Spatial patterns of rural poverty and their relationship with welfare-influencing factors in Bangladesh

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Abstract

This study determines the spatial variation of rural poverty in Bangladesh and its relation to people's livelihood assets affecting their ability to procure food. We estimated household income for over 1 million census households using a

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predictor model based on a nationally representative sample survey data set. We computed and mapped poverty indices for 415 rural subdistricts revealing distinct areas with high poverty incidence that correspond with ecologically depressed areas. However, other livelihood-influencing factors such as education, accessibility and services are significantly correlated with poverty. This indicates the need for continued focus on providing education and access to income-generating opportunities so that the poor can better meet their food needs. Geographically weighted regression analysis indicated spatial differences in the relative importance of various poverty-influencing factors. Multivariate clustering of the local parameter (β) estimates of the determinant factors revealed distinct spatial relationships, which have implications on poverty alleviation interventions specific to the different regions.

Keywords: Spatial variation; rural poverty; livelihoods; geographical targeting; Bangladesh

Introduction

Despite declining population growth rates from 2.15% p.a. in the 1981-91 decade to 1.54% p.a. in the 1991-2001 decade (BBS, 2003), and even assuming modest improvements in rice productivity and irrigation infrastructure, Bangladesh is expected to face shortfalls in food grain production amounting to 2 million tons by 2010 (World Bank and BCAS, 1998). While striving to increase food production nationally, Bangladesh also faces difficult challenges in ensuring household food security, particularly for the poor and the landless. With its high population density of 839 persons per km^2 (BBS, 2003), agricultural landholdings are already small, averaging 0.68 ha per farming household (BBS, 2000). About 41% of the 19 million rural households (77% of the national total) are landless (BBS, 2003). For these, and the growing numbers of poor urban households, having access to food hinges upon improving their ability to afford it. Therefore, tackling food insecurity in Bangladesh cannot be considered in isolation from the broader concerns of combating poverty and improving livelihoods.

Achievements made in overall poverty reduction—on average at 1% per year between 1991-92 and 2000 (Ministry of Finance, 2003)—have changed the geographic scale at which spatial variation of poverty occurs in Bangladesh. Further poverty alleviation efforts need to be carefully targeted at pockets of high poverty incidence. The reasons for being poor may differ among these poverty hot spots; thus, interventions needed to alleviate conditions, including improving access to food, would differ geographically. The geographical dimension is particularly pertinent in the rural sector, which constitutes over 75% of Bangladesh's population.

Estimating and mapping poverty measures at *upazila* level

This process involved two main steps: (1) estimating household income for a large number of households by income predictor modelling; and (2) computing poverty indicators at spatially disaggregated levels for mapping.

Household income estimation modelling

Direct economic measures of poverty are obtained from sample surveys such as the Household Expenditure and Income Surveys (HIES), the latest being conducted for Bangladesh in 2000. However, the limited sample size and geographical coverage do not permit direct use of these estimates at spatially disaggregated levels because of statistical bias. The small area estimation (SAE) approach of Ghosh and Rao (1994) circumvents this problem by using the detailed household survey data to derive income/expenditure estimators, which are then applied to broad coverage census data to get estimates for a rather larger number of households of the target population. This then permits more highly disaggregated poverty indices to be computed. This approach is increasingly being used in a number of countries (Elbers et. al., 2003, Lanjouw, 2003).

In our study, we adopted the SAE approach to estimate income poverty, from which poverty indicators may be computed at *upazila* (subdistrict) level. Table 1 shows the hierarchy of administrative units in Bangladesh and their approximate size. The total number of households in 2001 was estimated to be 25.31 million (BBS, 2003) with the average household size at 4.9.

The basis of the SAE approach is, using the sample survey, to develop a regression relationship between the direct poverty measure (y_i) for household i and a number of explanatory variables ($x_{1i}, \dots x_{ki}$) available in the survey data set as well as for a larger number of households of the target population, preferably the entire set of households covered in a census. The regression parameters are then applied to the larger data set to estimate the poverty measure of interest which may then be summarized at more detailed spatial scales beyond the district level—at *upazila*, or preferably union, level.

For the detailed household data set, we used a sample survey conducted in 2000-01 by the International Rice Research Institute, using a nationally representative sample originally drawn by the Bangladesh Institute of Development Studies in 1987 to study the trends in rural poverty (Hossain et al., 1994, Rahman and Hossain, 1994). This survey data set contains a larger number of household-level income determinants than the HIES. The sample was drawn using a multi-stage (district-*upazila*-union-village-household) random sampling method and consisted of 1888 households from 62 villages belonging to 57 districts (see Hossain et al., 2002, for details of the sampling methodology).

For the census data set, the Bangladesh Bureau of Statistics provided household- and member-level data for a 5% sample of the 2001 Population Census, taken by systematic sampling of enumeration areas (EAs) within each *upazila*. The sample consists of 1.26 million households. Although almost all the unions in the country are represented in this 5% EA sample, some have very few households (minimum of 1); hence the decision to estimate and map poverty indicators at *upazila* level.

We first explored regression models for household income estimation using as predictors variables representing factors that might influence the income-earning capacity of the household. These would include landholding size, number of family members of working age and amount of non-land fixed assets used in production activities. Access to irrigation infrastructure encourages adoption of high-yielding crop varieties that boost farm productivity. Labour productivity and opportunities for economic activities depend on the quality of labour, which in turn is enhanced through education. Estimating labour and capital separately for agriculture and non-agricultural activities provides information on the relative contribution of these factors of production and their respective marginal returns to income. Village location with respect to infrastructure facilities, such as roads and availability of electrical supply, augments household productivity by improving production efficiency and facilitating mobility to engage in higher productive economic activities.

The best income determination model using household-level data generated by the 62-village survey was able to explain 78% of the variation in household incomes across the sampled households. Table 2 summarizes the results of the regression modelling. The *t*-values for the regression coefficients suggest that the most significant factors influencing household incomes are accumulation of non-agricultural capital, employment of family members in non-farm activities, migration of household members and land endowment.

However, the full income determination model could not be used for predicting income of the census households because the Population Census did not include data for several significant predictor variables, particularly quantitative data on agricultural and non-agricultural capital and landholding size. We then developed an alternative model, whereby the predictor variables selected must be common to both the sample survey and Population Census data sets. Table 3 lists the variables that we included. We tried to include as complete a representation of income-influencing factors as possible, in some cases by resorting to using qualitative equivalents or proxies of the missing quantitative variables.

We substituted landholding size (variable 1, Table 2) with the qualitative variable 11 in Table 3, i.e. whether the household owns agricultural land. As a proxy for non-agricultural capital (variable 4, Table 2), we used the dummy variable 8 in Table 3, i.e. whether the household is engaged in business. From the sample survey data we found strong correlations of landholding and capital with the average educational level of working members. So we used the interaction terms (variables 12, 13 and 14, Table 3) to capture the effects of the missing variables. Ownership of good-quality housing, i.e. *pucca* (brick type) and semi-*pucca* types are indicative of capital accumulation. Also, since the effect of education would be higher for households with workers attending college than those dropping out at primary or secondary school levels, we used dummy variables to represent the first, second and third adult members of the household who attended college (variables 4, 5 and 6, Table 3). We included the dummy variable 7 for religion to capture a relevant social factor for Bangladesh.

Table 3 shows results of the model estimation. This regression model accounts for 57% of the variation of predicted incomes across the 1888 sampled households. The lower predictive power of this model, compared with the full estimation model, is largely due to the omission of quantitative measures for agricultural and non-agricultural capital and landholding size. The income prediction model thus obtained was used for estimating income for the available census households. In a similar exercise using the 2000 HIES data to regress household expenditure against 31 predictor variables, the R^2 obtained was 0.59 (BBS-UNWFP, 2004).

For our study, we concentrated on the rural *upazila*, omitting 26 urban *thana*, 26 *upazila* with no reported rural households and another 18 with more than 50% of the households reported as urban. Five *upazila* are not spatially represented in the *upazila* boundaries map supplied by the Department of Land Records and Survey, so their figures were added to the *upazila* of which they were formerly part. This gave us 432 *upazila*, for which we estimated household incomes for "dwelling households" (defined in the census as those used for residential purposes).

Statistical examination of the poverty estimates for the census households revealed unacceptably high standard errors for 17 *upazila*, of which 15 were found to have fewer than 500 households. We further excluded these 17 *upazila* in our reporting of estimated income. On average, the estimated annual income is US$218 for the 1.076 million census households (of the 5% EA sample of 1.26

million households) within the 415 *upazila*. The average annual household income, at US$204, is lower for rural households. For comparison, the average figure calculated using the 2000 HIES data is US$193 for rural households.

Upazila-*level poverty and income inequality indices and their mapping*

The predicted income for the 1 million census households allowed us to estimate poverty at the *upazila* level as the smallest spatial unit of disaggregation. We computed three poverty indices represented by the Foster, Greer and Thorbeck (1984) equation (1):

$$p_k = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{l - i_j}{l}\right)^k \cdot c(i_j < l).100 \qquad (1)$$

where n is total number of households; i_j is the income or expenditure of the jth household; l is the poverty line; and $c(i_j < l)$ is 1 when income is below the poverty line and 0 otherwise. k can take on values of 0, 1 and 2, providing three commonly used indices—poverty incidence as represented by the Head Count Index (HCI), intensity by the Poverty Gap Index (PGI) and severity by the Squared Poverty Gap Index (SPGI).

In setting the poverty line income, we used the "cost of basic needs" method popularly adopted for Bangladesh (Hossain and Sen, 1992, Ravallion and Sen, 1996). This method first makes a costing of a normative consumption bundle of food items that gives a threshold per capita daily caloric intake needed for sustenance to obtain a food-poverty line. The costing of food items may be estimated using prevailing prices for the survey period. An average non-food expenditure typically incurred by households located at the food-poverty line is then added to get the total poverty line. Ravallion and Sen (1996) estimated the non-food component to be 30% of the food-poverty line. In our study, we adjusted the percentage to 40% to account for increase of the Consumer Price Index.

We used this method for estimating two poverty lines. For the upper line, the caloric threshold was set at 2112 kilocalories, recommended for maintaining a healthy productive life of the average Bangladeshi; while the lower poverty line for delineating the extreme poor uses a threshold of 1800 kilocalories (Muqtada, 1986). We estimated prices for the food items nationally from the 2000 HIES data on the quantity and value of foods consumed by rural households. Our estimate of the upper poverty line is US$136 per capita per annum and of the lower poverty line, US$78. We calculated the HCI for both poverty lines (HCI_poor and HCI_epoor) and calculated the PGI and SPGI using the upper poverty line.

We also computed the Gini index based on the estimated per capita income for the *upazila*. This variable represents the overall income inequality, i.e. disparities in income distribution among all households, both poor and non-poor.

Table 4 gives indices of poverty and income inequality for rural households. Estimates from our study correspond closely with those estimated using the HIES (based on the comparison for rural households), especially for the incidence of poverty, i.e. HCI_poor. The other indices of poverty and income inequality tend to be 2 to 6 percentage points lower for the HIES-based estimates. Nationally, an estimated 43% to 45% of households in rural Bangladesh live below the poverty line, while about 17% to 18% live below the extreme poverty line.

Figs. 1 and 2 show the spatial variation at *upazila* level in the incidence of poverty and income inequality; the map classes represent the four quartiles of the mapped variable. The metropolitan *thana* and the *upazila* excluded from estimation are marked white. Distinct pockets of high poverty incidence are evident in the north-eastern, north-western and south-eastern parts. A similar spatial pattern emerges for the other computed indicators of poverty. In contrast, the spatial pattern for income inequality does not necessarily correspond with that of poverty. High levels of inequality occur in *upazila* showing low poverty incidence, particularly those along the western edge. Conversely, many of the poor *upazila* stretching across the northern belt have relatively lower Gini indices, suggesting that households are poor and less unequal in wealth.

Relating income poverty to other indicators of human welfare

The existence of pockets of high poverty incidence raises questions concerning the characteristics associated with these localities. Addressing these questions requires regressing poverty measures against possible explanatory variables, particularly the assets that people can access for supporting their livelihoods. In the context of the sustainable livelihoods framework (Scoones, 1998), these assets may be identified as natural, physical, human, financial and social capital. At *upazila* level, we developed a variety of indicators representing various aspects of human welfare (or conversely deprivation), which may influence the ability of households to earn their living and therefore influence poverty incidence. These include (1) their household assets, i.e. their human capital (quantity and quality of labour), and physical capital (e.g. machinery, vehicles); and (2) their opportunities for livelihood enhancement, i.e. their natural capital (quality of land) and access to facilities (physical capital such as road and electrical infrastructure and social capital such as education and health facilities) and sources of off-farm employment.

These indicators may be categorized as aggregated household characteristics (e.g. percentage of landless households in the *upazila*), representing "community" characteristics (e.g. percentage of net cultivated area under tenancy, average travel time to various local services and facilities) and representing "area" variables (e.g. percentage of the *upazila* area of certain soil or land type). The data come from a variety of sources including the 1996 Agricultural Census (BBS, 2000), the 2001 National Irrigation Census (NMID, 2002), the Agro-Ecological Zoning Project of the Bangladesh Agricultural Research Council/ Food and

Agriculture Organization/ United Nations Development Programme, and the infrastructure database of the Local Government and Engineering Department.

We estimated several area variables using geographic information systems (GIS) overlay of biophysical maps (soil, land type, climate) with the *upazila* boundaries. We also used GIS techniques to derive selected variables. For example, we computed physical accessibility as the average travel time for villagers to reach a number of commonly visited public facilities (the two nearest markets, the closest health centre, growth centre and *upazila* headquarters) using a methodology adapted from Deichmann (1997). This variable captures the level of road infrastructure development and the spatial distribution of key public facilities that rural people need.

Global regression modelling

We first regressed the income poverty indices for the 415 *upazila* against selected indicators representing the various dimensions of human welfare. We were necessarily limited to variables for which data of comprehensive geographical coverage are available. Table 5 summarizes results of the regression relationships between the HCI and 10 explanatory variables that account for just over 80% of the variances for HCI_poor and 70% for HCI_epoor. All independent variables used contribute significantly to the regression relationships, except for the high land variable in the regression model for HCI_poor.

We note that in the downstream regression involving poverty incidence as regards *upazila* (derived from imputed household income) as the dependent variable, including aggregated values of the explanatory variables, education and electrification, which have been used at household level for income prediction, may raise concern about endogeneity. Elbers et al. (2004) point out that the endogeneity problem may arise if the imputed variable is used in the right-hand side (RHS) of the downstream regression as an explanatory variable. They further showed mathematically that in the case of using the imputed poverty indicator on the left-hand side, "essentially such regressions yield results no different from what would follow from similar regressions involving the true welfare indicators" (Elbers et al. 2004, p. 17-18) and that the more basic issue is one of proper model specification and interpretation of aggregate relationships as causal or direct. Peter Lanjouw (personal communication, 2004) pointed out that the *t*-statistic for the regression coefficients of the concerned RHS variables might be overestimated. Given the high *t*-values of these variables (Table 5), the likelihood of altering their statistical significance by more rigorous treatment appears remote.

Geographically weighted regression modelling

The regression models depicted in Table 5 assume that the relationships of explanatory variables to the poverty indicators hold true across the whole of Bangladesh. However, some relationships may be intrinsically different across space, giving rise to spatial non-stationarity of the relationships between the explanatory and dependent variables. An explanatory variable may be highly significant in its relationship with poverty incidence in some geographical area but not in another; or it may yield a positive relationship in some area but a negative relationship elsewhere. It is not uncommon for human-related phenomena and interactions to be spatially non-stationary.

In this study, we applied geographically weighted regression (GWR) techniques (Fotheringham et al., 2002) to determine if spatial differences occur in the relationships between poverty incidence and the explanatory variables. Such spatial differences, if they exist, would suggest the need for affected regions to be treated differently in poverty alleviation efforts.

In GWR, the vector of parameter estimates (i.e. the intercept and the regression coefficients) is not fixed over the entire study area but is a function of geographical location (Eq. 2):

$$y_i = \boldsymbol{\beta}_{\mathbf{0}}\left(x_i, y_i\right) + \sum\nolimits_k \boldsymbol{\beta}_k\left(x_i, y_i\right)\mathbf{X}_{ik} + \varepsilon_i \tag{2}$$

where the β parameters are to be estimated at location i whose coordinates are given by the vector (x_i, y_i).

The regression model is calibrated for a location (called the regression point) by using all other available data points to which weights are applied according to a continuous distance-decay function rather than a discrete window of fixed size. The decay function is user selected and may be fixed (commonly the Gaussian function is used) or adaptive. In the latter case, the shape of the function, defined by the adaptive bandwidth, may vary depending on the density of data points in the immediate neighbourhood of the regression point. This ensures that local parameter estimates are not made using too few data points for regression points located in areas of low data density. The spatially variable weighting function can be statistically calibrated (Fotheringham et al., 2002).

We used the GWR software (Charlton et al., 2003) to calculate local parameter estimates for the same set of 10 explanatory variables used in the global regression modelling. To provide the spatial dimension for the computation, the input data (poverty indices and explanatory variables) were associated with centroids of their respective 415 *upazila*. The localized regression modelling was carried out with the adaptive bandwidth set to include the closest 25% of the 415 data points. The outputs are a set of local β parameters (with corresponding standard errors and *t*-statistics) describing the relationship between the explanatory and the dependent variables for each *upazila*.

Analysis of variance showed that the GWR models are significant improvements over the global models, i.e. that there are significant spatial variations in the relationships of the explanatory to both dependent variables. Monte Carlo tests (due to Hope 1968, JRSB 30(3), 582-598, cited by

Fotheringham et al., 2002) were done to determine the significance of the spatial variability in the local β parameter estimates. The results indicate highly significant spatial variations in the local parameter estimates for six of the explanatory variables—land tenancy, livestock ownership, irrigation, travel time, prevalence of high land and clayey soils—indicating the varying relationships of these variables on poverty incidence across space.

Table 6 summarizes the GWR results. Only the education attainment variable consistently has negative local β estimates, with highly significant *t*-values, for all 415 *upazila*, indicating the consistent potential of raising household incomes through improved educational opportunities to rural households.

The local β estimates for the other explanatory variables vary from negative to positive values, flanking the global estimates. In the case of the high land variable, only 32% of the local β estimates have the same, positive (+), sign as the global estimate. Fig. 3 shows that positive local β estimates for high land percentage are confined to upper Rajshahi, Sylhet and Chittagong Divisions, while the rest of Bangladesh has negative local β estimates. The negative relationship is particularly strong in Khulna Division and for the *upazila* east of Dhaka City. This is a clear instance of a global parameter estimate suggesting a relationship that is a direct opposite of the prevalent trend as revealed by the local parameter estimates.

Determining geographical differences in the relationship between poverty incidence and explanatory variables

We next subjected the local β estimates for the 10 explanatory variables to multivariate K-means clustering to determine if relationships between the explanatory and the poverty indices vary geographically. Specific combinations in the relationships of the explanatory variables to the dependent variable would thus characterize spatial clusters of *upazila* that emerge.

The result for the dependent variable HCI_epoor (Fig. 4) does indeed show distinct spatial clusters. Cluster 1 appears as a belt straddling the northern edge of Bangladesh and stretching downward, parallel with the Jamuna River, and bifurcates, separating the country into three other contiguous areas—one in the southern coastal region (Cluster 2), and the other two western and eastern regions, which are grouped into the same cluster (Cluster 3). A fourth cluster is geographically separated into an area that coincides rather closely with Sylhet District and roughly a band separating Cluster 1 and Cluster 2. A similar, although less distinct, pattern was obtained for HCI_poor.

General discussion

While the distinct spatial concentrations of the rural poor in Bangladesh (Fig. 1) highlight the need for targeting poverty alleviation efforts at these areas, the greater income disparities evident outside these poverty hot spots (Fig. 2) suggest that the poor in the relatively wealthier *upazila* would require equal attention. The pockets of high poverty incidence generally coincide with the ecologically poor areas of Bangladesh:

1. The low-lying depression area, called *haor*, in the north-east;
2. The drought-prone area on relatively higher land in the north-west;
3. Several *upazila* fringing the major rivers, particularly along the Jamuna River; and
4. Several of the south-eastern *upazila*, including the Chittagong Hill Tract.

The *upazila* associated with areas 1, 2 and 3 generally share similar relationships between poverty incidence and significant explanatory variables, as indicated by membership in Cluster 1 in Fig. 4; the policy implications of this are further explored.

Despite the apparent geographical association of the poverty pockets with ecologically unfavourable areas, few of the biophysical variables correlate significantly with the poverty indices. The significant ones include the prevalence of high land, low and very low-lying land and heavy textured soil types. These partly explain the association of high poverty incidence with the *haor* and the hilly areas. Climatic variables such as rainfall availability emerge as insignificant, partly because of the non-linear relationship of rainfall with poverty. Other factors, particularly irrigation, mask the significance of associated climatic constraints, particularly drought, in explaining poverty over geographical space.

In contrast, the socio-economic explanatory variables dominate the overall regression relationships with poverty incidence. The *t*-values for the regression coefficients of the explanatory variables for the extreme poverty incidence (HCI_epoor in Table 5) suggest that extremely poor households are particularly adversely affected by land-related factors (landlessness, prevalence of low-lying land and high land). Given the high levels of landlessness and tenancy (43% of households are landless and almost 20% of households operate on rented land), scope is limited for improving access to land for poor rural households. This is also a difficult policy issue in such a densely populated country. Lifting the extreme poor out of poverty requires improving their opportunities to engage in other income-generating activities, or moving them out of these severely constrained areas. Their economic mobility can be enhanced through improving access to education, health and employment markets.

Indeed, educational attainment correlates most strongly with poverty incidence. The *t*-values for the three infrastructure variables in Table 5—electrification, irrigation and road accessibility—suggest that improvements in infrastructure continue to be important interventions for poverty alleviation in the areas of high poverty incidence. Although road infrastructure in Bangladesh has improved overall in the past decade, scope remains for improving road quality and locating public facilities, particularly in areas that pose physical problems, i.e. the *haor* and the hilly areas. Improved accessibility in these areas also would provide opportunities for intensifying and diversifying agricultural and food production using improved technologies.

We now focus on specific characteristics and policy implications arising out of regional differences in the relationships between poverty incidence and explanatory variables, based on the results of the *upazila* clustering shown in Fig. 4. We noted that Cluster 1 *upazila* are generally associated with the three main ecologically depressed areas listed above. The incidence of poverty and extreme poverty of these *upazila* are higher than those belonging to other clusters (detailed data not included). The local β estimates for land tenancy are strongly negative, while tenancy rates are generally low. This indicates that in situations where land endowment is poor, having the opportunity for renting more land area would help increase household food production. The local β estimates for livestock ownership are also strongly negative, indicating the importance of livestock as insurance for poor households within the poorer parts of Bangladesh.

Innovative agricultural interventions in these areas are important both for increasing the productivity of rice as the dominant crop and for diversifying production systems (including livestock and fisheries) appropriate to the natural ecology of the area. The abundance of water and deep flooding provides opportunities for developing technologies for agriculture-aquaculture systems appropriate for poor rural communities but infrastructure and micro-credit support need to accompany these. While drought contributes to depressed crop productivity in the north-west, other factors such as poor accessibility and high labour participation in agriculture tend to dominate the statistical relationship with poverty incidence. This, however, does not diminish the importance of developing drought-coping strategies for improving agricultural productivity and improving food security in these areas.

Cluster 2 is most distinct physiographically, coinciding mainly with the coastal zone of Bangladesh. The regression relationships of the explanatory variables with poverty incidence within this region show the greatest departure from the global model. Poverty incidence is low in the western part towards Khulna (where livestock ownership, educational attainment and prevalence of clayey soils are high) and is high in the eastern part towards Chittagong (Fig. 1). Accessibility by road to local services is generally poor and the predominantly positive β estimates suggest the potential benefits that improved accessibility could have on poverty reduction. Irrigation infrastructure also remains poor in this region. Its negative relationship with poverty suggests the need for tapping the freshwater resources to take advantage of the rich soils for intensifying cropping in the dry season, as well as improved management of the brackish and saline water resources for aquaculture and fisheries development.

The Cluster 3 *upazila* occupy two diametrically opposed (western and eastern) parts of Bangladesh but share common relationships of the explanatory variables for poverty incidence. Their local β estimates generally reinforce the global model most strongly. However, because of marked differences in physiography and agro-ecology, land endowments are different in the two parts. The incidence of poverty and extreme poverty is generally lower in the western part, covering southern Rajshahi and northern Khulna Divisions. In fact, this part has more high land area and is more drought-prone but the higher irrigation coverage is key in achieving high productivity despite the biophysical constraints. The eastern part is relatively better endowed (with more extensive medium and low land, higher rainfall and educational attainment); yet these resources do not seem to have been effectively deployed for improving livelihoods.

Both spatially and in terms of defining local parameter estimates, Cluster 4 appears to represent intermediate conditions between Clusters 1 and 2. The main difference in the spatial relationships of the explanatory variables for Cluster 4, compared with Cluster 3, is the generally negative local β estimates for tenancy.

Conclusions

While the pockets of high poverty incidence that we have mapped correspond with ecologically poor areas for food production, the significant correlates are other livelihood-influencing factors such as education, accessibility and services.

The right policies and commitment for providing education and access to income-generating opportunities would increase the capacity of the poor, particularly the landless, to meet their food needs. In addition, targeting different interventions in various regions of Bangladesh is warranted. Agricultural research and development in the environmentally constrained northern poverty belt (heavy flooding in the north-east, drought in the north-west, erosion along the major rivers) should focus on risk-averting, diversified production systems that gradually stabilize and increase food production. Innovative management of the dual saline and freshwater regimes in the south-western coastal areas for crop production and fisheries and aquaculture development would both boost household food security and add value to agricultural production. The pay-off that irrigation and improved road infrastructure has had on increasing food productivity in the drought-affected central western part is indicative of the potential for further productivity growth eastward to contribute to national production levels needed to support the growing Bangladesh population. Finally, geographical targeting of poverty alleviation programmes should not preclude reaching the poor within relatively better-off *upazila* where income inequality remains high.

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Figure Legends

Fig. 1. Incidence of poverty at *upazila* (subdistrict) level, Bangladesh

Fig. 2. Income inequality at *upazila* (subdistrict) level, Bangladesh.

Fig. 3. Local parameter estimates for prevalence of high land in *upazila* (subdistricts) of Bangladesh from geographically weighted regression modelling. Dependent variable is the Head Count Index for the upper poverty line.

Fig. 4. Clusters of *upazila* (subdistricts) of Bangladesh based on local parameter estimates of 10 explanatory variables from geographically weighted regression modelling. Dependent variable is the Head Count Index for the lower poverty line.

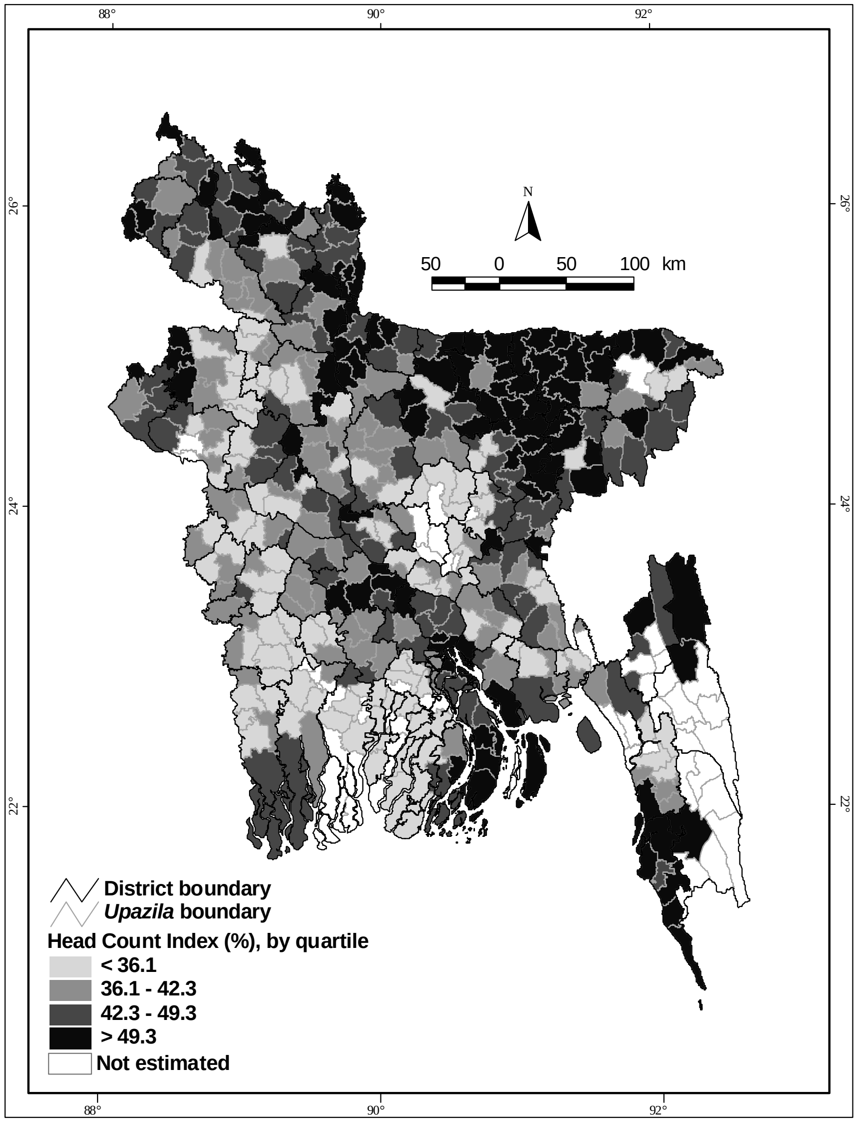
88°
90°
92°
26°
24°
22°
N
50 0 50 100 km
District boundary
Upazila boundary
Head Count Index (%), by quartile
< 36.1
36.1 - 42.3
42.3 - 49.3
> 49.3
Not estimated

Fig. 1

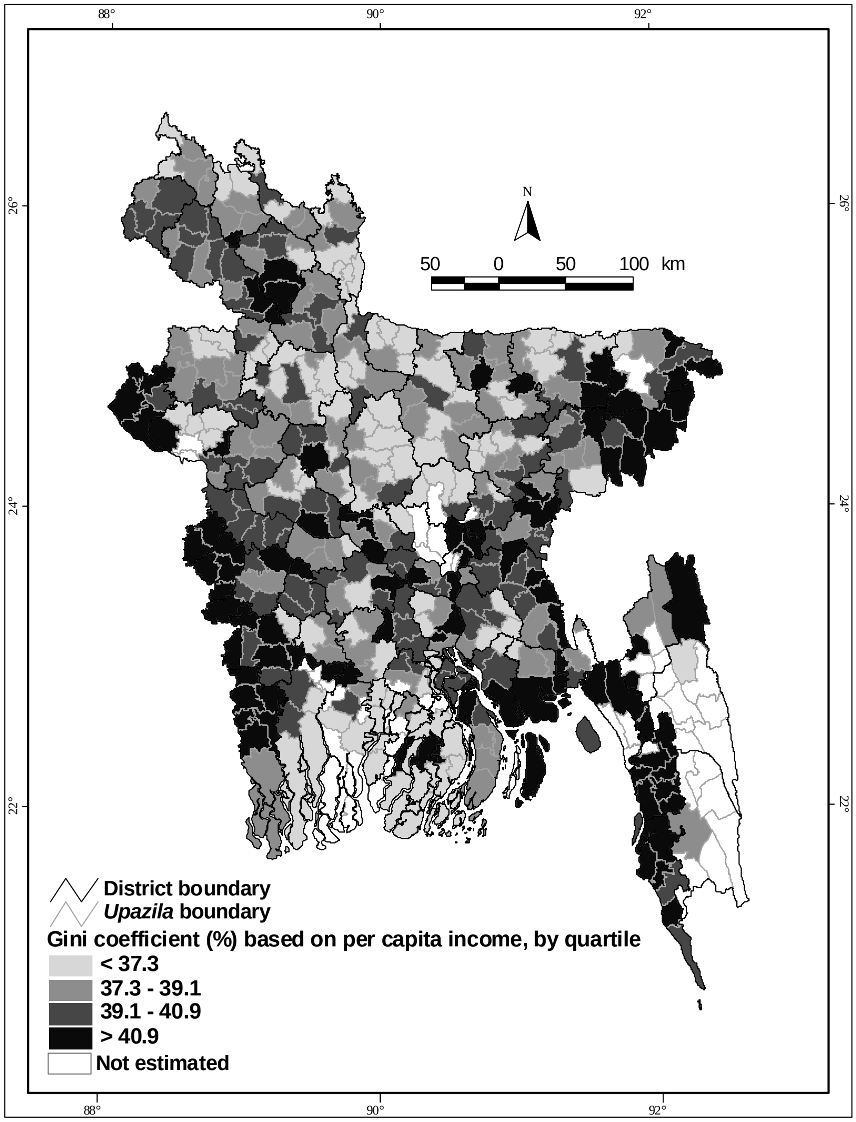
88°
90°
92°
26°
24°
22°
N
50 0 50 100 km
District boundary
Upazila boundary
Gini coefficient (%) based on per capita income, by quartile
< 37.3
37.3 - 39.1
39.1 - 40.9
> 40.9
Not estimated

Fig. 2

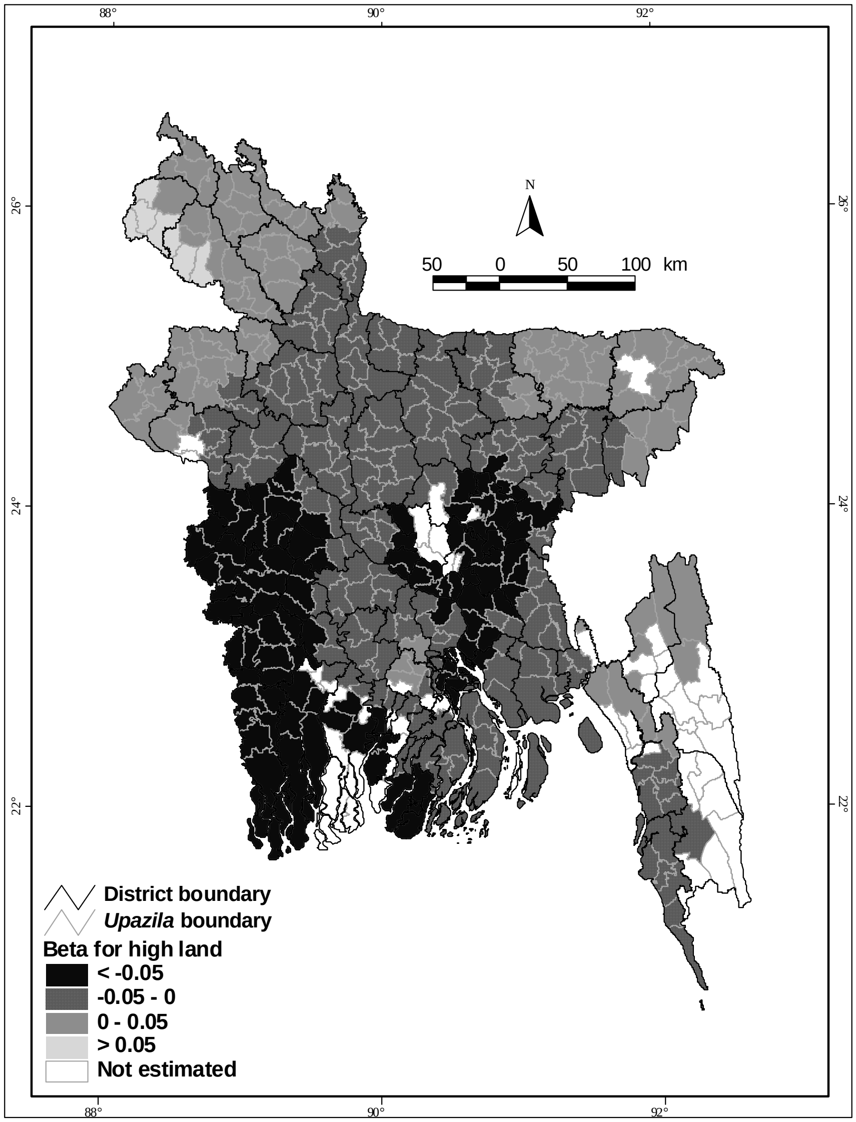
88°
90°
92°
26°
24°
22°
N
50
0
50
100
km
District boundary
Upazila boundary
Beta for high land
< -0.05
-0.05 - 0
0 - 0.05
> 0.05
Not estimated

Fig. 3

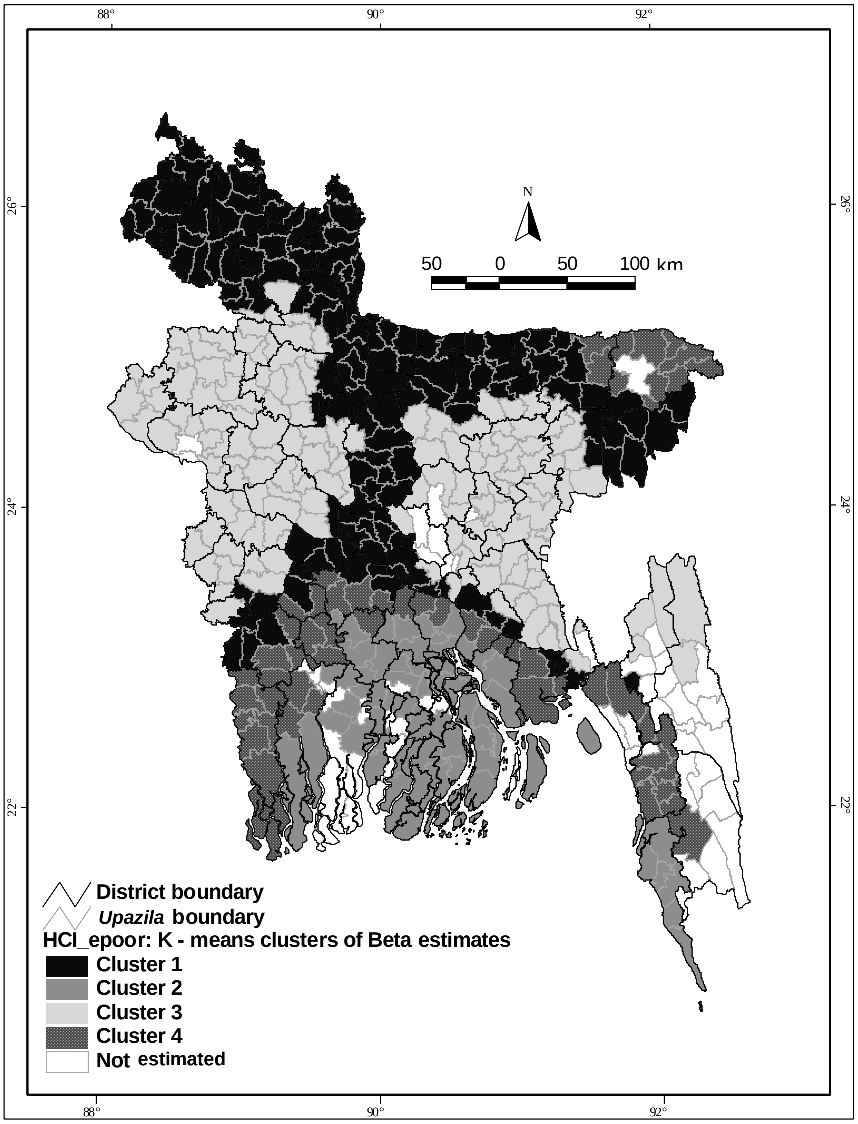
88°
90°
92°
26°
24°
22°
N
50 0 50 100 km
District boundary
Upazila boundary
HCI_epoor: K - means clusters of Beta estimates
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Not estimated

Fig. 4

Table 1
The hierarchy of administrative units[a] in Bangladesh with corresponding number and size

Administrative unit	Division	District	*Upazila*/ *thana* (subdistrict)	Union/ ward	Village
Number of units	6	64	507	6888	87,928
Mean number of households	4,217,933	395,431	49,916	3674	288

[a] The terms *upazila* and union are associated with rural areas, *thana* and ward with urban areas.

Table 2
Contribution of predictor factors to rural household incomes in Bangladesh: estimates based on 62-village sample survey, 2001

	Variable	Mean	Marginal return (US$)	*t*-value of the coefficient	Contribution to income (%)
1	Land owned (ha)	0.53	339.25	9.92	14.6
2	Irrigated land (%)	44.40	271.31	4.29	5.2
3	Agricultural capital (US$)	150.52	1.21	9.47	14.5
4	Non-agricultural capital (US$)	412.02	0.31	38.46	10.5
5	Agricultural worker (person)	0.81	59.70	2.31	3.9
6	Non-agricultural worker (person)	0.86	390.81	15.61	27.1
7	Average education of worker (yr)	4.35	25.01	4.22	8.8
8	Household with migrant member (%)	10.30	637.61	10.92	5.3
9	Villages with paved roads (%)	34.20	105.50	2.04	2.9
10	Households with electricity (%)	31.49	284.11	4.23	7.3

Adjusted R^2 = 0.78 F = 682.37 n = 1888

Table 3
Income predictor model developed from household sample survey data to estimate household (HH) income in Bangladesh using 2001 Population Census data

	Variable	Mean value	Marginal return (US$)	*t*-value of coefficient
1	Agricultural workers (persons/HH)	0.81	235.0	5.674
2	Non-agricultural workers (persons/HH)	0.86	297.0	6.392
3	Average education of worker (yr)	7.99	31.6	5.629
4	College education of HH head (dummy)	0.073	394.7	2.785
5	College education of 2nd member (dummy)	0.017	660.3	2.527
6	College education of 3rd member (dummy)	0.082	446.7	3.496
7	Religion (dummy; non-Muslim = 1)	0.90	-93.0	-0.812
8	Trade as main source of income (dummy)	0.14	325.1	3.016
9	Interaction: trade and education of HH head	0.69	49.6	2.565
10	Households with electricity (%)	31.49	3.2	3.607
11	Ownership of agricultural land (dummy)	0.596	117.3	1.610
12	Interaction: electricity and trade as main source of income	7.73	10.9	4.562
13	Interaction: ownership of *pucca* (brick-type) house and ownership of agricultural land	0.063	1539.4	10.227
14	Interaction: ownership of semi-*pucca* house and ownership of agricultural land	0.201	493.2	5.193
	Adjusted R^2 = 0.57; F = 180.59; n = 1888			

Table 4
Estimates of income inequality and poverty for rural households in Bangladesh, 2001

Mean estimates (%) based on:	Small area estimation method[a]		Actual HIES data[b]
	All households	Rural households	Rural households
Gini index for per capita income	39.3	41.0	36.5
Head Count Index (general poor)	42.9	44.6	43.6
Head Count Index (extreme poor)	17.3	18.0	12.0
Poverty Gap Index	15.9	16.6	13.6
Squared Poverty Gap Index	7.8	8.1	6.3

[a] Estimated income using household data of Population Census 2001 based on coefficient of income function from 62-village study, International Rice Research Institute.
[b] Household Income and Expenditure Survey, 2000.

Table 5
Factors contributing to spatial variation in incidence of poverty and extreme poverty at *upazila* (subdistrict) level: regression estimates (n = 415)

Variable	Mean value	HCI_poor[a]		HCI_epoor[b]	
		Coeff	t[c]	Coeff	t[c]
(Constant)		68.729	35.24	10.803	15.35
Landless households (%)	43.35	0.044	2.02	0.053	6.71
Agricultural area under tenancy (%)	19.95	0.094	3.03	0.032	2.84
Livestock per household (HH) (no.)	8.65	0.302	2.83	0.183	4.74
Average years of schooling of adult HH members	3.28	-8.507	-24.45	-2.091	-16.65
Households with electricity supply (%)	22.35	-0.099	-5.53	-0.019	-2.89
Net cropped area served by modern irrigation facilities (%)	52.89	-0.032	-4.49	-0.012	-4.76
Travel time by road to main service facilities (min)	25.60	0.019	2.26	0.008	2.70
High land (%)	26.89	0.002	0.25[†]	0.010	3.25
Low and very low land (%)	12.42	0.063	4.99	0.028	6.15
Area with clay and loamy clay soil (%)	41.32	-0.043	-5.98	-0.011	-4.31
	R^2	0.81		0.71	
	F	179.4		103.9	

[a]Head Count Index (HCI) for upper poverty line.
[b]HCI for lower poverty line.
[c]All t values, except the one marked †, are significant beyond the 0.10 level.

Table 6

Range of local (regarding *upazila*, or subdistricts) β parameter estimates for the explanatory variables modelled by geographically weighted regression, compared with the global estimates. The dependent variable is the Head Count Index for the upper poverty line

Variable	β parameter estimates[a]			Cases of same sign as global β (%)	Cases for which β is significant (%)
	Min local	Global	Max local		
Landless households (%)	-0.085	0.044	0.217	73	20
Agricultural area under tenancy (%)	-0.507	0.094	0.306	65	26
Livestock per household (HH) (no.)	-0.548	0.302	1.655	62	29
Average years of schooling of adult HH members	-11.535	-8.507	-6.100	100	100
Households with electricity supply (%)	-0.212	-0.099	0.056	94	63
Net cropped area served by modern irrigation facilities (%)	-0.104	-0.032	0.050	57	29
Travel time by road to main service facilities (min)	-0.180	0.019	0.211	66	26
High land (%)	-0.134	0.002	0.055	32	27
Low and very low land (%)	-0.063	0.063	0.151	75	35
Area with clay and loamy clay soil (%)	-0.102	-0.043	0.052	69	28

[a]Min local, minimum of the local β parameter estimates for 415 *upazila* (subdistricts); Global, β estimate from the global regression model; Max local, maximum of the local β parameter estimates for 415 *upazila*.