Welfare estimations from imagery: A test of domain experts' ability to rate poverty from visual inspection of satellite imagery

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Abstract

Background : Rapidly and yet accurately estimating welfare levels at different spatial scales is critical to ensuring that no region is left behind in the quest for poverty reduction and eradication. Useful as the traditional workhorse of household surveys are, they are expensive to implement and often have time lags between them. Recent advances in remote sensing (mainly satellite imagery) and Artificial Intelligence (in the fields of machine learning, deep learning, and transfer learning) have led to increased accuracies in poverty and welfare estimation. These systems are, however, largely opaque in terms of explaining how these impressive results are achieved. To achieve explainable AI, domain knowledge of poverty features become essential and this requires collaboration between humans and machines. Methods : The present study uses domain experts to estimate welfare levels and indicators from high-resolution satellite imagery. We use the wealth quintiles from the 2015 Tanzania DHS dataset as ground truth data. We analyse the performance of the visual estimation of relative wealth at the cluster level and compare these with wealth rankings from the DHS survey of 2015 for that country using correlations, ordinal regressions and multinomial logistic regressions. Findings : Of the 608 clusters, 115 (19%) received the same ratings from human experts and the independent DHS rankings. For 59% of the clusters, experts' ratings were slightly lower (Md = 2.50, n = 358) than DHS rankings (Md = 3.00, n = 135), z = -11.32, p = <0.001, with a moderate effect size, r = -0.32. On the one hand, significant positive predictors of wealth are the presence of modern roofs and wider roads. For instance, the log odds of receiving a rating in a higher quintile on the wealth rankings is 0.917 points higher on average for clusters with buildings with slate or tile roofing compared to those without. On the other hand, significant negative predictors included poor road coverage, low to medium greenery coverage, and low to medium building density. Other key predictors from the multinomial regression model include settlement structure and farm sizes. Significance : These findings are significant to the extent that these correlates of wealth and poverty are visually readable from satellite imagery and can be used to train machine learning models in poverty predictions. Using these features for training will contribute to more transparent ML models and, consequently, explainable AI.

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