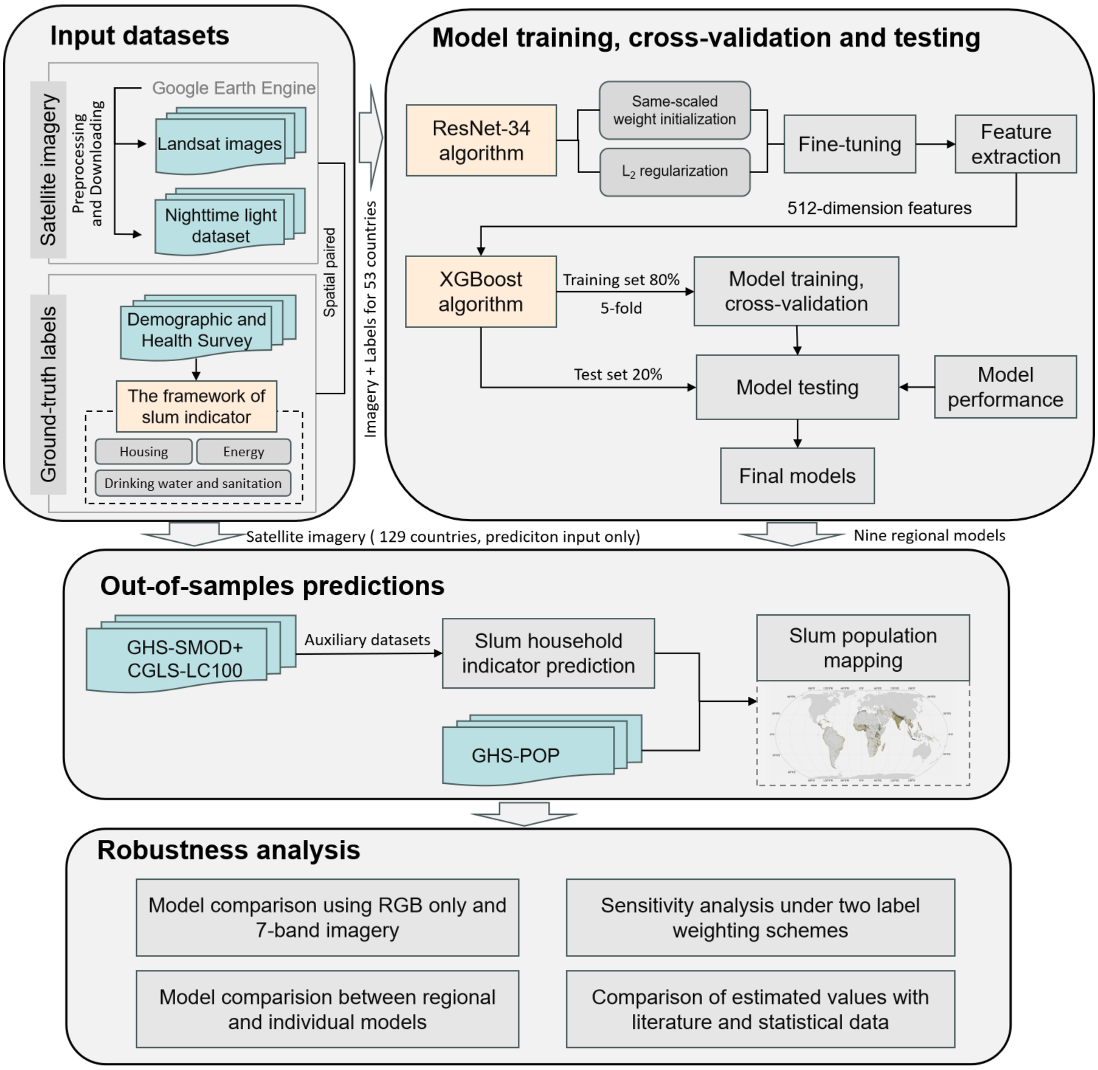

Figure 1 Workflow of this study. Blue backgrounds represent datasets, yellow backgrounds indicate the indicator framework or model architecture, and gray backgrounds denote specific processes or procedural steps.

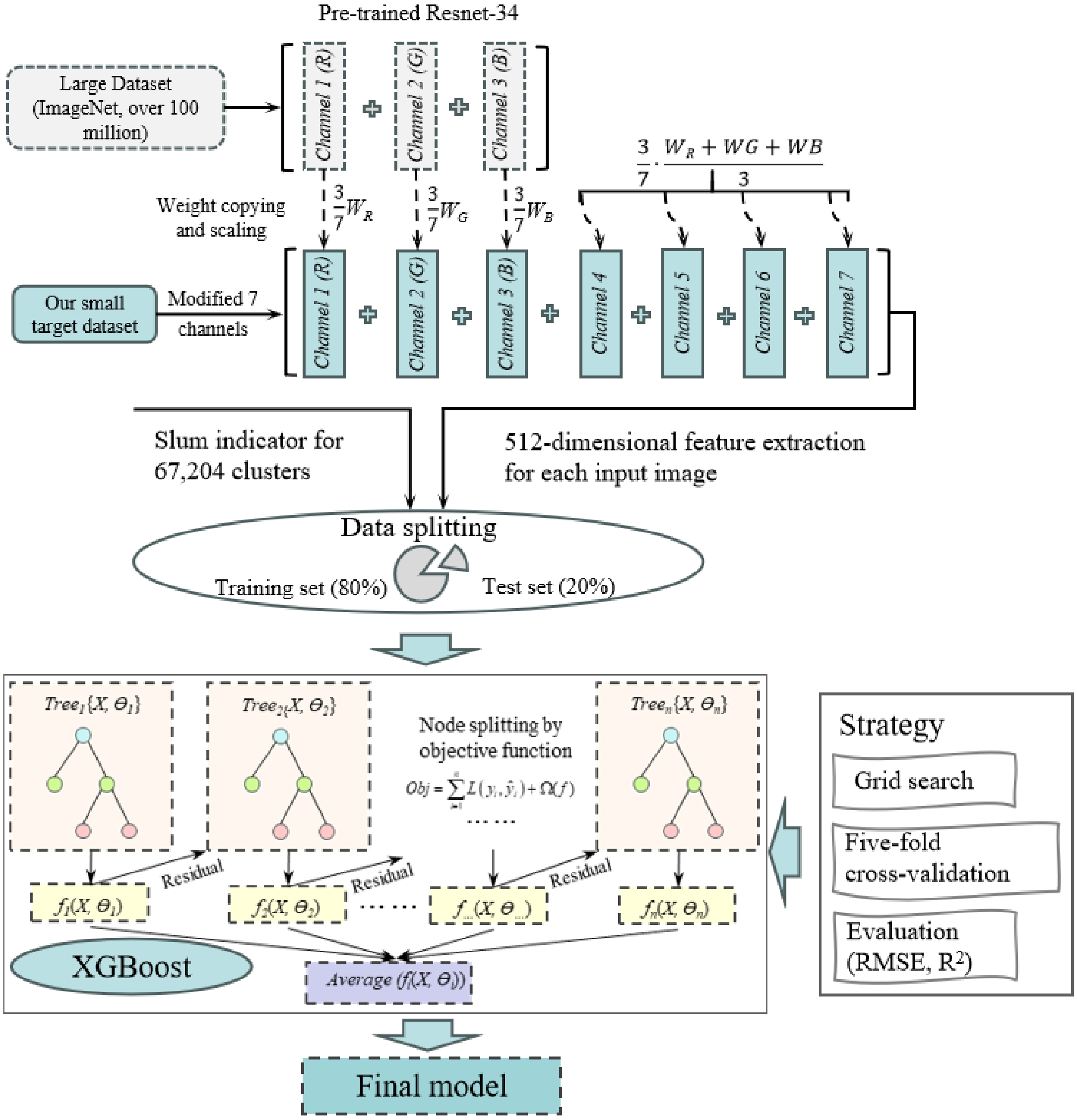

Figure 2 Schematic of the proposed model architecture. It integrates transfer learning by fine-tuning ResNet-34 to extract high-dimensional spatial–spectral features from multispectral imagery, followed by XGBoost regression for predictive modeling.

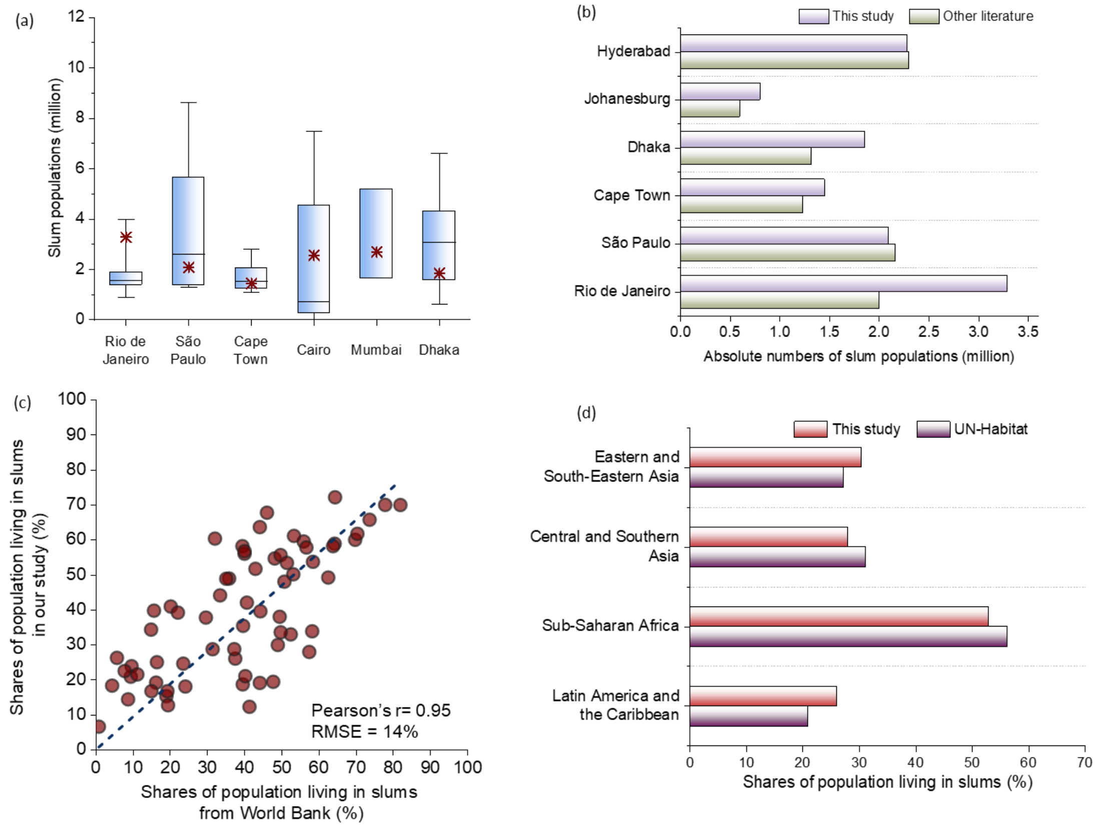

Figure 7 Comparison of our slum population estimates with data from previous literature and official statistics, presented as both absolute numbers and relative shares. (a) Comparison with scaled-up values from previous studies for six cities: Rio de Janeiro (n=9), São Paulo (n=5), Cape Town (n=12), Cairo (n=6), Mumbai (n=3), and Dhaka (n=11). Scaled-up values are derived by extrapolating slum population counts from multiple sampled slums to the city level. Asterisks indicate estimates from this study. Box plots display the median (central line), interquartile range (box), and minimum-maximum range (whiskers). (b) Comparison with official city-level statistics for the same six cities. (c) Comparison of country-level slum population shares between our estimates and World Bank data; each dot represents a Global South country. (d) Comparison of regional-level slum population shares between our estimates and UN-Habitat data.

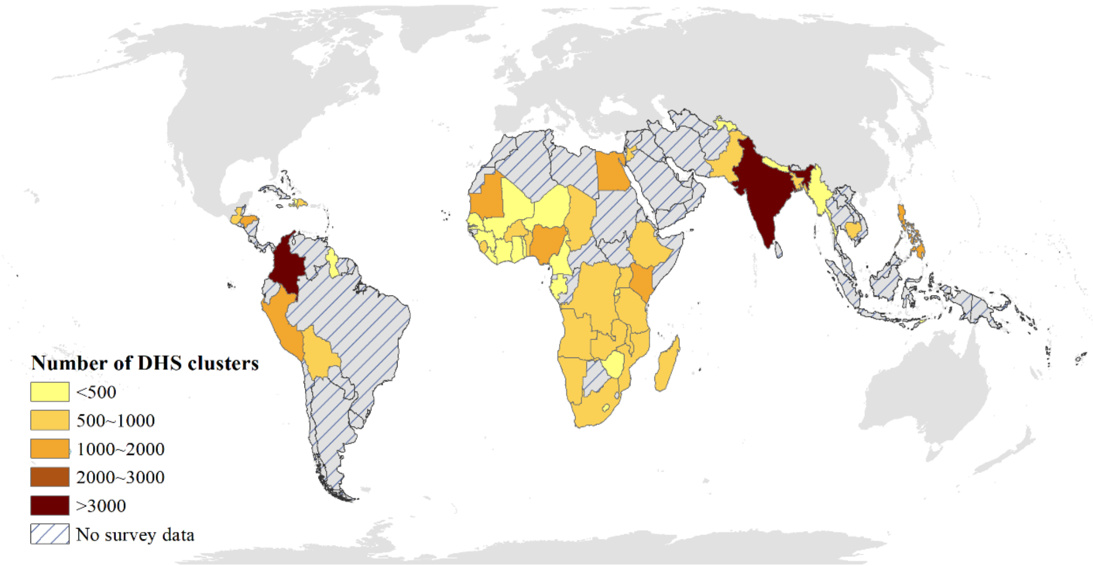

Figure S1 Number of clusters from Demographic and Health Surveys in 53 Global South countries. The highest legend category (>3,000 clusters) includes only Colombia (n = 4,868) and India (n = 30,170).