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Mapping Real-Time Child Malnutrition in India Using Machine Learning

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Introduction

- Rapid changes in the double burden of malnutrition and changes in the agricultural-food systems (AFS) threaten achieving the Sustainable Development Goals (SDG) [1] [2]
- Consequence: pace of change outdates survey data very quickly
- Study objective: demonstrate how prediction models can guide aid decision-making in AFS about suitable intervention sites in real time
- **In the absence of real time survey data, do prediction models based on machine learning (ML) map real-time child malnutrition at the district level more accurately than past household surveys?**
- **And considering a systems approach which predictors in the AFS are important in real-time mapping?**

Methods

- Systematic selection of publicly available geo-spatial predictors based on High-Level Panel of Experts on Food Security and Nutrition and derived indicators [1] [3]

68 of 113 indicators suitable for districts with available data

26 for past and real time

13 for all districts

- Model comparisons for predicting 2019-21 child malnutrition outcomes using 2015/16 data (DHS India Round V and VI):
- Benchmark: Past outcomes from survey data
- ML: 1) OLS , 2) LASSO, 3) LASSO+ OLS

Findings & Interpretation

Out-of-sample quality

	R-squared					RMSE				
	Under weight	Wasting	Any anemia	Stunting	Over weight	Under weight	Wasting	Any anemia	Stunting	Over weight
OLS	0.270	0.076	0.049	0.185	0.027	0.227	0.086	0.626	0.293	0.031
LASSO	0.343	0.025	0.139	0.303	0.127	0.088	0.113	0.187	0.085	0.028
LASSO +OLS	0.331	0.024	0.138	0.302	0.101	0.090	0.118	0.193	0.086	0.028
Past Data	0.554	0.107	0.154	0.485	0.114	0.096	0.087	0.181	0.082	0.032

For both measures the darker shadings indicate higher out-of-sample prediction quality.

Predictor importance

Link to AFS framework	Variables	Statistical significant coefficients
Bio-physical and environmental drivers	• Land use • Coefficient of variation of precipitation • Land surface temperature std. anomaly • Average EVI in day of year • Max. EVI in day of main growing season • Total change of EVI in main growing season • Average number of natural disasters per year over 10-years	1 0 0 3 3 3 4
Innovation, technology and infrastructure drivers	• Road density • Freight transport: Rail density	2 4
Political and economic drivers	• Nightlight growth (annual percent) • Number of violent events	4 1
Food Environments	• Share of paved roads of all roads • Major road density	0 0

Conclusion

- Indicator selection based on data availability and systems approach provide important predictors for child malnutrition outcomes
- ML prediction models only sometimes more accurate than past data for intervention site selection
- Even for benchmark prediction quality low

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