variables included?	y
5	Is the software mentioned?	y
6	Are alternative specifications of within-class heterogeneity considered (e.g., LGCA vs. LGMM) and clearly documented?	y
7	Are alternative shape/functional forms of the trajectories described?	y
8	If covariates have been used, can analyses still be replicated?	y
9	Is information reported about the number of random start values and final iterations included?	y
10	Are the model comparison (and selection) tools described from a statistical perspective?	y
11	Are the total number of fitted models reported, including a one-class solution?	y
12	Are the number of cases per class reported for each model (absolute sample size, or proportion)?	y
13	If classification of cases in a trajectory is the goal, is entropy reported?	y
14	Is a plot included with the estimated mean trajectories of the final solution?	y
15	Are characteristics of the final class solution numerically described (i.e., means, SD/SE, n, CI, etc.)?	y
16	Are the syntax files available (either in the appendix, supplementary materials, or from the authors)?	y

Table 3. Model fit using alternative link functions

	G	loglik	npm	BIC	%C1
linear	1	1,509	9	-2,976	100
beta	1	4,216	11	-8,382	100
splines	1	6,964	14	-13,866	100

Table 4. Model fit with 1 to 6 latent classes

	G	loglik	npm	BIC	%C1	%C2	%C3	%C4	%C5	%C6
M1	1	6,964	14	-13,866.	100					
M2	2	6,977	17	-13,877	42	58				
M3	3	7,031	20	-13,973	96	3	1			
M4	4	7,037	23	-13,969	39	57	3	1		
M5	5	7,053	26	-13,988	41	9	46	3	1	
M6	6	7,040	29	-13,950	4	45	31	15	1	3

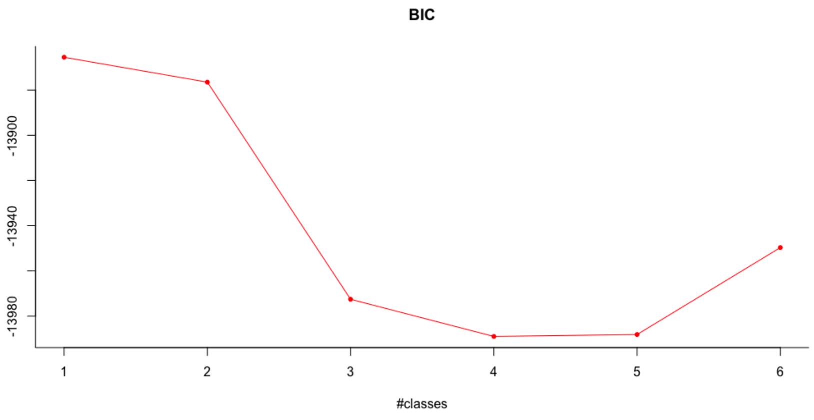

Figure 3. BIC against number of latent classes

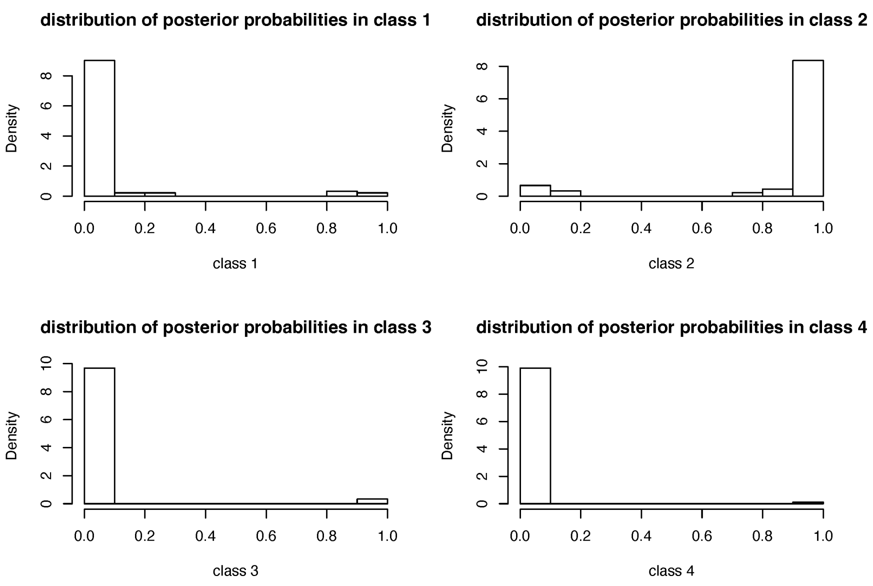

Figure 4. Posterior probabilities of four classes

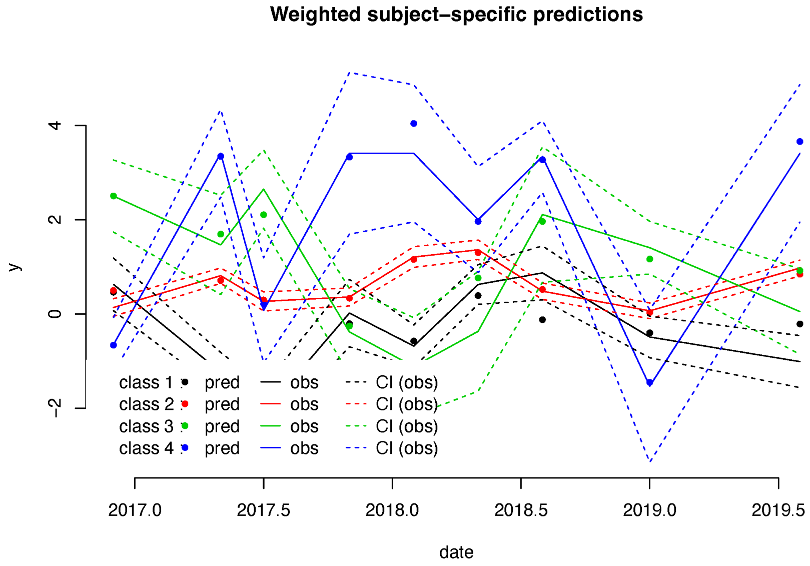

Figure 5. Model fit

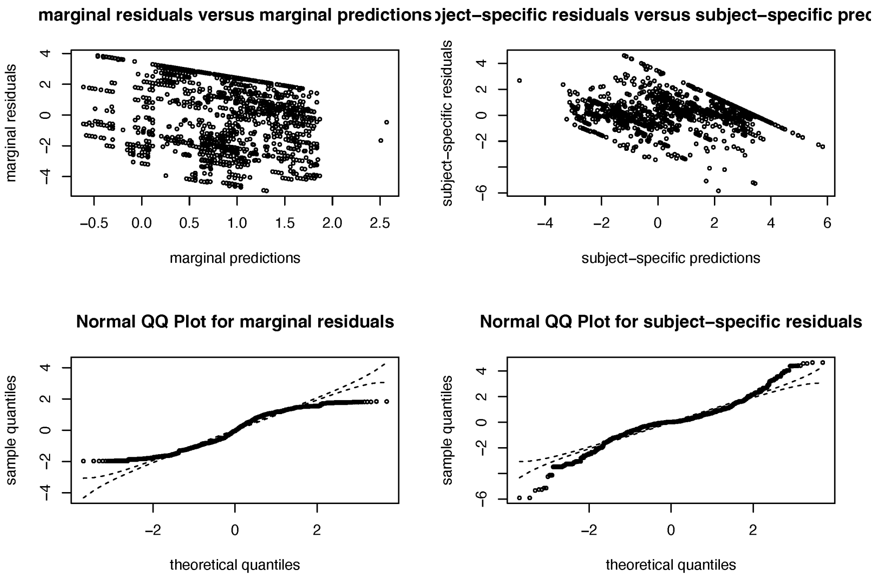

Figure 6. Residual plot

2.2 Cox Regression

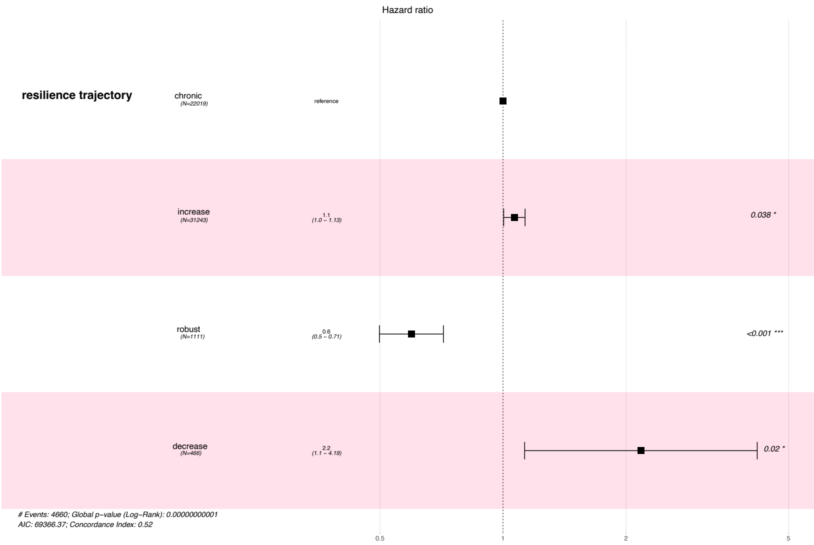

Figure 7. Univariate cox regression results

REFERENCES

Raleigh, C., Linke, A., Hegre, H., and Karlsen, J. (2010). Introducing acled: an armed conflict location and event dataset: special data feature. *Journal of peace research* 47, 651–660

Van De Schoot, R., Sijbrandij, M., Winter, S. D., Depaoli, S., and Vermunt, J. K. (2017). The grolts-checklist: guidelines for reporting on latent trajectory studies. *Structural Equation Modeling: A Multidisciplinary Journal* 24, 451–467