Mapping poverty using mobile phone and satellite data

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Abstract
Poverty is one of the most important determinants of adverse health outcomes globally, a major cause of societal instability, and one of the largest causes of lost human potential. Traditional approaches to measuring and targeting poverty rely heavily on census data, which in most low and middle-income countries (LMICs) are unavailable or out-of-date. Alternate measures are needed to compliment and update estimates between censuses. This study demonstrates how public and private data sources that are commonly available for LMICs can be used to provide novel insight into the spatial distribution of poverty. We evaluate the relative value of modelling three traditional poverty measures using aggregate data from mobile operators and widely available geospatial data. Taken together, models combining these data sources provide the best predictive power (highest r2=0.78) and lowest error, but generally models employing mobile data only yield comparable results, offering the potential to measure poverty more frequently and at finer granularity. Stratifying models into urban and rural areas highlights the advantage of utilising mobile data in urban areas and different data in different contexts. The findings indicate the possibility to estimate and continually monitor poverty rates at high spatial resolution in countries with limited capacity to support traditional methods of data collection.

1.0 Background

In 2015, approximately 700 million people lived in extreme poverty[1]. Poverty is a major determinant of adverse health outcomes including child mortality[2], and contributes to population growth[3], societal instability and conflict[4]. Eradicating poverty in all its forms remains a major challenge and the first target of the Sustainable Development Goals (SDGs)[5]. To eradicate poverty, it is crucial that information is available on where affected people live. Such data improve the understanding of causes of poverty, enable improved allocation of resources for poverty alleviation programs, and are a critical component for monitoring poverty rates over time. The latter issue is especially pertinent for efforts aimed at reaching the SDGs, which need to be monitored at national and subnational levels over the coming 15 years[5].

The definition of poverty and the measurement methods used to identify poor persons are part of a longstanding discussion in development economics[6–9]. Different approaches exist to calculate indicators of living standard, including the construction of unidimensional and multidimensional indices, as well as the use of monetary or non-monetary metrics. A further discussion for living standard indices regards the methods used to set appropriate thresholds (poverty lines) under which a person is defined as poor[10–12]. Monetary based metrics identify poverty as a shortfall in consumption (or income) and measure whether households or individuals fall above or below a defined poverty line[13,14]. In contrast, asset-based indicators define household welfare based on asset ownership (e.g. refrigerator, radio, or bicycle), dwelling characteristics, and access to basic services like clean water and electricity[15]. Moreover, poverty indicators can capture the status of a household or individual at a given point in time, or identify chronic versus transient poverty over time[14,16–18].

Every approach used to calculate indicators of living standards for a population has its advantages and disadvantages, and each indicator discerns different characteristics of the population. Consumption data can be highly noisy due to recall error or because expenditures occurred outside the period captured in surveys, but provide a better shorter-term concept of poverty [19,20]. Asset-based measures have been regarded as a better proxy for the long-term status of households as they are thought to be more representative of permanent income or long-term control of resources[20–22]. The same population can be ranked quite differently along a poverty distribution when comparing consumption and asset-based measures and many assumptions are necessarily accepted in order do such comparisons. These include assumptions that the data represent the same populations in the same time period; that the indicators are well matched in their wording and response options; and that the poverty measures have a similar distribution of responses[20,23]. Further, it is difficult to compare asset-based measures to income or consumption as it is not straightforward to link the productive potential of a household to their assets owned; this can be particularly relevant in rural areas where the return on physical assets can be strongly environmentally related and interactions among assets may be important[24]. These factors necessitate a flexible approach to modelling poverty as indicators representing asset-based, consumption-based, and income-based measures are not necessarily expected to produce similar results.

While numerous high-resolution indicators of human welfare are routinely collected for populations in high-income countries, the geographic distribution of poverty in LMICs is often uncertain[25]. Small area estimation (SAE) forms the standard approach to produce sub-national estimates of the proportion of households in poverty. SAE uses statistical techniques to estimate parameters for sub-populations by combining household survey and census data to utilise the detail in household surveys and the coverage of the census. Common variables between the two are used to predict a poverty metric across the population[26–28]. These techniques rely on the availability of census data, which are typically collected every ten years and often released with a delay of one or more years, making the updating of poverty estimates challenging. Recently, there are promising signs that novel sources of high-resolution data can provide an accurate and up-to-date indication of living conditions. In particular, recent work illustrates the potential of features derived from remote sensing and Geographic Information System data[29–35] (hereafter called RS data) and mobile operator call detail records (CDRs)[36–39]. However, the predictive power in integrating these two data sources, and their ability to estimate different measures of poverty has not been evaluated.

RS and CDR data capture distinct and complimentary correlates of human living conditions and behaviour. For example, RS data of physical properties, such as rainfall, temperature, and vegetation capture information related to agricultural productivity, while distance to roads and cities reflects access to markets and information. Similarly, monthly credit consumption on mobile phones and the proportion of people in an area using mobile phones indicate household access to financial resources, while movements of mobile phones and the structure and geographic reach of the calling networks of individuals may be correlated with remittance flows and economic opportunities[39–41].

RS and CDR data are generated at different spatial scales, which further complement each other. The CDR indicators used in this study are derived from data aggregated at the level of the physical cell towers to preserve the privacy of individual subscribers. Thus the spatial resolution of these data is determined by tower coverage, which is larger in rural areas and fine-scaled in urban areas. By contrast, RS data can be relatively coarse in urban areas and only capture physical properties of the land. As RS and CDR data are continually collected, the ability to produce accurate maps using these data types offers the promise of ongoing subnational monitoring required by the SDGs.

Here, we use overlapping sources of RS, CDR, and traditional survey-based data from Bangladesh to provide the first systematic evaluation of the extent to which different sources of input data can accurately estimate three different measures of poverty. To date, the predictive power in integrating these data sources, and their ability to estimate different measures of poverty, has not been evaluated. We use hierarchical Bayesian geostatistical models (BGMs) to construct highly granular maps of poverty for three commonly used indicators of living standards: the Demographic and Health Surveys (DHS) Wealth Index; an indicator of household expenditures (Progress out of Poverty Index, PPI)[42]; and reported household monetary income. We additionally compare our results with previous poverty estimates for Bangladesh at coarser and finer resolutions.

2.0 Materials and methods

2.1 Spatial scale and data processing

All data used in this study were processed to ensure that projections, resolutions, and extents matched. The spatial scale of analysis was based on approximating the mobile tower coverage areas using Voronoi tessellation[43] and models were built on the scale of the Voronoi polygons (figure 1). This allowed us to maintain the fine spatial detail in mobile phone data within urban areas, as Voronoi polygon size, and corresponding spatial detail, varies greatly from urban to rural areas (minimum 60m, maximum 5km) as shown in the figure. All datasets were then summarised to spatially align with these polygons. In practice, each polygon was assigned RS and CDR values representing the mean, sum, or mode of the corresponding data. The survey data are matched to the Voronois based on the GPS located lat/long of PPI data, the lat/long representing the centroid of each DHS cluster, and the home tower of each income survey respondent. Where multiple points from the same output (WI, PPI, income) fell within the same polygon, we used the mean aggregated value.

2.2 Poverty data

We utilised three geographically referenced datasets representing asset, consumption, and income-based measures of wellbeing in Bangladesh (see the electronic supplementary material, figure S1 and section A.1). These data were obtained from three sources: the 2011 Bangladesh DHS; the 2014 FII survey[44] with data collected on the PPI (www.progressoutofpoverty.org); and national household surveys conducted by Telenor Group subsidiary Grameenphone (GP) between November 2013 and March 2014 collecting household income data.

The DHS wealth index (WI) is constructed by taking the first principal component of a basket of household assets and housing characteristics such as floor type and ceiling material, which explains the largest percentage of the total variance, adjusting for differences in urban and rural strata[45]. A final composite combined score is then used as a wealth index whereby each household is assigned its correspondent quintile in the distribution and each individual belonging to the same household shares the same WI score. A higher score implies higher socioeconomic status (range= -1.45-3.5). Here we used aggregated average WI scores per primary sampling unit (PSU) for 600 PSUs (207 in urban areas and 393 in rural areas) to estimate the mean WI of sampled populations residing in each Voronoi polygon.

The PPI is a measurement tool built from the answers to 10 questions about a household's characteristics and asset ownership, scored to compute the likelihood the household is living above or below a poverty line. In Bangladesh, these poverty scorecard questions were determined using data from the 2010 Household Income and Expenditure Survey (HIES)[42,46], and used in a nationally representative survey of 6,000 Bangladeshi adults undertaken in 2014[44]. Together with basic demographics and access to financial services information, the 10 questions needed to construct the PPI were collected. These data were used to assign a poverty measure to each individual interviewed: the likelihood they have per-capita expenditure above or below a poverty line. Here we estimate the mean likelihood (range=12.3-99.7%) of populations residing in each Voronoi polygon to be below the $2.50 a day poverty line.

Income data were obtained from two independent, sequential household surveys run by GP. For each survey, face-to-face interviews were conducted with 90,000 individuals, and their corresponding household income was collected, together with basic demographic information for each survey participant (e.g., gender, age, profession, education) and phone usage. Information about income was directly asked to respondents, who were requested to place themselves within pre-set income bins. Among GP subscribers, CDRs were successfully linked to phone numbers for 76,000 participants. Here we converted income bins to USD (range=0-1285$) and modelled the average USD for each Voronoi polygon.

2.3 CDR and RS data

CDR features were generated from 4 months of mobile phone metadata collected between November 2013 and March 2014. GP subscribers consented to the use of their data for the analysis. GP, the largest mobile network operator in Bangladesh, had 48 million customers at the time of the analysis, with a network covering 99% of the population and 90% of the land area[47]. CDR features range from metrics such as basic phone usage, top-up patterns, and social network to metrics of user mobility and handset usage. These features are easily made available in data warehouses and do not rely on complex algorithms. They include various parameters of the corresponding distributions such as weekly or monthly median, mean and variance (see the electronic supplementary material).

We further identified, assembled, and processed twenty-five raster and vector datasets into a set of RS covariates for the whole of Bangladesh at a 1-km spatial resolution These data were obtained from existing sources and produced ad hoc for this study to include environmental and physical metrics likely to be associated with human welfare[31,33,48–50] such as vegetation indices, nighttime lights, climatic conditions, and distance to roads or major urban areas. A full summary of assembled covariates is provided in the supplementary material.

2.4 Covariate selection

Prior to statistical analyses, all CDR and RS covariate data were log transformed for normality. Bivariate Pearson's correlations were computed for each pair of covariates to assess multicollinearity, and for high correlations ($r > .70$), we eliminated covariates that were less generalizable outside Bangladesh. For example, population data are widely available (e.g. www.worldpop.org.uk/) but births data may not be; similarly, volumes of calls could be computed and compared across countries, but charges may be country-specific.

In order to identify the set of predictors most suitable for modelling the WI, PPI, and income data, we employed a model selection stage as is common in statistical modelling[51]. For this we used non-spatial generalised linear models (glms), implemented via the R *glmulti* package[52,53], to build every possible non-redundant model for every combination of covariates. Models were built on a randomly selected 80% of the data to guard against overfitting. Models were chosen using Akaike's information criterion (AIC), which ranks models based on goodness of fit and complexity, while penalizing deviance[52]. A full IC-based approach such as this allows for multi-model inference. Where multiple glms had near-identical AIC values, we selected the model with the fewest number of covariates. For the CDR data only, we used forward and backward stepwise selection ($p=0.05$) prior to model selection to reduce the initial CDR inputs from 150 to 30 or less. The covariate selection process was completed for all three poverty measures for national, urban, and rural strata, and using RS-only, CDR-only, and CDR-RS datasets (27 resulting models). This allowed us to explore differences in factors related to urban and rural poverty, as well as to explicitly compare the ability of RS-only, CDR-only, and CDR-RS datasets to predict poverty measures. The resulting models were then used in the hierarchical Bayesian geostatistical approach (see supplementary information, tables S2A-C).

2.5 Prediction mapping

Using the models selected by the previous step, we employed hierarchical Bayesian geostatistical models (BGMs) to predict the three poverty metrics at unsampled locations across the population. We chose BGMs as they offer several advantages for addressing the limitations and constraints associated with modelling geolocated survey data. These include straightforwardly imputing missing data, allowing for the specification of prior distributions in model parameters and spatial covariance, and estimating uncertainty in the predictions as a distribution around each estimate[54,55].

Additionally, we needed to account for spatial autocorrelation in the data as they are aligned to the tower locations, which are clustered across varying spatial scales (described in **2.1** and fig. 1). BGMs can achieve this through incorporating a spatially varying random effect. Here, the Voronoi polygons themselves form the neighbourhood structure for this spatial random effect, and neighbours are defined within a scaled precision matrix[56]. The matrix represents the spatially explicit processes that may affect poverty estimates. It is passed through a graph function in the model which assumes the neighbour relations are connected[57], that is all adjacent polygons share a boundary. This function accounts for the spatial covariance in the data by allowing observations to have decreasing effects on predictions that are further away.

Here, all BGMs were implemented using integrated nested Laplace approximations (INLA)[58], which uses an approximation for inference and avoids the computational demands, convergence issues, and mixing problems sometimes encountered by MCMC algorithms[59]. The model is fit using R-INLA, with the Besag model for spatial effects specified inside the function[60,61]. In the Besag model, Gaussian Markov random fields (GMRFs) are used as priors to model spatial dependency structures and unobserved effects. GMRFs penalize local deviation from a constant level based on the precision parameter τ where the hyperpriors are loggamma distributed[56]. The hyperprior distribution governs the smoothness of the field used to estimate spatial autocorrelation[56]. The spatial random vector $\mathbf{x} = (x_1, \ldots, x_n)$ is thus defined as

$$x_i | x_i, i \neq j, \tau \sim \mathcal{N}\left(\frac{1}{n_i}\sum_{i\sim j} x_j, \frac{1}{n_i \tau}\right)$$

where n_i is the number of neighbours of node i, $i \sim j$ indicates that the two nodes i and j are neighbours. The precision parameter τ is represented as

$$\theta_1 = \log \tau$$

where the prior is defined on θ_1[60]. The geostatistical models defined for the WI, PPI, and income data were applied to produce predictions of the each poverty metric for each Voronoi polygon as a posterior distribution with complete modelled uncertainty around estimates. The posterior mean and standard deviation for each polygon were then used to generate prediction maps with associated uncertainty (fig. 2 and figures S2-S6 in the supplementary material). Model performance was based on out-of-sample validation statistics calculated on a 20% test subset of data. Pearson product-moment correlation coefficient (r) (or Spearman's rho (ρ) for n<100), root-mean-square-error (RMSE), mean absolute error (MAE), and the coefficient of determination (r^2) were calculated for all BGMs. Finally, because glms do not incorporate prior information for model parameters, we ran each model through INLA while excluding the random spatial effect to obtain non-spatial Bayesian estimates and compare model fit and performance due to the explicit spatial process.

3.0 Results

We find models employing a combination of CDR and RS data generally provide an advantage over models based on either data source alone. However, RS-only and some CDR-only models performed nearly as well (table 1). While the combined CDR-RS model performed well in both urban (r^2=0.78) and rural (r^2=0.66) areas, and at the national level (r^2=0.76), the performance of RS-only and CDR-only models were more context-dependent. For example, PPI and income models did not improve predictions in urban areas, but in rural areas the RS-only models performed nearly as well for both indicators. The fine spatial granularity of the resultant poverty estimates can be seen in figure 2, which shows the predicted distribution of poverty for all three measures. Spatially, the models exhibit higher uncertainty where fewer data are available, such as the peninsular areas surrounding Chittagong in the southeast where mobile towers are sparse. We also find that explicitly modelling the spatial covariance in the data was critically important. This resulted in improved measures of fit and lower error for all CDR-RS and CDR-only models based on the deviance information criteria (DIC), a hierarchical modelling generalisation of the AIC[62] (electronic supplementary material, table S3).

Separating estimation by urban and rural regions further highlights the importance of different data in different contexts (electronic supplementary material, tables S2 *A*-*C*). Nighttime lights, transport time to the closest urban settlement, and elevation were important nationally and in rural models; climate variables were also important in rural areas. Distance to roads and waterways were significant in urban and rural strata. In general, the addition of CDR data did not change the selection of RS covariates at any level. Top-up features derived from recharge amounts and tower averages were significant in every model, affirming their importance in poverty work. People predicted to be poorer top up their phones more frequently in small amounts. Percent nocturnal calls, and count and duration of SMS traffic were significant nationally. Mobility and social network features were important in all three strata. In urban areas, SMS traffic was important, whereas multimedia messaging and video attributes were key in rural areas.

Models were most successful at reconstructing the wealth index (WI) to model poverty (r^2=0.76); consumption-based and income-based poverty proved more elusive. WI models have better fit, lower error, and higher explained variance based on out-of-sample validation (fig. 3). Combined CDR-RS data produced the best WI models and lowest error ($r^{2\ (CDR\text{-}RS)}$=0.76, $r^{2\ (RS)}$=0.74, $r^{2\ (CDR)}$=0.64; RMSE $^{(CDR\text{-}RS)}$=0.394, RMSE $^{(RS)}$=0.413, RMSE $^{(CDR)}$= 0.483). However, for the PPI models, the best model predicting the probability of falling below $2.50/day was the RS-only model (fig. 2*B* and *E*, $r^{2\ (RS)}$=0.32; RMSE $^{(RS)}$=57.439). The model discerns many urban areas but also predicts areas with very low poverty likelihood and high uncertainty outside urban areas, especially around Sylhet in the northeast. Income predictions (fig. 2*C* and *F*) show greater variation across the country, and the best national model was for combined CDR-RS data ($r^{2\ (CDR\text{-}RS)}$=0.27, RMSE $^{(CDR\text{-}RS)}$=105.465).

The resulting predictions line up well with existing SAE estimates for Bangladesh, and with high resolution maps of slum areas in Dhaka. The urban CDR-RS model has the highest explained variance for any model ($r^{2\ (CDR\text{-}RS\_urb)}$=0.78) and the urban CDR-only model outperforms the national CDR-only model ($r^{2\ (CDR\_urb)}$=0.70). Precision and accuracy are slightly lower, but the improved correlation highlights the advantage of utilizing CDRs within a diverse urban population. To explore this further we compared our WI predictions against a spatially explicit dataset of slum areas in Dhaka[63] (fig. 4). We find the mean predicted WI of slum and non-slum areas to be significantly different, t (615) = -17.2, $p<.001$, predicting slum areas to be poorer than non-slum areas.

To compare our method to previous poverty estimates at administrative level three (upazila), we used the same methodology at the lower spatial resolution, utilising the upazila boundaries to form the random spatial effect in the model, and covariates from the best national level model for each poverty measure. We find strong correlations (r=-0.91 and -0.86 for the WI; 0.99 and 0.97 for the PPI; and -0.96 and -0.94 for income, respectively, $p<.001$ for all models) between our upazila predictions and earlier estimates of poverty derived from SAE techniques based on data from the 2010 Household Income and Expenditure(HIES) survey and 2011 census[64] (fig. 5). The r values reported for WI and income are negative at administrative level 3 because as the proportion of people below the poverty line as estimated by Ahmed et al. decreases, the WI value and income in USD of the sampled population increases. That is, people who are wealthier as estimated by the WI and income data are also less likely to live below the poverty line according to earlier estimates. The geostatistical method presented here thus accurately maps heterogeneities at small spatial scales while correlating well with earlier coarser estimates. All remaining WI, PPI, and income prediction maps are provided in the supplementary material.

4.0 Discussion

This work represents the first attempt to build predictive maps of poverty using a combination of CDR and RS data. The results demonstrate that CDR-only and RS-only models perform comparably in their ability to map poverty indicators, and that integrating these data sources provides improvement in predictive power and lower error. These results are promising as the CDR data here produce accurate, high-resolution estimates in urban areas not possible using RS data alone. As such, CDRs potentially allow for estimation of wealth at much finer granularity – including the neighbourhood or even the household or individual – than the current generation of RS technologies[36]. While CDRs are proprietary data, they are increasingly used in research, and have formed the basis for hundreds of published articles over the past few years[65]. They also provide significant advantages in temporal granularity: CDRs update in real-time versus RS data, which update far less frequently. Although in this study we have not utilised dynamic validation data, it is a clear future application for CDRs in real-time to better comprehend the dynamic nature of poverty.

The higher accuracy of predictions for the asset-based WI over other poverty metrics is presumably due to several factors. The predictive power for assets has been shown to be higher than for consumption[35] in addition to the aforementioned issues of survey question wording and response options[20,23]. Further, income and consumption can vary hugely by day, week, and can be related to changes in household size, job loss or gain, piecework, or harvest outcomes. Assets and housing characteristics are generally considered more stable[20–22]. For the datasets used in this study, WI data are based on clusters of households, and this sampling strategy provides more robust estimates and less variability than the individually based PPI and income data. Greater success in predicting the WI is also presumably due to the WI measuring a wider range of living standard across the population. That is, the full range of distribution from poorest to wealthiest in the population is represented in these data. Alternatively, by considering a streamlined 10 questions, the PPI is meant to identify the poorest individuals in a population. Similarly, in the income data, there were very few respondents in higher income categories.

The higher error associated with CDR-only models is not surprising considering the noise inherent in these data. CDR features are derived from daily and weekly measurements aggregated over short temporal intervals, while RS covariates are generally comprised of long-term averages or comparatively fewer dynamic measurements of location and access such as roads or proximity to urban centres. Bearing this in mind, we find CDR data useful for estimating poverty in the absence of ancillary datasets.

Our findings provide further support for correlations between socio-economic measures and nighttime light intensity[36,48,49], access to roads and cities[50,66], entropy of contacts[37,40], and mobility features[39]. The universal coverage of cell towers across Bangladesh made it possible to predict poverty at high-resolution in both urban and rural areas. Within urban areas, the high correlation with maps of slums in Dhaka suggests we are capturing the poorest populations. Even if the poorest populations are not generating call data[36], and thus not included in the CDRs, we still see a clear difference in WI predictions between slum and non-slum areas using tower level CDR aggregates. This finding extends recent work which predicted wealth and poverty at the district level, but were unable to verify predictions at finer scales[36].

Utilising CDRs and RS data within BGMs to produce accurate, high-resolution poverty maps in low- and middle-income countries offers a way to complement census-based methods and provide more regular updates. Regularly updated poverty estimates are necessary to enable subnational monitoring of the SDGs during intercensal years and are critical to ensure mobilization of resources to end poverty in all its dimensions as set out in Goal 1 of the SDGs. Poverty estimates are time sensitive and become obsolete when factors such as migration rates, infrastructure, and market integration change[67]. Further, the methods presented here offer a workaround to estimating poverty with household survey data, which can be time consuming and expensive to obtain.

To end poverty in all its dimensions it is likely that methods that exploit information from, and correlations between, many different data sources will provide the greatest benefit in understanding the distribution of human living conditions. To leverage data from differing sample sizes, temporal and spatial scales, BGMs provide such a rigorous framework. This study further provides an example of how aggregated CDR data can be processed in such a way that detailed maps can be created without revealing sensitive user and commercial information. As insights from CDRs and other remote sensing data become more widely available, analysing these data at regular intervals could allow for dynamic poverty mapping and provide the means for operationally monitoring poverty. The combination of spatial detail and frequent, repeated measurements may distinguish the transitorily poor from the chronically poor, and allow for monitoring economic shocks[68]. This offers the potential for a fuller characterisation of the spatial distribution of poverty and provides the foundation for evidence-based strategies to eradicate poverty. Researchers would do well to utilise the additional information and granularity afforded by CDR data with matched individual-based consumption data to further infer novel and useful information from mobile data.

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Table 1. Cross-validation statistics based on a random 20% test subset of data for all Bayesian geostatistical models.

	WHOLE COUNTRY		
Poverty Metric	Model	r-squared	RMSE
DHS WI	CDR - RS	**0.76**	**0.394**
	CDR	0.64	0.483
	RS	0.74	0.413
PPI	CDR - RS	0.25	57.907
	CDR	0.23	58.562
	RS	**0.32**	**57.439**
Income	CDR - RS	**0.27**	**105.465**
	CDR	0.24	107.155
	RS	0.22	108.682
	URBAN		
Poverty Metric	Model	r-squared	RMSE
DHS WI	CDR - RS	**0.78**	**0.424**
	CDR	0.70	0.552
	RS	0.71	0.433
PPI	CDR - RS	0.00	**60.128**
	CDR	**0.03**	60.935
	RS	0.00	60.384
Income	CDR - RS	**0.15**	**168.452**
	CDR	0.15	172.738
	RS	0.05	176.705
	RURAL		
Poverty Metric	Model	r-squared	RMSE
DHS WI	CDR - RS	**0.66**	**0.402**
	CDR	0.50	0.483
	RS	0.62	0.427
PPI	CDR - RS	0.18	57.397
	CDR	0.17	57.991
	RS	**0.21**	**57.162**
Income	CDR - RS	0.14	81.979
	CDR	0.13	82.773
	RS	**0.23**	**76.527**

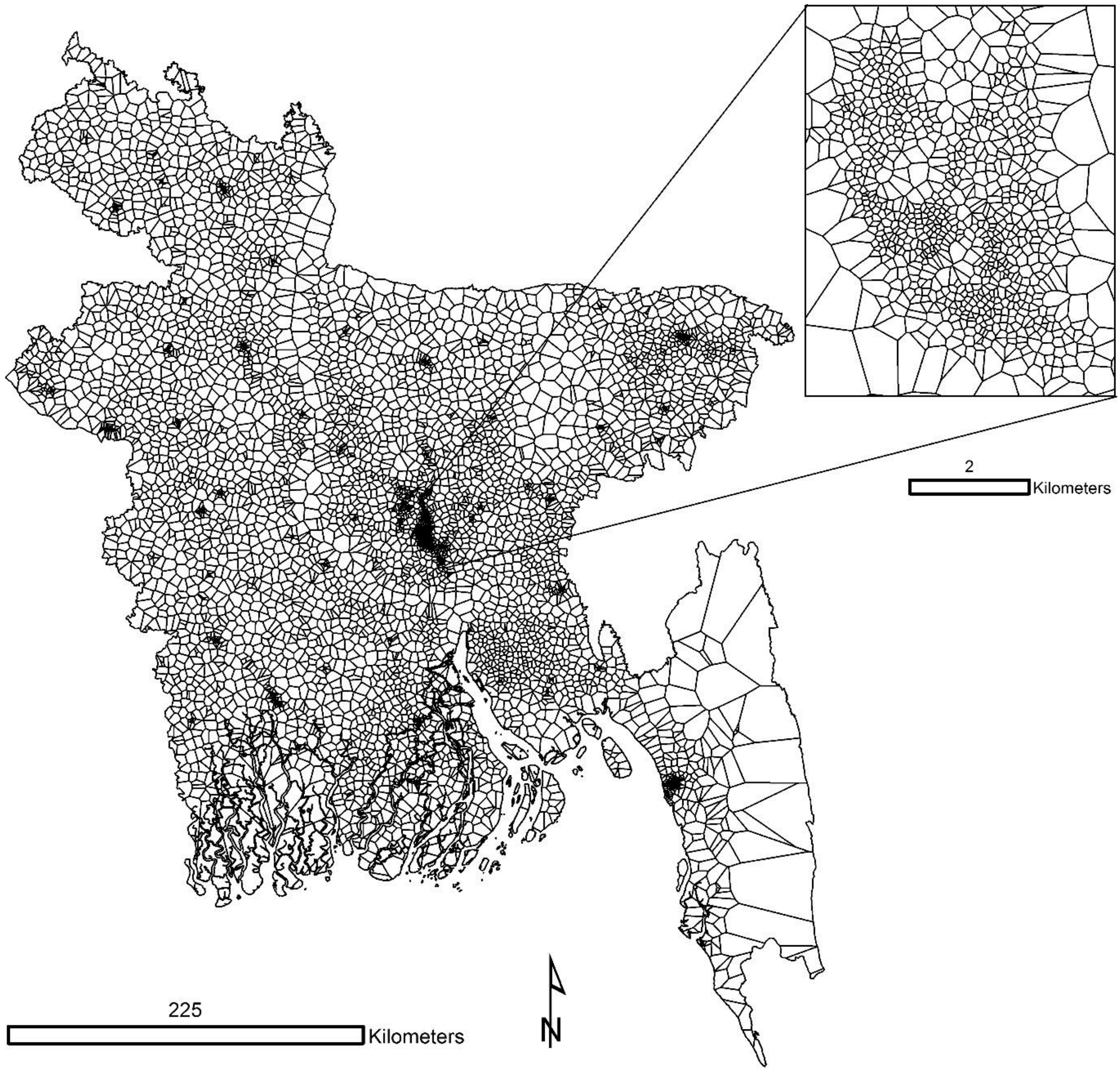

Figure 1. Spatial structure of Voronoi polygons based on the configuration of mobile phone towers in Bangladesh. The zoom window shows the spatial detail of Dhaka.

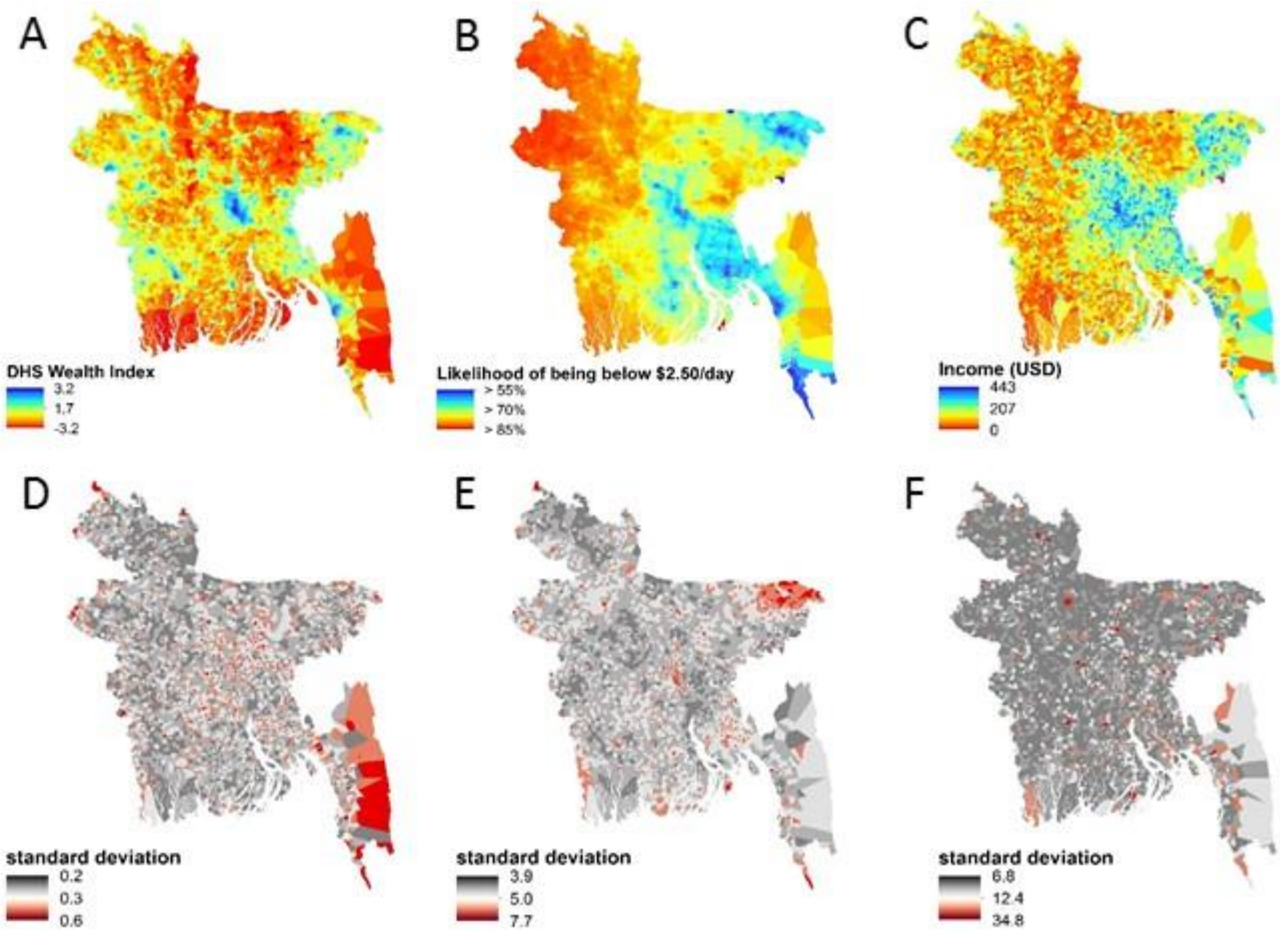

Figure 2. National level prediction maps for mean wealth index (A) with uncertainty (D); mean probability of households being below $2.50/day (B) with uncertainty (E); and mean USD income (C) with uncertainty (F). Maps were generated using call detail record features, remote sensing data, and Bayesian geostatistical models. The maps show the posterior mean and standard deviation from CDR+RS models for the wealth index and income data (A, C), and the RS model for the PPI (B). Red indicates poorer areas in prediction maps, and higher error in uncertainty maps.

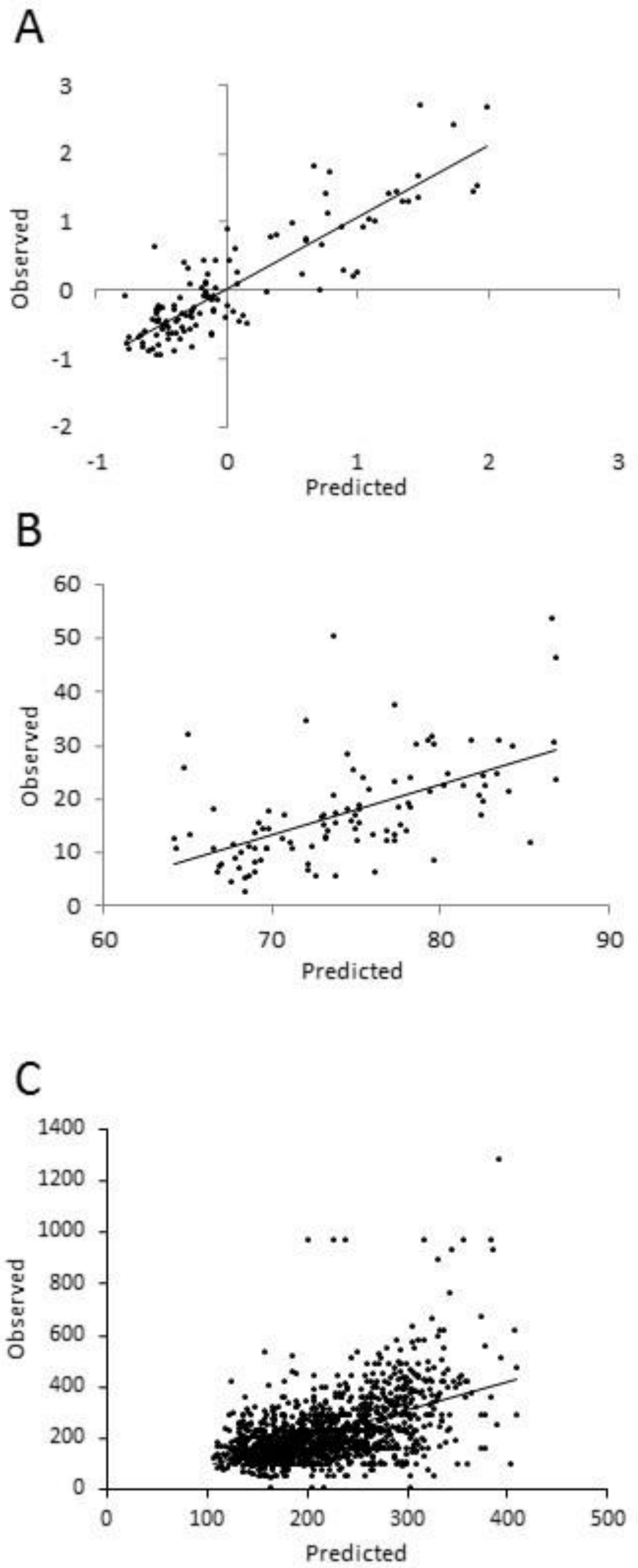

Figure 3. Out-of-sample observed vs. predicted values for (A) DHS wealth index using mobile phone and remote sensing data: r^2=0.76, n=117, p<.001, RMSE=0.394; (B) Progress out of Poverty Index using remote sensing data: r^2=0.32, n=100, p<.001, RMSE=57.439; and (C) income using mobile phone and remote sensing data: r^2=0.27, n=1384, p<.001, RMSE=105.465

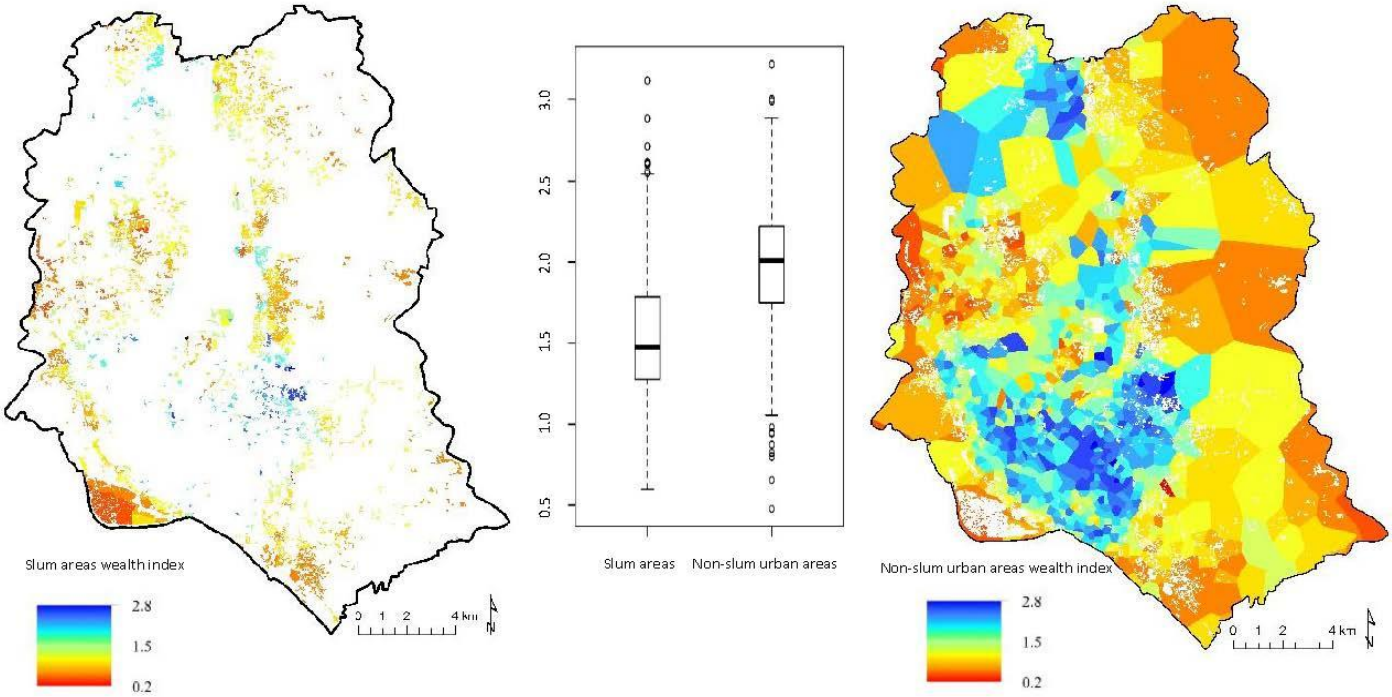

Figure 4. Comparison of predicted mean DHS wealth index values between slum and non-slum areas in Dhaka as delineated by Gruebner et al. 2014. t(615)= -17.2, p<.001. The 95% confidence interval using a Student's t distribution with 615 degrees of freedom is (–0.48, -0.38)

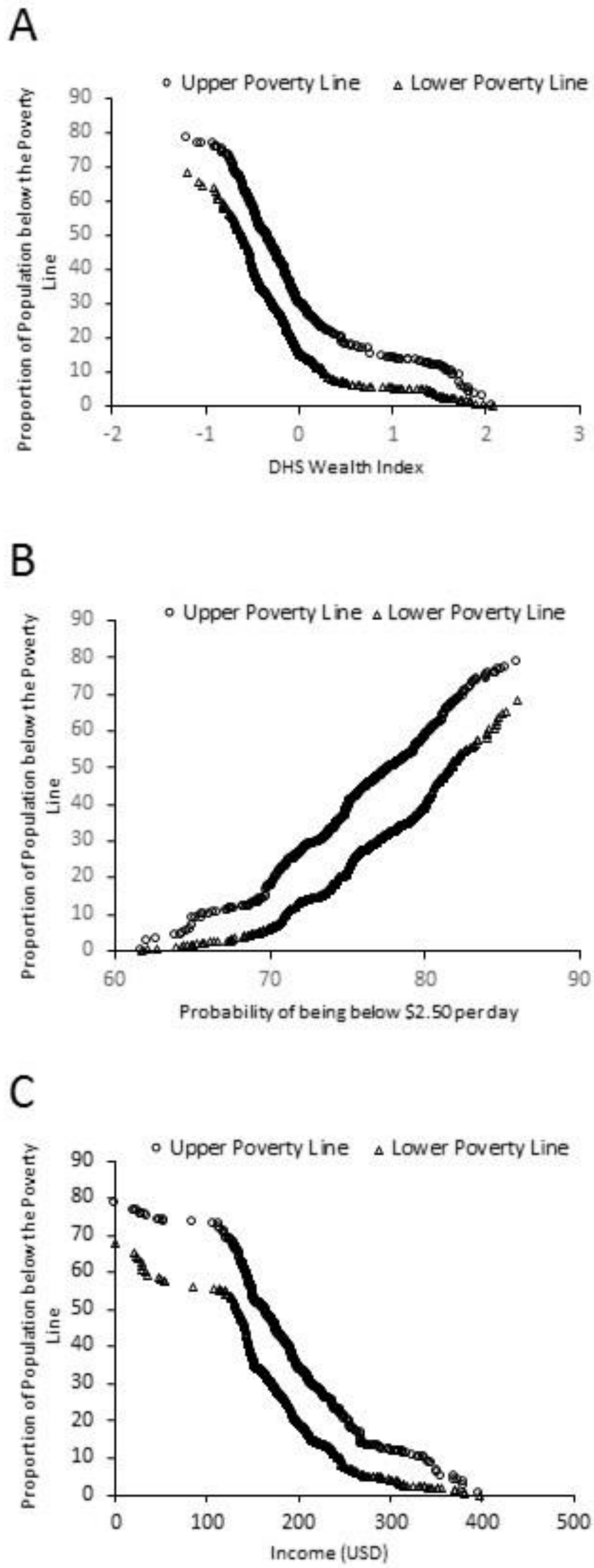

Figure 5. Comparison of the proportion of people falling below upper (∘) and lower (△) poverty lines estimated by Ahmed *et al*. 2010 and (A) predicted mean wealth index using mobile phone and remote sensing data, (B) predicted probability of being below $2.50 per day using remote sensing data, and (C) predicted income using mobile phone and remote sensing data. All models were predicted at the upazila scale (Admin unit 3). Pearson's r correlations: -0.91 and -0.86 for the WI; 0.99 and 0.97 for the PPI; and -0.96 and -0.94 for income, respectively (p<.001 for all models

Mapping poverty using mobile phone and satellite data
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Supplementary Information

A. Input data

A.1. Geolocated survey data
The growing number of georeferenced household survey data from low and middle-income countries allows us to explore poverty metrics and comparisons between them while explicitly considering their geographic distribution. In Bangladesh, we utilised three geographically referenced datasets representing asset, consumption, and income-based measures of wellbeing (Figure S1).

A.1.1. Demographic and Health Survey Wealth Index

The Demographic and Health Surveys (DHS) were designed primarily to collect household data on marriage, fertility, family planning, reproductive and child health, and HIV/AIDS in almost all lower income countries[1]. Through the assembling of indicators correlated with a household's economic status (e.g. ownership of television, telephone, radio as well as variables describing type of floor and ceiling material and other facilities), a wealth index is calculated for each country at each time[2] based on the idea that the possession of assets and access to services and amenities are related to the relative economic position of the household in the country[3]. By its construction, the wealth index is a relative measure of wealth within each survey; however, a new methodology has been developed in order to make it comparable across countries and through time[4]. Moreover, recent adjustments have been made to the methods of constructing the wealth index to overcome criticism that the original score was not adequately capturing the differences between urban and rural poverty or identifying the poorest of the poor[3].

The wealth index is constructed using a principal component analysis (PCA), which includes a long list of assets owned by households as well as other indicators. (The complete list of indicators included in the PCAs for each survey, as well as PCA analysis and results can be found at http://dhsprogram.com/topics/wealth-index/Wealth-Index-Construction.cfm). The first factor from the PCA, capturing the largest percentage of the variance within the dataset, is derived adjusting for urban and rural strata[3,5]. In practice, a national index and two area-specific indexes representing urban and rural strata are individually constructed using sets of assets/services specific to each in order to better capture differences between urban and rural areas, and compare the wealth index between them[3]. Subsequently, applying regression techniques described in Rutstein[3] and Rutstein[6], the three indexes are combined into a single wealth distribution and a composite national index is derived. This method ensures comparability between urban and rural areas.

Here we used the 2011 Bangladesh DHS[7] (Figure S1*A*), a nationally representative survey based on a two-stage stratified sample of households, where 600 enumeration areas (EA or cluster) were first selected with probability proportional to the EA size, (207 clusters in urban areas and 393 in rural areas). This first stage of selection provided a listing of households for the second stage, where a systematic sample of 30 households on average was selected per cluster, to create statistically reliable estimates of key demographic and health variables[7,8]. In recent DHS surveys where HIV/AIDS data are not collected, geolocations for each cluster are available. The survey cluster coordinates represent an estimated centre of the cluster and are collected in the field through GPS receivers. To maintain respondents' confidentiality, GPS positions for all clusters are randomly displaced by a maximum of five kilometres for rural clusters and a maximum of two kilometres for urban clusters[9–11].

A.1.2. Progress out of Poverty Index

The Progress out of Poverty Index (PPI) (Figure S1*B*) was designed to be easily collected, simple and cost-effective to implement and verify[12], while applying a rigorous methodology through selecting assets based on their statistical relationship with poverty[12,13]. In the case of Bangladesh, an easy-to-use poverty scorecard[13] of 10 questions was created in March 2013, based on data from the Bangladesh 2010 Household Income and Expenditure Survey (HIES). The questions selected are aggregated into a score highly correlated with poverty status as measured by the HIES. The scores included in the scorecard are then translated into likelihoods that the household has per-capita expenditure above or below a given poverty line[13].
A nationally representative survey of all adults in Bangladesh was undertaken by InterMedia Financial Inclusion Insight Project (www.finclusion.org) in 2014 (wave 2), where 6,000 Bangladeshi individuals aged 15 and above were interviewed[14] and geolocations for each individual were included in the survey. In Bangladesh, InterMedia adopted a stratified sample strategy, whereby divisions and subdivisions were first identified and interviews within each subdivision were distributed in proportion to population size. In order to select the individuals to interview, households were first randomly selected using electoral rolls to randomly assign starting points in each selected subdivision. After having identified the starting point, subsequent households were selected using the right-hand rule, and the Kish Grid method was applied to select an individual respondent from each household[14,15].

A.1.3. Market research household surveys and income data

Two sequential large-scale market research household surveys were run by Telenor through its subsidiary, Grameenphone (GP), during 2 time periods between November and December 2013 (N=82,834, of which 55.3% GP subscribers) and February and March 2014 (N=87,509, of which 54.5% GP subscribers) (Figure S1*C*). The country was stratified in 226 sales territories by the phone company, and for every territory, an equal number of unions (in rural areas) and wards (in urban areas) were randomly selected. Four hundred households were surveyed in each territory, where a household was defined as a group of people sharing food from the same chula (fire/gas burner) or living under the same roof. Systematic sampling was then undertaken to select households by selecting every fourth household, starting from the selection of a random geographic point and direction within each ward or union. In the case of more than one household present in the complex or building, the fourth household was selected. In cases of non-response, the next household was then selected. Non-response rate was approximately 10% of households. Respondents within the household were selected via the Kish grid method[15] among those who were eligible. Eligibility was defined as individuals with their own phone, between 15 and 65 years of age. If a phone was shared between family members, usually the male head of household was interviewed. When the selected person was not home, the surveyors returned multiple times to try to reach the selected person. A very low non-response rate (less than 1-2%) was detected among respondents. The surveys were undertaken during working hours. To avoid that too many housewives were interviewed, given that men are more likely away for work, a ceiling on the number of housewives who could participate was also established. Sampling weights were applied to ensure national representativeness and correct for population sizes in urban and rural areas. Data quality control mechanisms were implemented and undertaken by the company; however, some sources of error were detected in matching household locations to phone number (approximately 20% of the cases).

A.2. Mobile phone call detail records (CDRs)

For the household income survey respondents described above, we collected 3-months of mobile phone metadata by subscriber consent. These metadata included call detail records (CDR) and top-up information, which were further processed into features. For each survey participant, 150 features from seven different feature families were constructed (Table S1). Household income was then linked to these metadata, resulting in three months of phone usage, matched with household income for each survey respondent. To preserve user anonymity, the local operator removes all personally identifying information from the data before analysis.

To be able to map poverty in other countries we focused on features that are easily reproducible, and easy to implement by local data warehouses. Most mobile operators generate similar features. CDR features range from metrics such as basic phone usage, top-up pattern, and social network to metrics of user mobility and handset usage. They include various parameters of the corresponding distributions such as weekly or monthly median, mean, and variance. In addition, we received pre-aggregated datasets of tower-level activity from 48,190,926 subscriber SIMs over a 4-month period. This includes monthly number of subscribers per home cell, where home cell corresponds to most frequent tower. These per-user features are not directly used, but further aggregated to the Voronoi polygons, and the aggregate features are used in covariate selection, model fitting, and prediction.

At the time of data acquisition, the mobile phone operator had an approximate 42% market share, and was the largest provider of mobile telecommunication services in Bangladesh. Multi-SIM activity is common in Bangladesh, but we believe that this should not create a systematic bias in poverty estimates because the geographic coverage of the operator is so extensive. In order to comply with national laws and regulations of Bangladesh, and the privacy policy of the Telenor group, the following measures were implemented in order to preserve the privacy rights of Grameenphone customers:

1) All customers are de-identified and only Telenor/Grameenphone employees have had access to any detailed CDR-/top-up data;
2) The processing of detailed CDR/top-up data resulted in aggregations of the data on a tower-level granularity; the tower-level aggregation makes re-identification impossible.

Hence, the resulting aggregated dataset is truly anonymous and involves no personal data. Compared with other countries of comparable income levels, Bangladesh has a high mobile phone penetration, which includes rural areas. Fifty percent of the population above the age of fifteen has a mobile subscription[16]. The proportion of households with at least one mobile phone is increasing rapidly; between 2011 and 2014, household ownership across the whole of Bangladesh rose from 78% to 89%, with much of that growth concentrated among rural households[17].

A.3. Remote Sensing-GIS covariates

Ancillary data layers used as remote sensing-GIS (hereafter RS) covariates were identified, assembled, and processed for the whole of Bangladesh at a 1-km spatial resolution. These data are described in Table S1 and include 25 raster and vector datasets obtained from existing sources or produced ad hoc for this study to include environmental and physical metrics likely to be associated with human welfare[18–22]. These data differed in spatial and temporal resolution, type, accuracy, and coverage. In order to align all data for model fitting and prediction, the following steps were taken:

1) Bangladesh was rasterized at a resolution of 30-arcsec (0.00833333 degree, corresponding to approximately 1-km at the equator);

2) Vector datasets were rasterized at a resolution of 30-arcsec;
3) When necessary, raster datasets were resampled to a resolution of 30-arcsec using an interpolation technique appropriate for the resolution and type of the original dataset;
4) All datasets were spatially aligned to make every pixel representing the same location coincident and match the rasterized study area.

Furthermore, for ad hoc datasets such as distance to roads and waterways, we used a customized Azimuthal Equidistant projection centred in the middle of the study area and clipped to a buffer extending 100 metres beyond its boundary to project the input data. This buffered area was rasterized to a resolution of approximately 927 metres, corresponding to 30-arcsec at the centre of the study area where distortion is smallest. Euclidean distance was calculated for each distance-to covariate within the customized projection. The resultant layers were then projected back to GCS WGS84, and made coincident with the rasterized study area. All datasets representing categorical variables (e.g. protected areas, global urban extent, etc.) were projected, rasterized, and/or resampled to 1-km resolution, spatially aligned to the rasterized study area, and converted into binary covariates, representing the presence or absence of a given feature. This resulted in twenty-five 1-km raster datasets, which were used to extract the mean, mode, or sum of each covariate for each Voronoi polygon, dependent on the type of dataset. These values were used for covariate selection, model fitting, and prediction.

A.3.1 GPS data displacement

In addition to the aforementioned processing, additional steps were undertaken to appropriately account for the displacement inherent in DHS data. When these data are collected, the latitude and longitude of the centre of each DHS cluster (representing numerous households) is collected in the field with a GPS receiver. To maintain respondents' confidentiality, GPS latitude/longitude positions for all DHS clusters are randomly displaced by a maximum of five kilometres for rural clusters and two kilometres for urban clusters. The displacement is restricted so the points stay within the country, within the DHS survey region, and within the second administrative level[9–11]. In order to account for the displacement in our analyses, we created buffers around each cluster centroid of 2 km and 5 km for urban and rural clusters, respectively, and subsequently extracted the RS covariate data for each buffer zone. For continuous covariates, the minimum, maximum, and mean values were calculated and extracted. For categorical covariates, the modal value was calculated and extracted.

B. Statistical analyses and prediction mapping

B.1. Covariate selection via generalized linear models

Stratifying models into urban and rural components produced the best fit models as measured by AIC. Top-up data produced the most important CDR feature family for all poverty measures and models. Within this feature family, significant covariates included recharge amounts and frequencies per tower, spending speeds and time between refills, and fractions of the lowest and highest available top-up amounts. Advanced phone usage was also an important CDR feature family, especially for PPI and income models. Sum, revenue, count, and volume of ingoing and outgoing multimedia messaging, Internet usage, and videos were prominent. Basic phone usage covariates measuring incoming and outgoing text counts were important for every model save for rural WI models. Mobility covariates including number and entropy of places and radius of gyration were also significant features in all three strata and poverty measures, as were social network features such as number and entropy of contacts.

Nighttime lights and covariates representing access - especially transport time to closest urban settlement and distance to roads - were the most important RS covariates for all three poverty measures and strata. Vegetation productivity, as measured by the Enhanced Vegetation Index (EVI), and elevation were also prominent RS features in all three strata, whereas climate variables featured prominently in rural models.

B.2. Prediction mapping via Bayesian geostatistical models

Using the models selected and described in Tables S2*A-C*, we employed hierarchical Bayesian geostatistical models (BGMs) for prediction as described in our manuscript. All prediction maps not highlighted in our manuscript can be found in Figures S2-S6. Model performance was based on out-of-sample validation statistics calculated on a 20% test subset of poverty data input points (see Table 1 in manuscript). The performance of models built with CDR-only or RS-only data varied based on poverty measure and strata. RS-only models were more successful at predicting the WI for all three strata (r^2= 0.74, 0.71, 0.72 for national, urban, and rural models), as compared to CDR-only models. However, the CDR-only models performed nearly as well (r^2= 0.64, 0.70, 0.50 for national, urban, and rural models), and all urban WI models including CDRs outperformed national level models. The urban CDR-RS model exhibits the highest explained variance for any model (r^2=0.78), and the urban CDR-only model outperforms the national CDR-only model (r^2=0.70 versus r^2=0.64, respectively). For PPI and income measures of poverty, CDR data produced the best models in urban areas, whereas RS data produced the best models in rural areas. This highlights the compatibility of these two datasets for predicting different measures of poverty at different scales, as the best estimates and lowest error corresponded to the data with fine-scale spatial heterogeneity (CDRs in urban areas; RS data in rural areas). To that end, national poverty models generally performed best when utilising both CDRs and RS data.

To compare full model performance against a spatial interpolation model, we modelled the training data for all three poverty indicators using only the spatial random effect in the INLA model (see section 2.5 in manuscript). These results are shown in Table S3. We compared out-of-sample r^2 and RMSE values against results from the full models (see Table 1 in manuscript). The results show a spatial pattern in the WI data as the model built with only a spatial random effect yields an r^2=0.49, RMSE=0.578. When compared to the full model, the addition of covariate data increases the r^2 to 0.76, and the RMSE decreases to 0.394. Similarly for income, the data do show a slight spatial pattern, but the addition of covariate data to the model increases the predictive power and decreases the error. For the PPI, the covariates do not show a strong influence in the modelling results, and the model was driven by the spatial process, which suggests there's an underlying spatial covariate that we're not capturing in the model that could explain the data.

Model fit based on the spatial effect can also be considered using DIC, a hierarchical modelling generalization of the AIC and BIC, which can be useful in Bayesian modelling comparison. The BIC allows for comparing models using criterion based on the trade-off between the fit of the data to the model and the corresponding complexity of the model. Models with smaller DIC values are preferred over models with larger DIC values as the measure favours better fit and fewer parameters[23]. These results are shown in Table S4. For nearly every model with CDR data, DIC is greatly improved by accounting for the spatial covariance in the data structure. However, the income models see slight or no improvement from including the random spatial effect, likely due to the fact that they include and are thus penalised for many covariates.

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Table S1. Summary information for remote sensing-GIS and mobile phone call detail record datasets used for covariate selection and Bayesian geostatistical poverty mapping.

Category	Description	Source	Resolution (Degrees)	Year
		RS-GIS		
Accessibility	Accessibility to populated places with more than 50k people	European Commission Joint Research Centre (http://forobs.jrc.ec.europa.eu/products/gam/)	0.0083333	2000
Population	Population count [per pixel]	WorldPop (http://www.worldpop.org.uk/)	0.0008333	2010
Population	Population count [per pixel]	CIESIN - Global Rural Urban Mapping Project (http://sedac.ciesin.columbia.edu/data/collection/grump-v1/sets/browse)	0.0083333	2000
Population	Population density [per sqkm]	CIESIN - Global Rural Urban Mapping Project (http://sedac.ciesin.columbia.edu/data/collection/grump-v1/sets/browse)	0.0083333	2000
Climate	Mean Aridity Index	CGIAR-CSI (http://www.cgiar-csi.org/data)	0.0083333	1950-2000
Climate	Average annual Potential Evapotranspiration [mm]	CGIAR-CSI (http://www.cgiar-csi.org/data)	0.0083333	1950-2000
Night-time lights	VIIRS night-time lights [W cm-2 sr-1]	NOAA VIIRS (http://ngdc.noaa.gov/eog/viirs.html)	0.0041667	2014
Elevation	Elevation [meter]	CGIAR-CSI (http://srtm.csi.cgiar.org/)	0.0083316	2008
Vegetation	Vegetation	MODIS MOD13A1 [Enhanced vegetation index]	0.0041667	2010-2014
Distance	Distance to roads [meter]	Input data from OSM (http://extract.bbbike.org/)	0.0083333	2014
Distance	Distance to waterways [meter]	Input data from OSM (http://extract.bbbike.org/)	0.0083333	2014
Urban/Rural	Urban/Rural	MODIS-based Global Urban extent	0.0041670	2000-2001
Urban/Rural	Urban/Rural	CIESIN - Global Rural Urban Mapping Project (http://sedac.ciesin.columbia.edu/data/collection/grump-v1/sets/browse)	0.0083333	2000
Urban/Rural	Global Human Settlement Layer	Global Land Cover Facility (www.landcover.org)	0.002818	2014
Protected Area	Protected areas	WDPA (http://www.protectedplanet.net/)	Vector	2012
Land Cover	Land cover	ESA GlobCover Project (http://due.esrin.esa.int/page_globcover.php)	0.0027777	2009
Land Cover	Land cover	IGBP MODIS MCD12Q1 (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12q1)	0.0041670	2012
Land Cover	Land cover	ONRL DAAC Synergetic Land Cover Product (SYNMAP) (http://webmap.ornl.gov/wcsdown/wcsdown.jsp?dg_id=10024_1)	0.0083333	2000-2001
Demographic	Pregnancies	WorldPop (http://www.worldpop.org.uk/)	0.0008333	2012
Demographic	Births	WorldPop (http://www.worldpop.org.uk/)	0.0008333	2012
Ethnicity	Georeferenced ethnic groups	ETH Zurich (http://www.icr.ethz.ch/data/geoepr)	Vector	2014
Climate	Mean annual precipitation	WorldClim (http://www.worldclim.org/download)	0.0083333	1950-2000

Climate	Mean annual temperature	WorldClim (http://www.worldclim.org/download)	0.0083333	1950-2000
Call Detail Records				
Basic phone usage	Outgoing/incoming voice duration, SMS count, etc.	Telenor/Grameenphone	NA	2013-2014
Top-up transactions	Spending speed, recharge amount per transaction, fraction of lowest/highest recharge amount, coefficient of variation recharge amount, etc.	Telenor/Grameenphone	NA	2013-2014
Location/mobility	Home district/tower, radius of gyration, entropy of places, number of places, etc.	Telenor/Grameenphone	NA	2013-2014
Social Network	Interaction per contact, degree, entropy of contacts, etc.	Telenor/Grameenphone	NA	2013-2014
Handset type	Brand, manufacturer, camera enabled, smart/feature/basic phone, etc.	Telenor/Grameenphone	NA	2013-2014
Revenue	Charge of outgoing/incoming SMS, MMS, voice, video, value added services, roaming, internet, etc.	Telenor/Grameenphone	NA	2013-2014
Advanced phone usage	Internet volume/count, MMS count, video count/duration, value added services duration/count, etc.	Telenor/Grameenphone	NA	2013-2014

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Table S2*A*. Wealth Index models for RS-only, CDR-only, and CDR+RS data: national, urban, and rural strata.

AIC	NATIONAL	URBAN	RURAL
RS-only	690.61	333.44	161.42
CDR-only	907.78	373.97	164.14
CDR-RS	651.76	318.12	115.52
MODEL			
RS-only	1 + transport time to closest urban settlement + nighttime lights + EVI + elevation	1 + distance to roads + distance to waterways + nighttime lights + elevation	1 + transport time to closest urban settlement + annual temperature + annual precipitation + distance to roads + distance to waterways + nighttime lights
CDR-only	1 + recharge average per tower + percent nocturnal calls + number of places + entropy of contacts + outgoing internet sessions + sum outgoing internet sessions + incoming voice duration + count incoming content management system + count sum incoming content management system + volume of incoming multimedia messages + recharge amount per transaction + count incoming multimedia messages + count incoming texts + weekly recharge amount	1 + recharge average per tower + number of places + entropy of contacts + spending speed + average outgoing text count + sum count incoming content management system + weekly recharge amount	1 + recharge average per tower + percent nocturnal calls + entropy of places + radius of gyration + interactions per contact + recharge amount (CV) + number of retailers visited weekly (CV) + sum incoming video duration + count incoming multimedia messages + weekly recharge frequency (CV) + sum incoming video count + recharge amount per transaction (CV)
CDR-RS	1 + transport time to closest urban settlement + nighttime lights + EVI + elevation + recharge average per tower + percent nocturnal calls + outgoing internet sessions + count incoming content management system + recharge amount per transaction + count incoming texts + weekly recharge amount	1 + distance to roads + distance to waterways + nighttime lights + elevation + recharge average per tower + spending speed + average outgoing text count + weekly recharge amount	1 + transport time to closest urban settlement + annual temperature + distance to roads + distance to waterways + nighttime lights + recharge average per tower + percent nocturnal calls + entropy of places + radius of gyration + interactions per contact + recharge amount (CV) + number of retailers visited weekly (CV) + sum incoming video duration + weekly recharge frequency (CV) + sum incoming video count + recharge amount per transaction (CV)

*CV=coefficient of variation

Table S2*B*. Progress out of Poverty Index models for RS-only, CDR-only, and CDR+RS data: national, urban, and rural strata.

AIC	NATIONAL	URBAN	RURAL
RS-only	41676	14099	27465
CDR-only	41562	14044	27421
CDR-RS	41502	14043	27382
MODEL			
RS-only	1 + annual precipitation + annual temperature + transport time to closest urban settlement + distance to roads + EVI + nighttime lights	1 + annual precipitation + annual temperature + transport time to closest urban settlement + elevation	1 + annual precipitation + annual temperature + transport time to closest urban settlement + distance to water + EVI + nighttime lights
CDR-only	1 + subscribers per tower + recharge average per tower + entropy of places + entropy of contacts + average outgoing text count + sum outgoing multimedia messages + fraction of 10 Thaka top-ups (min amount) + outgoing internet sessions + sum outgoing internet sessions + sum count incoming content management system + number of retailers visited weekly (CV) + sum revenue outgoing multimedia messages + spending speed variance + count incoming multimedia messages + sum count incoming multimedia messages + count incoming texts + sum count incoming texts + weekly recharge frequency (CV) + median time between refills + incoming video count + outgoing internet volume + time variable (CV)	1 + subscribers per tower + recharge average per tower + sum outgoing multimedia messages + count outgoing internet sessions + sum count outgoing internet sessions + number of retailers visited weekly (CV) + volume of incoming multimedia messages + outgoing text charges + sum revenue outgoing multimedia messages + incoming video duration + sum incoming video duration + spending speed variance + sum count incoming multimedia messages + weekly recharge amount + incoming video count + sum incoming video count + number of retailers visited weekly	1 + subscribers per tower + recharge average per tower + number of places + entropy of places + sum duration outgoing value added services + count outgoing texts + sum count outgoing texts + sum volume of outgoing multimedia messaging + fraction of 300 Thaka top-ups + count outgoing internet sessions + sum count outgoing internet sessions + incoming voice duration + number of retailers visited weekly (CV) + volume of incoming multimedia messages + outgoing text charges + sum outgoing text charges + sum revenue outgoing multimedia messages + spending speed variance + count incoming texts + sum count incoming texts + weekly recharge frequency (CV) + median time between refills + outgoing internet volume + recharge amount per transaction (CV) + time variable (CV)
CDR-RS	1 + annual precipitation + annual temperature + transport time to closest urban settlement + distance to road + elevation + subscribers per tower + recharge average per tower + entropy of places + entropy of contacts + average outgoing text count + sum outgoing multimedia messages + outgoing internet sessions + sum outgoing internet sessions + number of retailers visited weekly (CV) + sum revenue outgoing multimedia messages + spending speed variance + count incoming multimedia messages + sum count incoming multimedia messages + count incoming texts + sum count incoming texts + weekly recharge frequency (CV) + median time between refills + incoming video count + outgoing internet volume + time variable (CV)	1 + annual precipitation + annual temperature + EVI + elevation + subscribers per tower + recharge average per tower + sum outgoing multimedia messages + number of retailers visited weekly (CV) + volume of incoming multimedia messages + sum volume of incoming multimedia messages + incoming video duration + sum incoming video duration + sum revenue outgoing multimedia messages + spending speed variance + sum count incoming multimedia messages + weekly recharge amount + incoming video count + sum incoming video count + number of retailers visited weekly	1 + annual precipitation + annual temperature + transport time to closest urban settlement + distance to water + EVI + nighttime lights + subscribers per tower + recharge average per tower + outgoing multimedia messages + fraction of 300 Thaka top-ups + number of retailers visited weekly (CV) + volume of incoming multimedia messages + outgoing text charges + sum revenue outgoing multimedia messages + spending speed variance + median time between refills + time variable (CV)

*CV=coefficient of variation

Table S2*C*. Income models for RS-only, CDR-only, and CDR+RS data: national, urban, and rural strata.

AIC	NATIONAL	URBAN	RURAL
RS-only	83194	17295	64569
CDR-only	83109	17180	64413
CDR+RS	82895	17129	64330
MODEL			
RS-only	1 + nighttime lights + transport time to closest urban settlement + annual temperature + EVI + distance to raod + distance to water + annual precipitation + elevation	1 + nighttime lights + transport time to closest urban settlement + distance to roads	1 + nighttime lights + annual temperature + distance to roads + annual precipitation + elevation
CDR-only	1 + percent nocturnal calls + number of places + entropy of places + entropy of contacts + radius of gyration + interactions per contact + spending speed + outgoing video duration + sum outgoing video duration + average outgoing text count + sum outgoing text count + fraction of 300 Thaka top-ups + fraction of 10 Thaka top-ups + recharge amount (CV) + number of retailers visited weekly (CV) + recharge amount per transaction + spending speed variance + sum spending speed variance + sum count incoming texts + handset weight + outgoing voice duration + sum outgoing voice duration + sum outgoing internet volume + time variable (CV) + fraction of 200 Thaka top-ups	1 + percent nocturnal calls + number of places + entropy of places + radius of gyration + spending speed + outgoing video duration + sum outgoing video duration + average outgoing text count + sum outgoing text count + fraction of 300 Thaka top-ups + number of retailers visited weekly (CV) + volume of incoming multimedia messages + sum volume of incoming multimedia messages + recharge amount per transaction + count incoming multimedia messages + sum count incoming multimedia messages + sum outgoing voice duration + outgoing internet volume + sum outgoing internet volume + recharge amount per transaction (CV) + time variable (CV)	1 +number of places + entropy of places + entropy of contacts + spending speed + duration outgoing value added services + sum duration outgoing value added services + sum outgoing video duration + handset weight + software OS version + fraction of 300 Thaka top-ups + fraction of 10 Thaka top-ups + coefficient of variation: recharge amount + number of retailers visited weekly (CV) + volume of incoming multimedia messages + sum volume of incoming multimedia messages + spending speed variance + sum spending speed variance + sum count incoming multimedia messages + count incoming texts + sum count incoming texts + weekly recharge amount + outgoing voice duration + sum outgoing voice duration + outgoing internet volume + time variable (CV)
CDR-RS	1 + nighttime lights + transport time to closest urban settlement + EVI + distance to road + percent nocturnal calls + number of places + entropy of places + entropy of contacts + radius of gyration + spending speed + outgoing video duration + sum outgoing video duration + average outgoing text count + sum outgoing text count + recharge amount (CV) + number of retailers visited weekly (CV) + recharge amount per transaction + spending speed variance + sum spending speed variance + sum count incoming texts + handset weight + outgoing voice duration + sum outgoing voice duration + sum outgoing internet volume + time variable (CV) + fraction of 200 Thaka top-ups	1 + nighttime lights + transport time to closest urban settlement + annual temperature + distance to roads + annual temperature + percent nocturnal calls + number of places + radius of gyration + spending speed + outgoing video duration + sum outgoing video duration + average outgoing text count + sum outgoing text count + fraction of 300 Thaka top-ups + number of retailers visited weekly (CV) + volume of incoming multimedia messages + recharge amount per transaction + count incoming multimedia messages + sum count incoming multimedia messages + outgoing voice duration + outgoing internet volume + sum outgoing internet volume + recharge amount per transaction (CV) + time variable (CV)	1 + nighttime lights + annual precipitation + number of places + entropy of places + entropy of contacts + spending speed + sum outgoing video duration + handset weight + software OS version + fraction of 300 Thaka top-ups + fraction of 10 Thaka top-ups + coefficient of variation: recharge amount + number of retailers visited weekly (CV) + weekly recharge amount + outgoing voice duration + sum outgoing voice duration + outgoing internet volume + time variable (CV)

*CV=coefficient of variation

Table S3. Comparison of r^2 and RMSE for INLA models run with only a structured spatial random effect (Spatial interpolation) and the full model (Spatial model + covariates).

Poverty Metric	Spatial interpolation	Spatial model + covariates (from Table 1)
	R^2, RMSE	R^2, RMSE
DHS WI	0.49, 0.578	0.76, 0.394
PPI	0.31, 58.727	0.32, 57.439
Income	0.10, 123.963	0.27, 105.465

Table S4. Comparison of deviance information criterion (DIC) model fit for Bayesian geostatistical models run with a structured spatial random effect (Spatial model) and without (Non-spatial model).

		WHOLE COUNTRY	
Poverty Metric	Model	Spatial model	Non-spatial model
		DIC	DIC
DHS WI	CDR - RS	463.7	574.6
	CDR	272.5	862.2
	RS	465.7	581.5
PPI	CDR - RS	1361.3	1439.8
	CDR	1349.7	1473.1
	RS	1358.6	1421.4
Income	CDR - RS	66142.5	66143.0
	CDR	66314.6	66314.3
	RS	66482.6	66480.4
		URBAN	
Poverty Metric	Model	Spatial model	Non-spatial model
		DIC	DIC
DHS WI	CDR - RS	449.4	576.0
	CDR	239.2	873.2
	RS	454.1	582.0
PPI	CDR - RS	1371.6	1432.3
	CDR	1365.7	1470.1
	RS	1358.3	1417.7
Income	CDR - RS	66180.6	66179.8
	CDR	66363.3	66365.7
	RS	66693.0	66690.3
		RURAL	
Poverty Metric	Model	Spatial model	Non-spatial model
		DIC	DIC
DHS WI	CDR - RS	458.0	574.5
	CDR	63.1	873.5
	RS	451.5	595.5
PPI	CDR - RS	1376.9	1444.6
	CDR	1342.9	1475.9
	RS	1357.7	1419.4
Income	CDR - RS	66262.5	66260.6
	CDR	66395.0	66392.1
	RS	65548.9	66503.8

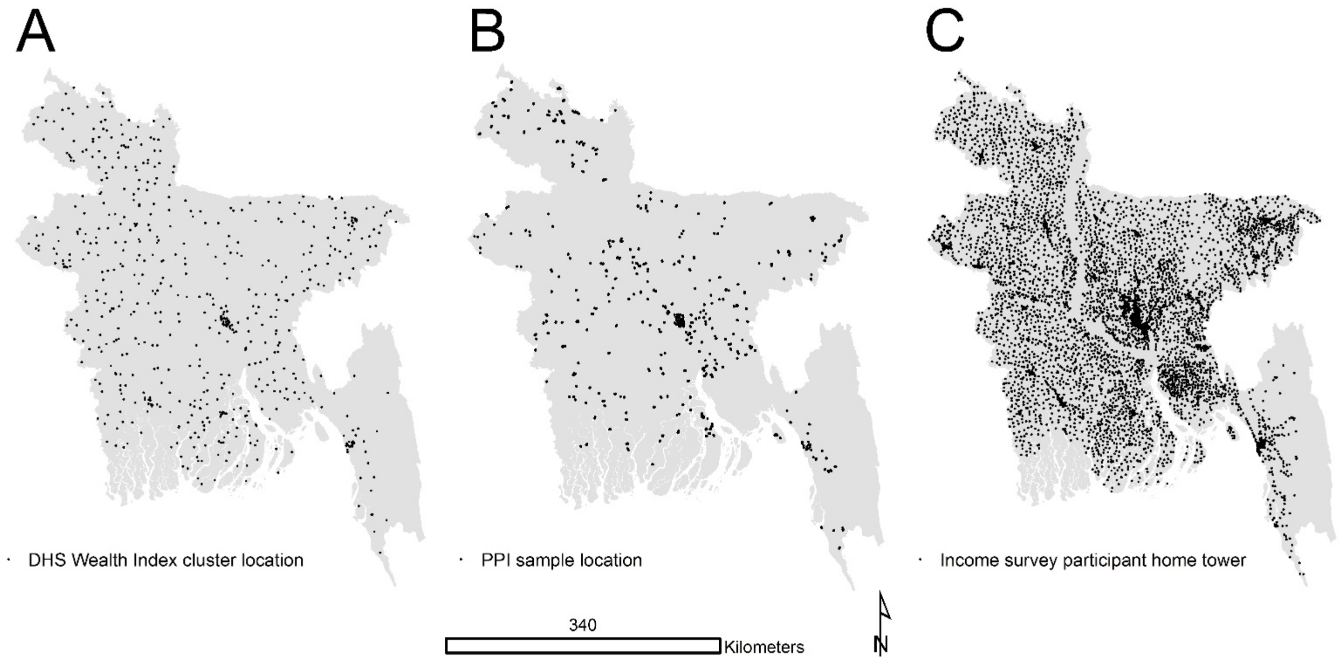

Figure S1. Survey sample locations for DHS wealth index (A), Progress out of Poverty Index (B), and income survey respondents (C).

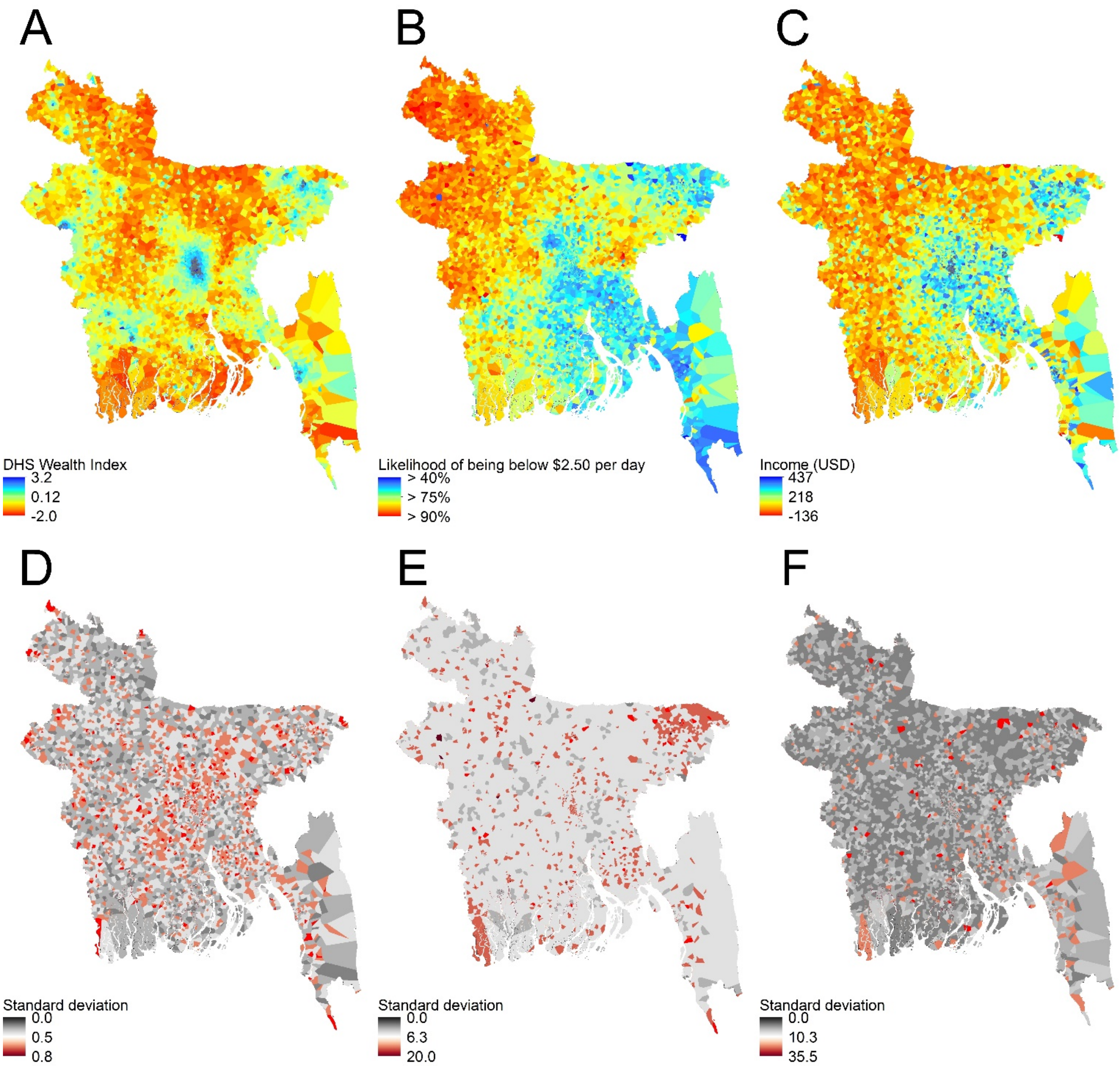

Figure S2. National level prediction maps for mean wealth index (A) with uncertainty (D); mean probability of households being below $2.50/day (B) with uncertainty (E); and mean USD income (C) with uncertainty (F). Maps were generated using call detail record features only and Bayesian geostatistical models. Red indicates poorer areas in prediction maps, and higher error in uncertainty maps.

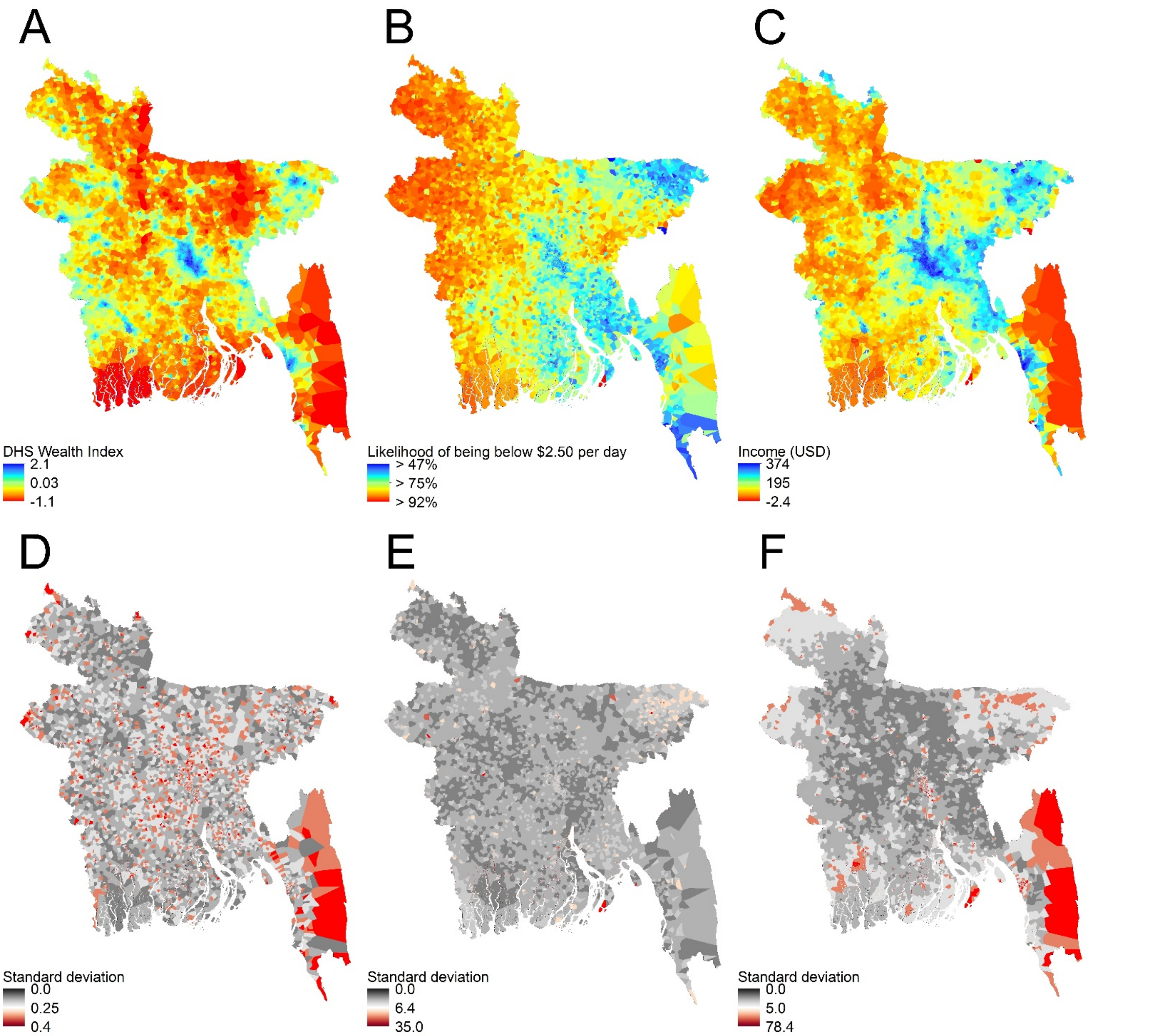

Figure S3. National level prediction maps for mean wealth index (A) with uncertainty (D); mean probability of households being below $2.50/day (B) with uncertainty (E); and mean USD income (C) with uncertainty (F). Wealth index and income maps were generated using remote sensing data only; PPI maps were generated using call detail record features and remote sensing data. All maps were generated using Bayesian geostatistical models. Red indicates poorer areas in prediction maps, and higher error in uncertainty maps.

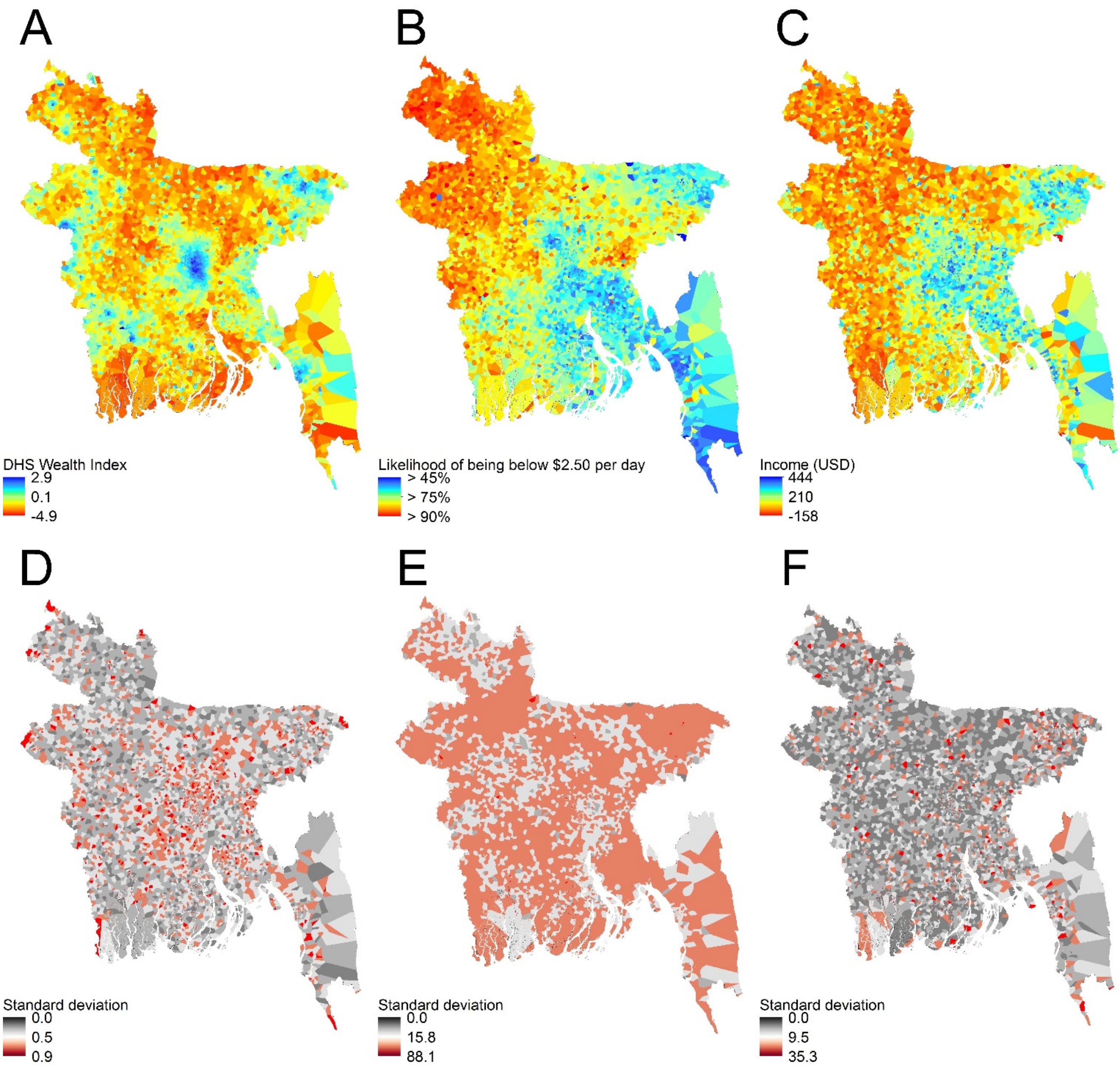

Figure S4. Stratified urban/rural prediction maps for mean wealth index (A) with uncertainty (D); mean probability of households being below $2.50/day (B) with uncertainty (E); and mean USD income (C) with uncertainty (F). Maps were generated using call detail record features only and Bayesian geostatistical models. Red indicates poorer areas in prediction maps, and higher error in uncertainty maps.

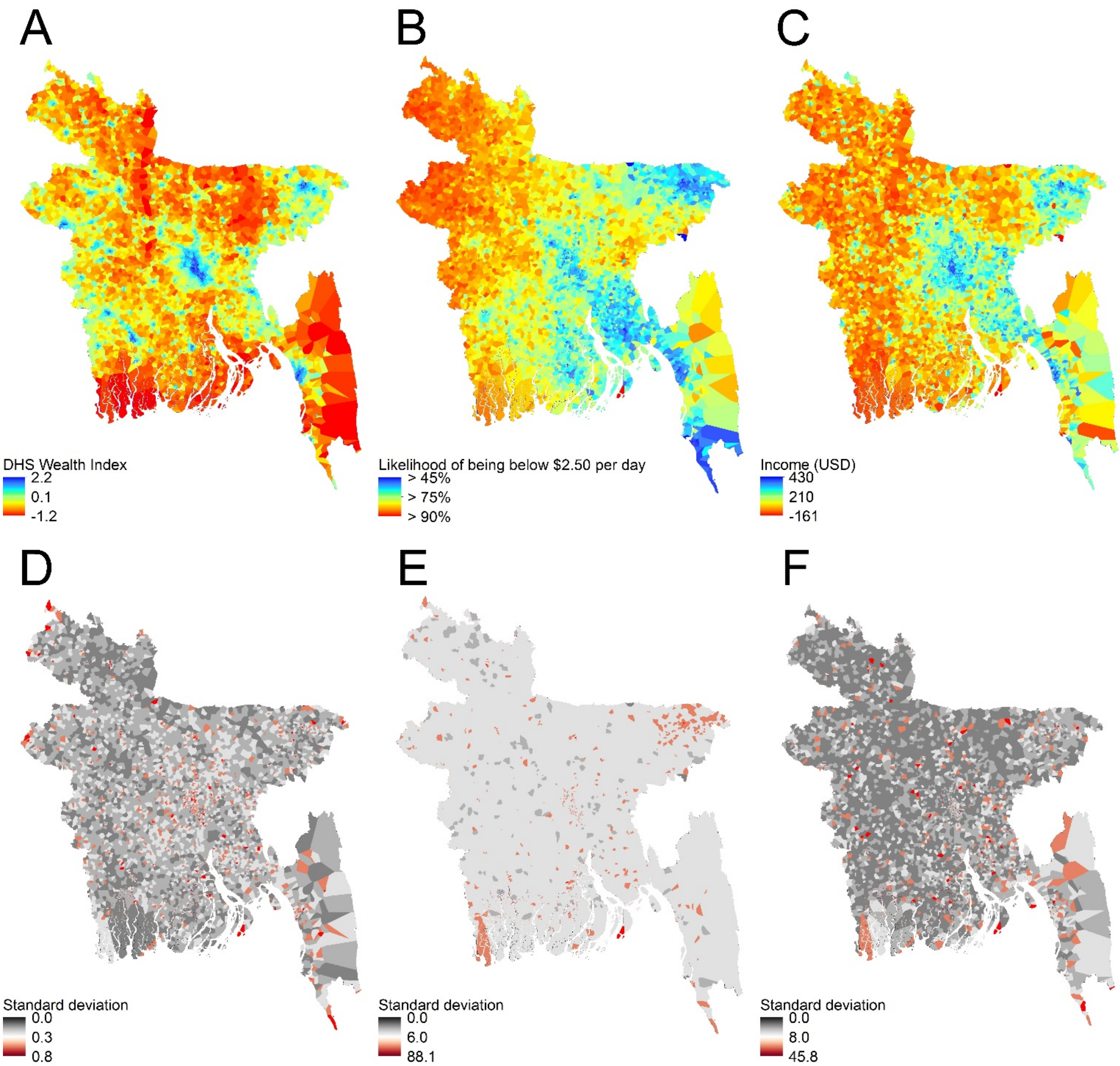

Figure S5. Stratified urban/rural prediction maps for mean wealth index (A) with uncertainty (D); mean probability of households being below $2.50/day (B) with uncertainty (E); and mean USD income (C) with uncertainty (F). Maps were generated using call detail record features, remote sensing data, and Bayesian geostatistical models. Red indicates poorer areas in prediction maps, and higher error in uncertainty maps.

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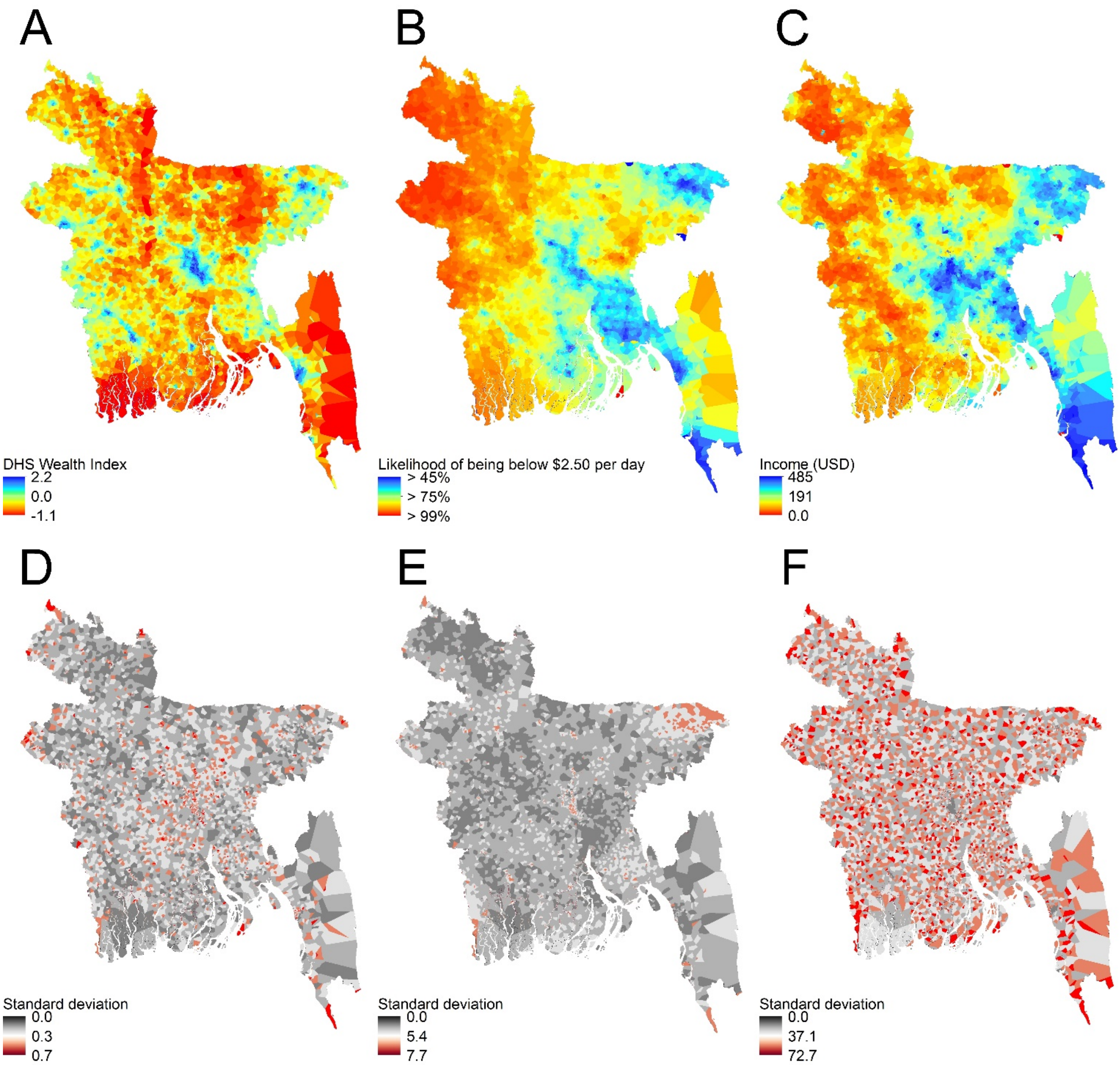

S6. Figure S5. Stratified urban/rural prediction maps for mean wealth index (A) with uncertainty (D); mean probability of households being below $2.50/day (B) with uncertainty (E); and mean USD income (C) with uncertainty (F). Maps were generated using remote sensing data only and Bayesian geostatistical models. Red indicates poorer areas in prediction maps, and higher error in uncertainty maps.