Spatial clustering of rural poverty and food insecurity in Sri Lanka

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Abstract

We mapped poverty, with reference to a nutrition-based poverty line, to analyse its spatial clustering in Sri Lanka. We used the Divisional Secretariat poverty map, derived by combining the principal component analysis and the synthetic small area estimation technique, as the data source. Two statistically significant clusters appear. One cluster indicates that low poverty rural areas cluster around a few low poverty urban areas, where low agricultural employment and better access to roads are key characteristics. The other indicates a cluster of

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high poverty rural areas, where agriculture is the dominant economic activity, and where spatial clustering is associated with factors influencing agricultural production. Agricultural smallholdings are positively associated with spatial clustering of poor rural areas. In areas where water availability is low, better access to irrigation significantly reduces poverty. Finally, we discuss the use of poverty mapping for effective policy formulation and interventions for alleviating poverty and food insecurity.

Keywords: Spatial clustering; food poverty line; subdistrict level; water and land resources; geographical targeting; Sri Lanka

Introduction

Historically, Sri Lanka has placed a high value on basic human needs, channelling assistance to rural areas to promote food security and employment, and to assure that the poor have access to primary health care, basic education and an adequate diet. This policy has resulted in the country achieving significant advances in some areas of human welfare compared to other low-income countries. Life expectancy at birth (74 years), infant mortality rate (16 per 1000 live births), adult literacy rate (92%) and the combined primary, secondary and tertiary school enrolment ratio (66%) at present are comparable to levels in the more developed countries (UNDP, 2003). Yet, about one quarter of the population remains below the official income poverty line (DCS, 2003).

Over the years, successive governments have introduced various interventions to alleviate income poverty. But, whether the benefits of these interventions actually reached those intended is doubted because of shortcomings in identifying and locating the poor. As in many other countries, Sri Lankan national poverty assessments are compiled using household and community surveys and disaggregated into broad categories such as urban, rural and estate sectors and for a larger geographical unit such as an administrative district. Aggregate poverty statistics at the resolution of district level are too limiting for identifying spatial patterns of poverty within and across districts, and for assessing the causes and effects of spatial variations of poverty in smaller geographical units. There is a growing demand for poverty information at a finer resolution to enable a narrower geographic targeting aimed at maximizing the coverage of the poor while minimizing leakage to the non-poor (Henninger and Snel, 2002).

We use the poverty estimates at Divisional Secretariat (DS) level, a lower administrative unit than a district, to test whether the poor in Sri Lanka are spatially clustered, determine how far spatial clustering influences incidence of poverty and investigate the association of availability and access to water and land resources and infrastructural facilities with poverty and its spatial clustering across DS divisions.

Subnational poverty maps

Poverty maps depict the spatial variation of indicators of human well-being across units in geographically disaggregated layers (Henninger, 1998, Hentschel et al., 2000, Davis, 2002, World Bank, 2004). Sri Lanka is divided into four administrative layers: 9 provinces, 25 districts, 325 DS divisions and about 14,000 *Grama Niladari* (GN), or village officer divisions (DCS, 1998). Of the four administrative layers, the GN division is an ideal unit for subnational poverty mapping analysis. But we take the DS division as our unit of analysis because of limitations on the availability of ancillary data for estimating poverty at the GN level.

The poverty line in this article, an estimate of the cost of a bundle of food items adequate for receiving the minimum nutritional requirement[1] (DCS, 2003), is essentially a food poverty line. The poverty estimate, the proportion of households below the food poverty line, represents households that are both poor and food insecure. A household is poor if it spends more than 50% of its expenditure on food and its per adult equivalent food expenditure is below the food poverty line. Thus the poverty estimate here is essentially an indicator of poverty and food insecurity in Sri Lanka.

The district poverty estimates (Fig. 1B) show no significant variation of poverty across districts in the North Central, Uva and Sabaragamuwa Provinces (Fig. 1A). The incidence of poverty in the Anuradhapura and the Polonnaruwa

Districts (about 29%) in North Central Province is almost identical so that district-level poverty maps are too aggregate to find any variation across or within districts.

The DS divisional poverty estimates (Fig. 1C), derived by combining the principal component analysis and the synthetic small area estimation technique[2] (Amarasinghe et al., in press), vary from 1% to 46%. Even in the provinces, such as North Central, Uva and Sabaragamuwa, where the variation of poverty across districts does not seem significant, the variation of poverty across DS divisions is significant. Moreover, most DS divisions with low incidence of poverty (below 1 standard deviation from the national average) are located in a cluster in the Colombo and Gampaha Districts, and most DS divisions with high incidence of poverty (above 1 standard deviation from the national average) are located in a cluster in four districts: Ratnapura, Badulla, Moneragala and Hambantota. The distribution of the DS division's poverty levels is highly skewed (Table 1), with 74% of the DS divisions falling above the national average poverty level.

The DS poverty maps can be useful for spatial targeting of poverty interventions. The World Bank (2002) reports that while many households in the upper income strata receive the welfare benefits of the *Samurdhi* programme[3], designed to help the poor, many in the lower-income strata miss these welfare benefits. Indeed, the *Samurdhi* programme has different criteria for identifying the poor households that are eligible for welfare assistance. But the selection criteria flaws coupled with regional and local-level political interferences have often contributed to the *Samurdhi* programme's significant leakages to the non-poor.

The poverty map can locate DS divisions with highly inefficient resource allocation (Fig. 2). For example, only 3000 households of the four least poor DS divisions (category 1 in Fig. 1 and Table 1) are poor but more than 12,000 households receive the highest financial assistance under the *Samurdhi* welfare programme. And nine of the poorest DS divisions (category 6 in Fig. 1 and Table 1) have 31,000 poor households but only 19,000 households receive the highest financial assistance. If resources are distributed proportionately to the poverty levels of DS divisions, then all poor households can receive welfare benefits at a level (about 970 LKR[4], or about US$10) higher than the highest financial assistance distributed at present (Amarasinghe et al., 2005). This certainly is adequate to reduce the food poverty gap or food insecurity of many poor households and can perhaps reduce the number of food-insecure poor households in many DS divisions.

Because of the lack of poverty information at geographically disaggregated unit level, the poverty determinants analyses conducted so far have ignored poverty and food insecurity for detailed geographic units and the influences of spatial dependencies of neighbouring units. We investigate the extent of spatial clustering of poverty across DS divisions and its influence on the incidence of poverty and the factors associated with spatial clustering of poverty.

Spatial clustering of locations of poverty

Spatial clustering shows the similarity or dissimilarity of poverty in neighbouring units and spatial autocorrelation measures the strength of the spatial clustering (Cliff and Ord, 1973, Getis and Ord, 1992, Anselin, 1995). The global Moran's I statistic, the slope of the regression line of the scatterplot of the standardized percentage of poor households, and spatial lag[5] of the percentage of poor households (Fig. 3) indicate the strength of the spatial similarity of the whole area. Negative values of x- and y-axes in Fig. 3 indicate below-average values.

The first and the third quadrant points in Fig. 3 suggest positive spatial autocorrelation and hence similar units. The first quadrant points show high poverty DS divisions with high poverty neighbours (high-high), while the third quadrant points show low poverty DS divisions and low poverty neighbours (low-low). The second and fourth quadrant points suggest negative spatial autocorrelation and hence dissimilar units. The second quadrant points show low poverty DS surrounded by high poverty neighbours (low-high) while the fourth quadrant points show high poverty DS divisions surrounded by low poverty neighbours (high-low).

Statistically significant global Moran's I (significant at 0.001 level) confirms the hypothesis that poor (or non-poor) locations are often found in spatial clusters, meaning that a poor (or non-poor) location is often surrounded by poor (or non-poor) neighbours.

Local Moran's I indicator, estimated using the spatial data analysis package Geoda 9.0 (Anselin, 2003), identifies the locations with statistically significant spatial autocorrelation. Fig. 4A shows the DS divisions with high and Fig. 4B with low levels of poverty and surrounded by similar neighbourhoods. Fig 4C shows DS divisions with low and Fig. 4D with high levels of poverty but surrounded by dissimilar neighbourhoods.

High poverty DS divisions and high poverty neighbourhoods are mainly rural (Fig. 4A), and agricultural economic activities are the main source of income of most households. For example, at least every two in three households have an agricultural operator in Kurunegala, Anuradhapura, Polonaruwa, Moneragala and Hambantota Districts. But the similarities are significant in only four districts: Badulla, Moneragala, Hambantota and Ratnapura (black-shaded units).

Low poverty DS divisions and low poverty neighbourhoods (Fig. 4B) are mainly found in Puttlam, Gampaha, Colombo, Kalutara, Galle and Kandy Districts. But the similarities are significant in only Colombo, Gampaha, Kalutara and Galle Districts (black-shaded units). Only a few of the DS divisions in the low-low poverty group are urban centres, the rest are mainly rural. Non-agricultural activities contribute substantially to the household income in rural units. For example, only 1 in 20 households in Colombo District, 2 in 11 households in Gampaha District, and less than 1 in 3 households in Kalutara, Galle and Puttalam Districts have an agricultural operator.[6] Low agricultural employment suggests that the economic activities of rural neighbours are closely associated with the economic activities of urban DS divisions in these districts.

Figs. 4C and 4D show some spatial outliers where these units and their neighbours have contrasting levels of poverty. The shaded DS divisions in Fig. 4C have low levels of poverty but the neighbouring divisions have high levels. Moran’s I statistic of these is significant in only the Nuwara Eliya DS division, which has significant non-agricultural income activities such as tourism but is surrounded by poor DS divisions with significant agricultural economic activities. The shaded units in Fig. 4D have high levels of poverty but the neighbouring units have low levels. But Moran’s I statistic of these units is not significant.

The identification of spatial clusters has many advantages. First, it helps locate similar and dissimilar neighbourhoods and their influence on incidence of poverty. Second, it could identify physical, social, economic and institutional factors that contribute to spatial similarity or dissimilarity. Third, it helps design effective spatially targeted interventions that can trigger a higher rate of poverty alleviation within a locality than the intervention designs at national or regional level.

Spatial association

What are the main determinants of poverty and spatial similarity or dissimilarity of poverty, especially of the DS divisions in rural areas? More than three-quarters of the population in Sri Lanka live in rural areas and their main livelihood is agriculture or agricultural labour. Thus the availability and access to water and land are crucial factors for the livelihood of poor people. Although the rainfall totals are high in most areas, substantial intra-annual variations are severe constraints for productive agriculture in many areas. Thus a small quantity of irrigation is required to supplement water deficits in *maha*, or the main season, and irrigation is a must for agriculture in *yala*, or the second season. So, access to irrigation through infrastructure is necessary for alleviating poverty in many of the rural areas. This was substantiated in studies comparing the contribution of irrigated and rainfed agriculture in reducing poverty (JBIC, 2002).

Successive governments in the past have invested heavily in new irrigation infrastructures or in rehabilitation of old ones. In fact, irrigation investment was the major plank of rural development and poverty reduction and of the national food security strategy. While some districts benefited from these irrigation investments, others such as Moneragala and Hambantota did not. This is primarily due to lack of information on geographical distribution of poverty, except where statistics show that poverty is high in the rural sector. Lack of irrigation facilities is not the only cause of poverty. There is no information on how poverty is spatially concentrated and what other factors, such as access to land and infrastructural facilities, are contributing to spatial concentration of poverty.

Variables used

Availability of and access to water

In the absence of data on water availability, seasonal rainfall is taken as a proxy for this in DS divisions, and the availability of irrigation infrastructure in major and minor irrigation schemes is taken as a proxy for access to water supply. A higher level of water availability and access to irrigation infrastructure is expected to increase agricultural production and, hence, living conditions and to reduce clustering of poverty. Variables (1 to 4) used were:

1. *Average* maha *season rainfall.* The *maha* season (October to March) is the main growing season where rainfall needs to be supplemented only with a little irrigation for crop production. The average *maha* season rainfall varies from 730 mm to 1400 mm across DS divisions.
2. *Average* yala *season rainfall*. The *yala* season (April to September) receives 140 mm to 960 mm of rainfall and irrigation is required for crop production in most areas.
3. *The irrigable area under major and* 4. *minor irrigation schemes as a percentage of total crop area.* The irrigable area under major and minor irrigation schemes varies from 0% to 79% and 0% to 28% across DS divisions and indicates the physical area of water availability under irrigation schemes. The total area equipped with irrigation facilities (both major and minor irrigation schemes) varies across districts but is substantial in Polonnaruwa (83%), Anuradhapura (67%) and Hambantota (47%) Districts.

Availability of and access to land

The extent of landholding sizes per operator and holding size patterns are taken as proxies for land availability. The large agricultural landholding areas are expected to increase income and reduce poverty and, hence, clustering. Variables (5 to 8) used were:

5. *Smallholding*[7] *size per agricultural operator*. The average holding size varies from 0.5 to 1.1 ha.
6. *Smallholding area below 0.4 ha* varies from 10% to 50%.
7. *Smallholding area between 0.4 and 0.8 ha* varies from 20% to 36%.
8. *Percentage of agricultural operators not owning land* varies from 0 to 0.7 (every 7 out of 10 operators).

Employment and infrastructure facilities

The number of agricultural operators shows the extent of population employed in agriculture. The extent of infrastructure development in DS divisions can be considered as a proxy variable for access to markets and also for access to employment opportunities, especially for rural people, in the non-agricultural sectors. Variables (9 to 11) used were:

9. *Number of agricultural operators per household* indicates the agriculturally active population per household in each DS division and varies from 0 to 1.21 (almost five agricultural operators in every four households).
10. *Average distance to roads*[8] varies from 0 to 12 km.
11. *Average distance to towns* is the average of the distance of DS divisions calculated from towns to a 5- to 8-km buffer zone.

Regression analysis

We assessed the influence of the above factors on the incidence of poverty and on the spatial clustering of poverty of the DS divisions using ordinary least square (OLS) regression. The hypotheses here are that spatial clustering of poverty is significantly associated with the level of poverty of DS divisions and that spatial clustering of availability and access to water and land and infrastructure (Figs. 5-7) are significantly associated with spatial clustering of poverty.

Table 2 gives the regression results. Local Moran's I is included in the OLS2 in Table 2 to assess the influence of spatial similarities or dependence of the neighbouring units on the variations of poverty of the DS division. The increment of R^2 from OLS1 to OLS2 shows the magnitude of the contribution of spatial dependence in explaining the variation of the level of poverty across the DS divisions.

The third regression (OLS3 in Table 2) assesses the extent of association of spatial clustering of explanatory variables on the spatial clustering of the incidence of poverty. The hypothesis here is that the spatial clustering of access and availability of land and water are associated with the spatial clustering of the incidence of poverty. The OLS3 has Local Moran's I of the percentage of poor households as the dependent variable and Local Moran's I of each explanatory variable in OLS1 as explanatory variable in this case.

OLS on the entire data set

First, the regression analysis is conducted for the entire data. The DS divisions with lower poverty levels are located in the wet zone[9] districts: Colombo, Gampaha, Kalutara, Galle, Matara, Kandy and Nuwara Eliya. In general, these units have higher rainfall, smallholdings (mostly homesteads and self-owned), low agricultural employment, and are close to major urban centres in the districts. Thus the significant coefficients of OLS1 are not surprising. But the analysis of the entire data set seems to have masked the association of access to water (availability of irrigation) and poverty, especially in the DS divisions with agriculture dominating livelihoods.

Although the spatial autocorrelation is significant, inclusion of Local Moran's I in the OLS2 regression has not resulted in a significant increase in the explanatory power of the variation of poverty. Non-significant coefficients of Local Moran's I are because the Local Moran's I is high for both high-high (Fig. 4A) and low-low (Fig. 4B) poverty clusters, whereas the level of poverty is significantly different between the two clusters. Therefore, in order to better understand the influence of the level and spatial clustering of access and availability of water and land on the level and spatial clustering of poverty, we conduct separate analyses for the two clusters.

OLS on high-high poverty neighbourhoods

The DS divisions in the high-high poverty cluster are mainly rural and most livelihoods depend on agriculture. Availability and access to land and water resources are crucial in reducing poverty. Most of the DS divisions in the high-high poverty cluster are in the dry zone and have similar rainfall patterns and water availability. But access to water (explained in terms of major irrigated area) and land ownership are significantly associated with lower poverty (OLS1). However, the R^2 of OLS1 is small (10%). The OLS2 regression shows that much of the variation of poverty in the high-high poverty cluster is explained by the local spatial autocorrelation variable. In addition, the higher percentage of minor irrigated area, where water is stored in small irrigation tanks usually affected by the intra- and inter-annual variations of rainfall, and lack of land ownership are positively associated with the higher incidence of poverty. The spatial autocorrelation variable in OLS2 explains 76% of the variation of poverty (difference between OLS1 and OLS2 R^2s).

In the OLS3 regression, we assess the factors associated with spatial clustering of poverty. Spatial clustering of two factors, high percentage of irrigated crop areas and large landholding area per agricultural operator, is associated negatively with spatial clustering of DS divisions with a high proportion of poor households. Spatial clustering of two other factors, high percentages of smallholding size classes (less than 0.4 ha and between 0.4 and 0.8 ha) is associated positively with spatial clustering of DS divisions with a high proportion of poor households.

The OLS3 regression results indicate the positive influence of the availability of irrigation water supply and large landholding sizes on the lower spatial clustering of poor in rural areas. For example, the DS divisions of three districts—Anuradhapura, Polonnaruwa and Hambantota—have both a high proportion of irrigated land area and large landholding sizes per operator. But the relatively larger irrigation areas in Anuradhapura and Polonnaruwa than in Hambantota make spatial clustering of poor not significant in the former two districts but significant in the latter district.

The DS divisions in Moneragala District also have a large agricultural land area per operator as in Polonnaruwa District but they have very low irrigation facilities. Inadequate infrastructural supply providing irrigation is a cause for poor DS divisions in Moneragala District to be located in spatial clusters.

Badulla and Ratnapura Districts, unlike others, have a low number of agricultural operators per households. The substantial labour resources in the two districts engaged in the plantation sector are not counted as agricultural operators. Of those who are considered agricultural operators, many operate in small agricultural landholdings. Thus smallholding sizes in these two districts are a possible cause for the spatial clustering of poor DS divisions.

The analysis on the high-high poverty cluster shows that differential access to land and water resources is indeed associated with spatial clustering of poor DS divisions, and is especially true for the significant spatial clustering of DS divisions in the two districts, Hambantota and Moneragala.

OLS on low-low poverty neighbourhoods

Most of the DS divisions in the low-low poverty cluster (Fig. 4B) are located in the wet zone. The DS divisions with lower *yala* season rainfall, larger landholding sizes per operator, larger proportion of minor irrigated area and long distance to towns are significantly associated with DS divisions with a high poverty level. The relatively poorer DS divisions in the low-low poverty group are located away from the main urban centres and the landholdings per household are large, with a substantial agricultural component supporting the livelihoods of the people. Although major irrigation is not prominent in the low-low poverty group, minor irrigation is prominent and is significantly associated with units with higher poverty.

The inclusion of the spatial autocorrelation variable in the OLS2 regression shows a slight increase in R^2 (about 18%). However, all statistically significant coefficients in OLS1 except the minor irrigated area were not significant in OLS2. Nonsignificance of the OLS2 coefficients could be because many of the explanatory variables in the low-low poverty group are clustered in areas where low poverty clustering is significant. Here also we conducted a regression analysis (OLS3) to assess the association of spatial clustering of the explanatory variables with the spatial clustering of poverty.

The proportion of spatial clusterings of minor irrigated area, number of agricultural operators per household and average distance to roads are positively associated with spatial clustering of low poverty DS divisions. And spatial clustering of the proportion of smallholding sizes (less than 0.4 ha) is negatively associated.

While the number of agricultural operators, proportion of irrigated area and average distance to roads are low and similar, the proportion of smallholding sizes below 0.4 ha is high and similar in the DS divisions and their neighbourhood.

These indicate that non-agricultural activities are the major sources of income-generating activities of the DS divisions in the low-low poverty areas.

The OLS2 regression analysis of the two poverty clusters showing spatial similarities explains substantial variation of the poverty of DS divisions. The OLS3 analysis used OLS regression in assessing the association of spatial clustering of explanatory variables and poverty. However, the statistically significant global Moran's Is of errors of OLS3 regression indicate that better spatial regression models are required to determine the exact magnitude of the contribution of spatial clustering of explanatory variables on spatial clustering of poverty. Identification of spatial similarities of poverty and those of contributing factors are useful for designing spatially targeted interventions for alleviating poverty. Such interventions can target several factors that are similar in different spatial clusters.

Conclusions

We assess the spatial patterns of poverty in Sri Lanka at the subdistrict or administrative DS level. Poverty maps for the DS divisions depict the proportion of poor households below the official poverty line.

The poverty map shows significant spatial variation of poverty across DS divisions. The DS division poverty maps can be used for geographical targeting of poverty alleviation interventions. In the *Samurdhi* poverty alleviation programme, poverty maps can be used to distribute financial assistance equitably between the DS divisions. If the allocated resources are then distributed properly, all poor households can receive substantially higher financial assistance than at present. This could lead to a significant drop in the food poverty gap and possibly reduce the food insecurity of many poor households.

The poverty maps also show significant spatial clustering of poor and non-poor areas. The clusters of DS divisions with a high percentage of poor households are found in four rural districts where agriculture is the main source of livelihood of the majority of households. The clustering of DS divisions of low poverty around major urban centres suggests that, in predominantly agricultural areas, poor people have only limited economic opportunities to escape poverty.

The analysis also shows spatial autocorrelation, which measures the strength of spatial clustering, and explains substantial variation of the incidence of poverty across DS divisions. In rural areas where water is scarce, the spatial clustering of major and minor irrigated areas and large agricultural holdings are associated with less spatial clustering of poor households. The clustering of areas with a high proportion of smallholding sizes (below 0.4 ha) is positively associated with the clustering of poor DS divisions. This shows that access to irrigation infrastructure is a major factor in reducing poverty. But, where the agricultural smallholdings are concentrated, the incidence of poverty tends to be high. Massive investments in new or rehabilitated irrigation schemes alone may not be an effective intervention in some poverty-stricken areas.

Although the proportion of irrigation land per DS division and the average landholding sizes are crude proxies for the availability and access to water and land resources at DS divisional level and may not permit one to derive statistically valid estimates, the analysis shows that availability of and access to water and land resources is a major factor of spatial concentration of poverty in rural areas.

The analysis provides an overview of the spatial variations in poverty at a finer resolution than current national statistics provide at a coarse resolution for an administrative district. A major constraint in the present analysis is the unavailability of reliable information, especially for accurately measuring the access to resources, markets and services. Nonetheless, our analysis provides a starting point for the development of poverty maps and spatial and statistical analyses to identify *where* the poor live and to understand the specifics of *why* they are poor.

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[1] The minimum daily calorie requirement estimate for an adult is 2030 Kcal (Vidyaratne and Tilakaratne, 2003).

[2] The poverty level of a DS division is estimated using the "synthetic area" small area estimation method (Ghosh and Rao, 1994). The number of poor households of a DS division is estimated using Eq. 1:

$$\hat{Y}_{ij} = \frac{I_{ij}}{\sum_j I_{ij}} \hat{Y}_i \qquad (1)$$

where $\hat{Y}_i$ is the survey estimate of the number of poor households of the i^{th} district and I_{ij} is the value of the index generated using auxiliary variables of the j^{th} DS division in the i^{th} district. The index I_{ij} is proportional to a linear combination (1.694 Z_1 + 1.822 Z_2) of the first two principal components of 30 variables ranging from household demography, assets, agricultural employment, agricultural productivity, agricultural income and proximity to infrastructural facilities. At the district level, poverty = district dummies + 1.694 Z_1 + 1.822 Z_2, R^2= 0.68 (for details, see Amarasinghe et al., in press).

[3] The *Samurdhi* programme has three main components: (1) welfare or consumption grants, (2) savings and credits and (3) rural infrastructural development. The welfare component provides financial support and serves short-term goals and claims 80% of the total *Samurdhi* budget. The other two components have long-term objectives in reducing poverty.

[4] LKR = Sri Lankan rupee. US$1 = 95 LKR in 2002.

[5] The spatial lag variable is calculated using the eight nearest neighbours of DS divisions.

[6] Agricultural operator is defined as a person responsible for operating agricultural land or livestock or both, conducts activities alone or with assistance from others or only directs day-to-day operations (DCS, 2003).

[7] Smallholdings are defined as agricultural areas below 8 ha.

[8] The distance to roads and towns is the average of the Euclidean distances from the centre of the source cell to the centre of the surrounding cells. We calculated the Euclidean distance grid using ArcInfo GRID.

[9] Rainfall patterns divide Sri Lanka into three climatic zones: wet, intermediate and dry. The wet zone receives more than 2500 mm of annual rainfall, the intermediate zone between 1750 and 2500 mm, and the dry zone less than 1750 mm of annual rainfall.

Figure Legends

Fig. 1. Spatial variation of percentage of poor households across (A) provinces, (B) districts and (C) Divisional Secretariat divisions.

Fig. 2. Difference between the percentage of the *Samurdhi* programme's households with the highest financial assistance and percentage of households below the poverty line.

Fig. 3. Scatterplot of percentage poor households versus lag percentage poor households.

Fig. 4. Divisional Secretariat (DS) divisions with statistically significant spatial autocorrelation of percentage of poor households of (A) high poverty unit and high poverty neighbourhood, (B) low poverty unit and low poverty neighbourhood, (C) low poverty unit and high poverty neighbourhood, and (D) high poverty unit and low poverty neighbourhood. Note that the spatial autocorrelation is estimated for all DS divisions except for those in the Northern and Eastern provinces.

Fig. 5. Spatial similarity or dissimilarity of (A) percentage of major irrigated area, and (B) percentage of minor irrigated area within the (I) high-high and (II) low-low poverty clusters.

Fig. 6. Spatial similarity or dissimilarity of (A) smallholding size per agricultural operator, and (B) smallholding size below 0.4 ha within the (I) high-high and (II) low-low poverty clusters.

Fig. 7. Spatial similarity or dissimilarity of (A) number of agricultural operators per household, and (B) average distance to roads within the (I) high-high and (II) low-low poverty clusters.

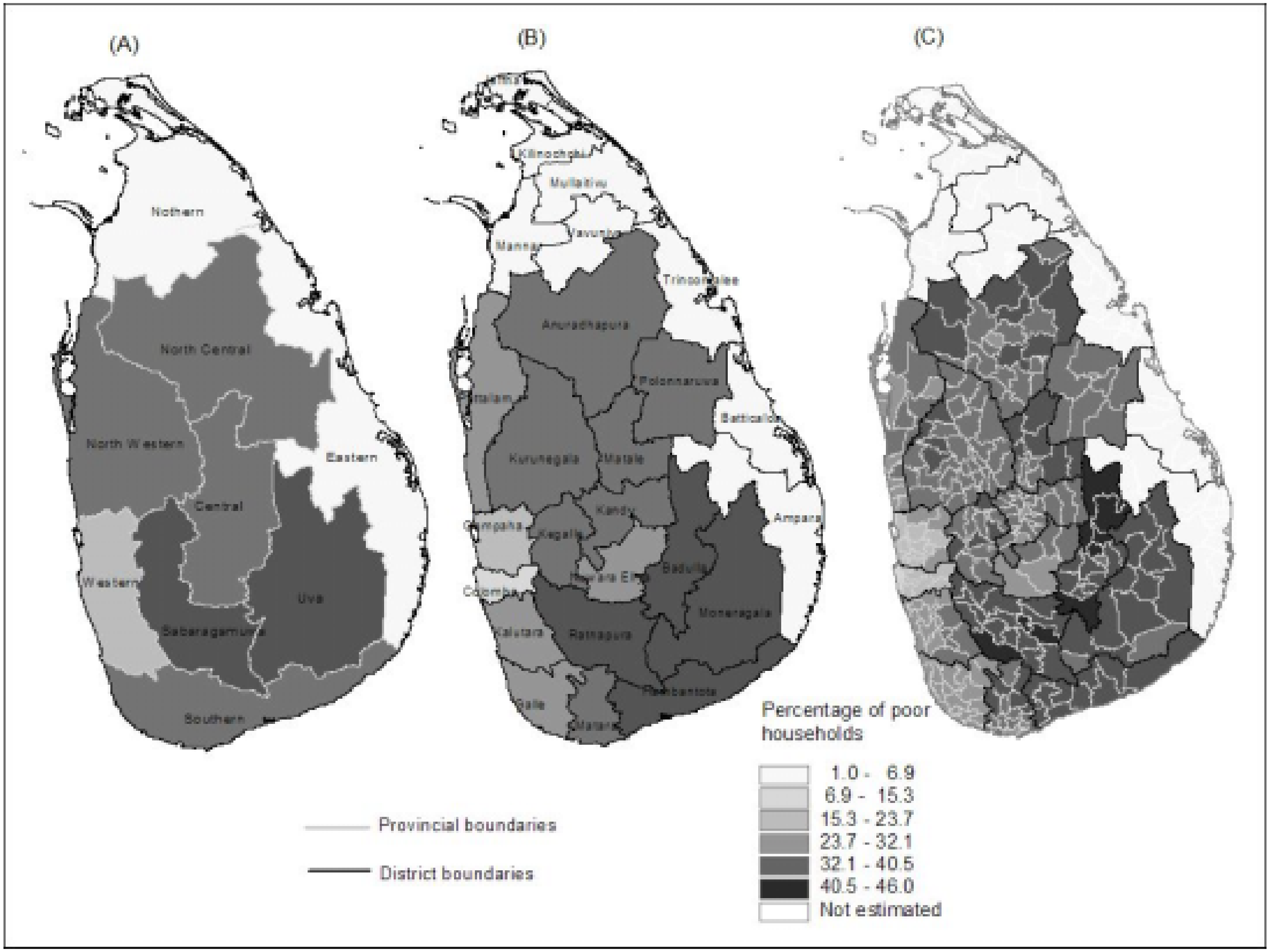
(A)
(B)
(C)
Nothern
North Central
North Western
Eastern
Central
Western
Uva
Southern
Kilinochchi
Mullaitivu
Mannar
Anuradhapura
Polonnaruwa
Batticaloa
Kurunegala
Matale
Kandy
Kegalle
Ampara
Badulla
Moneragala
Kalutara
Ratnapura
Galle
Hambantota
Provincial boundaries
District boundaries
Percentage of poor households
1.0 - 6.9
6.9 - 15.3
15.3 - 23.7
23.7 - 32.1
32.1 - 40.5
40.5 - 46.0
Not estimated

Fig. 1

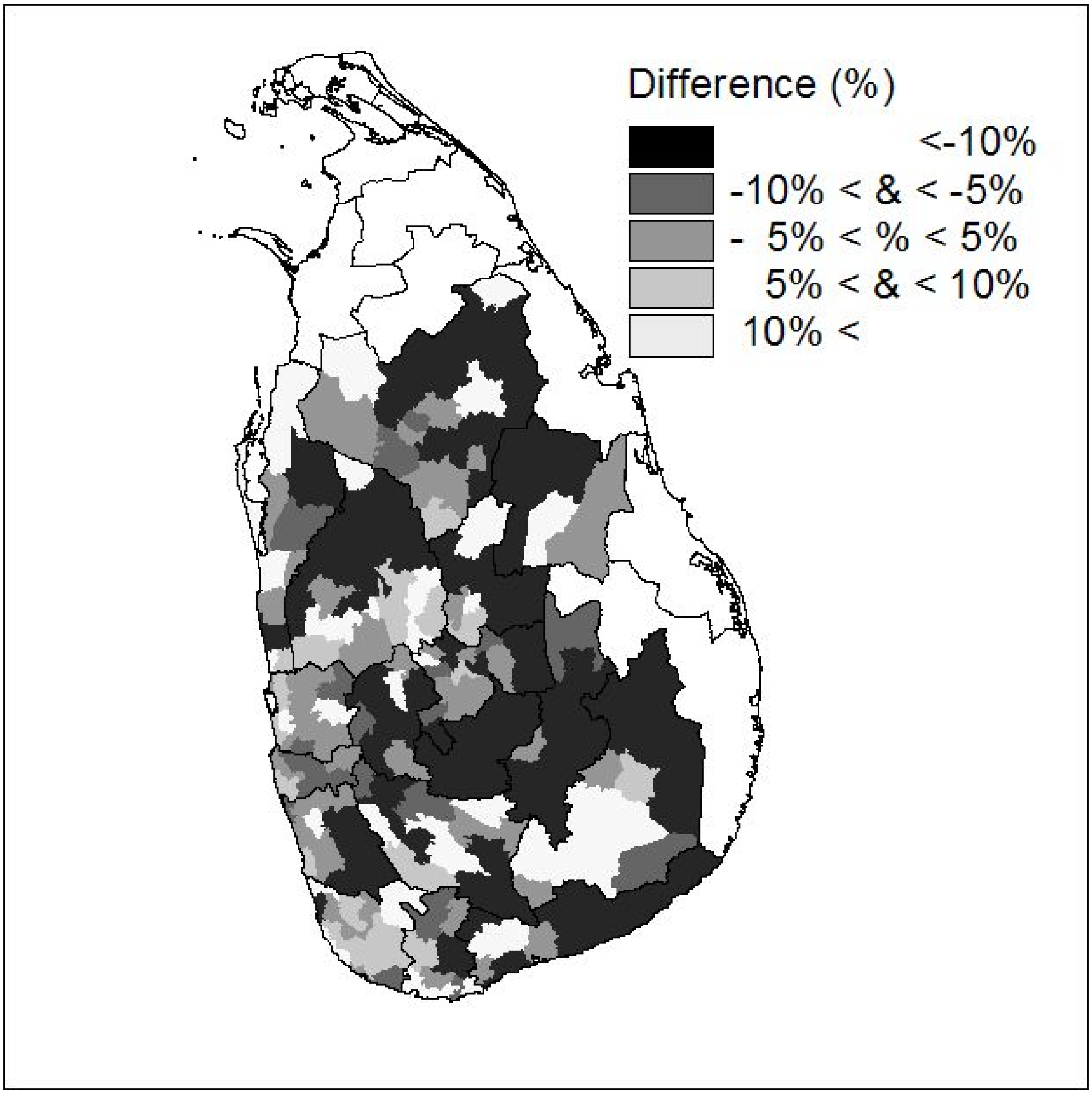

Fig. 2

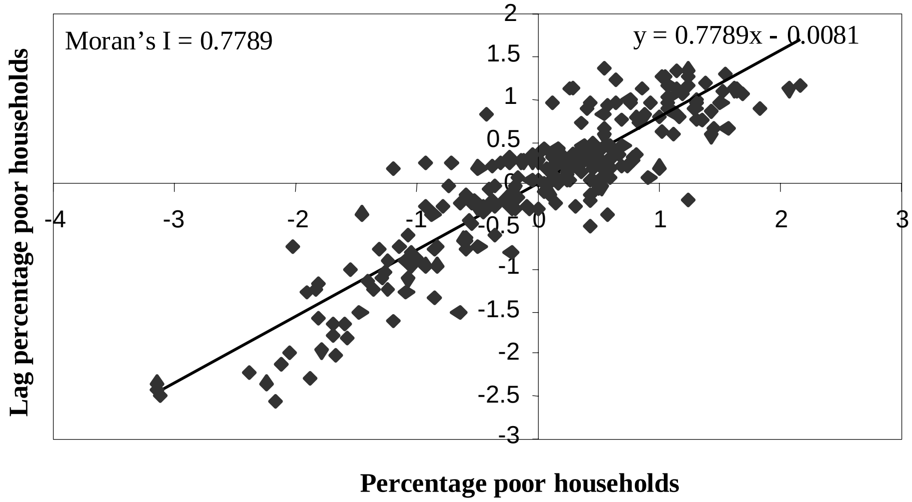
Moran’s I = 0.7789
y = 0.7789x - 0.0081
Lag percentage poor households
Percentage poor households
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-4
-3
-2
-1
0
1
2
3

Fig. 3

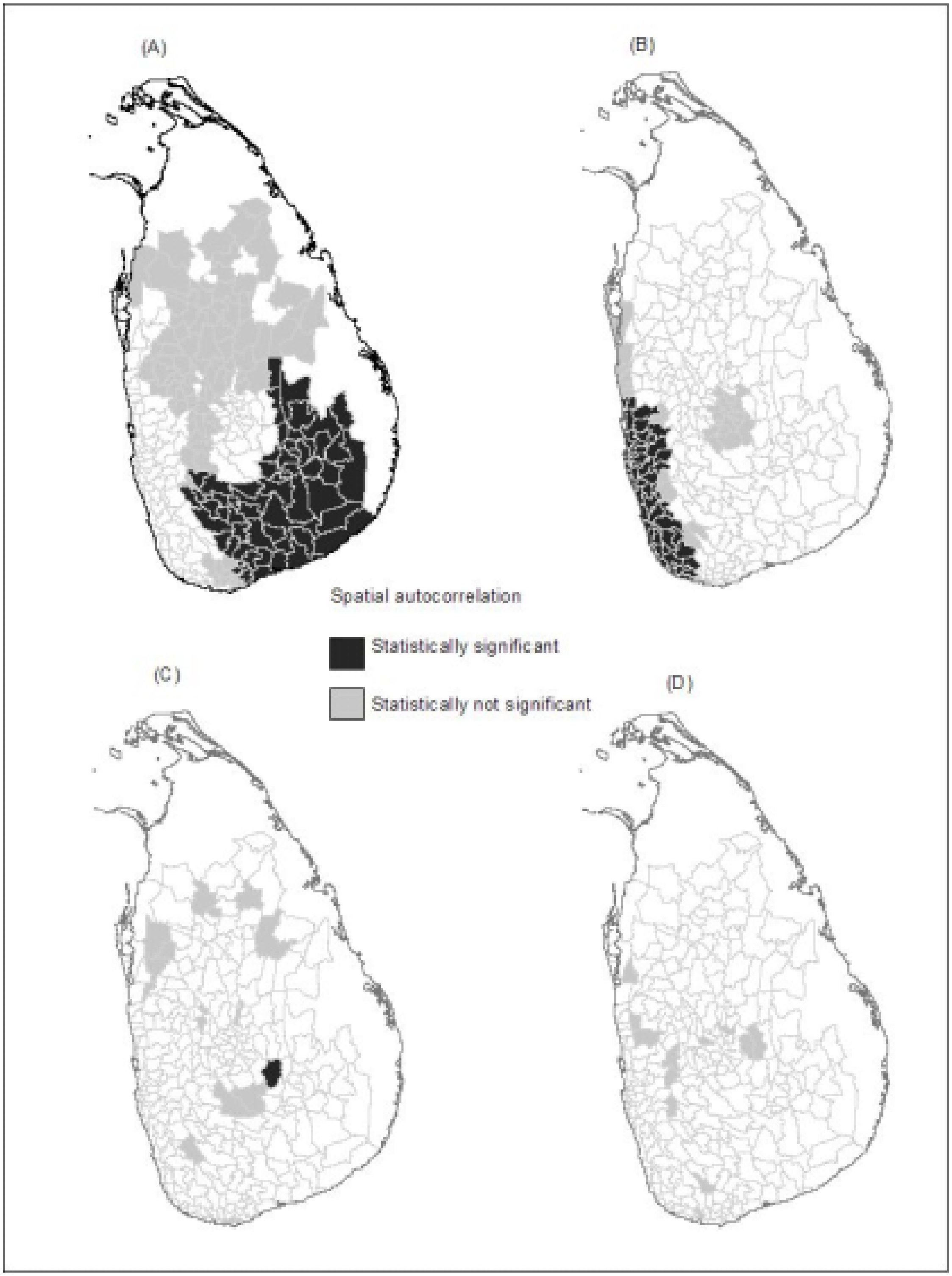
(A)
(B)
Spatial autocorrelation
Statistically significant
Statistically not significant
(C)
(D)

Fig. 4

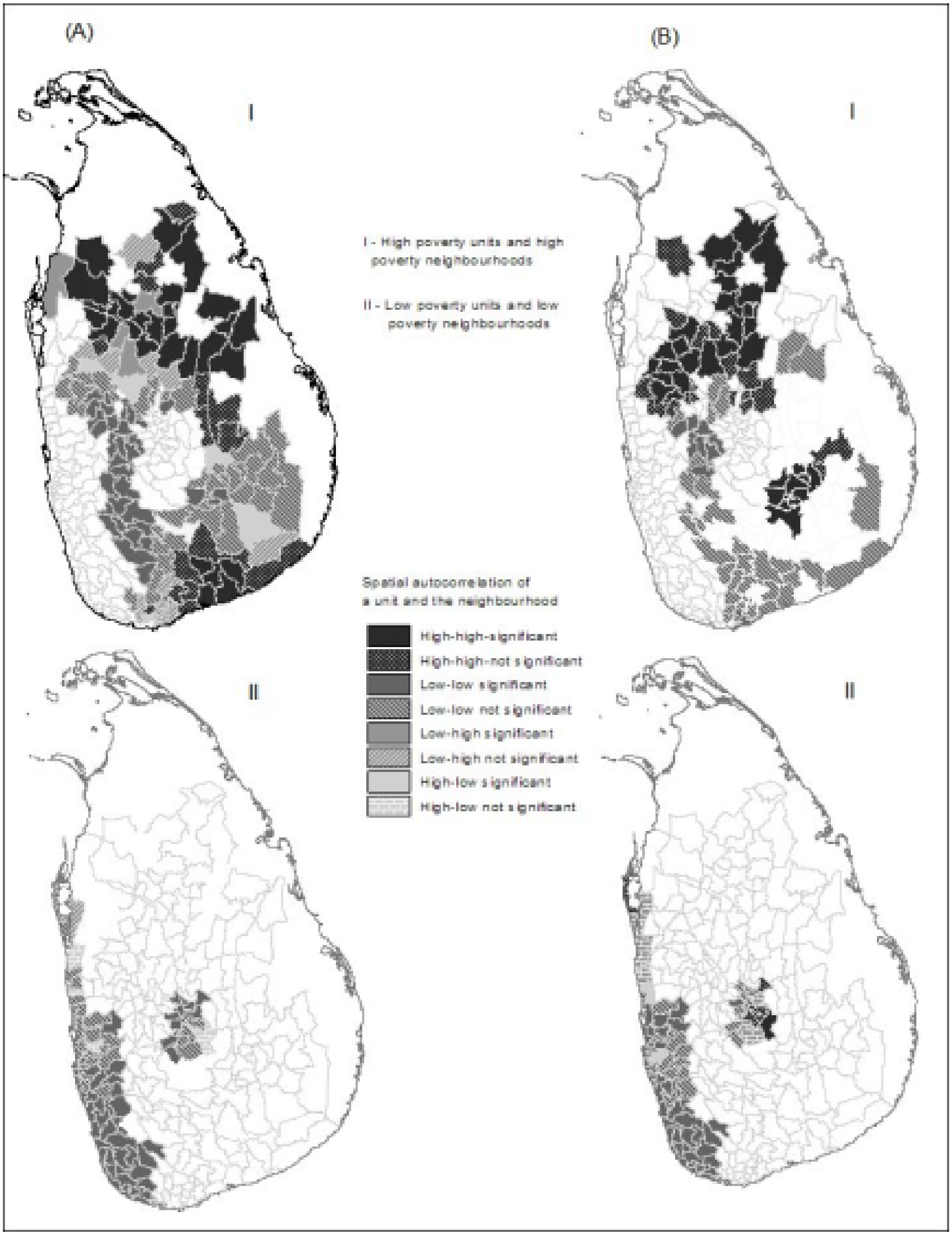
(A)
(B)
I
I
II
II
I - High poverty units and high poverty neighbourhoods
II - Low poverty units and low poverty neighbourhoods
Spatial autocorrelation of a unit and the neighbourhood
High-high-significant
High-high-not significant
Low-low significant
Low-low not significant
Low-high significant
Low-high not significant
High-low significant
High-low not significant

Fig. 5

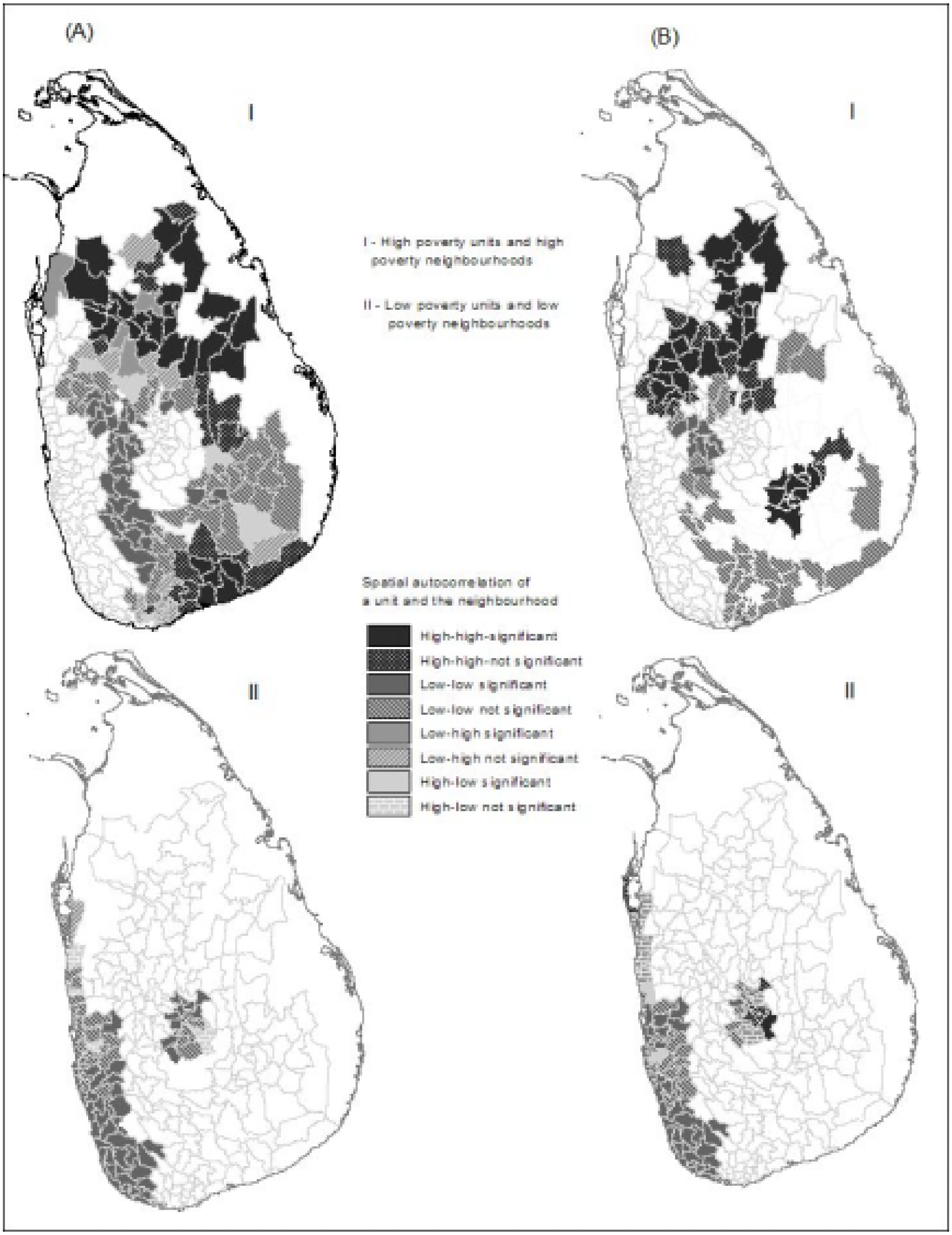
(A)
(B)
I
II
I - High poverty units and high poverty neighbourhoods
II - Low poverty units and low poverty neighbourhoods
Spatial autocorrelation of a unit and the neighbourhood
High-high-significant
High-high-not significant
Low-low significant
Low-low not significant
Low-high significant
Low-high not significant
High-low significant
High-low not significant

Fig. 6

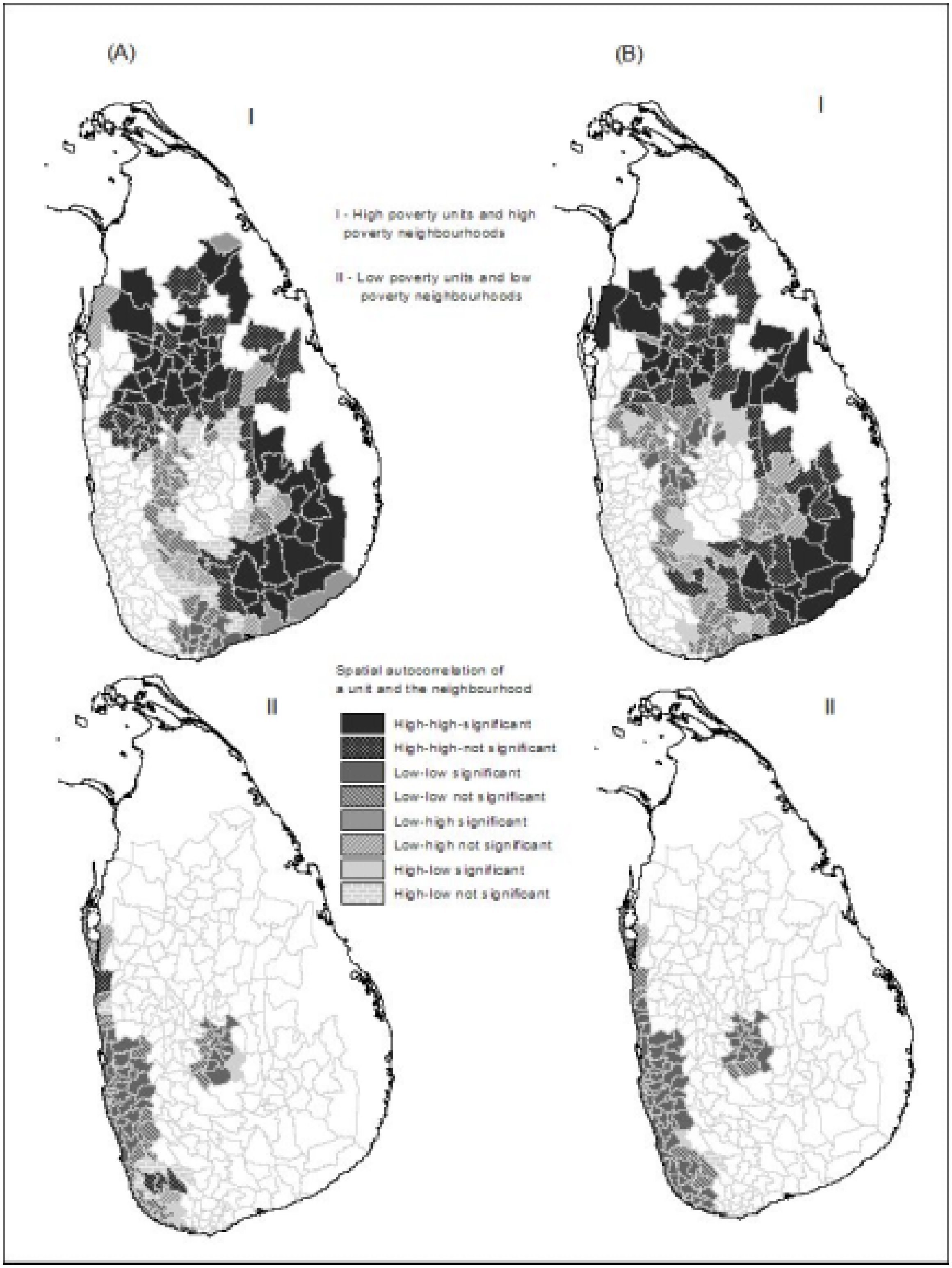
(A)
(B)
I
I - High poverty units and high poverty neighbourhoods
II - Low poverty units and low poverty neighbourhoods
Spatial autocorrelation of a unit and the neighbourhood
High-high-significant
High-high-not significant
Low-low significant
Low-low not significant
Low-high significant
Low-high not significant
High-low significant
High-low not significant
II

Fig. 7

Table 1

Summary statistics: distribution of Divisional Secretariat (DS) divisions, percentages of poor households and population over different poverty groups

	Poverty group (% of poor households)[a]	DS divisions[b] (no.)	Households		Population	
			Total (1000s)	% below poverty line	Total (1000s)	% below poverty line
1	1.0 - 6.9	4	236	1.1	968	1.3
2	6.9 – 15.3	19	686	11.7	3035	13.9
3	15.3 - 23.7	45	820	19.7	3507	24.0
4	23.7 - 32.1	105	1310	28.6	5208	33.9
5	32.1 - 40.5	67	761	35.5	3242	40.9
6	40.5 - 46.0	9	72	42.6	315	49.4
	Total (Ave.)	249	3885	(23.7)	16,275	(27.8)

Source: Authors' estimates.

[a] The incidences of poverty of groups 3 and 4 are 1 standard deviation (SD) below and above the national average, of groups 2 and 5 are between 1 and 2 SD below and above the national average and of groups 1 and 6 are beyond 2 SD below and above the national average.

[b] Poverty estimates are available for 16 districts outside the north and the east. These districts have 249 DS divisions. The average poverty of DS divisions is 23.7% and the SD is 8.4%.

Table 2
Coefficients of regressions assessing determinants of poverty and poverty clustering and standard errors, with standard errors in parentheses

Explanatory variables	Divisional Secretariat (DS) divisions in the analysis							
	All DS divisions (n = 249)		DS divisions with high-high poverty neighbourhoods (n = 138)			DS divisions with low-low poverty neighbourhoods (n = 84)		
	OLS1[a]	OLS2[a]	OLS1[a]	OLS2[a]	OLS3[b]	OLS1[a]	OLS2[a]	OLS3[b]
1. Average *maha* season rainfall (mm)	0.14 (0.10)	0.12 (0.09)	-0.09 (0.08)	0.04 (0.03)	0.06 (0.07)	0.91 (0.22)*	0.02 (0.17)	0.29 (0.22)
2. Average *yala* season rainfall (mm)	-0.41 (0.11)*	-0.32 (0.11)*	-0.01 (0.09)	0.03 (0.04)	0.04 (0.09)	-1.32 (0.21)*	-0.09 (0.15)	-0.34 (0.29)
3. Major irrigation area (% total crop area)	0.01 (0.05)	0.01 (0.6)	-0.09 (0.05)*	-0.02 (0.02)	-0.11 (0.03)*	0.34 (0.30)	0.03 (0.18)	0.29 (0.96)
4. Minor irrigation area (% total crop area)	0.003 (0.05)	0.01 (0.5)	-0.02 (0.04)	0.05 (0.02)*	-0.08 (0.03)*	0.02 (0.10)*	0.16 (0.07)*	0.71 (0.27)*
5. Smallholding size per agric. operator (ha)	0.15 (0.07)	0.05 (0.8)	-0.18 (0.11)	0.02 (0.04)	-0.20 (0.11)*	0.30 (0.10)*	-0.11 (0.07)	0.37 (0.21)
6. Smallholding area below 0.4 ha (%)	0.05 (0.07)	-0.05 (0.07)	-0.31 (0.14)*	-0.06 (0.05)	0.42 (0.16)*	0.07 (0.06)	-0.03 (0.04)	-0.72 (0.18)*
7. Smallholding area between 0.4 and 0.8 ha (%)	0.38 (0.05)*	0.31 (0.05)*	0.02 (0.07)	0.01 (0.02)	0.54 (0.11)*	0.11 (0.09)	0.00 (0.05)	-0.05 (0.17)
8. Agricultural operators not owning land (%)	0.16 (0.05)*	0.16 (0.05)*	0.08 (0.4) *	0.04 (0.02)*	-0.01 (0.07)	0.13 (0.17)	-0.07 (0.10)	0.26 (0.72)
9. No. of agricultural operators per household	0.18 (0.06)*	0.16 (0.07)*	-0.04 (0.05)	-0.02 (0.02)	0.03 (0.04)	0.01 (0.14)	0.05 (0.09)	1.83 (0.31)*
10. Average distance to roads (km)	-0.03 (0.07)	0.10 (0.05)	0.04 (0.05)	0.01 (0.02)	-0.02 (0.07)	-0.12 (0.25)	-0.03 (0.15)	2.53 (0.75)*
11. Average distance to towns (km)	0.12 (0.06)*	0.10 (0.05)*	0.01 (0.05)	-0.02 (0.02)	-0.03 (0.04)	0.22 (0.07)*	0.06 (0.05)	-0.01 (0.11)
Local Moran's I[c]	-	-0.13 (0.05)*	-	0.75 (0.02)*	-	-	-0.37 (0.03)*	-
Adjusted R^2	0.52	0.53	0.10	0.86	0.16	0.72	0.90	0.87
Global Moran's I of errors	0.55	0.54	0.46	0.02	0.43	0.30	0.14	0.38

[a]OLS1 and OLS2 incidence of poverty as dependent variable, % poor households.
[b]OLS3 local spatial autocorrelation of incidence of poverty as dependent variable, local Moran's I.
[c]Local spatial autocorrelations of % poor households.
* Significant at least at p = 0.05 level.