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Locating the Poor: Spatially Disaggregated Poverty Maps for Sri Lanka

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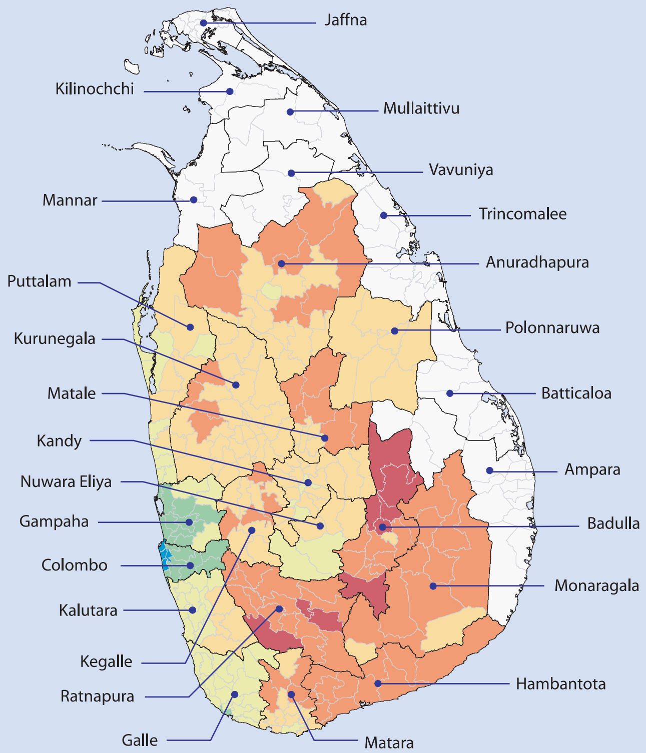

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International Water Management Institute
P O Box 2075, Colombo, Sri Lanka

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The authors: Upali A. Amarasinghe, Madar Samad, and Markandu Anputhas are Senior Researcher, Principal Researcher, and Research Officer, respectively, of the International Water Management Institute, Colombo, Sri Lanka.

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Cover map shows the spatial variation of the percentage of poor households below the poverty line across Divisional Secretariat divisions in Sri Lanka except those in the Northern and Eastern provinces.

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Summary

Historically, Sri Lanka has placed a high value on basic human needs: channeling assistance to the rural areas to promote food security and employment, and assuring that the poor have access to primary health care and basic education. This policy has resulted in a high level of achievements in some areas of human well-being such as education and health. Yet, the achievements to date in terms of improving household incomes and food security, especially in rural areas, are rather disappointing. A quarter of the population still lives below the official poverty line. A key question is, despite the achievement in vital areas of human welfare like health and education, why does income poverty continue to persist among a sizable segment of the population? This study attempts to answer this question on the premise that inadequate spatially disaggregated information on poverty and inefficient targeting of resources for poverty alleviation are the major reasons for the slow progress in reducing the income poverty.

The study generates poverty maps for Sri Lanka at subdistrict level (Divisional Secretariat Division [DS division]) by combining the small-area estimation and the principal-component methods. The report identifies who the poor are and where they live. The report also demonstrates how poverty maps can assist in identifying the spatial patterns of clustering of poor areas, the reasons for such clustering and how to use maps for geographical targeting of poverty-alleviation interventions.

The spatial autocorrelation analysis shows two statistically significant clusters: one indicating low-poverty rural DS units that cluster around a few low-poverty urban DS divisions, and the other indicating high-poverty rural DS divisions that cluster around high-poverty rural DS divisions. A high nonagricultural employment and improved physical infrastructure such as roads are key characteristics of the first cluster. Spatial clustering of poor areas in the second cluster is significantly associated with factors influencing agricultural production, such as access to, and availability of, land and water resources. A large number of small landholding sizes are significantly associated with spatial clustering of poor areas in the second cluster. In the drier areas, inadequate access to irrigation supplies is a factor that explains significant spatial clustering.

Further, the DS division poverty maps show that the incomes of 45 percent of households that are benefiting from the *samurdhi*—a program for reducing the severity of poverty—are not below the official poverty line. The study shows that geographical targeting of the poorest DS divisions in the Samurdhi Financial Program could decrease the severity of food insecurity and may even lead to lowering the incidence of poverty in the DS divisions and help reduce substantial disparities of welfare fund allocation among the DS divisions.

The present study is a subnational poverty mapping analysis based on secondary data of the Population and Agriculture Census and Consumption and Expenditure Survey of Sri Lanka. The results show a good overview of the spatial variation of poverty at finer resolution than what is currently available at the district level. The study shows that finer-resolution poverty maps can be used to identify where the poor live and analyze and underlie location-specific causes of poverty more effectively than from aggregate statistics.

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Introduction

Sri Lanka's achievements in some areas of human welfare, such as health and education, have been described as remarkable for a low-income country. Its life expectancy at birth (74 years) and adult literacy rate (92%) are higher than the world averages of 63 years and 77 percent, respectively (UNDP 2003). Infant mortality rate (19 per 1,000 live births), and the combined primary, secondary and tertiary school enrolment ratio (66%) are comparable to the levels of upper middle-income economies (UNDP 2003). Despite these achievements in social welfare, poverty continues to be a major problem in the country. It is estimated that, at present, about one-quarter of the population lives below the national poverty line (DCS 2003a).

Over the years, many poverty alleviation programs have been launched in Sri Lanka. But, many doubt whether the benefits of these interventions actually reached those intended because of shortcomings in identifying and locating the poor. The poverty information is presently compiled from household or community surveys, and presented sector-wise (rural, urban and estate sectors) and spatially (in terms of administrative districts in the country). The aggregate poverty information on these scales is useful for broad national-level interventions such as food subsidies, income-support schemes and other national social-welfare programs aimed at assisting the poor. But, often they are too coarse for designing and targeting location-specific poverty-alleviation programs. This is especially true when the subnational units are large or have diverse occupational patterns.

It is well recognized that geographic targeting, as opposed to across the board-based interventions, is more effective at maximizing the coverage of the poor while minimizing leakage to the nonpoor. Geo-referenced poverty maps when integrated with more conventional sources of information serve two main purposes. First, they help identify poor areas. Second, they assist in analyzing location-specific causes of poverty. These in turn help design better geographically targeted interventions.

Many countries use poverty maps in various ways in their poverty-alleviation programs (Henninger and Snel 2002). Nicaragua uses poverty maps to determine resource allocation for poverty alleviation and provides expanded health-care coverage to the poorest areas. In Cambodia, poverty maps assist the World Food Program to distribute food to the neediest areas and the Asian Development Bank to identify the poorest areas for rural development project work. The Republic of South Africa uses poverty maps to distribute grants equitably among municipalities. It also used these maps to identify high-risk areas for preventing the cholera outbreak in 2001 and to develop crime prevention strategies. Many other countries use or expect to use poverty maps for geographical targeted resource allocation and policy formulation.[1]

[1]Reports of poverty mapping and their uses in other countries are available at http://population.wri.org

In Sri Lanka, there has not been any effort to analyze in detail the spatial patterns of poverty with the aid of finer-resolution poverty maps. This report is an attempt to fill this void. The overall aim of this report is to demonstrate the potential use of poverty maps in policy interventions in poverty-alleviation programs. The more specific objectives of this study are:

a. to identify the poor and determine where they are located.

b. to determine whether there is spatial clustering of the poor.

c. to assess the influence of spatial clustering on the incidence of poverty and to identify the principal factors associated with the spatial clustering of poverty.

d. to demonstrate the use of poverty maps in geographical targeting of poverty-alleviation programs.

The rest of the report is organized as follows. Section 2 describes the spatial variation of poverty maps at the DS level, a lower administrative unit than a district. Section 3 identifies the clusters of spatial similarities or dissimilarities of poor and nonpoor areas. The next section investigates the influence of spatial clustering on the incidence of poverty and the association of spatial clustering with the availability of, and access to, land and water resources. Section 5 illustrates how poverty maps could assist in effective resource distribution for poverty alleviation using the case of the Samurdhi Program in Sri Lanka. The final section highlights the main conclusions and policy implications of the study.

Poverty Mapping

Do finer-resolution poverty maps of Sri Lanka provide more information on spatial variability of poverty? Where are the geographic areas which are doing better? And where are poor people concentrated?

Choice of Indicators

Poverty maps depict the spatial variation of indicators of human well-being across geographically disaggregated units (Henninger 1998; Hentschel et al. 2000; Henninger and Snel 2002; Davis 2002; World Bank 2004). The indicators relate to various dimensions of poverty:

- *Economic dimensions,* which deal with consumption, expenditure or income where indicators can include head count index (proportion of population below poverty of certain thresholds of consumption, expenditure, income or combinations of all three), poverty gap, squared poverty gap and food ratio.
- *Social dimensions,* which deal with nutrition, water and sanitation, and health and education where indicators can include the proportion of population with calorie intake below the minimum requirement and the proportion of population with access to clean drinking water, sanitation, electricity, health-care facilities and schools.
- *Enabling environments,* which deal with access to *geographic capital for production*, *vulnerability* and *geographical isolation*, where
    - *Geographic capital for production* can be the proportion of population with access to *natural capital* such as land, water, forest, wildlife, aquatic resources and fisheries or with access to *physical capital* such as roads, markets, information, transportations, credits and technology or with access to *social capital* such as networks, social groups, and process of decision making.

- *Vulnerability* is illustrated with poor agricultural endowments (degraded land, poor water quality), external shocks (floods, droughts, crimes, social unrest, pest/wild animal attacks), health risks (waterborne diseases) and climatic changes of rainfall variability.
- *Geographical isolation* is illustrated with poor access to geographical infrastructure such as markets, roads and transportation.

The economic dimension of poverty is the focus of this study. Poverty is measured in terms of the official poverty line specified by the Department of Census and Statistics (DCS 2003a). It is a nutrition-based (food poverty) poverty line and is defined as the per capita monthly food expenditure (in adult equivalents) per household needed to meet the minimum nutritional intake of 2,030 kilocalories per day.[2] On this basis the official poverty line for 2002 was set at Rs1, 294 per person.[3] Thus, poverty estimate here is essentially an indicator of poverty and food insecurity in Sri Lanka.

Unit of Analysis

The unit of analysis for poverty mapping in this report is the DS division. For administrative purposes, Sri Lanka is divided into four layers: 9 provinces, 26 districts, 325 DS divisions and about 14,000 *Grama Nildhari* (GN) divisions or villages (DCS 1998). Of these four administrative layers, the GN division is the most appropriate unit for subnational poverty mapping analysis. But, most ancillary data on income activities required for subnational poverty estimation are available only for DS divisions. Therefore, we take the DS division as the unit of analysis for poverty mapping in this report.

The household income and expenditure survey is the basis for computing the poverty line. The survey provides reliable poverty estimates only at the district level (DCS 2003a). Therefore, poverty estimation in DS divisions requires other methods. In this study, we combine the poverty estimates at the district level with the synthetic area *small-area estimation methods* (Ghosh and Rao 1994) and *principal component analysis* (Chatfield and Collins 1980; Manly 1986) to obtain poverty estimates for DS divisions (see appendix A for details of methods of estimation).

DS Division Poverty Map

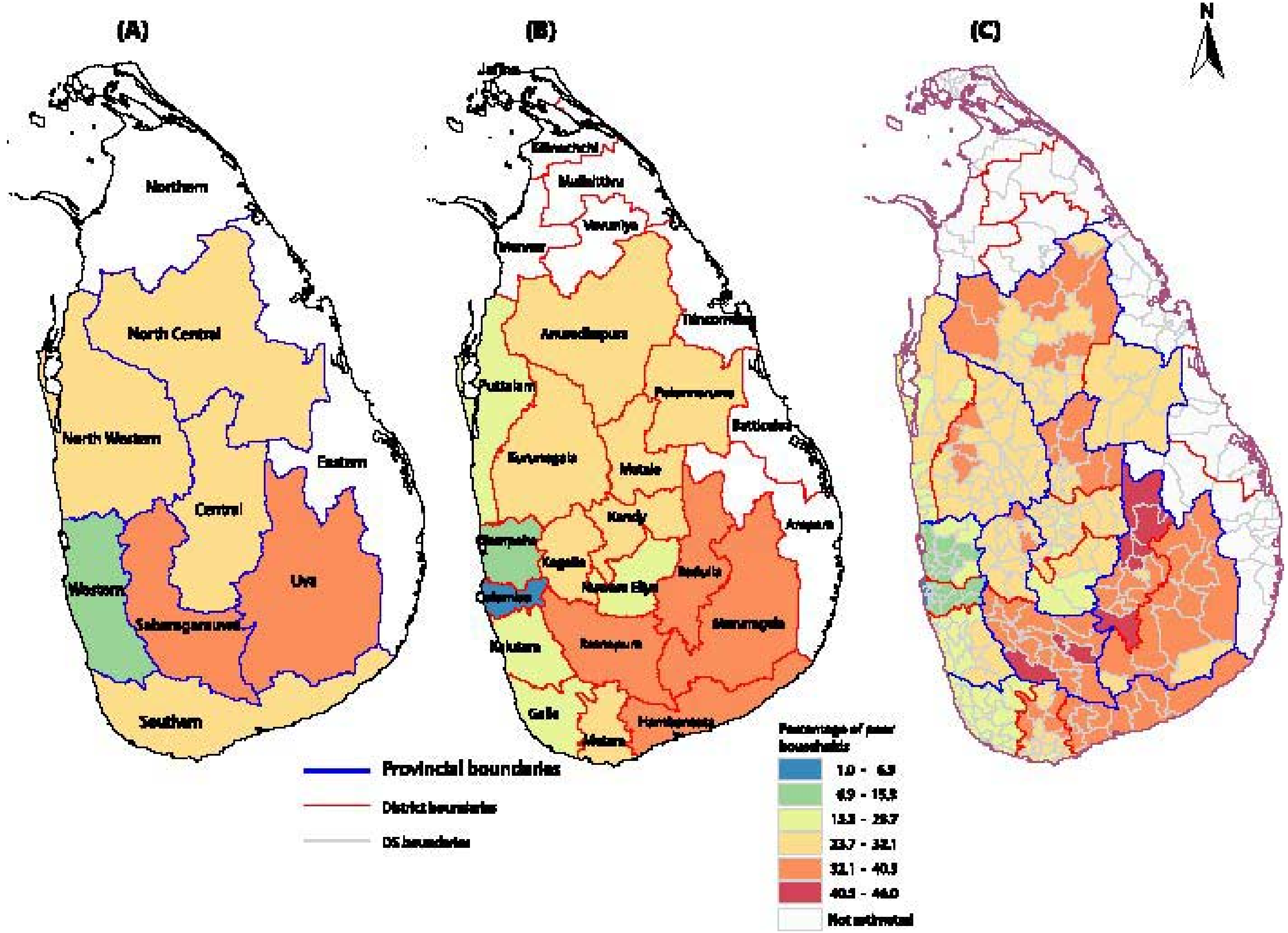
The provincial and district poverty maps (figures 1A and 1B) depict the DCS'estimates of the percentage of poor households in the provinces and districts (DCS 2003a). Figure 1C shows the spatial variation of the estimates of the percentage of the poor households across DS divisions as computed in this study. The weighted average of the incidence of poverty of all DS divisions is 23.7 percent while the standard deviation is 8.4 percent. Six categories illustrate the variation of the percentage of poor households across DS divisions.

Among the districts, Colombo is in the least poverty group (group 1 in figure 1B). But, only four DS divisions in the Colombo district fall in

[2]The adult equivalent of food expenditure is estimated on the basis of the cost of a bundle of food items required for an adult to obtain a minimum nutritional requirement. The minimum calorie requirement per person in Sri Lanka was estimated as 2,030 calories per day (Vidyaratne and Tilakaratne 2003). The adult equivalent values are obtained by making adjustments to the age and sex of the members of the household. In 2002, the average household size and the adult equivalent household size were estimated as 4.2 and 3.4, respectively. Thus the daily minimum calorie requirement per person is equivalent to about 2,510. The national poverty line indeed varies with the methodology used for estimation. This study does not assess the comparability of this estimation method with other international poverty line estimation methods. We only use the district poverty estimated through this method for testing the subnational poverty estimation method.

[3]In this report, Rs means Sri Lankan rupees. Rs1,294 is equivalent to 39.21 purchasing power parity (PPP) US$ (Rs33 = 1 purchasing power parity US$) per person per month or 1.31 PPPUS$ per person per day in 2002 (DCS 2003a). Recently, this poverty line was revised by taking into account the nonfood items expenditure of households (DCS 2005). The new poverty line is set at Rs1,493. For the purpose of this study we use the food poverty line set at Rs1,294. Details of the computation of the poverty line are given in DCS 2003a.

FIGURE 1.
Spatial variation of percentage of poor households below poverty line across (A) provinces, (B) districts, and (C) DS divisions.



the poorest category (group 1 in figure 1C), and they are major urban centers closely connected to the financial hub of the country located in the Colombo DS division. The other DS divisions in the Colombo district and the majority of DS divisions in the Gampaha district are in the next poverty group (group 2 in figure 1C). The units in the second group are also mainly urban or close to the major urban centers.

Groups 1, 2 and 3, respectively, in figure 1 show where the incidence of poverty is two standard deviations, between one and two standard deviations and within one standard deviation *below* the national average. Groups 4, 5 and 6, respectively, in this figure show where the incidence of poverty is within one standard deviation, between one and two standard deviations and two standard deviations *above* the national average.

Ratnapura in the Uva province, Badulla and Monaragala in the Sabaragamuwa province and Hambantota in the Southern province are the

FIGURE 2.
Distribution of DS divisions in terms of incidence of poverty.

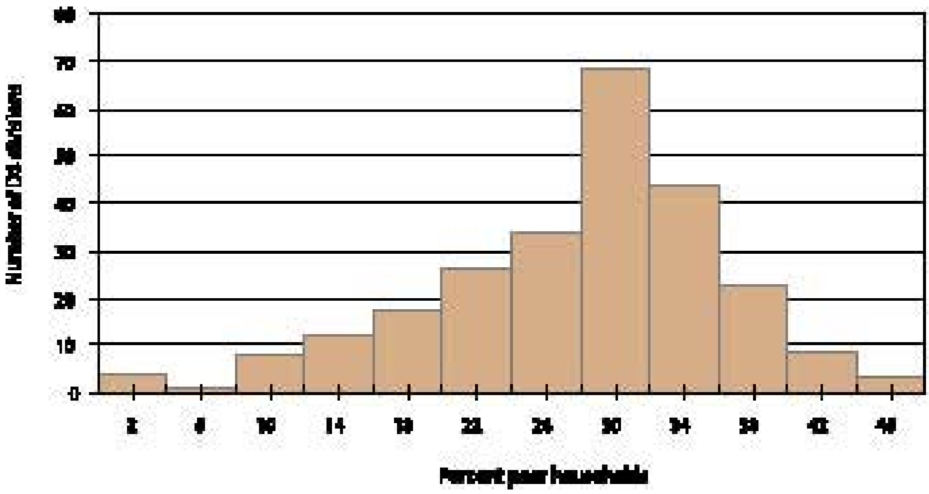


TABLE 1.
Summary statistics: Distribution of DS divisions, percentages of poor households and population over different poverty groups.

	Poverty group (% of poor households)	Number of DS divisions[i]	Households		Population	
			Total (1,000s)	% below poverty line	Total (1,000s)	% below poverty line
1	1.0 - 6.9[ii]	4	236	1.1	968	1.3
2	6.9 – 15.3[ii]	19	686	11.7	3,035	13.9
3	15.3 - 23.7[ii]	45	820	19.7	3,507	24.0
4	23.7 - 32.1[ii]	105	1,310	28.6	5,208	33.9
5	32.1- 40.5[ii]	67	761	35.5	3,242	40.9
6	40.5 - 46.0[ii]	9	72	42.6	315	49.4
	Total	249	3,885	23.7	16,275	27.8

Source: Authors' estimates.

i - Poverty estimates are available for 16 districts outside north and east and they have 249 DS divisions.

ii - Incidence of poverty of a) groups 3 and 4 is one standard deviation below and above the national average, b) groups 2 and 5 is between one and two standard deviations below and above the national average, and c) groups 1 and 6 is beyond two standard deviations below and above the national average.

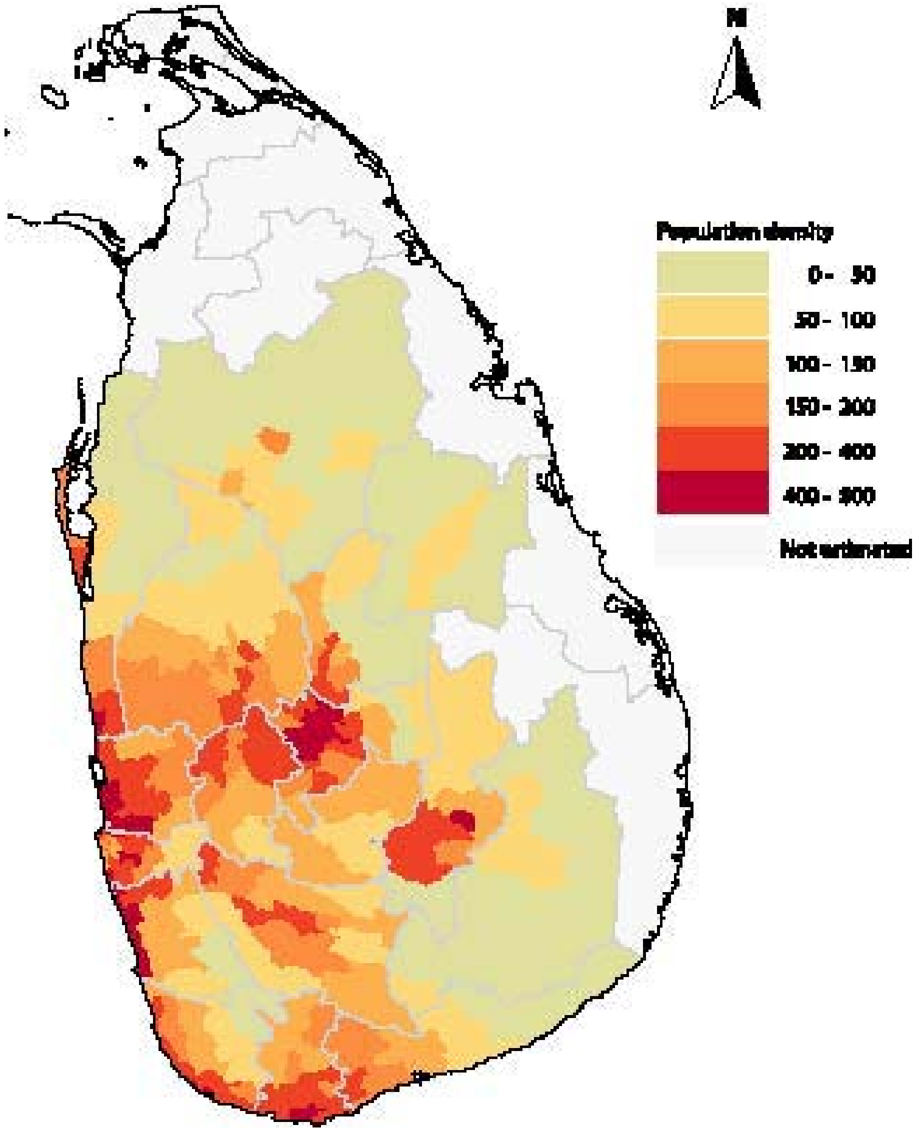
poorest districts (group 5 in figure 1B). But some DS divisions in the Badulla and Ratnapura districts have significantly higher poverty levels (group 6 in figure 1C) and some other DS divisions have significantly lower poverty levels (group 4 in figure 1C).

The poverty distribution across DS divisions is highly skewed (bar chart in figure 2 indicates more values are above the average) with 73 percent of the DS divisions falling above the national average poverty level (table 1).

DS Division Poverty Density Map

The poverty density map, the number of poor people per unit area (usually per km^2), gives spatial information on the concentration of poor people. The DS division poverty density map (figure 3), derived from the DS division poverty map, shows that while some DS divisions, such as Colombo, have the lowest incidence of poverty, they also have the highest poverty density or concentration of poverty.

FIGURE 3.
Poverty density: The number of poor people per km^2.



The poverty density map assists the decision makers to design appropriate regional-specific policy interventions for reducing poverty. Though the percentage of the poor people is lower in most urban or peri-urban areas, the poverty density or concentration of poor people is higher because of the high population density. So, no uniform intervention can be effective in both places. For example, while poverty-alleviation interventions in urban or peri-urban areas could generate nonagricultural employment opportunities, interventions in rural areas could augment resources for productive agriculture.

Spatial Clustering of Poor Areas

Do poor people or nonpoor people in Sri Lanka live close to each other? Are there clusters of areas in Sri Lanka with high or low concentration of poverty?

Spatial clustering shows spatial similarity or dissimilarity of poverty in neighboring units (figure 4). Two types of spatial similarities exist: poor units mainly surrounded by poor units or

FIGURE 4.
Types of spatial similarities or dissimilarities.

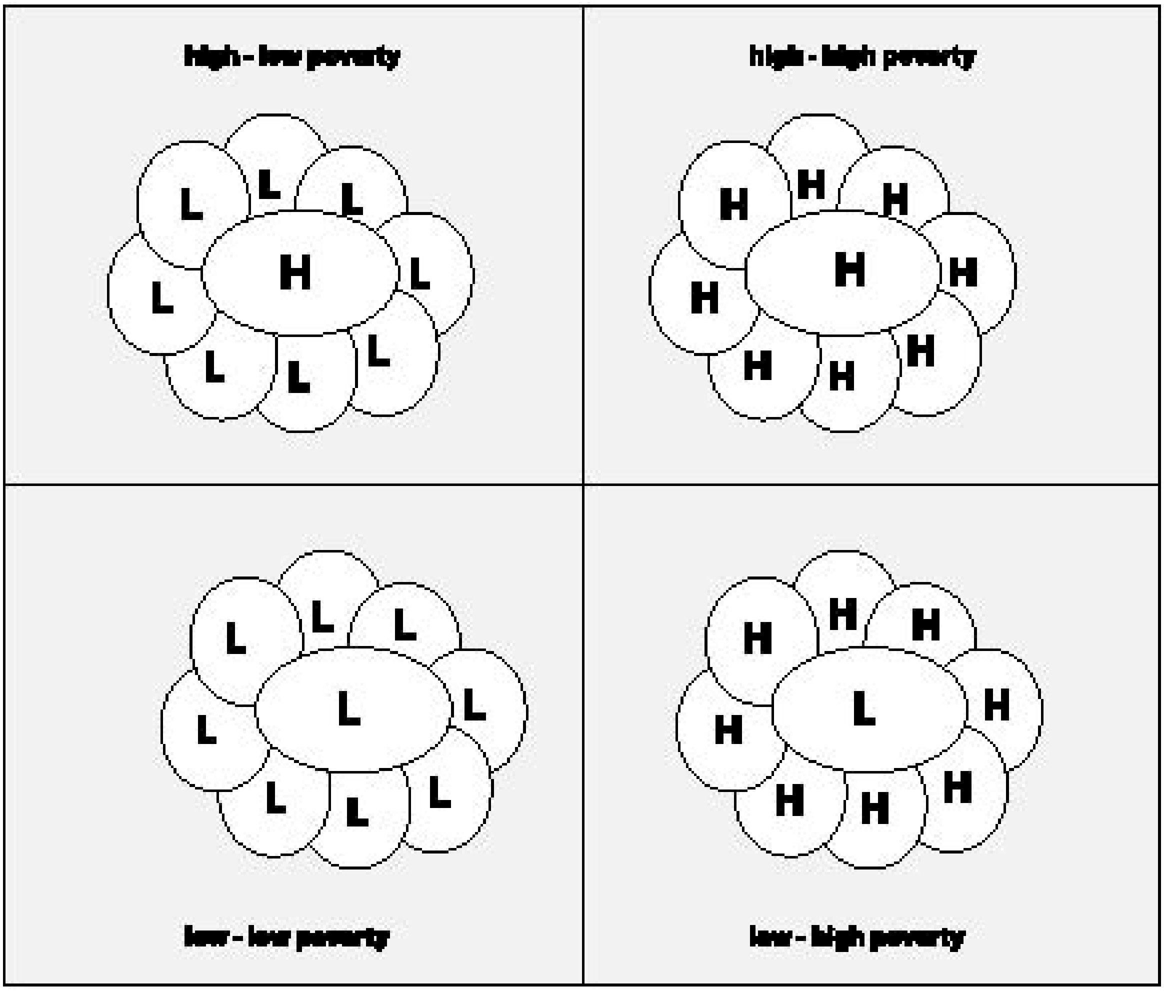
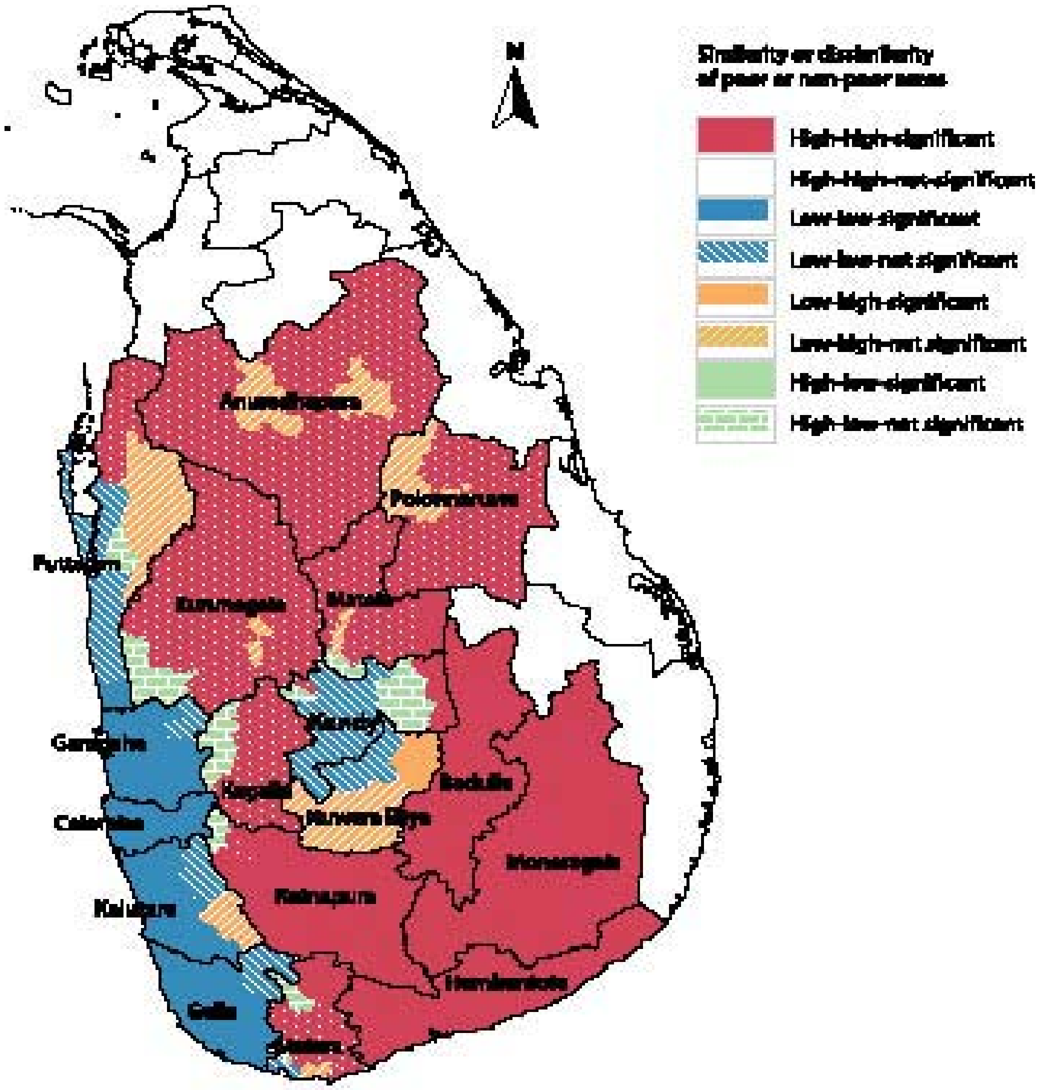


FIGURE 5.
The DS divisions with spatially similar or dissimilar poverty neighborhoods.



high-high poverty clustering (first quadrant) and nonpoor units mainly surrounded by nonpoor units or low-low poverty clustering (third quadrant). Two types of spatial dissimilarities also exist: poor units are mainly surrounded by nonpoor units or high-low poverty clustering (second quadrant) and nonpoor units are surrounded by poor units or low-high poverty clustering (fourth quadrant).

The local spatial autocorrelation, measured by local Moran's I statistic (Anselin 1995), indicates the strength of the spatial similarity or dissimilarity of neighboring units (details of statistical tests and results are given in annex C). Local Moran's I is positive for both high-high and low-low spatial similarities and is negative for both high-low and low-high spatial dissimilarities. Figure 5 shows the DS divisions with spatially similar or dissimilar neighborhoods. Of the 249 DS divisions in the analysis, the high-high poverty cluster has 138 DS divisions (units in red), but the spatial similarity is significant in only units in solid red. The low-low poverty cluster has 84 DS divisions (units in blue). The rest of the 27 units are in the low-high and high-low poverty clusters.

The high-high poverty clusters of DS divisions are mainly found in rural areas, where agricultural economic activities are the main sources of income of most households. Most DS divisions in Kurunegala, Anuradhapura, Polonnaruwa, Monaragala, Hambantota, Ratnapura, Kegalle, Matale and Matara districts are in this cluster, where every two in three households have an agricultural operator.[4] But the spatial similarities of only four districts are statistically significant: Badulla, Monaragala, Ratnapura and Hambantota. The DS divisions where spatial similarities are not significant have varying levels of prosperity due to variation in economic activities such as tourism to employment in the urban centers.

The low-low poverty clusters of DS divisions are mainly found in the Gampaha, Colombo, Kalutara, Galle, Kandy and Puttalam districts. Only a few of the DS divisions in this group are urban centers while the others are mainly rural. However, nonagricultural activities contribute substantially to the household income of the rural units in this cluster. For example, only 1 in 20 households in the Colombo district, only 2 in 11 households in the Gampaha district, and about 2 in 6 households in the Kalutara, Galle and Puttalam districts have an agricultural operator per household. This suggests that the economic activities of the rural neighbors are closely associated with those of the urban DS divisions in these districts. The neighboring units of DS divisions with statistically not significant spatial similarity have varying types of livelihood activities. Employment in some DS divisions is very much influenced by the economic activities of the urban centers while the livelihood systems in other divisions mainly depend on agriculture.

In figure 5, there are some spatial outliers where these units and their neighbors have contrasting levels of poverty or spatial dissimilarity. The dissimilarity of DS divisions in the low-high poverty cluster is statistically significant in only one DS division (orange in figure 5). This unit, the Nuwara Eliya DS division, has substantial nonagricultural income activities such as tourism but it is surrounded by poor DS divisions with significant agricultural economic activities. Unlike in the low-low poverty cluster, the economic activities in the central unit seem to have no influence on the economic activities of the neighboring units.

The units in green in figure 5 have high levels of poverty but the neighboring units have low levels of poverty. But none of the dissimilarities here are statistically significant.

The identification of spatial clusters of similarities or dissimilarities has many advantages. First, it helps locate similar and dissimilar neighborhoods and their influence on the 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 the national or regional level.

Determinants of Poverty and Spatial Clustering

Do spatial similarities influence the level of poverty? And what factors matter in spatial similarity or dissimilarity? Specifically, do access and availability of water, land and infrastructure matter in spatial similarity of poor or nonpoor and to what extent do they matter?

What are the main determinants of poverty and spatial similarity or dissimilarity of poverty,

[4] An agricultural operator is defined as a person responsible for operating the agricultural land or livestock or both, and conducts activities by himself or with the assistance from others or only directs day-to-day operations (DCS 2003b).

especially those of the rural DS divisions? Most Sri Lankans still live in rural areas and their livelihood mainly depends on agriculture or agricultural labor. Thus the availability and access to water, land and infrastructure are crucial factors for the livelihood of poor people. Although the annual rainfall totals are high, intra-annual variations are severe constraints to productive agriculture in many areas. Thus in many rural areas, a small quantity of irrigation is required to supplement water deficits in *maha* (the main or wet season, October to March) and irrigation is a must for agriculture in *yala* (the second or dry season, May to September). So, access to irrigation is necessary for alleviating poverty in many rural areas. This was substantiated in studies that compared the contribution of irrigated and rain-fed agriculture in reducing poverty (JBIC and IWMI 2002).

Successive governments in the past have invested heavily in new irrigation infrastructure or rehabilitating the old ones. In fact, irrigation investment was the major plank of rural development, poverty reduction and the national food-security strategy. While some districts benefited from these investments, others, such as Badulla, Monaragala, 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 contribute to spatial concentration of poverty.

The main factors of influence of poverty and clustering of poverty in the analysis are availability and access to water, land and infrastructure, and employment. However, at the level of aggregation of DS divisions the exact information on the availability and access to water resources is not available. But we use some proxy variables to indicate the availability and access to water and land resources in our analysis.

Availability and Access to Water

Due to the paucity of data on water availability seasonal rainfall is taken as a proxy for water availability, and the availability of irrigation infrastructure in major and minor irrigation schemes is taken as a proxy for access to water supply. The hypothesis here is that the higher level of water availability and access to it through irrigation infrastructure are expected to increase agricultural production and hence the living conditions and to reduce clustering of poverty.

Rainfall

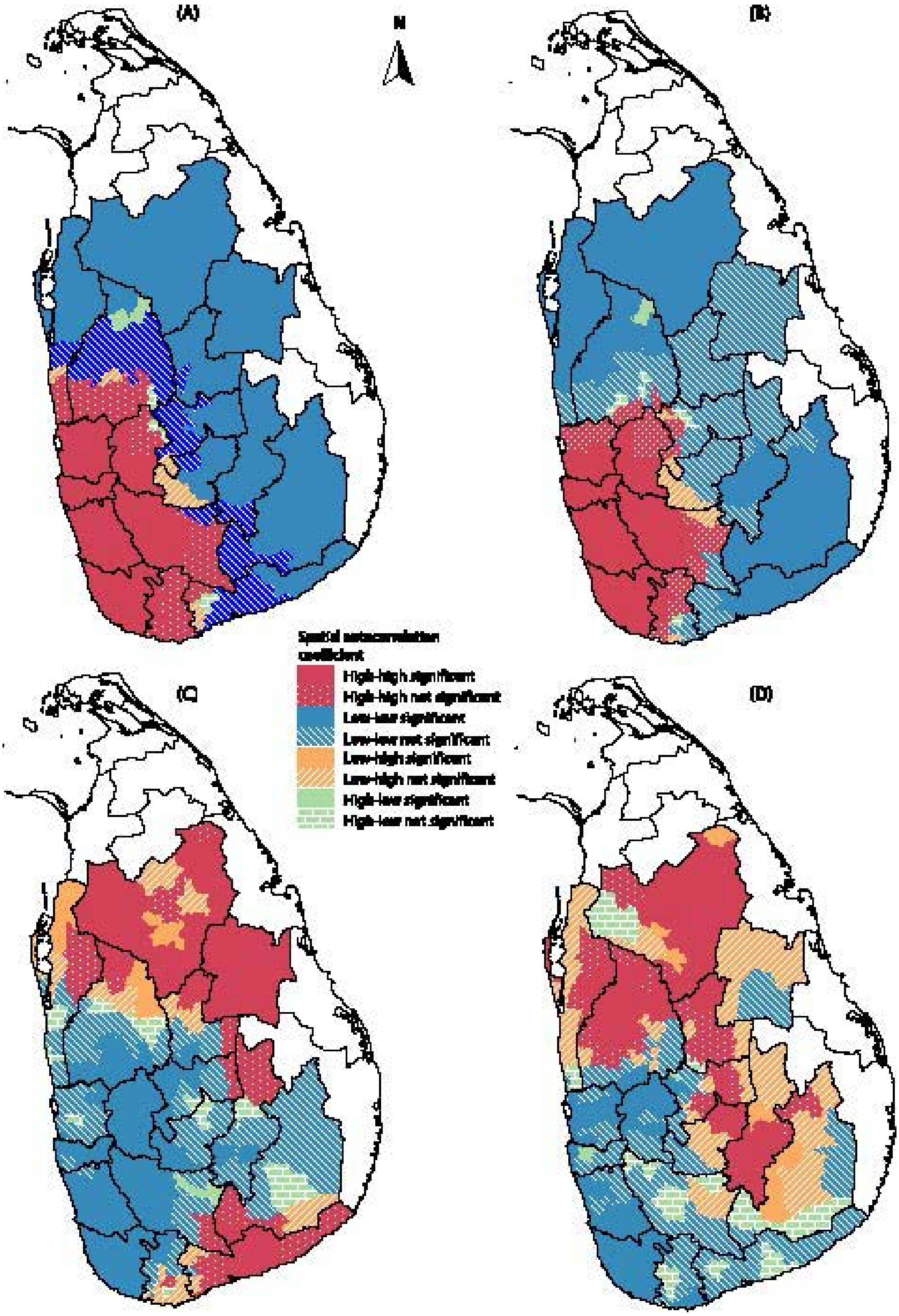
1. *Average maha rainfall.* Maha is the main cultivation season where rainfall needs to be supplemented only with a few irrigation turns for crop production. The average maha rainfall varies from 730 mm to 1,400 mm across DS divisions. Spatial similarities divide most DS divisions into two distinct clusters. High-high rainfall similarities mainly exit in the low-low poverty cluster and low-low rainfall similarities exist in the high-high poverty cluster (figure 6A).
2. *Average yala rainfall*. Yala receives 140 mm to 960 mm of rainfall and irrigation is required for crop production in most areas. The high-high and low-low rainfall spatial similarities, respectively, exist in the low-low and high-high poverty clusters (figure 6B). But, unlike in maha, low-low rainfall spatial similarities are not significant for a large number of DS divisions.

Irrigation

3. *Irrigable area under major irrigation schemes as a percentage of total crop area.*
4. *Irrigable area under minor irrigation schemes as a percentage of total crop area.*

FIGURE 6.

Local spatial autocorrelation coefficient of (A) maha rainfall, (B) yala rainfall, (C) percent major irrigated area, and (D) percent minor irrigated area.



The irrigable area under major and minor irrigation schemes varies from 0 to 79 percent and from 0 to 28 percent 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 (figures 6C, 6D).

Significant high-high similarities of major irrigated areas are mainly found in the DS divisions of three districts: Polonnaruwa, Anuradhapura and Hambantota (figure 6C), where poverty clusters also show a high-high similarity. The DS divisions with low-low similarity of major irrigated areas are scattered in both low-low and high-high poverty clusters.

Many of the DS divisions with a high proportion of minor irrigated areas and high-high spatial similarities are found in the high-high poverty cluster. The only exception is the Hambantota district, where major irrigation infrastructures exist in most DS divisions. The proportion of minor irrigated area is low (ranging from 3% to 22%) and low-low spatial similarities are significant in many of the DS division of the low-low poverty cluster.

Availability and Access to Land

The extent of landholding sizes per operator and holding size patterns are taken as proxies for land availability. The hypothesis here is that large agricultural landholding areas are expected to increase income, reduce poverty and hence clustering.

5. *Smallholder landholding*[5] *size per agricultural operator,* where average landholding size varies from 1.27 acres (0.5 ha) to 2.74 acres (1.1 ha).
6. *Percentage of smallholder landholding area below 1 acre (0.4 ha)* varies from 10 to 50 percent.
7. *Percentage of smallholder landholding area between 1 acre (0.4 ha) and 2 acres (0.8 ha)* varies from 20 to 36 percent.

Most of the agricultural operators of the DS divisions in Anuradhapura, Polonnaruwa, Monaragala, Hambantota and Kurunegala districts in the high-high poverty cluster have large agricultural landholding sizes (figure 7A). In these DS divisions and their neighbors, the proportion of large landholding sizes (above 2 acres) dominates the agricultural area (figures 7B, 7C, 7D). The DS divisions of the Ratnapura and Kegalle districts in the high poverty cluster and the Kalutara, Galle and Matara districts in the low-low poverty cluster have high proportions of landholding sizes ranging from 0 to 1 acre and 1 acre to 2 acres (figures 7B, 7C).

8. *Percentage of agricultural operators without landownership* varies from 0 to 0.7 (every 7 out of 10 operators). Figure 8B, however, shows that only a few DS divisions in the Kurunegala and Hambantota districts have a large number of agricultural operators without landownership. Most of the agricultural operators in the low-low poverty cluster own lands. They are mainly homesteads and each is below 0.4 hectare in size.

Employment and Infrastructural Facilities

The extent of the population employed in agriculture is shown by the number of agricultural operators. The extent of infrastructural development can be considered as a proxy variable for access to both markets and employment opportunities, especially for rural people, in the nonagriculture sectors.

9. *Number of agricultural operators per household* indicates the agriculturally active population per household in each DS division and this varies from 0 to 1.21 (almost 5

[5]Smallholder landholdings are defined as agricultural areas below 20 acres.

FIGURE 7.

Local spatial autocorrelation coefficient of (A) agricultural holding size per operator, (B) proportion of holding sizes below 1 acre, (C) proportion holdings between 1 acre and 2 acres, and (D) proportion of holding sizes above 2 acres.

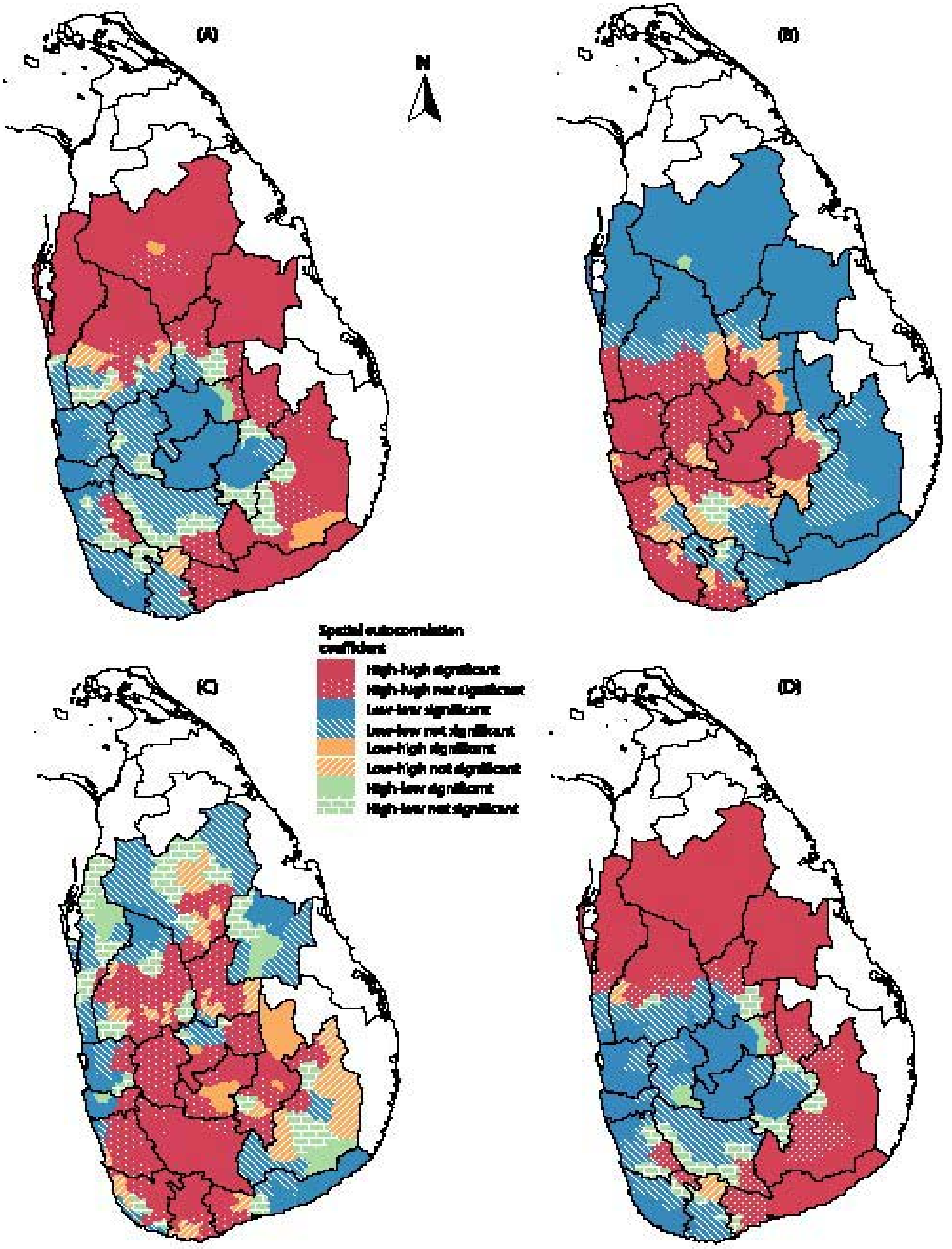


FIGURE 8.
Local spatial autocorrelation coefficient of (A) number of agricultural operators per household, (B) proportion of agricultural operators not owning land, (C) distance to roads, and (D) distance to towns.

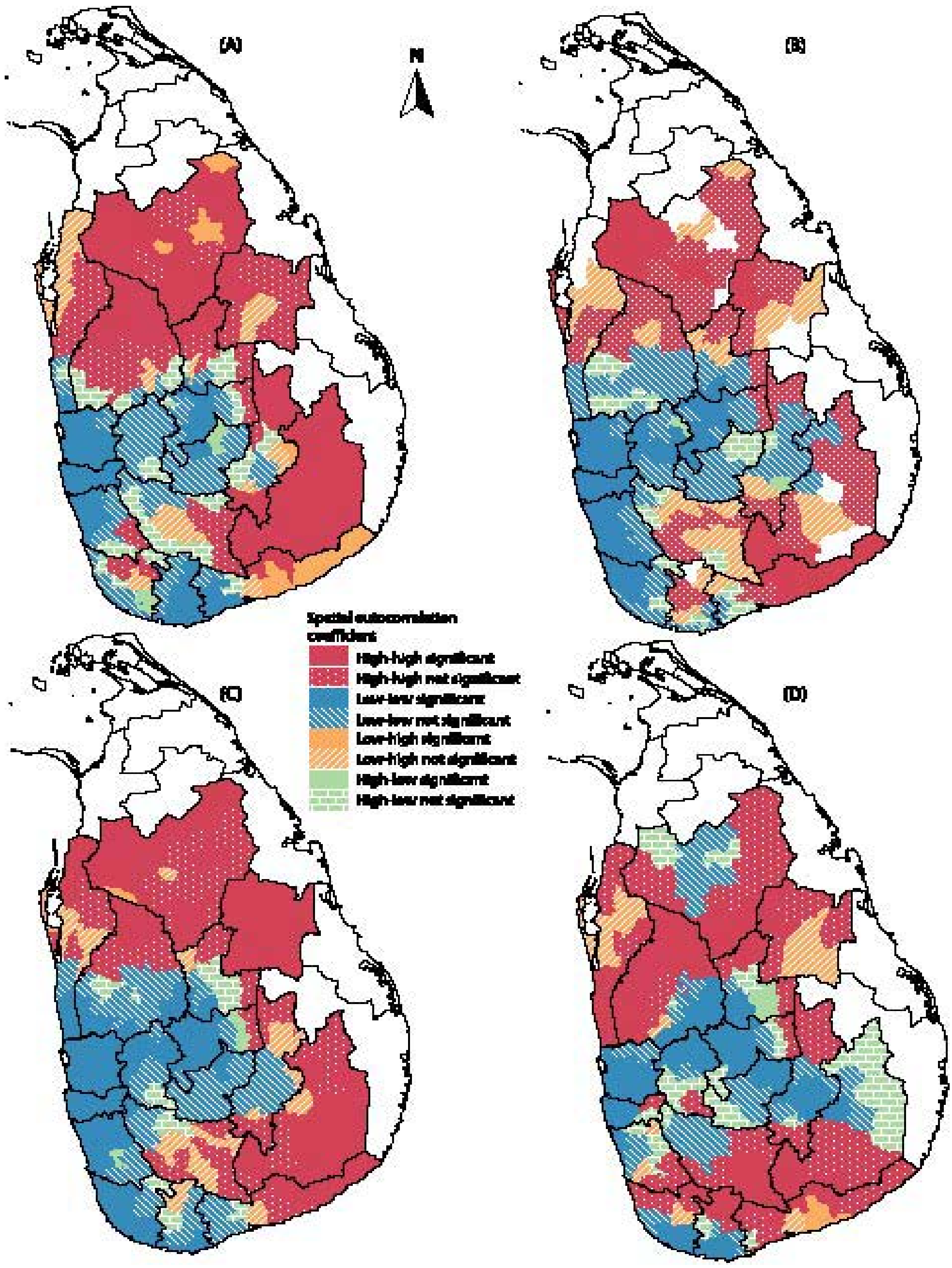


TABLE 2.
Coefficients and standard errors of regressions assessing determinants of poverty and poverty clustering.

Explanatory variables	DS divisions in the analysis							
	All DS divisions (n = 249)		DS divisions with high-high poverty neighborhoods (n = 138)			DS divisions with low-low poverty neighborhoods (n = 84)		
	OLS1[a]	OLS2[a]	OLS1[a]	OLS2[a]	OLS3[b]	OLS1[a]	OLS2[a]	OLS3[b]
1. Average maha 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 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 agricultural 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 without landownership (%)	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)
12. 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.

*Statistically significant at least at 0.05 level.

agricultural operators in every 4 households). The DS divisions with high agricultural employment are found in the high-high poverty cluster while those with low agricultural employment are found in the low-low poverty cluster (figure 8A).

10. *Average distance to roads*[6] varies from 0 to 12 kilometers. Road density is generally high in DS divisions in the low-low poverty cluster and low in the high-high poverty cluster (figure 8C).

11. *Average distance to towns* is the average of the distance of DS divisions calculated from towns to the 5–8 kilometer buffer zone.

The influence of the above factors on the levels of poverty and the spatial clustering of poverty of the DS divisions are assessed using ordinary least square (OLS) regression. The first regression (OLS1 in table 2) assesses the influence of the various factors (explanatory variables) on the incidence of poverty (dependent variable). The second regression (OLS2 in table 2) includes Local Moran's I, a measure of the local spatial autocorrelation, as an explanatory variable. It assesses the influence of spatial similarities or dependence of the neighboring units on the poverty levels 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, water and infrastructure are associated with the spatial clustering of the level of poverty. OLS3 has Local Moran's I measuring the local spatial autocorrelation of the percentage of poor households as the dependent variable. The explanatory variables of OLS3 are Local Moran's I's, measures of local spatial autocorrelations, of the independent variables in OLS1.

OLS on entire data set. First, the regression analysis is conducted for the entire data. The DS divisions with relatively low poverty levels are located in the wet-zone[7] districts Colombo, Gampaha, Kalutara, Galle, Matara, Kandy and Nuwara Eliya. In general, these units have a) higher rainfall and hence better water availability, b) small landholdings, which are mostly homesteads and self-owned, and c) a few agricultural operators and hence low agricultural employment, and are close to major urban centers 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 where agriculture dominates livelihoods.

Although 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. This can be expected because Local Moran's I is high for both high-high and low-low poverty clusters. Therefore, in order to better understand the influence of access and availability of water on the level and spatial clustering of poverty, we conduct separate analyses for the two clusters.

OLS on high-high poverty neighborhoods. DS divisions in this cluster are mainly rural and most livelihoods depend on agriculture, and the availability and access to land and water resources are crucial in lowering 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 landownership are significantly associated with lower poverty (OLS1). However, R^2 of OLS1 is very small (10%). The OLS2 regression shows that much

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[6]The distance to roads and towns is the average Euclidean distances from the center of the source cell to the center of the surrounding cells. Euclidean distance grid was calculated from ArcInfo GRID (Shahriar et al. 2002).

[7]Rainfall patterns divide Sri Lanka into three climatic zones: wet, intermediate and dry. The wet zone receives about 2,350 mm of annual rainfall while the intermediate and dry zones receive 1,450 mm of annual rainfall.

of the variation of poverty in this cluster is explained by the local spatial autocorrelation variable. In addition, the higher percentage of minor irrigated area, where water is stored in minor irrigation tanks and usually affected by the intra- and inter-annual variations of rainfall, and lack of landownership, is positively associated with a higher incidence of poverty.

The spatial autocorrelation variable in OLS2 explains 76 percent of the variation of poverty (difference between OLS1 and OLS2 R^2s). Therefore, next in the OLS3 regression, we assess the factors associated with spatial clustering of poverty. The hypothesis here is that the spatial clustering of the indicators of availability and access to water and land resources influences spatial clustering of DS divisions with varying poverty levels.

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 percentage of small landholding size classes (less than 1 acre and between 1 acre and 2 acres) is associated positively with spatial clustering of DS divisions with a high proportion of poor households.

This indicates the positive influence of availability of irrigation water supply and large landholding sizes on lower spatial clustering of the poor in rural areas. For example, the DS divisions of three districts, Anuradhapura, Polonnaruwa and Hambantota, have a high proportion of irrigated land area and also 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 the Monaragala district also have large agricultural land area per operator as in the Polonnaruwa district but they have very low irrigation facilities. Inadequate infrastructure that provides irrigation is a cause for poor DS divisions in the Monaragala district to be located in spatial clusters.

The Badulla and Ratnapura districts, unlike others, have a fewer number of agricultural operators per household. A substantial number of laborers in these two districts are engaged in the plantations sector, and are thus not counted as agricultural operators. Of those who are considered as agricultural operators, many operate in small agricultural landholdings. Thus small landholding sizes in these two districts are a possible cause for the spatial clustering of poor DS divisions.

This shows that differential access to land and water resources is indeed associated with spatial clustering of poor DS divisions. This is especially true of the significant spatial clustering of DS divisions in the two districts of Hambantota and Monaragala.

OLS on low-low poverty neighborhoods. Most of the DS divisions in this cluster (blue in figure 5) are located in the wet zone. The DS divisions with lower yala rainfall, larger landholding sizes per operator, larger proportion of minor irrigated area and long distances to towns are significantly associated with DS divisions with a high poverty level. The relatively poorer DS divisions in this group are located away from the main urban centers, and landholdings are large with a substantial agricultural component supporting the livelihoods of the people. Although major irrigation is not prominent in this group minor irrigation is, and the latter 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 became not significant in OLS2. This could be because many of the explanatory variables in this 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 spatial clustering of the proportion of minor irrigated area, number of agricultural operators per household and average distances to roads are positively associated with spatial clustering of low poverty in DS divisions. And spatial clustering of the proportion of small landholding sizes (less than 1 acre) is negatively associated with spatial clustering of low poverty in DS divisions.

While the number of agricultural operators, the proportion of irrigated area and the average distance to roads are low and similar, the proportion of landholding sizes below 1 acre is high and similar in the DS divisions and their neighborhoods. These indicate that nonagricultural activities are the major sources of income that generate activities of the DS divisions in the low-low poverty neighborhoods.

The regressions (OLS1 and OLS2) of the two poverty clusters showing spatial similarities explain the substantial variation of the poverty of DS divisions. In this analysis we have used ordinary least squares regression in assessing the association of spatial clustering of explanatory variables and poverty. However, the Global Moran's I's of the regression errors are significant in both regressions (OLS3's). This indicates 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. Identifying spatial similarities of both poverty and contributing factors is useful for designing spatially targeted interventions for alleviating poverty. Such interventions can target several factors which are similar in different spatial clusters.

Poverty Maps in Geographical Targeting

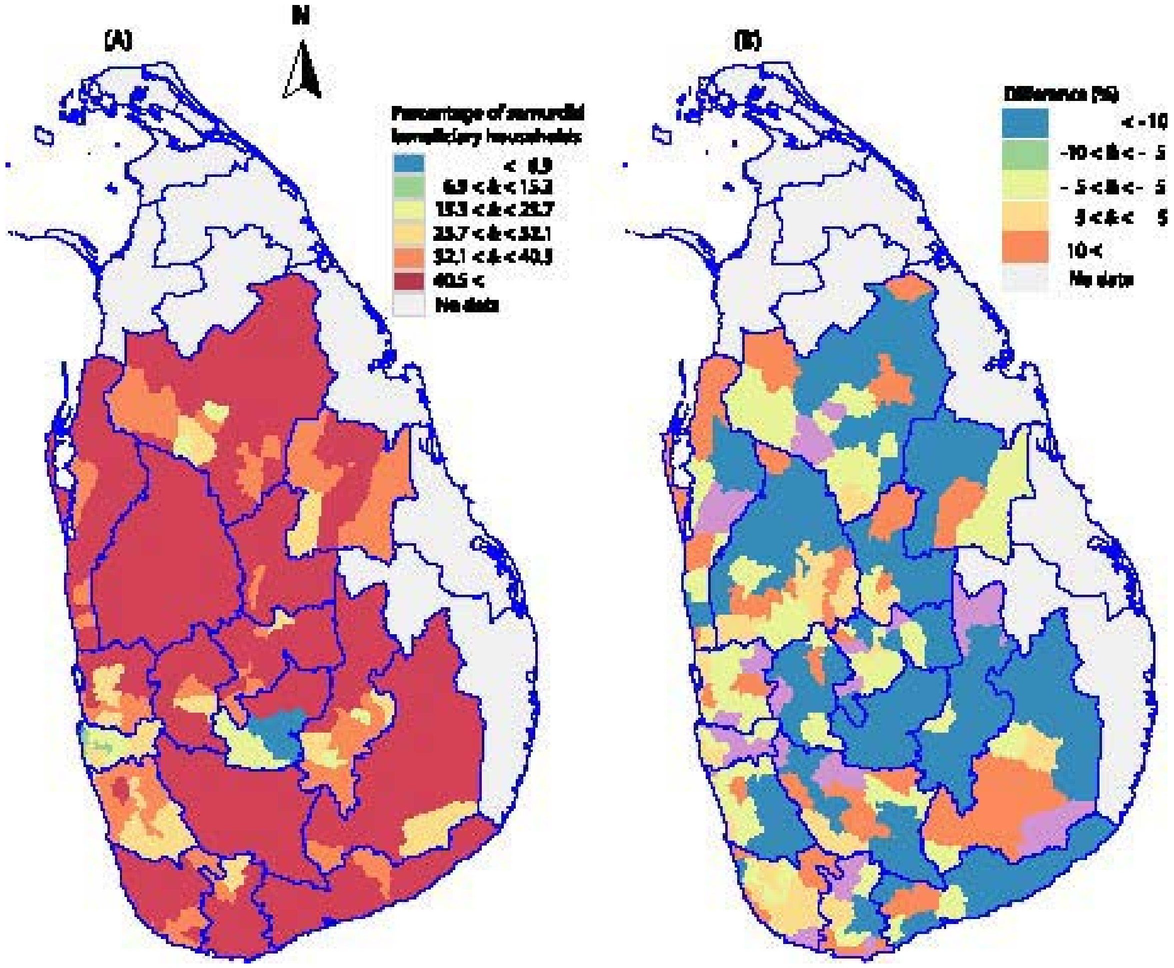
How efficient is the Samurdhi Development Program in reaching the poor? And how can the DS division poverty maps assist in geographical targeting for efficient resource allocation?

The Samurdhi Program in Sri Lanka, started in 1995 as a follow-up to the *Janasaviya*[8] Program, aims at integrating youth, women and disadvantaged groups into economic and development activities for social stability and poverty alleviation (Samurdhi Authority 1996). The Samurdhi Program has three main components: a) welfare or consumption grant's, b) savings and credits, and c) rural infrastructural development. The welfare component has short-term goals of alleviating food insecurity of poor households. It provides monthly financial assistance of Rs1,000, 750, 500, 400, 350, 250 or 140, depending on the income and physical assets of the households and claims 80 percent of the total Samurdhi budget. The other two components have long-term objectives in reducing poverty.

Various assessments have shown that the samurdhi consumption grant's allocation is highly inefficient. The World Bank (2002) reports that while 36 percent of the poorest households missed samurdhi assistance more than 40 percent of beneficiaries were in the 60 percent of the wealthiest population. It should be noted here that the selection of the poor households for the Samurdhi Program is not based on the official poverty line but on a different set of criteria. The consumption grant beneficiaries were selected on the basis that the combined household income was below a threshold income of Rs1,500 (about US$15) per month in 2002. However, in many cases, personal preferences, political interferences, ethnic background and other subjective evaluation creep into the selection criteria. In other cases, the indicators used in assessing income levels are not appropriate for different regions. Because of these discrepancies, the number of financially assisted families in the welfare program is

[8]Janasaviaya Program, started by the government in 1989, aimed at alleviating poverty in rural areas through self-employment. It provided Rs2,500 for an eligible household.

FIGURE 9.
The percentage of the samurdhi beneficiary households and the difference between the percentages of the samurdhi beneficiary households receiving Rs750 or more and the poor households.



substantially higher than that of the actually poor, based on household surveys. In fact, the total number of welfare recipient samurdhi households (1,653,000) is 80 percent higher than the estimated number of households (920,000) below the poverty line (table 3). Comparison of figure 9A with the DS division poverty map (figure 1C) shows that the number of welfare recipient households in almost all the DS divisions is higher than the number of poor households.

However, the startling inefficiency in the welfare component is the significant leakage of consumption grants to the nonpoor households. While many nonpoor households in the least poor DS divisions received the highest level samurdhi welfare assistance (Rs750 or above), many poor households in the most poor DS divisions did not receive this assistance (figure 8B). For example, only 83,000 households in the DS divisions in the first and second poverty category are poor, but more than 105,000 households received the highest welfare assistance according to the samurdhi criteria (table 3). On the other hand, 675,000 households of the DS divisions in the poverty categories 5, 6 and 7 are poor, but only 538,000 households received the highest welfare assistance according to the samurdhi criteria.

The resource allocation efficiency of the samurdhi welfare fund across the DS divisions can be improved using the DS division poverty maps. The total financial assistance in the

TABLE 3.
Number of poor and samurdhi beneficiary households.

Poverty groups (% of poor households)		Total number (1,000s)		Number of samurdhi households in different financial assistance categories (1,000s)						
		DS divisions	Poor households	Total	Rs 750	Rs 500	Rs 400	Rs 350	Rs 250	Rs 140
1	1.0 – 6.9	4	3	26	12	0	0	8	6	0
2	6.9 – 15.3	19	80	209	93	0	22	59	34	1
3	15.3 – 23.7	45	162	320	164	1	41	66	47	1
4	23.7 – 32.1	105	374	647	319	2	117	129	78	2
5	32.1 – 40.5	67	270	414	200	2	95	71	42	4
6	40.5 – 46.0	9	31	37	19	0	13	4	2	0
Total		249	920	1,653	807	5	288	335	208	8

Source: Authors' estimates.

welfare program in 2002 to the districts outside Northern and Eastern provinces was roughly Rs 892 million or about US$9 million (US$1.00 = Rs 95 in 2002). By using these maps, we will propose to the relevant authorities to distribute the samurdhi fund in proportion to the number of poor households in each DS division. This would eliminate the distributional disparities across DS divisions and would assist in reducing the magnitude of the leakage to the nonpoor households, while increasing the coverage to the poor household.

If the household selection criteria for samurdhi welfare assistance are the same as those of the poverty line then all poor households can be provided with Rs970 per month or Rs220 more than the highest-level financial assistance (scenario 1 in table 4). And the increased allowance certainly reduces the food poverty gap of many poor households and may even be sufficiently large enough for some poor households to emerge out of the food poverty line. Scenarios 2 to 5 in table 3 show the possible alternative coverages of the samurdhi welfare fund allocation to nonpoor families while providing the maximum allocation of Rs750 to the poor households.

In addition to the DS division poverty map, other guidelines are required for efficient resource allocation at the household level. The DS division poverty map could only assist in distributing the resources among the DS divisions. The present research does not suggest a method for selecting samurdhi beneficiary households within DS divisions. However, information, through econometric modeling or through participatory poverty assessment techniques, that relates household poverty with other exogenous factors offers a way of designing these guidelines. These guidelines can be specific to a region or to a cluster of regions with similar characteristics.

TABLE 4.
Scenarios of samurdhi welfare fund allocations among the poor households.

Scenarios	Number of poor households (1,000s)	Number of households in different financial assistance categories (1,000s)						
		Total	Rs 750	Rs 500	Rs 400	Rs 350	Rs 250	Rs 150
2002 allocation	920	1,653	805	5	288	335	212	7
Scenario 1[i]		920	920	—	—	—	—	—
Scenario 2[ii]		1,326	920	406	—	—	—	—
Scenario 3[ii]		1,427	920	—	507	—	—	—
Scenario 4[ii]		1,599	920	—	—	579	—	—
Scenario 5[ii]		1,731	920	—	—	—	811	—

Source: Author's estimates.

i This scenario, which estimates the maximum financial assistance that can be provided for all poor households, shows that each of the 920 poor households could receive financial assistance of Rs970, Rs 220 more than the highest-level financial assistance at present.

ii Scenarios 2 to 5 show that if Rs750 is allocated to each household below the official poverty line (for 920,000 households), the remaining samurdhi welfare fund can provide an income support for an additional 406,000 households at the rate of Rs500 per month or 507,000 households at the rate of Rs400 per month or 579,000 households at the rate of Rs350 per month or 811,000 households at the rate of Rs 250 per month.

Policy Discussion and Conclusions

This report presents the results of subnational poverty estimation using aggregate poverty statistics and how they can help policy interventions. In particular, they estimate the poverty map across the DS division level in Sri Lanka. The poverty map depicts the proportion of households below the poverty line, which is based on household expenditure for food for obtaining the minimum calorie requirement.

The DS division poverty map provides policymakers and researchers with important spatially disaggregated poverty information that was not available earlier. The district-level poverty, the only spatially disaggregated information available to date, is adequate only for broad national-level policy formulation and intervention designs. The DS-level poverty map however increases the scope of the spatial analysis for determinants of poverty and the formulation of geographically targeted poverty alleviation programs.

In this report, the DS division poverty map is first used to assess the extent of the spatial clustering of poor areas and then to assess the influence of spatial similarities of the incidence of poverty of the DS divisions. Two dominant spatial clusters exist in the studied area: one showing spatial similarity of high-poverty DS divisions surrounded by high-poverty neighborhoods, and the other showing spatial similarity of low-poverty DS divisions surrounded by low-poverty neighborhoods.

The DS divisions with high-high poverty spatial clustering are mainly located in the rural areas where agriculture is the main source of livelihood of the majority of households. However, the spatial similarity is statistically significant only in four districts: Monaragala, Badulla, Ratnapura and Hambantota. In areas where spatial similarities are not significant, the DS divisions have varying levels of economic prosperity due to nonagricultural economic activities.

The DS divisions with low-low spatial similarity are mainly found in the Western, Southern and the Central provinces. The spatial similarity is significant only in the DS divisions around a few major urban centers. The economic activities of the spatially similar DS divisions in this cluster are very much influenced by the economic activities of the major urban centers.

The regression analyses on the two clusters show that local spatial autocorrelations, which measure the strength of spatial similarity, explain a significant part of the spatial variation of the incidence of poverty. This is especially true in the high-high poverty cluster, where units with higher spatial dependence have higher poverty levels. Several factors contribute to the variation of spatial dependencies of poverty in this cluster. Spatial clustering of large landholdings indicating land availability, and spatial clustering of a higher proportion of major and minor irrigated areas indicating access to water resources for productive purposes are associated with low spatial clustering of poverty. These two factors indicate the contribution of availability of land and access to water to productive agriculture or agricultural labor, which is an integral part of the poverty-alleviation strategy in the rural areas. However, spatial clustering of a high proportion of small landholding sizes (below 1 acre) is positively associated with the clustering of poverty. This indicates that fragmentation of agricultural land into smallholdings has not created adequate income-generating opportunities thus contributing to a high concentration of poverty. This shows that massive investments in new schemes or rehabilitating old irrigation schemes alone may not be an effective intervention in some poverty-stricken areas where availability of water or land is a major constraint.

Although many DS divisions in the low-low poverty cluster are rural, nonagricultural economic activities and better infrastructural facilities have a positive influence in reducing poverty in this cluster.

The poverty maps can be used to locate the poorest areas to increase the efficiency of resource allocation in pro-poor intervention programs. Allocating the samurdhi welfare fund in proportion to the number of poor households removes the misallocation of resources among DS divisions. This could lead to either more poor households getting welfare benefits or more benefits distributed to the poor households. But it is not completely sufficient to identify the poor households and remove the leakages to the nonpoor as at present. This requires further studies for determining guidelines to identify poor households within the different poverty clusters.

The present study is a subnational poverty mapping analysis based on secondary data of the Population and Agriculture Census and Consumption and Expenditure Survey of Sri Lanka. The results show a good overview of the spatial variation of poverty at finer resolution than what is currently available at the district level. They also show the potential of finer-resolution poverty maps to identify where the poor live and the specifics of why they are poor.

Many other finer-resolution poverty maps can help formulate policy and design geographically targeting interventions. Some of these maps are on severity of poverty, nutritional poverty, and availability and access to resources—especially those of access and availability to water and land resources—and others are on access to safe drinking water supply and sanitation, electricity, roads, markets, etc. In addition to these, maps of spatial clustering of major indicators or determinants of poverty would be helpful in efficient resource allocation.

Many of these maps can be prepared by combining household information of the census of population and housing and the sample survey of household income and expenditure. But the resources—human, the technological knowledge and the computer hardware and software—required for such analyses are prohibitively expensive for the regional-level institutions. Thus the challenge for the researchers in the next phase is to develop a methodology for poverty maps that can be easily prepared at the regional level. Though some streamlining is required, routine information collected by the DS divisions on the household and the GN divisions is more than adequate for such an analysis.

Annex A

Estimation Methodology of Subnational Poverty

Small-Area-Estimation Methods

Small-area-estimation methods are statistical techniques, which provide efficient estimates for small areas. The population census or socioeconomic surveys would not be able to provide these estimates (Ghosh and Rao 1994). *A small area* can be a small geographic unit such as an administrative area, an agro-ecological region, a river basin or a small demographic unit such as a rural or urban population, a subgroup of ethnicity, race or age. Usually, the scope of a population census is narrow, given the available finances and the time frame, where information of only a few key variables is collected from the households. The scope of sample surveys is also narrow in the sense that though information on several variables can be obtained simultaneously, only a small number of households can be sampled due to the high cost. Sample surveys, therefore, yield accurate estimates for aggregate geographic or demographic units only.

Small-area-estimation techniques combine census, survey and other auxiliary information to obtain estimates at smaller geographic or demographic units. Reviews of various small-area techniques used in estimation are found in Morrison 1971, Purcell and Kish 1979, Zidek 1982, Rao 1986, McCullagh and Zidek 1987, Statistics Canada 1987 and, more recently, in Chaudhuri 1992 and Ghosh and Rao 1994. The estimation techniques include the following:

- *Demographic methods* to estimate population for small areas or other characteristics for post-censual periods, based on current administrative records and data from the most recent population census.
- *Synthetic estimation,* where unbiased estimates of larger areas are used with auxiliary information of small areas to obtain estimates, assuming that small areas have the same characteristics as large areas (Gonzalez 1973).
- *Small-area models* where census and survey data are combined using empirical Bayes, hierarchical Bayes or empirical best linear unbiased prediction (Morris 1983; Datta and Ghosh 1991; Harville 1991).

In the recent past, poverty maps of many countries were developed using micro-level data by combining sample survey and population census data of households (Alderman et al. 2000; Bigman and Fofack 2000; Hentschel et al. 2000; Minot and Baulch 2002) using aggregated data at the community level (Minot 2000; Bigman et al. 2000).

Davis (2002) assessed the pros and cons of using different methods of poverty mapping. The choice of method of estimation always depends on the availability of auxiliary data for small-area units. In this study, only the estimates of poverty for districts and the auxiliary information for DS divisions within districts are available. Therefore, we use the *synthetic estimation* method to estimate poverty maps of the percentage of poor households at the DS division level.

Synthetic Estimation

Suppose an unbiased estimate $\hat{Y}_i$ of Y_i's of a large domain (such as a district) is available from a sample survey. Suppose also an item of auxiliary information X_{ij} for the j^{th} small area (such as a DS division) in the i^{th} domain is available, where several small areas *j* may cut across a large domain *i*. The synthetic estimate for the total of j^{th} small area is

$$\hat{Y}_j = \sum_i \frac{X_{ij}}{\sum_i X_{ij}} \hat{Y}_i \qquad \text{...} \quad (1)$$

The estimate for the small area is not unbiased, where the approximate bias of the estimate is

$E(\hat{Y}_j) - Y_j = \sum_i X_{ij} \left(\frac{Y_i}{X_i} - \frac{Y_{ij}}{X_{ij}} \right)$. A higher bias leads to a higher error and the estimate is not efficient. However, the small-area estimate is approximately unbiased if the ratio of Y_{ij}/Y_i is equal to X_{ij}/X_i. The estimate then has an approximately uniform minimal error.

The method here requires a significantly smaller data compilation and processing than the household unit method. The household-unit method requires combining data at household level collected from the population census and income and expenditure surveys. The synthetic estimation, however, requires a considerably less data-processing effort. It is even less complicated in the Sri Lankan context. The poverty information is already available at the district level, and a district is a union of a few DS divisions with no DS divisions intersecting two districts. Thus the challenge here is to find an auxiliary variable to satisfy an approximate unbiased requirement. Here our attempt is to find variable $X_{ij,}$ which is significantly linearly correlated with the incidence of poverty in DS divisions. The sources of the auxiliary information for the study are the Population Census of 2001 (DCS 2002a, b), the Agriculture Census (DCS 2003b) conducted by the Department of Census and Statistics and the information generated for DS divisions using GIS by the International Water Management Institute (Shahriar et al. 2002). Several auxiliary variables are available from these sources. Therefore, we use the principal component analysis to define an index of auxiliary information—a linear combination of the original auxiliary variables.

Index of Auxiliary Information

Incidence of poverty is associated with types and extents of economic activities of households. Although details of economic activities and their monetary value to households are not available, several variables that describe the profile of economic activities or poverty are available at the DS level. These variables include information on demography, assets, employment, agricultural productivity, income-generating modes and geographical location. These are known to be associated with variations of poverty (Ravellion 1992; Boltvinik 2004; Lok-Dessallien 2004; Fiess and Verner 2004; JBIC and IWMI 2002). Annex table 1 lists these variables, and year and source of data are shown in the last two columns.

Demography is explained first by three indicators, rural and estate-sector population, household size and population under 18, and they are shown to be associated positively with incidence of poverty.

The next set of information (except where suggested) refers to information on *agricultural holdings* of the *smallholding sector*. An *agricultural holding* is defined as "... the land and/or livestock used wholly or partly for agricultural production within a DS division subject to conditions such as one holding may consist of one or more parcels without regard to the ownership or legal operation of the land; a holding may consist of only crops, only livestock, or crops and livestock; a holding may consist of paddy, only highland or both..." (DCS 2003b). The agricultural holdings above 20 acres, and under the same unit of management are considered as estates. The agricultural holdings that are not identified as estates form the *smallholding sector*.

ANNEX TABLE 1.
Auxiliary information in the principal component analysis.

No.	Auxiliary information	Year	Source
1	Rural and estate-sector population (% of total)	2001	Pop. Census
2	Household size (population per household)	2001	Pop. Census
3	Population under 18 years (% of total population)	2001	Pop. Census
4	Number of housing units per household	2002	Pop. Census
5	Number of agricultural holdings per household	2002	Agri. Census
6	Agriculture holding size above 40 perches (» ¼ acre)[1] per household	2002	Agri. Census
7	Number of cattle/buffalo heads per households	2002	Agri. Census
8	Number of agricultural operators per household	2002	Agri. Census
9	Number of agricultural operators without land per household	2002	Agri. Census
10	Major irrigated area (% of total smallholding crop area)	2001	GOSL
11	Minor irrigated area (% of total smallholding crop area)		
12	Cropping intensity of paddy in 2002	2001	GOSL
13	Number of agricultural holdings between 40 perches and 1 acre per operator	2002	Agri. Census
14	Number of agricultural holdings between 1 acre and 2 acres per operator	2002	Agri. Census
15	Number of agricultural holdings above 2 acres per operator	2002	Agri. Census
16	Number of holdings between 40 perches and 1 acre (% of total)	2002	Agri. Census
17	Number of holdings between 1 acre and 2 acres (% of total)	2002	Agri. Census
18	Percentage of families receiving samurdhi financial benefits	2002	Samurdhi Authority
19	Major irrigation paddy cultivated area per household	2001	GOSL
20	Minor irrigation paddy cultivated area per household	2001	GOSL
21	Rain-fed paddy cultivated area per household	2001	GOSL
22	Tea area in the smallholding sector per household	2002	Agri. Census
23	Rubber area in the smallholding sector per household	2002	Agri. Census
24	Coconut area in the smallholding sector per household	2002	Agri. Census
25	Milk production of cattle per household	2002	Agri. Census
26	Milk production of buffalo heads per household	2002	Agri. Census
27	Number of goats/sheep/swine per household	2002	Agri. Census
28	Number of chickens per household	2002	Agri. Census
29	Average distance to roads	2003	IWMI-GIS
30	Average distance to towns	2003	IWMI-GIS

[1] 0.4065 ha = 1 acre = 160 perches.

Note: Pop. = Population; Agri. = Agricultural; GOSL = Government of Sri Lanka.

Sources: Samurdhi Authority 2002; Population Census (DCS 2002a, b); Agriculture Census (DCS 2003b); IWMI-GIS (Shahriar et al. 2002).

Assets. Indicators 4 to 7 are proxies for the assets of the households. Housing units are those that belong to the total population. The number of agricultural holdings includes both sizes: those below 40 perches where agricultural production is mainly for home consumption and those above 40 perches in size in the smallholding sector where production is mainly sold outside.

Agricultural employment. Indicators 8 and 9 explain the agricultural employment patterns in the smallholding sector. Indicator 8 is the number of agricultural operators and indicator 9 shows the landless agricultural labor in each DS division.

Agricultural productivity. Indicators 10-17 are determinants of agricultural productivity. Indicators 10 and 11 show the extent of irrigation under major and minor irrigated areas as a percent of total crop area. These show the extent of irrigation water availability. The productivities in irrigated areas are generally higher than in rain-fed areas. Indicator 12 shows the cropping intensity of all paddy lands where the higher the cropping intensity, the higher the annual productivity. Indicators 13-15 show the number of landholdings per operator in three operating classes: less than 1 acre, between 1 acre and 2 acres and more than 2 acres; and indicators 16 and 17 show the percentage of the landholding sizes of less than 1 acre and between 1 and 2 acres. A higher number of small landholding sizes among the operators would generally mean a lower agricultural productivity.

Agricultural income. Indicators 17-28 explain modes of agricultural income of households. Percent of households receiving samurdhi benefits[9] is taken as one mode of income. (In fact, this variable can itself be taken as an auxiliary index in the synthetic estimation. However, past estimates show that there is substantial allocation of benefits to the nonpoor households [DCS 2000]. Therefore, we need to improve upon this variable to explain the poverty variability across households). Indicators 17 to 19 show the variation of the income of paddy crops under different farming systems including those under major and minor irrigation and rain-fed conditions. Indicators 20 to 21 relate to the income of cash crops and the last four indicators relate to the income from animal husbandry.

The sixth set of indicators explains the *location* or *proximity* to infrastructural facilities. The auxiliary information index for the 26 variables is estimated using the principal component analysis (see annex B for details of estimating the index using the principal component analysis).

Let I_{ij} be the principal component auxiliary index for the jth DS division in the ith district. Then the estimate of percent poor households in 2002 for each DS division in equation (1) takes the form

$$\hat{Y}_{ij} = \frac{I_{ij}}{\sum_{j} I_{ij}} \hat{Y}_i$$

where, $\hat{Y}_i$ is the survey estimate of the number of poor households of the ith district and $\hat{Y}_{ij}$ and I_{ij} are the estimates of the number of poor households and the value of the index generated using auxiliary variables of the jth DS division in the ith district.

[9]The Samurdhi Financial Assistance Scheme provides poor households with a payment of Rs1,000, 750, 500, 400, 350, 250 or 140 per month depending on the income and physical assets of the households (Samurdhi Authority 1996) (US$1.00= Rs95 in 2002; 1 PPP US$ = Rs33).

Annex B

Principal Component Analysis in Estimating Auxiliary Index

The principal component analysis, a dimension-reduction technique in multivariate statistical analysis, finds linear combinations of a set of variables which are uncorrelated with each other so that the first few components explain most of the variations of the original set of variables. That is, if X_1, X_2, ..,X_p are the original variables (standardized by dividing their standard deviation), the new variables Z_1,Z_2,..,Z_p take the form

$Z_i = a_{i1}X_1 + a_{i2}X_2 + .. + a_{ip}X_p$ such that $Var(Z_1) > Var(Z_2) > .. > Var(Z_p)$ and

$$a_{i1}^2 + a_{i2}^2 + .. + a_{ip}^2 = 1.$$

The variance of Z_i is the i^{th} eigen value of the covariance matrix of the original variables (for details on principal component and its treatments see Manly 1986).

For our analysis, there are 30 auxiliary variables. First, we use district-level data in the principal component analysis to assess the strength of the linear relationship in explaining the levels of poverty. To capture any remaining variations between provinces, we included dummy variables for different provinces. Only the dummy variable for the Western province is significant. The first 6 principal components explain more than 90 percent of the variations of the 30 variables. Moreover, the first two principal components (Z_1 and Z_2) and the Western province dummy variable are statistically significant in explaining 68 percent of the variations of the estimates of poverty at the district level. That is, at the district level,

Percentage of poor households = 1.694 Z_1 + 1.822 Z_2, R^2= 0.68

We use the same relationship with principal components based on DS division data to estimate the auxiliary index and this is given by

I_i = (1.694 Z_{1i} + 1.822 Z_{2i})* Ni, where N_i is the number of households in i^{th} DS division.

Annex C

Identifying Spatial Clustering of Poor Areas

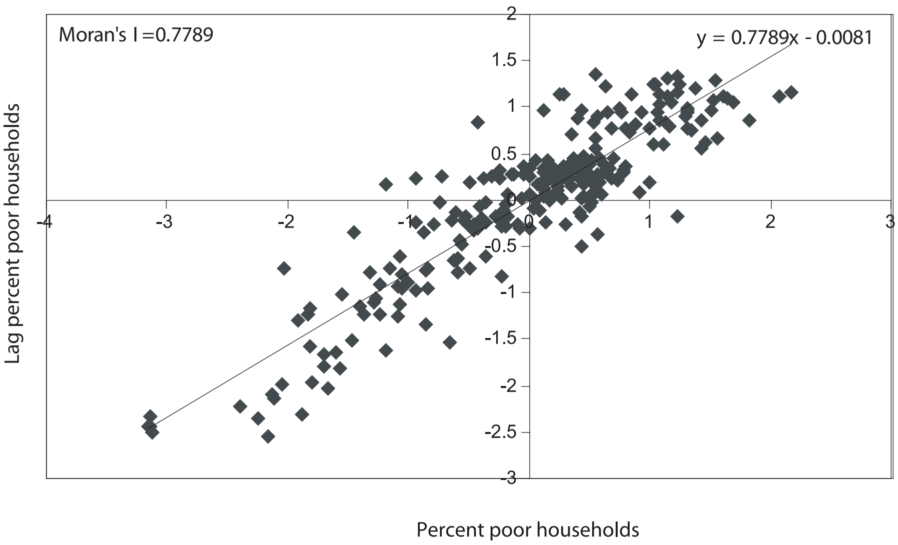
Spatial clustering shows the similarity or dissimilarity of neighboring units, and spatial autocorrelation measures the strength of the spatial clustering. Significant positive or negative autocorrelations of the poverty level show whether the neighboring units are similar or dissimilar.

Global Spatial Autocorrelation

Global Moran's I statistic measures the global spatial autocorrelation (see later in this section for estimating Global Moran's I). This statistic shows whether the spatial similarity of neighboring units in the whole study area is significant or not, but it does not show the location where similarity is significant. Annex figure 1 shows the scatter plot of the standardized percentage of poor households and spatial lag[10] of the percentage of the poor households. The negative values in the X and Y axes indicate the below-average values. Spatial autocorrelations measure the strength of the linear relationship of the original and the spatial lag variables in the scatter plot.

The points in the first quadrant (high-high) and the third quadrant (low-low) of annex figure C1 suggest positive spatial autocorrelations and thus spatial clustering. The points in the first quadrant show that DS divisions with a high percentage of poor households are surrounded by DS divisions with a high percentage of poor households. The points in the third quadrant show that DS divisions with a low percentage of poor households are surrounded by a low percentage of poor households in the neighborhoods.

ANNEX FIGURE 1.
Scatter plot of percentage of poor households and lag percentage of poor households of DS divisions.



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11 Spatial lag variable is calculated using the eight nearest neighbors of DS divisions.

The points in the second quadrant (high-low) and in the fourth quadrant (low-high) suggest negative spatial autocorrelations; thus there is no spatial clustering. The points in the second quadrant show that DS divisions with a high incidence of poverty are surrounded by DS divisions with a low incidence of poverty in the neighborhood. The fourth quadrant (high-low) shows that DS divisions with a low incidence of poverty are surrounded by DS divisions with a high incidence of poverty in the neighborhoods.

Global Moran's I statistic, the slope of the regression line, indicates the strength of the linear relationship of the variable and the spatial lag variable. A significantly high positive value confirms positive autocorrelations or spatial clustering. Global Moran's I statistic is estimated using the spatial data analysis package Geoda 9.0 (Anselin 2003). Global Moran's I for the percent poor households and the spatial lag variable are statistically significant (I = 0.79, significance level < 0.001). This confirms the hypothesis that poor (or nonpoor) locations are found in spatial clusters meaning that a poor (or nonpoor) location is often surrounded by poor (or nonpoor) neighbors.

Local Spatial Autocorrelation

Global Moran's I indicates only the significance of the similarity or dissimilarity of neighbors for the whole study area. But finding the locations of similar or dissimilar neighborhoods is also useful to identify causes and effects of spatial similarity or dissimilarity. Local Moran's I indicator (Anselin 1995) estimates spatial autocorrelation of an individual location with its neighbors and it indicates the strength of the similarity of a unit with its neighbors. Local Moran's I statistic is also estimated using the spatial data analysis package Geoda 9.0 (Anselin 2003).

Estimating Spatial Autocorrelation

Spatial autocorrelation assesses the spatial dependency or the similarity or dissimilarity of neighboring units. Some statistics that measure spatial autocorrelation are Moran's I, Geary C (Cliff and Ord 1973), G statistics (Getis and Ord 1992) and Local Moran's I (Anselin 1995). We use Global Moran's I to measure the global spatial autocorrelation and Local Moran's I to measure the spatial autocorrelation of a specific location.

Global Moran's I statistic measures the extent of the spatial association or the similarity or dissimilarity of neighboring units. A significant positive Global Moran's I indicates similar neighboring units while a significant negative Moran's I indicates dissimilar neighboring units. Let x_1, x_2, .., x_N be observations of N locations. Global Moran's I for N observations is defined as

$$I = \frac{N}{w_0} \frac{\sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} w(i,j)(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2}$$

where, w(i,j) define the spatial weight explaining the proximity of different locations and

$$w_0 = \sum_{i=1}^{N} \sum_{j=1} w(i.j)$$

The expected value and the variance under the assumption of randomly distributed x's (i.e., under the assumption that there are no spatial autocorrelation) are

E(I)=-1/(N-1) and

$$Var(I) = \frac{N((N^2 - 3N + 3)w_1 - Nw_2 + 3{w_0}^2) - K(N(N-1)w_1 - 2Nw_2 + 6w_0^2)}{w_0^2 (N-1)(N-2)(N-3)} - E^2(I)$$

where, $K = \frac{N\sum_{i=1}^{N}(x_i - \overline{x})^2}{(\sum_{i=1}^{n}(x_i - \overline{x})^2)^2}$, $w_1 = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(w(i,j) + w(j,i))^2$, $w_2 = \sum_{i=1}^{N}(w_{i.} + w_{.j})^2$ and $w_{i.}$ and $w_{.j}$ constitute the sum of i^{th} row and j^{th} column of the weight matrix.

Local Moran's I statistic measures the spatial autocorrelation of a specific location with its neighbors. A significant positive Local Moran's I indicates that the values of a location and its neighbors are similar in that they are either "high and high" or "low and low." A significant negative Moran's I indicates that the value of a location is dissimilar with the neighboring values. Local Moran's I for a location *i* is given by:

$$I_i = \frac{x_i - \overline{x}}{S_i^2} \sum_{j=1}^{N} w(i,j)(x_i - \overline{x})$$

where, $S_i^2 = \frac{\sum_{j=1, j\neq i}^{N} x_j^2}{N-1} - \overline{x}^2$. The expected value of variance of Local Moran's I under the assumption of random distribution, i.e., that there are no local spatial correlation, is given by

$$E(I_i) = \frac{-\sum_{j=1}^{N} w(i,j)}{N-1}, \quad Var(I) = \frac{1-b}{N-1} \sum_{j=1, j\neq i}^{N} w(i.j)^2 + \frac{(2b-N)\sum_{k=1,k\neq i}^{N}\sum_{k=1,k\neq j}^{N} w_{kj} w_{kj}}{(N-1)(N-2)} - [E(I_i)]^2$$

where, $b = \frac{N\sum_{i=1}^{N}(x_i - \overline{x})^4}{\left(\sum_{i=1}^{N}(x_i - \overline{x})^2\right)^2}$

P-Value. Observed significance probabilities (p-values) of both statistics are estimated as follows: Let $Z^{obs}(x_1, x_2,.., x_N) = \left| \frac{I - E(I)}{\sqrt{\mathrm{var}(I)}} \right|$ be the statistic for n observations (x_1,x_2,..,x_n) and let $Z^*(x_1^*, x_2^*,.., x_N^*)$ be the statistic value for a permutation of the original observations (x_1,x_2,..,x_n). Then the observed significance level of the permutation test is $p^{obs} = \frac{\#(Z^* > Z^{obs})}{K}$ where, k is the number of permutations.

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Postal Address
P O Box 2075
Colombo
Sri Lanka

Location
127, Sunil Mawatha
Pelawatta
Battaramulla
Sri Lanka

Telephone
+94-11-2787404

Fax
+94-11-2786854

E-mail
iwmi@cgiar.org

Website
http://www.iwmi.org

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