Online Appendix for the Paper

"*CLARE: A Causal machine Learning Approach to Resilience Estimation*"

Appendix C – Additional results

- **Alternative approaches to resilience estimation**

Table C.1: Forecasting food insecurity status out-of-sample using C&B RS – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure *(t)* = 0	**Food insecure *(t)* = 1**	**Total**
Binary C&B RS (median cutoff)	**Non-resilient *(t-1)* = 0**	4,727	442	5,169
	Non-resilient *(t-1)* = 1	3,671	1,254	4,925
	Total	8,398	1,696	10,094
	Correctly predicted	**56.29%**	**73.94%**	**59.25%**

Notes: This table shows the out-of-sample classification performance of the binary C&B model in forecasting food insecurity (defined as FCS ≤ 35) across all countries and waves 4 to 7. The classification uses the median C&B value as the cutoff. Rows indicate the predicted values (based on C&B), while columns represent the observed food insecurity status.

Table C.2: Predicting the Food Consumption Score out-of-country using C&B RS – All countries

Metrics	Value
Pearson's correlation coefficient	0.327
Spearman rank correlation coefficient	0.318
Normalized RMSE (RMSE over FCS sample mean)	0.367
Average C&B RS	67.82

Notes: This table reports the out-of-country performance of the C&B model in predicting the continuous Food Consumption Score (FCS) across all countries.

Table C.3: Predicting food insecurity status out-of-country using C&B RS – All countries

		Food insecure (FCS ≤ 35)		
		Food insecure = 0	**Food insecure = 1**	**Total**
Binary C&B RS (median cutoff)	**Non-resilient = 0**	12,598	1,458	14,056
	Non-resilient = 1	9,806	4,250	14,056
	Total	22,404	5,708	28,112
	Correctly predicted	**56.23%**	**74.46%**	**59.93%**

Notes: This table shows the out-of-country classification performance of the binary C&B model in forecasting food insecurity (defined as FCS ≤ 35) across all countries, using the median C&B value as the cutoff. Rows indicate the predicted values (based on C&B), while columns represent the observed food insecurity status.

Table C.4: Forecasting food insecurity status out-of-sample with the 'naïve' method – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure *(t)* = 0	**Food insecure *(t)* = 1**	**Total**
Lagged food insecure (FCS ≤ 35)	**Food insecure *(t-1)* = 0**	8,707	1,508	10,215
	Food insecure *(t-1)* = 1	1,293	801	2,094
	Total	10,000	2,309	12,309
	Correctly predicted	**87.1%**	**34.7%**	**77.2%**

Notes: This table shows the out-of-sample classification performance of the binary 'naïve' model in forecasting food insecurity (defined as FCS ≤ 35) across all countries and waves 4 to 7. The classification uses the median 'naïve' value as the cutoff. Rows indicate the predicted values (based on the 'naïve' model), while columns represent the observed food insecurity status.

Table C.5: Forecasting food insecurity status out-of-sample with the ‘realized resilience’ approach – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure *(t)* = 0	**Food insecure *(t)* = 1**	**Total**
Lagged Realized resilience (L1.Δ FCS < 0)	**Realized non-resilience *(t-1)* = 0**	4,353	839	5,192
	Realized non-resilience *(t-1)* = 1	4,045	857	4,902
	Total	8,398	1,696	10,094
	Correctly predicted	**51.8%**	**50.5%**	**51.6%**

Notes: This table shows the out-of-sample classification performance of the binary realized resilience model in forecasting food insecurity (defined as FCS ≤ 35) across all countries and waves 4 to 7. The classification uses the median realized resilience value as the cutoff. Rows indicate the predicted values (based on the realized resilience model), while columns represent the observed food insecurity status.

Table C.6: Predicting food insecurity status out-of-sample with supervised machine learning – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure = 0	**Food insecure = 1**	**Total**
Random forest prediction	**Food insecure = 0**	5,655	547	6,202
	Food insecure = 1	4,560	1,547	6,107
	Total	10,215	2,094	12,309
	Correctly predicted	**55.4%**	**73.9%**	**58.5%**

Notes: This table shows the out-of-sample classification performance of the random forest model in forecasting food insecurity (defined as FCS ≤ 35) across all countries and waves 4 to 7. The classification uses the median value as the cutoff. Rows indicate the predicted values (based on the random forest model), while columns represent the observed food insecurity status.

Table C.7: Predicting food insecurity status out-of-sample with a simple average of resilience subcomponents – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure = 0	**Food insecure = 1**	**Total**
Simple average classification (median cutoff)	**Food insecure = 0**	5,449	705	6,154
	Food insecure = 1	4,766	1,389	6,155
	Total	10,215	2,094	12,309
	Correctly predicted	**53.3%**	**66.3%**	**55.6%**

Notes: This table shows the out-of-sample classification performance of a simple weighted average of the standardized resilience components across all countries and waves 4 to 7. The classification uses the median value as the cutoff. Rows indicate the predicted values, while columns represent the observed food insecurity status.

- **Additional analyses and robustness checks for the CLARE indicator**

Table C.8: Forecasting food insecurity status out-of-sample using CLARE and only the top 3 most important variables – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure = 0	**Food insecure = 1**	**Total**
Binary CLARE (median cutoff)	**Non-resilient = 0**	5,753	400	6,153
	Non-resilient = 1	4,462	1,694	6,156
	Total	10,215	2,094	12,309
	Correctly predicted	**56.3%**	**80.9%**	**60.5%**

Notes: This table shows the out-of-sample classification performance of the binary CLARE in forecasting food insecurity (defined as FCS ≤ 35) across all countries and waves 4 to 7 using only the 3 most important variables as predictors. The classification uses the median value as the cutoff. Rows indicate the predicted values, while columns represent the observed food insecurity status.

Table C.9: Forecasting food insecurity status out-of-sample using CLARE based on SPEI shock data – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure = 0	**Food insecure = 1**	**Total**
Binary CLARE (median cutoff)	**Non-resilient = 0**	5,775	378	6,153
	Non-resilient = 1	4,440	1,716	6,156
	Total	10,215	2,094	12,309
	Correctly predicted	**56.5%**	**82%**	**60.9%**

Notes: This table shows the out-of-sample classification performance of the binary CLARE in forecasting food insecurity (defined as FCS ≤ 35) across all countries and waves 4 to 7 using the alternative weather data GS-SPEI for drought. The classification uses the median value as the cutoff. Rows indicate the predicted values, while columns represent the observed food insecurity status.

Table C.10: Forecasting food insecurity status out-of-sample using general-purpose CLARE – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure = 0	**Food insecure = 1**	**Total**
Binary CLARE (median cutoff)	**Non-resilient = 0**	5,773	381	6,154
	Non-resilient = 1	4,442	1,713	6,155
	Total	10,215	2,094	12,309
	Correctly predicted	**56.5%**	**81.8%**	**60.8%**

Notes: This table shows the out-of-sample classification performance of the binary CLARE in forecasting food insecurity (defined as FCS ≤ 35) across all countries and waves 4 to 7 using the multiple shock variable. The classification uses the median value as the cutoff. Rows indicate the predicted values (based on the random forest model), while columns represent the observed food insecurity status.

Table C.11: Forecasting food insecurity status out-of-sample using drought-specific CLARE with electricity asset index – All countries, waves 4 to 7

		Food insecure (FCS ≤ 35)		
		Food insecure = 0	**Food insecure = 1**	**Total**
Binary CLARE (median cutoff)	**Non-resilient = 0**	5,782	372	6,154
	Non-resilient = 1	4,433	1,722	6,155
	Total	10,215	2,094	12,309
	Correctly predicted	**56.6%**	**82.2%**	**61%**

Notes: This table shows the out-of-sample classification performance of the binary CLARE in forecasting food insecurity (defined as FCS ≤ 35) across all countries and waves 4 to 7 using the electricity asset index. The classification uses the median value as the cutoff. Rows indicate the predicted values (based on the random forest model), while columns represent the observed food insecurity status.

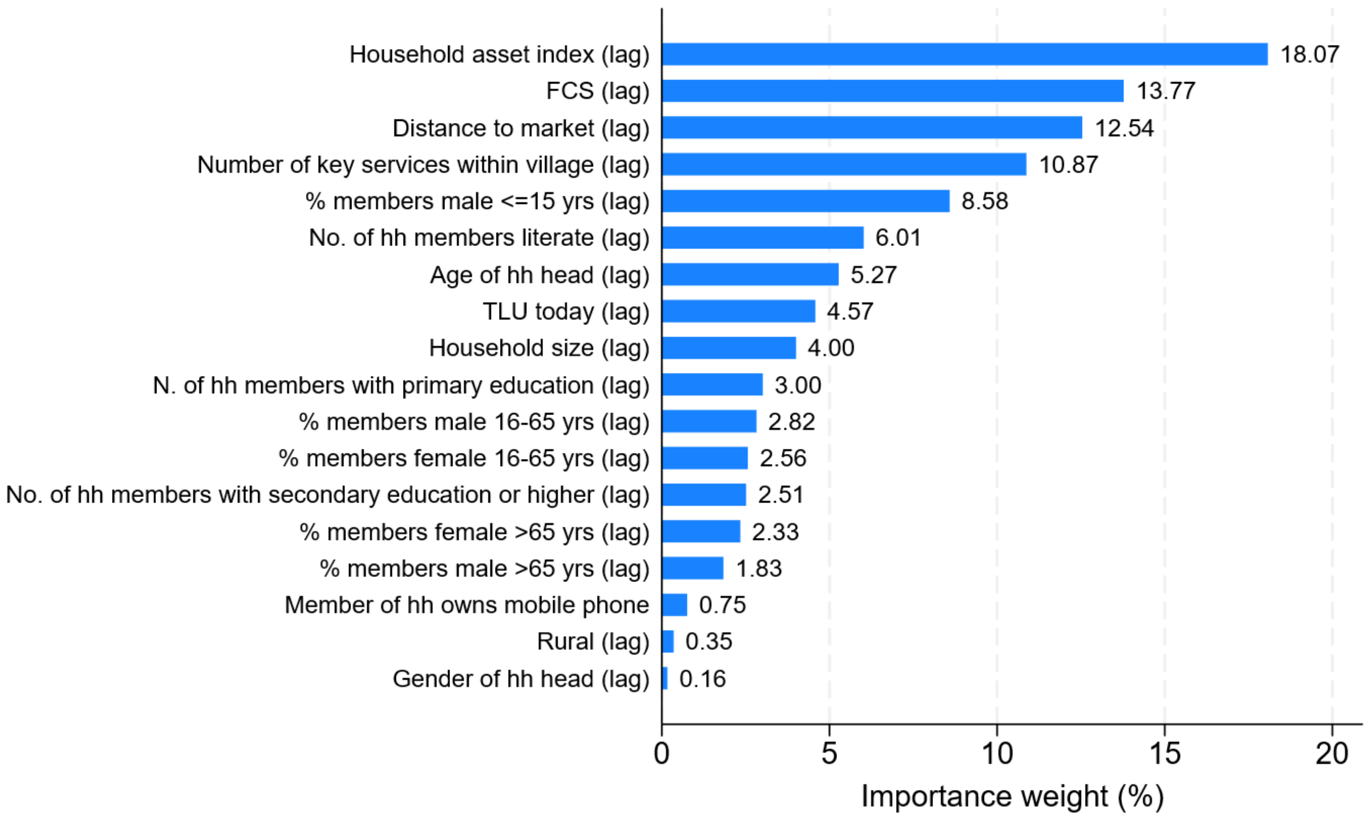
Table C.12: t-test differences between households above and below the median CLARE score (forecasting, all countries and waves)

Variable	Resilient>median (mean)	Non-resilient<median (mean)	Difference in means
Food Consumption Score (FCS)	59.932	43.460	***
Food insecurity	0.059	0.281	***
Drought (GS-EDDI)	0.174	0.183	-
Age of hh head (lag)	45.158	49.676	***
Gender of hh head (lag)	0.230	0.365	***
Household size (lag)	6.636	5.455	***
% members male <=15 yrs (lag)	0.209	0.173	***
% members male 16-65 yrs (lag)	0.752	0.771	***
% members female 16-65 yrs (lag)	0.261	0.234	***
% members male >65 yrs (lag)	0.029	0.064	***
% members female >65 yrs (lag)	0.029	0.085	***
Rural (lag)	0.633	0.860	***
No. of hh members literate (lag)	3.971	2.275	***
No. of hh members with primary education (lag)	1.227	0.581	***
No. of hh members with secondary education or higher (lag)	0.983	0.373	***
Household asset index (lag)	0.370	-0.425	***
Mobile owned (lag)	0.907	0.522	***
TLU today (lag)	1.492	0.813	***
Number of key services within village (lag)	4.132	3.852	***
Distance to market (lag)	18.859	25.485	***
	N: 28112		

Notes: This table reports mean differences in key characteristics between households classified as resilient (above the median CLARE score) and non-resilient (below the median) across all countries and waves 4 to 7. The CLARE scores refer to those from the forecasting exercise, as estimated across the full sample.

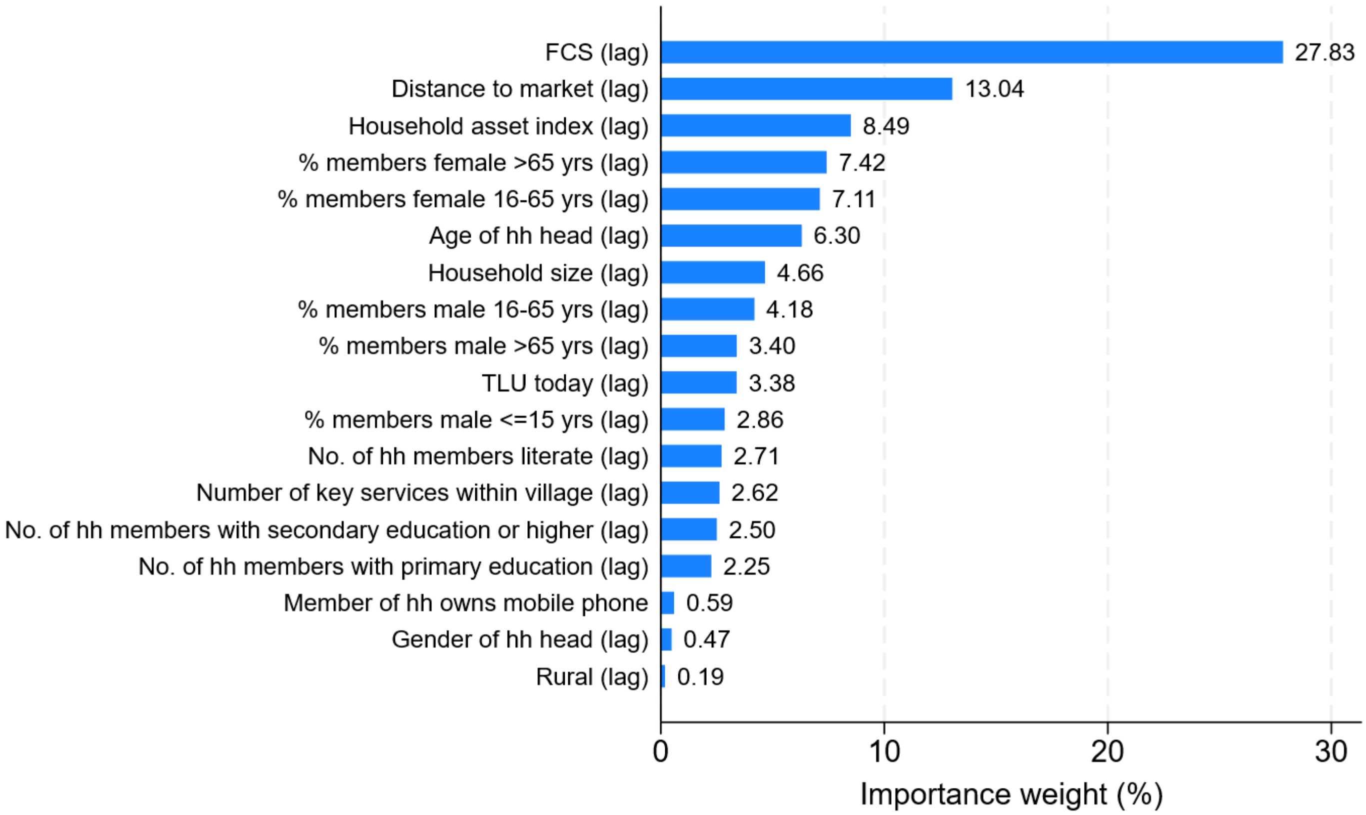
*** *p<0.01,* ** *p<0.05,* * *p<0.1.*

Figure C.1: Variable importance weights for drought-specific CLARE based on SPEI shock data (forecasting)



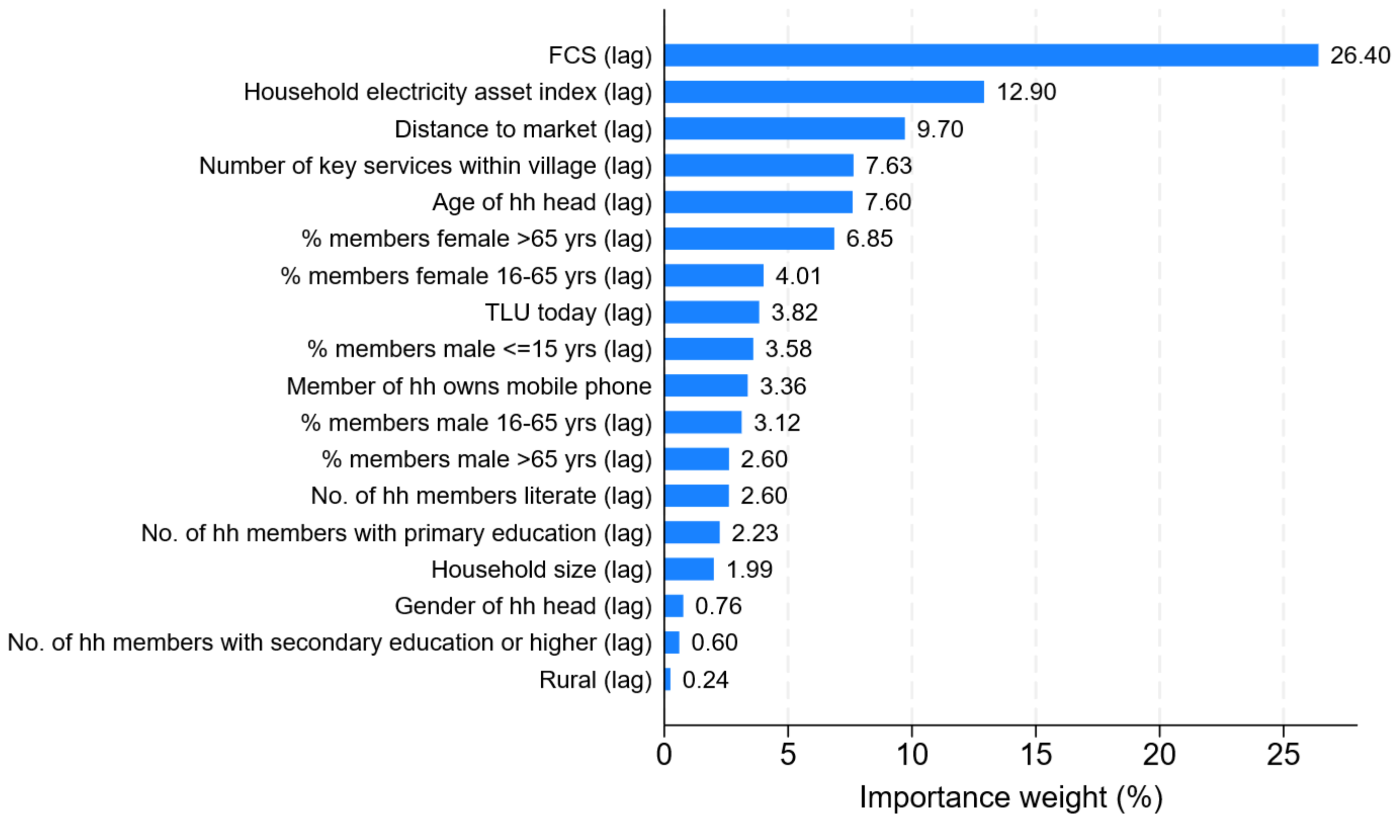
Notes: This figure displays the variable importance weights for the forecasting task, based on drought shocks constructed using the alternative SPEI weather data and estimated via causal forests. To maintain polarity without altering the correlation with the outcome, the following standardized variables have been included in the final CLARE aggregation (post-estimation) as their complements: *Age of the hh head (lag); Distance to market (lag); Gender of hh head (lag); Rural (lag); % members female >65 (lag); % members male 16-65 yrs (lag); % members male >65 (lag).*

Figure C.2: Variable importance weights for general-purpose CLARE (forecasting)



Notes: This figure displays the variable importance weights for the forecasting task, based on a general shock variable that captures exposure to multiple types of shocks, as estimated using causal forests. To maintain polarity without altering the correlation with the outcome, the following standardized variables have been included in the final CLARE aggregation (post-estimation) as their complements: *Age of the hh head (lag); Distance to market (lag); Gender of hh head (lag); Rural (lag); % members female >65 (lag); % members male 16-65 yrs (lag); % members male >65 (lag).*

Figure C.3: Variable importance weights for drought-specific CLARE with electricity asset index (forecasting)



Notes: This figure displays the variable importance weights for the forecasting task in a model that replaces the general asset index from the main specification with an electricity-specific asset index, as estimated using causal forests. To maintain polarity without altering the correlation with the outcome, the following standardized variables have been included in the final CLARE aggregation (post-estimation) as their complements: *Age of the hh head (lag); Distance to market (lag); Gender of hh head (lag); Rural (lag); % members female >65 (lag); % members male 16-65 yrs (lag); % members male >65 (lag).*