Mapping Wealth Index at 1 km Resolution in Low- and Middle-Income Countries from 2012 to 2024 Using Multi-Source Data

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SUMMARY

Ending poverty in all its forms everywhere is the first United Nations Sustainable Development Goal (SDG 1) for 2030. Poverty reduction has been a critical mission globally, particularly in low- and middle-income countries (LMICs). The absence of a pixel-scale time-series poverty dataset has impeded evidence-based policy formulation. Moreover, most studies on the impacts of geographical features, environmental factors, and climate change on poverty distribution are case-specific, lacking large-scale and long-term holistic analyses. To address these gaps, we estimate poverty distribution in global LMICs using multi-source data and analyzed their respective influences. Specificly, the International Wealth Index (IWI), derived from household survey data of the Demographic and Health Survey (DHS) Program, served as the dependent variable for the poverty estimation model. Samples were collected from 108 surveys across 47 countries during 2012–2024, with a total sample size of ~110,000. 56 indicators covering geographical features (urban-rural location, accessibility, elevation, slope, etc.), economic metrics (GDP, population, investment, etc.), environmental indicators (vegetation, soil, radiation, evapotranspiration, etc.), and climate variables (temperature, precipitation, extreme climate events, etc.) were selected to construct a Random Forest-based IWI estimation model. LASSO and Boruta methods were applied for feature selection, and inter-annual calibration was performed to enhance estimation accuracy. Results show that the test accuracy of country-specific models ranges from 0.58 to 0.93 (87% of countries >0.6; 47% >0.7), regional models from 0.73 to 0.89, and the global model reaches 0.86. Geographical location, environmental indicators, and climate variables exert heterogeneous impacts on IWI across countries; urban-rural location, slope, evapotranspiration, and temperature are the most influential factors overall. Finally, this study generates a 1 km resolution grid-scale IWI distribution dataset for global LMICs (2012–2024). In conclusion, this study provides data support for analyzing the spatiotemporal trends of global poverty and the impacts of various factors on poverty. It can assists countries in better understanding the current poverty situation, formulating poverty alleviation policies, and further advancing the achievement of SDG 1.