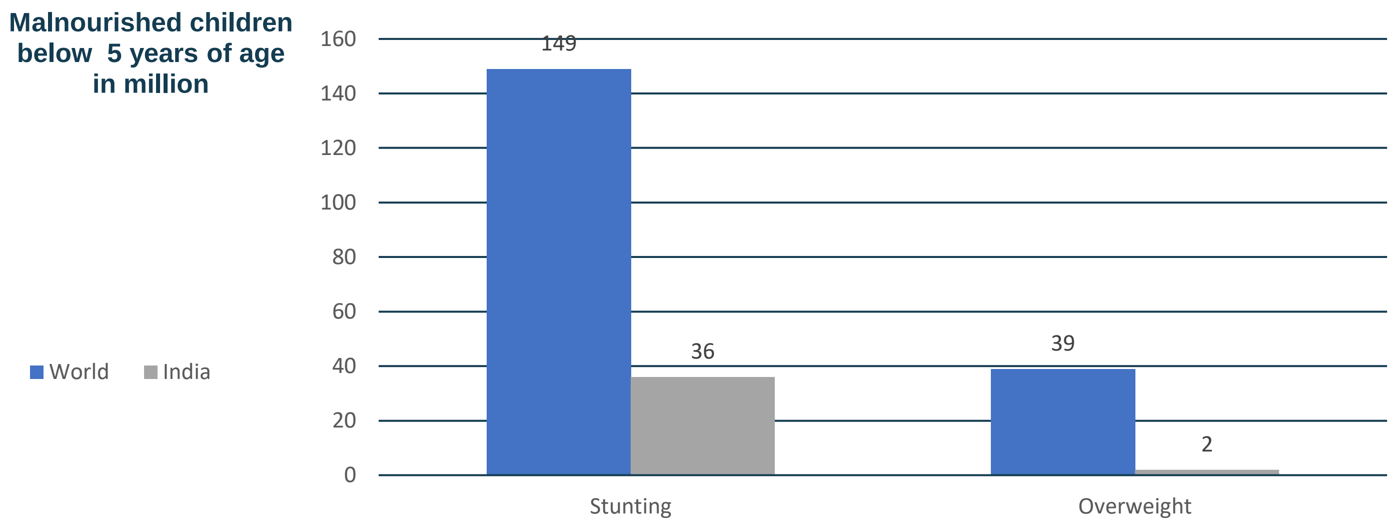
Innovative Methods and Metrics for Agriculture and Nutrition Actions

Policy Briefing Note

June 1, 2023



Source: Estimates for 2020 based on report by UNICEF et al. [1]

Machine learning maps overweight at real-time more accurately

KEY MESSAGES

- The agriculture-food system and the double burden of malnutrition change rapidly, outdating past survey data.
- Aid-decision-makers face challenges in selecting intervention sites due to inaccurate past data.
- Machinge learning models excel in mapping overweight, while past survey data perform best for micronutrient deficiencies.
- Selecting indicators based on data availability and a systems approach offers important predictors for child malnutrition outcomes.

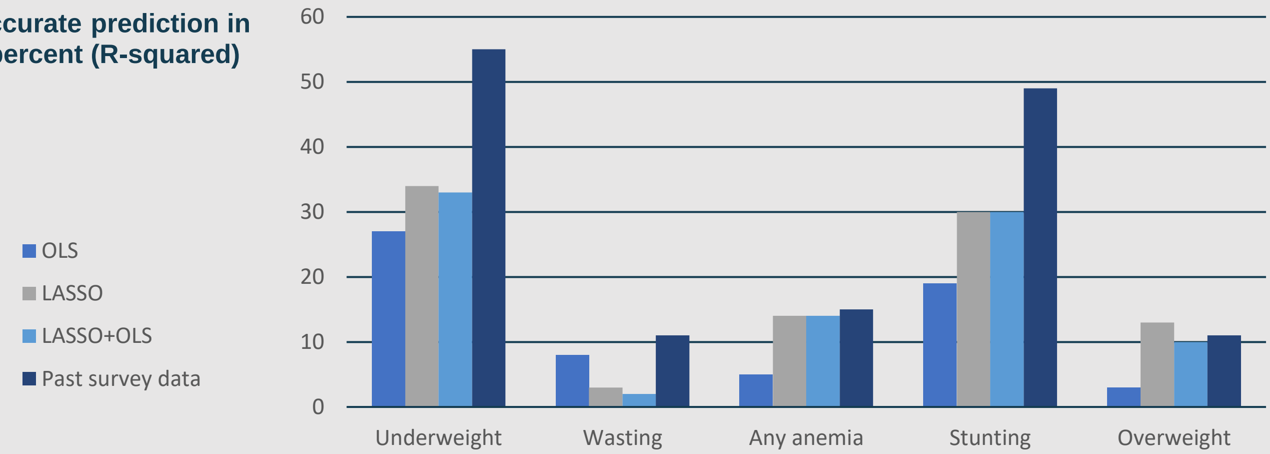
RATIONALE

In 2020, an estimated 149 million children under the age of five suffered from chronic undernourishment, while 39 million were overweight.[1] Many times, undernutrition along with overweight coexist within one household or even individual.[2] This double burden of malnutrition is particularly prevalent in low- and middle-income countries like India, making it harder to achieve the United Nations' goal of ending all forms of malnutrition.[3]

The causes of the double burden of malnutrition can be traced back to changes in the agricultural-food systems.[3] Factors like improved infrastructure and increased food availability have contributed to the problem. As the trend of increasing child weight in low- and middle-income countries accelerates in the past years, the pace of change outdates survey data very quickly.[4]

Thus, when decision-makers determine where to intervene, they might base their choices on inaccurate data. Finding accurate and real-time available information on the district level is crucial to tackling child malnutrition effectively.

Accurate prediction in percent (R-squared)



RECOMMENDATIONS

- When choosing intervention sites for child overweight, decision-makers should rely on machine learning models.
- When choosing intervention sites for child micronutirient deficiencies, decision-makers should rely on past survey data.
- When choosing intervention sites for child underweight or wasting, decision makers should assess whether greater predictive precision of machine learning models compared to past survey outweighs costs.
- More data should be made available for free, easily-accessible and at real-time to inform decision-makers with real-time predictions.

METHODS AND FINDINGS

This study demonstrates the applicability of prediction models at real time to inform decision-making for intervention sites. Interpretable and easily transferable machine learning models, based on indicators from an internationally acknowledged agricultural-food-systems framework, accurately map child malnutrition outcomes at the district level. The machine learning models excel in predicting overweight, while past survey data performs better for micronutrient deficiencies. The findings are mixed for underweight and wasting. Three predictors from the agricultural-food-systems framework gain particular importance in real-time mapping: frequency of natural disasters, growth rate in nightlight, and rail density reflecting freight transport.

Malnutrition outcomes and predictors for machine learning

To predict malnutrition at real time, I measure the outcomes of interest as the percentage of malnourished children below five years of age in a district using data from the last two rounds of the Demographic and Health Survey (DHS) in India 2015-16 and 2019-21. I consider following malnutrition outcomes: underweight, wasted, iron-deficient anemic, stunted, and overweight.

To derive predictors, I used the conceptional framework of the High-Level Panel of Experts on Food Security and Nutrition as a base.[2] Out of the 113 suggested indicators at the country level only 13 are available for free and at real-time for all 707 Indian districts.[5]

These predictors feed into the three prediction models: ordinary least squares (OLS) regression, the least absolute shrinkage and selection operator (LASSO), and LASSO+OLS where LASSO selects the predictors before OLS creates the estimates. I compare the out-of-sample prediction performance of these models to the past survey data using the measures R-squared and root mean squared error.

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Important predictors and comparison of prediction quality

Three of 13 predictors (frequency of natural disasters, growth rate in nightlight, and rail density reflecting freight transport) show statistical significance for four child malnutrition outcomes.

The LASSO model performs best for prediciting overweigt, while past survey data supersedes all models for micronutrient deficiencies. For underweight and wasting the past survey approach can predict a larger share correctly but the root mean squared error is worse than at least on machine learning model.

Overall, the prediction quality for malnutrition outcomes remains relatively low in all models (not more than 55.4%) – a common finding.[6] When selecting intervention sites based on overweight, the LASSO model is the preferred choice. For other malnutrition outcomes decision-makers have to explore whether greater predictive precision outweighs resource and time constraints.

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CITATION

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