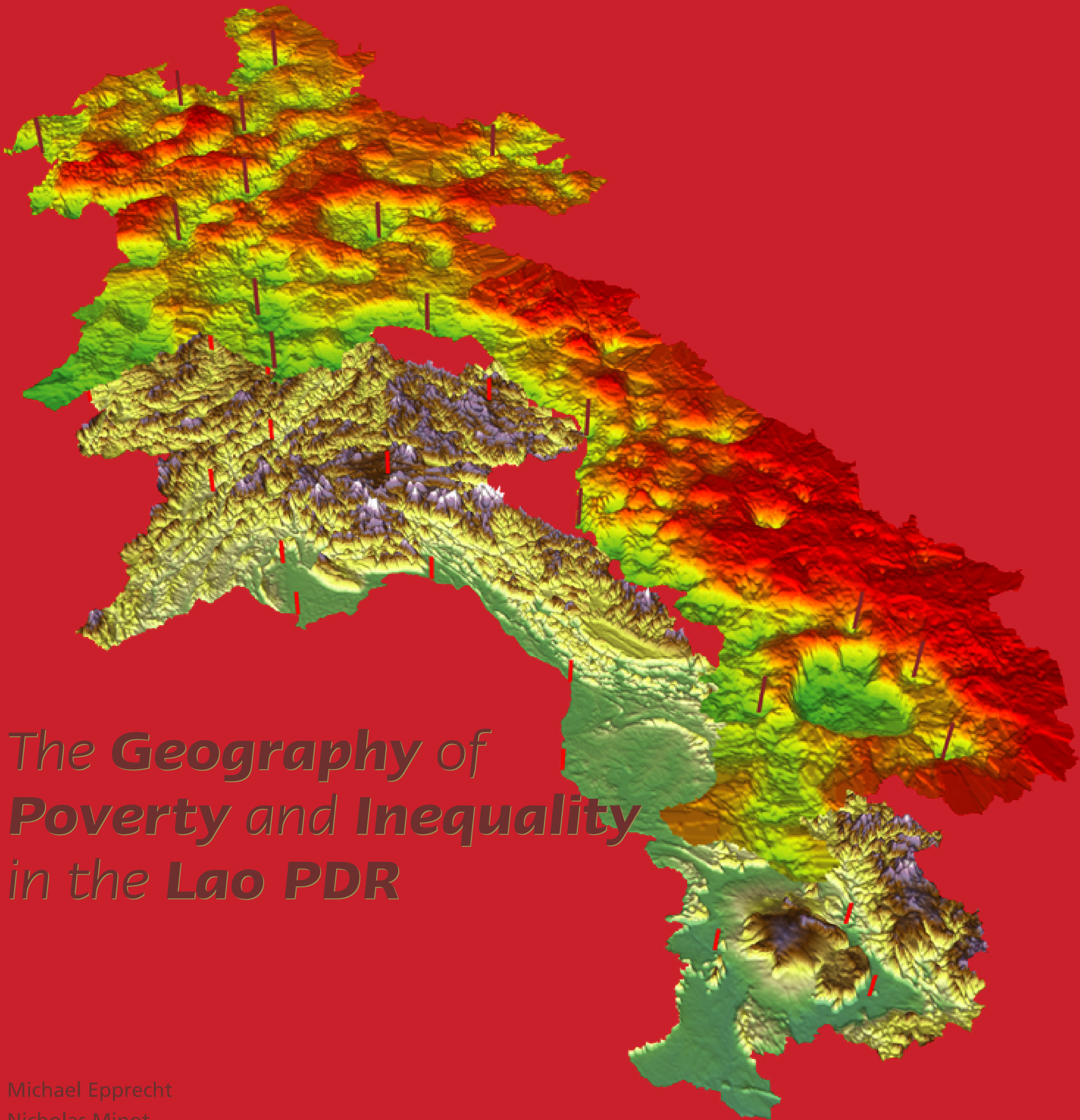

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NCCR north south
Swiss National Centre of Competence in Reasearch North-South

IFPRI
INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
sustainable solutions for ending hunger and poverty

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Swiss National Centre of Competence in Research (NCCR) North-South, Geographica Bernensia, Berne, Switzerland
International Food Policy Research Institute (IFPRI), Washington DC, USA

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Contact details:	National Centre of Competence in Research (NCCR) North-South Hallerstrasse 10, 3012 Bern, Switzerland T: +41 31 631 52 72; E: nccr-north-south@cde.unibe.ch; www.north-south.ch International Food Policy Research Institute (IFPRI) 2033 K Street, N.W., Washington, D.C. 20006-1002, U.S.A. T: +1 202 862 5600; E: ifpri@cgiar.org; www.ifpri.org
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PREFACE

Although poverty certainly has a great impact on society as a whole, it principally affects the lives of individuals and local communities. Defined as a state of deprivation, the phenomenon of poverty has multiple dimensions, and is not limited to only economic aspects. Poverty also encompasses dimensions such as vulnerability to various kinds of shock, the lack of opportunities for participating in decision-making and the lack of access to information, to name just a few.

Without a doubt, the commitment to poverty reduction plays a central role in the Lao PDR's development strategies, and many international organisations are supporting these efforts. Knowledge about poverty is of the outmost importance for informed decision-making and for evidence-based formulation of policies. Not only should the current status of poverty in the country be understood, but also how it is defined and perceived by the peoples concerned, and how it changes over time. With rapid national and regional economic growth, there are concerns about the inclusiveness of current policies in terms of people and places.

An increasing amount of data and information relating to poverty in the Lao PDR is becoming available. On the one hand there are studies looking at the characteristics of poverty in specific locations of the country, how it changes over time and how it is related to the driving forces (e.g. Chamberlain, 2007; Bechstedt, 2007). On the other hand, three Lao Expenditure and Consumption Surveys (LECS) have generated quantitative data at the national level, with two surveys carried out in the 1990s and one in 2003. These results have allowed the assessment of poverty at the national level (e.g. Kakwani *et al.,* 2001), its relationship to specific determinants and general economic growth (e.g. Andersson *et al.,* 2006; Engvall *et al.,* 2005), and most importantly, the making of comparisons over time (e.g. Richter *et al.,* 2005; World Bank, 2005; National Statistics Centre (NSC) *et al.,* 2006).

All aspects of poverty also have a geographical dimension, and information on the geographic distribution of poverty is becoming increasingly recognised as essential for poverty analysis and pro-poor policy-making. Combining information from the 2003 Lao Expenditure and Consumption Survey (LECS III) and the 2005 National Population and Housing Census, this book presents for the first time, estimates of different poverty and welfare measures at a spatially highly disaggregated level. This allows not only an understanding of the detailed spatial patterns of poverty and inequality within the Lao PDR but also allows an analysis of its relation to many geographic features.

This undertaking would not have been possible without the fruitful collaboration among various institutions. Supported by the Swiss Agency for Development and Cooperation (SDC), four institutions shared data, knowledge and experience in a joint project entitled "Socio-Economic Atlas and Poverty Maps for the Lao PDR": the Department of Statistics (DOS) of the Ministry of Planning and Investment (MPI), the Lao National Mekong Committee Secretariat (LNMCS), the Swiss National Centre of Competence in Research (NCCR) North-South and the International Food Policy Research Institute (IFPRI). In addition to this book, another output of the project is the 'Socio-Economic Atlas of the Lao PDR' (Messerli *et al.,* 2008).

This book is intended to reach as wide an audience as is possible. It provides interested students, researchers, decision-makers, and also the wider public with information on the geography of poverty and inequality in the Lao PDR in 2005. While chapters 2-5 provide a detailed description of the research methods and results, chapters 1 and 6 summarise the most salient features for the general reader. We hope that this book will make an important contribution to the effectiveness and inclusiveness of current and future poverty reduction strategies.

ABSTRACT

This study uses a relatively new method called "small area estimation" to estimate various measures of poverty and inequality for the provinces, districts and villages of the Lao People's Democratic Republic (Lao PDR). The method was applied by combining information from the 2002-03 Lao Expenditure and Consumption Survey and the 2005 Population and Housing Census.

The results indicate that the poverty rate (P_0) in the Lao PDR is greatest in the remote areas of the east and southeast along the Vietnamese border. Poverty rates are intermediate in the lowland area of the Mekong River basin in the west. The lowest poverty rates are found in Vientiane and other cities. These estimates are reasonably accurate for the provinces and districts, but the village-level estimates must be used with caution since many are not very precise. Comparing these results with previous estimates of poverty, we find a fairly good agreement among the different studies.

Mapping the density of poverty (the total number of poor people in a given area) reveals that, although the poverty rates (the percentage of a population living below a specific poverty line) are highest in the remote upland areas, these are sparsely populated areas, so most of the poor live in the Mekong River valley, in Vientiane, and in Savannakhet.

In the Lao PDR inequality in per capita expenditure is relatively low by international standards. It is greatest in urban areas and in parts of the northern upland areas and lowest in the south and central highlands, and on the Boloven Plateau.

District-level poverty is very closely associated with district-level average per capita expenditure. In other words, inequality does not explain much of the variation in poverty across districts.

This study also explores how the spatial patterns of poverty depend on various geographic factors using a global spatial regression model (in which coefficients are constant across space) and a local model (in which coefficients vary across space). In the global model, geographic determinants, including agro-climatic variables and market access, are able to explain the variation in village-level rural poverty to a large extent. Poverty is higher in villages with a rough terrain, higher seasonality in rainfall and located farther from towns and major rivers. By contrast, poverty rates are lower in areas with more flat land, with higher annual rainfall and a greater annual temperature range. These agro-climatic and market access variables are not as successful in explaining urban poverty.

The local regression model reveals that terrain roughness is associated with higher poverty throughout the Lao PDR, but more strongly so in areas where poverty rates are comparatively low and agricultural production is most commercialised and mechanised. The availability of flat land, on the other hand, is most closely related to lower poverty rates in remote upland areas where flat land tends to be particularly scarce. Access to markets measured as travel time to towns has the strongest positive association with poverty in areas where poverty rates are lowest, and agricultural production is most intensive. Overall, the relationship between agro-climatic variables and poverty varies significantly from one area of the Lao PDR to another.

Many anti-poverty programs in the Lao PDR are geographically targeted. The results from this study indicate that it may be possible to improve the targeting of these programs by making use of more precise estimates of poverty at the district and village level.

The ability of market access and agro-climatic variables to explain a large part of differences in rural poverty rates indicate that poverty in the remote areas is linked to low agricultural potential

and lack of market access. This illustrates the importance of improving market access. The fact that poverty is closely related to low agricultural potential suggests that efforts to restrict migration out of disadvantaged regions may not be a good strategy for reducing rural poverty.

Finally, the study notes that the small area estimation method is not very useful for annual poverty mapping because it relies on census data, but the inclusion of a small set of questions on specific housing characteristics in the agricultural census would make a more frequent updating of detailed rural poverty maps possible. Furthermore, it could be used to show detailed spatial patterns in other variables of interest to policy makers, such as income diversification, agricultural market surplus and vulnerability. Lastly, it can be used to estimate poverty rates among vulnerable populations too small to be studied with household survey data, such as the disabled, small ethnic minorities or other population segments.

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BACKGROUND

SECTION 1:
BACKGROUND

The Lao People's Democratic Republic (Lao PDR) places a high priority on reducing poverty and hunger. The international commitment to reduce poverty and hunger was formalised by the United Nations in its Millennium Declaration of September 2000. The Declaration, adopted by 169 countries, includes eight Millennium Development Goals, the first of which is to halve, between 1990 and 2015, the proportion of people that are poor and hungry.

In order to design programs to fight poverty, however, the possession of information on the characteristics and livelihoods of poor people is critical. One of the most important characteristics is where poor people live. Information on the geographic distribution of poverty is useful for policymakers and researchers for a number of reasons. First, it can be used to quantify suspected regional disparities in living standards and to identify those areas which are falling behind in the process of economic development. Second, it facilitates the targeting of programs such as education, health, credit and food aid whose purpose is, at least in part, to alleviate poverty. Third, it may shed light on the geographic factors associated with poverty, such as mountainous terrain or distance from major cities.

Until recently, the main sources of information on spatial patterns of poverty in the Lao PDR have been the Lao Expenditure and Consumption Surveys (LECS). These are the largest and most important surveys undertaken by the Department of Statistics (DOS) (formerly the National Statistics Centre (NSC)), and cover a wide range of topics related to household livelihoods. Each survey is conducted over a 12-month period. The first was conducted in 1992/93, the second in 1997/98, and the third and most recent survey was conducted in 2002/03. The three LECS surveys provide good information on national and regional developments. During the ten years between the first and the third survey, the national poverty rate fell by about 12 percentage points, from 46.0 percent to 33.6 percent. Rural poverty rates declined even more rapidly. There were substantial regional differences in poverty reduction over the ten year period. In the early stages, the decline in poverty largely benefitted Vientiane Capital City and other urban areas. After 1997/98, however, the rural areas in general, and the northern region in particular, have benefitted more from pro-poor developments. Furthermore, while the poverty rates fell in the south and central region steadily in both periods, it declined in the northern region relatively slowly during the first five years, but much more rapidly in the second half of the period (Andersson *et al.,* 2006; NSC *et al.,* 2006).

Geographic targeting is most effective when the geographic units are quite small, such as a village or district (Baker and Grosh, 1994; Bigman and Fofack, 2000). The only household information usually available at this level of disaggregation is census data, but census questionnaires are generally limited to household characteristics and rarely collect information on income or expenditure.

In recent years, a new technique called small-area estimation has been developed that combines household and census data to estimate poverty rates (or other variables) for more disaggregated geographic units (see Hentschel *et al.,* 2000; Elbers *et al.,* 2003). Although various approaches have been used, they all involve three steps. First, one selects household characteristics that exist in both the survey and the census, such as household composition, education, occupation, housing characteristics and asset ownership. Second, the household survey data are used to generate an equation that estimates poverty or expenditure as a function of these household characteristics. Third, census data on those same household characteristics are inserted into the equation to generate estimates of poverty for small geographic areas.

In an early study, Minot (2000) used the 1992-93 Vietnam Living Standards Survey data and a probit model to estimate the likelihood of poverty for rural households as a function of a series of household and farm characteristics. District-level averages of these same characteristics were then obtained from the 1994 Agricultural Census and inserted into this equation, generating estimates of rural poverty for each of the 534 rural districts in the country. Hentschel *et al.,* (2000) developed a similar method, which was applied to survey and census data from Ecuador. By using household-level data from a census, their method involves the use of equations to generate unbiased estimates of the headcount poverty rate and the standard error of the estimated incidence of poverty[1]. Elbers et *al.,* (2003) further developed the method by using simulations to generate various measures of poverty and inequality together with their standard errors, taking heteroskedasticity and location effects into account. Some variant of these approaches has been applied in at least a dozen countries, including Cambodia, Thailand, Mozambique, Malawi, South Africa, Panama, and Vietnam (see World Bank, 2000; Statistics South Africa and the World Bank, 2000; and Henninger and Snel, 2002; Minot *et al.,* 2006).

The present study has three objectives:

- to describe the spatial patterns in poverty and inequality in the Lao PDR;
- to explore the geographic determinants (including agro-climatic factors and market access) of urban and rural poverty in the Lao PDR, and
- to draw from these results implications for the design of socio-economic policies and poverty alleviation programs in the Lao PDR and for further research.

The book is organised in six sections. After this introductory section, Section 2 describes the data and methods used in this book. Section 3 examines the spatial patterns in poverty and inequality in the Lao PDR using three measures of poverty and three measures of inequality. Sections 4 and 5 explore the geographic determinants of poverty, using spatial regression analysis and a set of variables extracted from geographic information system (GIS) databases. Finally, Section 6 summarises the results and discusses some implications for policy and future research.

[1] The poverty headcount ratio is defined as the proportion of the population with per capita expenditures below the poverty line.

SECTION 2:

DATA & METHODS

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DATA & METHODS

2.1 Data

Statistical data

The poverty mapping portion of this study makes use of two household data sets: the third Lao Expenditure and Consumption Survey (LECS III) (NSC, 2004) carried out in 2002/03, and the 2005 Population and Housing Census (Government of the Lao PDR, 2006).

The LECS III was implemented by the Department of Statistics (DOS) (formerly the National Statistics Centre (NSC)) of the Lao PDR with funding from the Swedish International Development Agency (SIDA) and with technical assistance from Statistics Sweden. The sample of 540 villages selected using the DOS village list includes 8,092 households comprising 6,488 rural households and 1,604 urban households. The LECS survey data is of fairly good quality, judging by the amount of effort in the design and implementation, and by the small number of missing or out-of-range values.

The 2005 Population and Housing Census, also carried out by the DOS, refers to the situation as of March 1, 2005. It was conducted with the financial and technical support of SIDA and Statistics Sweden. Although the full Census results are not available we were able to obtain a 75 percent sample of the Census which was selected by DOS using a systematic sampling of three out of every four households on the list of households organised by administrative units. The sample includes 712,900 households with 4,123,988 individuals.

Geographic data

The geographic data used in this study was developed based on data obtained from a variety of sources described below. Two types of geographic data were needed: geographic information on the location and extent of the different administrative units required for the depiction of the various poverty estimates on maps, and the infrastructural and environmental data used in the analysis of the spatial determinants of poverty.

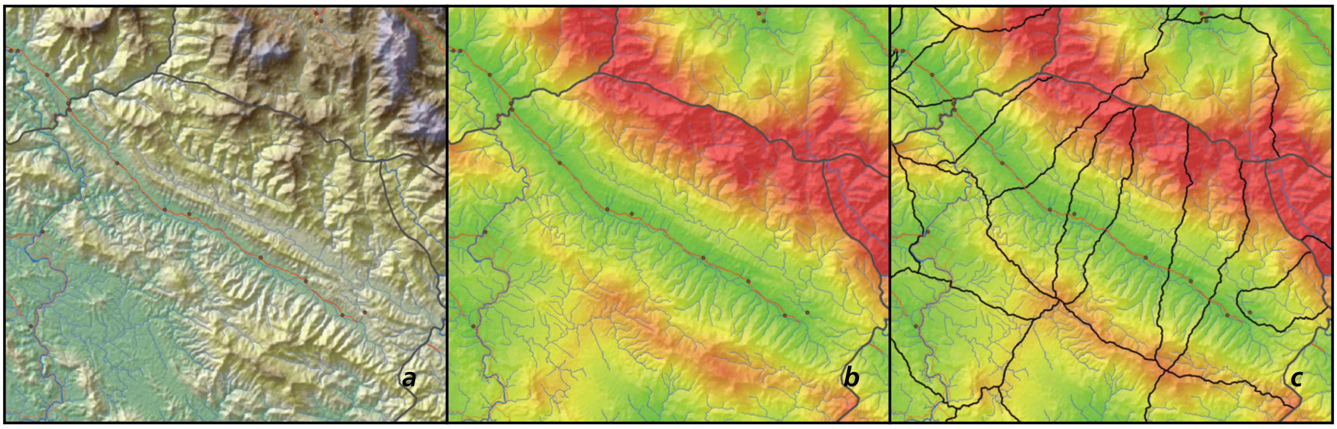
In 2005 the Lao PDR had three administrative levels[2]: the province, the district and the village. Digital files with the national, provincial and district administrative boundaries of the Lao PDR were obtained from the National Geographic Department (NGD). Although the LECS III and the 2005 Population Census were conducted before the Special Administrative Region Xaysomboune was integrated into the provinces of Vientiane and Xiengkhuang, it was decided that the tables and maps presented in this report would follow the present-day administrative divisions (see Figure 1).

Although villages are official administrative units, no official village boundaries exist. This lack posed an obstacle for the adequate mapping of village-level information. As there are 139 districts in the Lao PDR, and approximately 11,000 villages, the gap in spatial resolution between the two levels is enormous. Limiting the spatial representation of our analysis results to district level would therefore have resulted in a considerable loss of information

[2] Today, the Khumban has officially been introduced as an administrative level between the district and the village level.

Figure 1. Provinces and districts in the Lao PDR

Figure 2 a, b & c. Calculation of village polygons using "accessibility"



on the spatial variations in welfare within districts.

During the Census, GPS coordinates were taken of each village centre. We used these coordinates, provided by the DOS, as the basis for the development of village geometries in order to give a geographic representation of the various estimates of village welfare measures[3]. The simplest solution would have been to delineate village polygons equidistant between two closest village points - calculating so called Thiessen polygons. Yet, this study chose a different approach aimed at delineating the village areas according to the most probable areas of direct influence (e.g. agricultural use of land, etc.), based on comparatively best accessibility. We defined the village polygons using a concept of equal travel time between the two closest village centres. In other words, the resulting polygon boundaries are where any two persons would meet, if they started travelling towards each other from the two closest villages on the shortest travel path. Travel time was calculated as the hypothetically fastest travel time taking into account the best possible means of transport and various factors either constraining or facilitating movement such as overall road quality, slope, land cover for off-road travel and water bodies (Figure 2a). This resulted in an "accessibility surface"' calculated from each village as a starting point, illustrated in Figure 2b. More accessible places are shown in green, and the least accessible places are shown in red. Using such village accessibility information, village areas were delineated at equal travel distances between any two closest villages (Figure 2c). While the resulting polygons are used to depict the spatial distribution of poverty at village level in different colour shadings, the actual polygon boundaries, which clearly do not have any legal value and do not represent any real-world boundaries, are not drawn *per se* – only changes in colour shadings along the boundaries are visible on the resulting maps.

Various biophysical and infrastructure spatial datasets are a necessary ingredient for the analysis of the geographic determinants of poverty. While some of the data sets we used were derived from global spatial data layers, others were provided by national institutions, or they were developed based data provided by various national and international agencies:

- Terrain related data layers, such as elevation, slope, and terrain roughness, were calculated using the enhanced digital elevation data

[3] These village polygons were developed for representative purposes only, and do not, by any means represent any actual village boundaries or village areas.

obtained by the Shuttle Radar Topography Mission (SRTM) that generated what is up to now the most complete high-resolution digital topographic database of the earth (CGIAR-CSI, 2004).

- A 1km resolution global layer on the theoretical length of the agricultural growing period (LGP) was developed by the Food and Agriculture Organisation (FAO), from which we derived the Lao LGP information at the village level.
- Climatic data was derived from the global data sets available from Worldclim (Worldclim, 2005; Hijmans *et al.,* 2005).
- A national spatial data layer on soil suitability was obtained from the Lao National Agriculture and Forestry Research Institute (NAFRI).
- A spatial layer on road infrastructure was prepared using a combination of data from the National Geographic Department (NGD) and a road data set developed by the Ministry of Communication, Transportation, Post and Construction (MCTPC) and the World Bank mission in the Lao PDR.
- Different national travel time surfaces to specific 'targets' (e.g. villages, urban areas, roads, etc.) were calculated using ESRI ARC/INFO's *costdistance* function, based on a combination of the above described data sets.

Table 1. Household data sets used in the small-area estimation for the Lao PDR

Name of Survey	Year	Number of Households	Lowest level at which data are representative	Types of data collected	Use in this study
Lao Expenditure and Consumption Survey (LECS III)	2002-03	8,092	Region	Household composition, parents, education, labour force participation, expenditure, health, education, access to public service, victimization, nutrition, health, assets, housing, construction, household business, agriculture, other indicators of living standards	Used for Stage 1 analysis
Lao Population and Housing Census	2005	958,956	Any level	Household composition, characteristics of members, and housing characteristics	75% sample used for Stage 2 analysis

Sources: DOS.

2.2 Methods for the estimation of the incidence of poverty

The poverty line used in this study is the "village-level poverty line" used in the analysis of the 2002-03 Lao Expenditure and Consumption Survey (Richter *et al.,* 2005). The poverty line corresponds to the per capita expenditure (including the value of home production and adjusted to regional and seasonal price differences) required to purchase 2,100 Kcal per person per day using the food basket of households in the third quintile, plus a non-food allowance equal to what these households spend on non-food items. The poverty line was set at the village level, and ranged between 78,503 and 116,663 kip/person/month[4].

Poverty mapping is an application of the method called small-area estimation. The method is typically divided into three stages:

- Stage 0 involves identifying the variables that describe household characteristics that may be related to income and poverty and that exist in both the household survey and in the census.
- Stage 1 estimates a measure of welfare, usually per capita expenditure, as a function of these household characteristics using regression analysis and the household survey data.
- Stage 2 applies this regression equation to the same household characteristics in the Census data, generating predicted welfare for each household in the Census. This information is then aggregated up to the desired administrative unit, such as a district or province, to estimate the incidence of poverty and its standard error.

These methods of small-area estimation are described in more detail in Section A.1 of the Annex.

As already discussed, we were also interested in examining the geographic determinants of poverty. In this analysis, we looked at which agro-climatic and market access variables are best in "predicting" the poverty level of a village or district. Since agro-climatic conditions and degree of market access vary within each village and district, we needed some way of aggregating the observed heterogeneity in values over the village or district to get an "average" value. In addition, we took into account the fact that the poverty rate in a give village or district is likely to be closely correlated with the poverty rate in neighbouring villages or districts. The details of the methods used in this analysis are described in Section A.5 of the Annex.

[4] In 2003 1 US$ corresponded on average to about 7,900 kip.

SECTION 3:

SPATIAL PATTERNS IN POVERTY & INEQUALITY

SECTION 3:
SPATIAL PATTERNS IN POVERTY AND INEQUALITY

3.1 Household characteristics correlated with per capita expenditure

As described previously, the first step (Stage 0) in constructing a poverty map is to identify those household characteristics present in both the LECS III survey data and the 2005 Population and Housing Census. These characteristics include household size and composition, ethnicity, education of the head of household and his or her spouse, housing size, access to basic services, type of house roofs, walls and floors, together with several village-level averages of these variables. The use of village-level variables is recommended by Elbers *et al.,* (2003) as a way of increasing the explanatory power of the regression model and of reducing or eliminating spatial autocorrelation effects.

The second step (Stage 1) is to use regression analysis to generate an equation that "predicts" per capita consumption expenditure of a household based on those household characteristics, where the characteristics are variables present in both the Census and the LECS III. Statistical tests indicate that the coefficients in the urban model are significantly different to those in the rural model, implying that separate analyses should be carried out on rural and urban samples[5]. We therefore ran the analyses separately for the urban and rural households in the LECS III. After initial runs with the full set of explanatory variables, we dropped all individual variables that were not statistically significant and all sets of variables that were not jointly significantly different from zero.

The results of the rural and urban regression analyses are shown in Table 2. The rural model includes 56 explanatory variables (including the constant). The value of R^2 indicates that these household characteristics are able to "explain" 43 percent of the variation in per capita expenditure[6]. In the urban model, fewer explanatory variables are statistically significant and only 41 are included in the final model. The urban model explains about 36 percent of the variation in per capita expenditure. The explanatory power of these two models is somewhat lower than similar models estimated for Vietnam, where the values of R^2 were both slightly above 50 percent, but it is still is a relatively good result for cross-section data.

According to the results in Table 2, large households are strongly associated with lower per capita expenditure in both urban and rural areas[7]. The negative sign of the coefficient on household size implies that, other factors being equal, larger households are associated with lower per capita expenditure[8].

In rural areas, per capita expenditure is likely to

[5] The Chow test strongly rejects the hypothesis that the coefficients for the urban sub-sample are the same as those for the rural sub-sample (F=6.16, p< .001).

[6] Strictly speaking, the rural model can explain 43 percent of the variance in the logarithm of per capita consumption expenditure across households.

[7] The coefficients on household size and household size squared suggest a U-shaped relationship between household size and per capita expenditure, but the curve does not begin to curve upward until household size exceeds 12, a range which only includes 1-2 percent of Lao households.

[8] In the log-linear model, where $In(y) = X\beta$, the coefficient β_i represents the proportional change in y given a one-unit increase in X_i.

Table 2. Rural and urban regression models of per capita expenditure

	Rural model			Urban model		
N	6427			1594		
R-squared	0.4344			0.3599		
	Coefficient	t		Coefficient	t	
Size of household (members)	-0.1643	-15.5	***	-0.1956	-7.9	***
Square area of household	0.0063	9.3	***	0.0083	4.4	***
Proportion age 0-<=5 yrs (percent)	-0.0040	-5.8	***	-0.0015	-0.9	
Proportion age 5-<=10 yrs (percent)	-0.0023	-3.8	***	-0.0002	-0.1	
Proportion age 10-<=20 yrs (percent)	0.0012	2.0	**	0.0001	0.1	
Proportion age 20-<=60 yrs (percent)	0.0030	5.5	***	0.0026	2.4	**
Household has a female head	-0.0770	-2.3	**	-0.1568	-3.9	***
Head not completed primary school	0.0418	2.3	*			
Head has completed primary school	0.1322	3.3	***			
Head has not completed lower secondary school	0.0999	3.9	***			
Head has completed lower secondary school	dropped					
Head has not completed upper secondary school	0.0088	0.2				
Head has completed upper secondary school	0.0998	3.8	***			
Spouse has not completed primary school	0.0389	2.5	**			
Spouse has completed primary school	-0.0076	-0.2				
Spouse has not completed lower secondary school	0.0538	2.0	*			
Spouse has completed lower secondary school	dropped					
Spouse has not completed upper secondary	0.0877	1.0				
Spouse has completed upper secondary school	0.0665	2.2	**			
Size of living area	0.0007	3.5	***			
House uses electricity for cooking	0.0201	0.4		0.1210	2.0	*f
House uses fuel for cooking	0.0655	1.0		-0.0055	-0.1	
House uses coal for cooking	0.1276	2.3	**	0.0437	0.5	
House uses charcoal for cooking	0.1140	3.5	***	0.1443	3.4	***
House uses sawdust for cooking	-0.1286	-1.3		-0.0777	-0.7	
House uses gas for cooking	dropped			0.2228	2.3	**
House uses other energy for cooking	dropped			dropped		
House uses a modern toilet	0.0707	0.6		0.4734	3.7	***
House uses a normal toilet	0.1266	5.6	***	0.0912	2.5	**
House uses other type of toilet	0.0391	1.1		-0.0931	-1.7	*
Has brick walls	0.0955	3.0	***	0.1260	2.6	***
Has wooden walls	0.0512	2.6	**	0.0847	2.2	**
Has other type of walls	-0.0642	-1.3		-0.1865	-2.1	**
Has a tiled roof	0.1442	5.0	***	0.3283	6.2	***
Has a zinc roof	0.0926	4.2	***	0.2023	4.6	***
Has a wooden roof	0.0689	1.9	*	0.0482	0.5	
Has other type of roof	0.0504	1.3		0.3267	2.6	**
Northern lowlands	0.0765	2.0	**	-0.0953	-1.1	

Table 2. Rural and urban regression models of per capita expenditure (cont.)

	Rural model			Urban model		
N	6427			1594		
R-squared	0.4344			0.3599		
	Coefficient	t		Coefficient	t	
Northern midlands	0.0553	1.4		0.0561	0.6	
Northern highlands	0.0812	1.3		0.1291	1.3	
South-central midlands	-0.0349	-0.4		dropped		
South-central highlands	-0.1985	-2.5	**	-0.2800	-4.0	***
Boloven Plateau	0.4526	4.9	***	dropped		
South-central lowlands	-0.0534	-1.1		-0.0936	-1.2	
Vientiane plain	0.0802	1.4		-0.0834	-1.4	
Village uses electricity for cooking	0.7994	1.7		0.1455	0.5	
Village uses fuel for cooking	-1.4493	-2.6	**	0.9128	2.2	**
Village uses coal for cooking	0.2211	1.4		-0.2633	-0.7	
Village uses charcoal for cooking	0.1451	1.6		0.0263	0.2	
Village uses sawdust for cooking	-1.9303	-1.1		-0.9589	-1.2	
Village uses gas for cooking	-5.0388	-9.4	***	-0.2718	-0.5	
Village uses other energy for cooking	0.5888	1.1		7.8122	9.2	***
Village has a tiled floor	-0.0824	-0.2		-0.5485	-1.2	
Village has a concrete floor	0.5726	5.5	***	0.0068	0.0	
Village has a wooden floor	0.1860	3.7	***	-0.3420	-1.4	
Village has other type of floor	0.1125	1.4		-0.4485	-1.2	
Village with of Mon-Khmer ethnicity	-0.0648	-1.6				
Village with Hmong-Mien & Tibeto-Burman ethnicity	0.0931	1.3				
Village of other ethnicity	-0.1687	-1.7	*			
Constant	11.8297	146.6	***	12.6467	47.1	

Source: Regression analysis of 2002-03 Lao Expenditure and Consumption Survey, taking into account clustering and stratification and using robust estimates of standard errors.

Note: Omitted categories are head has no education; spouse has no education; percent of elderly in the house; house roof is made of grass; house walls are made of bamboo; household has no toilet; household has river water source; household uses wood for cooking; and household is in the south central Mekong corridor.

* coefficient is significant at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

be higher in households that have a small share of children (0-10 years old) and a large share of prime-age adults (20-60 years old). In urban areas, however, the proportion of children is not significant, though a large share of prime-aged adults is associated with higher per capita expenditure. Household composition appears to matter less in urban areas than in rural ones, perhaps because income-earning capacity in the cities and towns is less dependent on physical strength.

In both urban and rural areas, female-headed households tend to be poorer, even after controlling for education, household composition and other factors. This may be a reflection of gender discrimination in the job market or the effect of child-rearing responsibilities on income-earning opportunities.

In rural areas, the level of schooling of the head of household is a good predictor of a household's per capita expenditure, where the omitted category is no schooling. The results suggest that if the head has some schooling, particularly if he or she has completed primary school, per capita expenditure will generally be higher. The set of variables that describe the education level of the head of household are jointly significant at the 1 percent level (see Table 3).

In rural areas, the educational level of the spouse of the head of household is also statistically significant. In general, the households with an educated spouse have a higher per capita expenditure than those in which the spouse has no schooling. Somewhat surprisingly, the education levels of the head and the spouse do not seem to be good predictors of per capita expenditure among urban households (see Table 2).

Various housing characteristics are good predictors of expenditures. In both rural and urban areas having a roof made of tiles or zinc is associated with significantly higher per capita expenditure than having a grass roof. Similarly, a house with brick or wooden walls implies a significantly higher level of per capita expenditure than a house with bamboo walls.

The size of the house, measured in square metres, is a useful predictor in rural areas, where larger houses are associated with higher per capita expenditure. In urban areas, however, house size was not a good predictor, perhaps because some high-income households live in small units in the city centre while some lower income households may live in large houses farther from the centre. According to

Table 3. Statistical significance of groups of variables

Sector	Variables	df1	df2	F statistic	Probability	
Rural	Education of head of household	5	364	5.45	0.0000	***
	Education of spouse	5	364	2.57	0.0264	**
	Type of roof	4	365	7.50	0.0000	***
	Type of walls	3	366	4.80	0.0027	***
	Type of sanitary facility	3	366	10.68	0.0000	***
	Type of energy used for cooking	5	364	3.87	0.0020	***
	Agro-ecological region	8	361	5.27	0.0000	***
	Type of energy used for cooking at the village level	7	362	23.39	0.0000	***
	Type of floor at the village level	4	365	7.92	0.0000	***
	Ethnicity at the village level	3	366	3.54	0.0148	***
Urban	Type of roof	4	77	11.79	0.0000	***
	Type of walls	3	78	5.53	0.0017	***
	Type of sanitary facility	3	78	9.75	0.0004	***
	Type of energy used for cooking	6	75	2.66	0.0216	**
	Agro-ecological region	6	75	6.13	0.0000	***
	Type of energy used for cooking at the village level	7	74	27.71	0.0000	***
	Type of floor at the village level	4	77	3.67	0.0087	***

Source: Regression analysis of per capita expenditure using 2002-03 LECS data.

Note: The dependent variable is log the of per capita expenditure.

* coefficient is significant at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

the 2005 Census, houses in the Lao PDR have an average living area of about 45m^2, with 39m^2 in rural areas and 60m^2 in urban areas.

Sanitation facilities can also be used to separate poor from non-poor households. In rural areas, normal toilets are statistically significant indicators of higher per capita expenditure compared to households without a toilet. In urban areas, having a modern or a normal toilet is a significant predictor of expenditures compared to those households without toilets (see Table 2).

The types of cooking fuel are also significant indicators of the level of per capita expenditure. In both urban and rural areas, using charcoal is associated with higher per capita expenditure as compared to those households using wood or sawdust.

It is surprising that ethnicity - grouped into three commonly used broad categories - is not a statistically significant predictor of per capita expenditure after controlling for other factors. This does not imply that Lao of the Tibeto-Burman, Hmong-Mien, or Mon-Khmer ethno-linguistic families have the same standard of living as do Lao Tai-Kadai households. It means instead that, after differences in household composition, education and housing characteristics have been taken into account ethnicity is not of much additional help in predicting per capita expenditure.

Even after controlling for household characteristics, the village-level averages of some variables are still significant predictors of per capita expenditure. This is true of the village-level percentage of households using different types of cooking fuel and the percentage of households with different types of floors. Village-level ethnic composition is a good predictor in rural areas, but not in urban areas. The village-level variables suggest that a household's standard of living is partly a function of the standard of living of its neighbours.

3.2 Incidence of poverty

The incidence of poverty (also called the poverty rate or poverty headcount ratio) is defined here as the proportion of the population living in households whose per capita expenditure is below the poverty line. The poverty line is calculated as the minimum level of per capita expenditure for an active, healthy life (Section 2.2 describes the calculation of the poverty line in the Lao PDR). The poverty rate is the Foster-Greer-Thorbecke measure of poverty when α=0, also known as P_0 (see Section A.2 of the Annex). We will present national, regional, provincial, district and village level estimates of the poverty rate in turn. It is important that all the different levels are considered as lower levels (i.e. village) may provide high resolution poverty estimates which reflect the local conditions, whereby the higher aggregated poverty estimates at district and province levels can reveal larger scale factors related to welfare not easily identified in village level maps.

National and regional poverty rates (P_0)

The national headcount poverty rate, as estimated in this application of the small-area estimation method using a 75 percent sample of the 2005 Census data, is 34.7 percent, about one percentage point higher than the estimate from the 2002/03 LECS III (see Table 5). The small-area estimate of the urban poverty rate (19.8 percent) is virtually the same as the corresponding estimate from the LECS III (19.7 percent), while the small-area estimate for the rural poverty rate (40.0 percent) is 2.3 percentage points higher. One possible explanation for

Table 4. Characteristics of agro-ecological regions of the Lao PDR

Name	Description	Terrain features	Elevation range (meters above sea)	Area (approximate,km^2)	Population (approximate)	Population density (per./km^2)
Mekong Corridor	plains and lower slopes of lower part of the Mekong River and its tributaries	flat to moderately sloping	< 200	50000	1900000	38
Vientiane Plain	fertile lowland flood plains of lower Nam Ngum River and adjacent rolling hilly landscape	predominantly flat and rolling	150-200	6500	830000	128
Northern Lowlands	plains and lower slopes of upper part of the Mekong River and its main tributaries	flat to moderately steep	200-500	50000	1100000	22
Northern Midlands	upland plains of the north, narrow valley bottoms and their respective lower slopes	flat to steep	500-900	50000	700000	14
Northern Highlands	mountainous up and high-land areas of the north	steep	> 900	40000	500000	13
South-Central Lowlands	lower slopes of the southern mountain chains	moderately sloping	200-500	19000	260000	14
South-Central Midlands	upland areas of the south with predominantly poor acidic soils	moderately sloping to steep	500-900	5000	30000	6
South-Central Highlands	southern highland areas	moderately sloping	900-1450	4500	25000	6
Boloven Plateau	fertile basalt plateau	predominantly flat	500-1350	4000	125000	31

Source: Own, based on analysis of GIS data these differences is that the LECS survey may have under-sampled poor households in remote regions, but these households were better represented in the 2005 Population and Household Census.

The country is commonly divided into three administrative regions: the northern region, which includes the provinces of Phongsaly, Luangnamtha, Oudomxay, Bokeo, Luangprabang, Huaphanh and Xayabury; the central region, which covers Vientiane Capital City and the provinces of Vientiane, Xiengkhuang, Borikhamxay and Khammuane; and the southern region, which is made up of Saravane, Sekong, Champasack and Attapeu provinces. For this analysis, we removed Vientiane Capital City from the central region and considered it as a separate region. Vientiane Capital City has the lowest poverty rate (17 percent), while the poverty rate in the rest of the country varies from 38 percent in the north, to 38 percent in the centre, and 33 percent in the south. The estimates for Vientiane Capital City and the northern and southern regions are virtually identical to the respective estimates from the LECS III, while the estimated rate for the central region is slightly higher (3 percentage points) than the corresponding rate from the LECS III.

All regions, with the exception of Vientiane

Table 5. Comparison of poverty estimates at national and regional levels

	Headcount poverty rate (percent) and standard errors				
	2002-03 LECS		Small-area estimation method		Difference (percentage points)
	Poverty rate	Standard error	Poverty rate	Standard error	
National	33.6	0.013	34.7	0.010	-1.1
By urban/rural residence					
Urban	19.7	0.020	19.8	0.025	-0.1
Rural	37.7	0.015	40.0	0.010	-2.3
By region					
Vientiane Capital City	16.8	0.024	17.0	0.026	-0.2
Northern	38.0	0.025	38.1	0.014	-0.1
Central	35.4	0.021	38.4	0.010	-3.0
Southern	32.6	0.028	33.1	0.011	-0.5
By agro-ecological region					
Vientiane Plain	15.6	0.020	16.9	0.024	-1.3
Mekong Corridor	33.2	0.022	35.4	0.013	-2.2
Northern Lowlands	27.5	0.027	33.5	0.017	-6.0
Northern Midlands	46.2	0.040	41.6	0.021	4.6
Northern Highlands	42.4	0.040	42.2	0.031	0.1
South-Central Lowlands	60.0	0.065	59.9	0.030	0.1
South-Central Midlands	64.9	0.136	69.8	0.053	-5.3
South-Central Highlands	75.4	0.063	75.8	0.042	-0.4
Boloven Plateau	14.7	0.077	15.3	0.039	-0.6

Capital City, exhibit a variety of agro-ecological environments with greatly differing agricultural potential, ranging from flat fertile valley bottoms to steep and rocky upland areas. In a primarily agrarian society, it might therefore make sense to define such regions by agro-ecological characteristics, rather than by administrative boundaries. Following the broad categorisation of agro-ecological regions proposed by the Japan International Cooperation Agency (JICA, 2001) and Ishizuka *et al.*, (2003), we used GIS data to delineate nine agro-ecological regions in the Lao PDR, and categorized the Lao villages according to the general characteristics described in columns two to four in Table 4.

When considering these agro-ecological zones the range of poverty rates increases compared to that of the administrative regions: the poverty rate in the Boloven Plateau (15 percent) is the lowest of the different agro-ecological regions–even lower than the rate in the Vientiane plain (17 percent). The poverty rates in the Mekong corridor and the northern lowlands (35 and 34 percent, respectively) are both close to the national average while the northern midlands and northern highlands have poverty rates slightly above the national average (both about 42 percent). Apart from the Mekong corridor and the Boloven Plateau, we find in the remainder of the south-central part of the country poverty rates that are all well above the national average. With increasing altitude, the poverty

Table 6. Comparison of poverty estimates at the provincial level

	Headcount poverty rate (percent) and standard errors				
	2002-03 LECS		Small-area estimation method		Difference (percentage points)
	Poverty rate (P_0)	Standard error	Poverty rate (P_0)	Standard error	
Vientiane Capital City	16.8	0.024	17.0	0.026	-0.2
Phongsaly	50.8	0.053	38.0	0.020	12.8
Luangnamtha	22.8	0.045	36.4	0.018	-13.6
Oudomxay	45.1	0.078	46.4	0.017	-1.3
Bokeo	21.1	0.050	37.2	0.017	-16.1
Luangprabang	39.5	0.066	40.5	0.017	-1.0
Huaphanh	51.5	0.060	41.3	0.020	10.2
Xayabury	25.3	0.046	27.2	0.013	-1.9
Xiengkhuang	39.8	0.058	37.0	0.022	2.8
Vientiane Province	20.9	0.027	27.5	0.013	-6.6
Borikhamxay	28.8	0.057	36.6	0.012	-7.8
Khammuane	33.8	0.044	39.2	0.016	-5.4
Savannakhet	43.3	0.038	44.4	0.013	-1.1
Saravane	54.5	0.045	39.3	0.014	15.2
Sekong	41.9	0.084	47.9	0.019	-6.0
Champasack	18.4	0.042	25.3	0.012	-6.9
Attapeu	44.0	0.069	45.4	0.018	-1.4

Source: Authors' analysis.

rates also increase from 60 percent in the south-central lowlands to over 75 percent in the south-central highlands (see Table 5).

Table 5 also provides a comparison of the reliability of the small-area estimates, compared to those derived directly from the LECS III. One of the strengths of this poverty mapping method is that it calculates the standard errors, a measure of the accuracy of the estimate[9]. While at a national level, the standard errors of both estimates are very similar, they differ somewhat at disaggregated levels. However, the standard errors of the small-area estimation method are typically lower than those resulting from direct estimates from the LECS III.

Provincial poverty rates (P_0)

Table 6 gives the estimates of the incidence of poverty for each of the 17 provinces in the Lao PDR[10], while Figure 3 maps these estimates.

Table 7. Estimated poverty rate (P_0) for urban and rural areas by province

			Overall		Rural		Urban	
Code	Province	Rank (1 = poorest)	Poverty rate (P_0)	Standard error	Poverty rate (P_0)	Standard error	Poverty rate (P_0)	Standard error
1	Vientiane Capital City	17	0.17	0.026	0.21	0.027	0.16	0.032
2	Phongsaly	9	0.38	0.020	0.40	0.022	0.25	0.024
3	Luangnamtha	13	0.36	0.018	0.40	0.020	0.23	0.039
4	Oudomxay	2	0.46	0.017	0.50	0.019	0.28	0.045
5	Bokeo	11	0.37	0.017	0.39	0.017	0.26	0.056
6	Luangprabang	6	0.40	0.017	0.44	0.018	0.26	0.053
7	Huaphanh	5	0.41	0.020	0.43	0.023	0.26	0.039
8	Xayabury	15	0.27	0.013	0.28	0.013	0.25	0.037
9	Xiengkhuang	10	0.37	0.022	0.43	0.026	0.14	0.024
10	Vientiane Province	14	0.27	0.013	0.29	0.015	0.21	0.024
11	Borikhamxay	12	0.36	0.012	0.41	0.012	0.25	0.031
12	Khammuane	8	0.39	0.016	0.44	0.018	0.20	0.033
13	Savannakhet	4	0.44	0.013	0.51	0.015	0.22	0.024
14	Saravane	7	0.39	0.014	0.41	0.015	0.20	0.021
15	Sekong	1	0.47	0.019	0.53	0.023	0.29	0.022
16	Champasack	16	0.25	0.012	0.27	0.013	0.18	0.025
17	Attapeu	3	0.45	0.018	0.50	0.021	0.20	0.032

Source: Analysis of 2002-03 LECS and 2005 Population and Housing Census data.
Note: The poverty rate refers to proportion of the population that are in households whose per capita expenditure is below the overall poverty line.
The standard error is a measure of the accuracy of the poverty estimate.
The 95 percent confidence interval is approximately ± 2 times the standard error.

[9] It is worth noting, however, that these estimates of the standard errors of the poverty estimates do not explicitly take into account heteroskedasticity and location effects in the first-stage regression model. Sensitivity analysis suggests that this may result in underestimates of the standard errors (see Section A.4 of the Annex).

[10] This analysis tabulates and maps its results according to the new administrative system, dividing the country into 17 provinces and 139 districts.

Figure 3. Map of the incidence of poverty (P_0) of each province

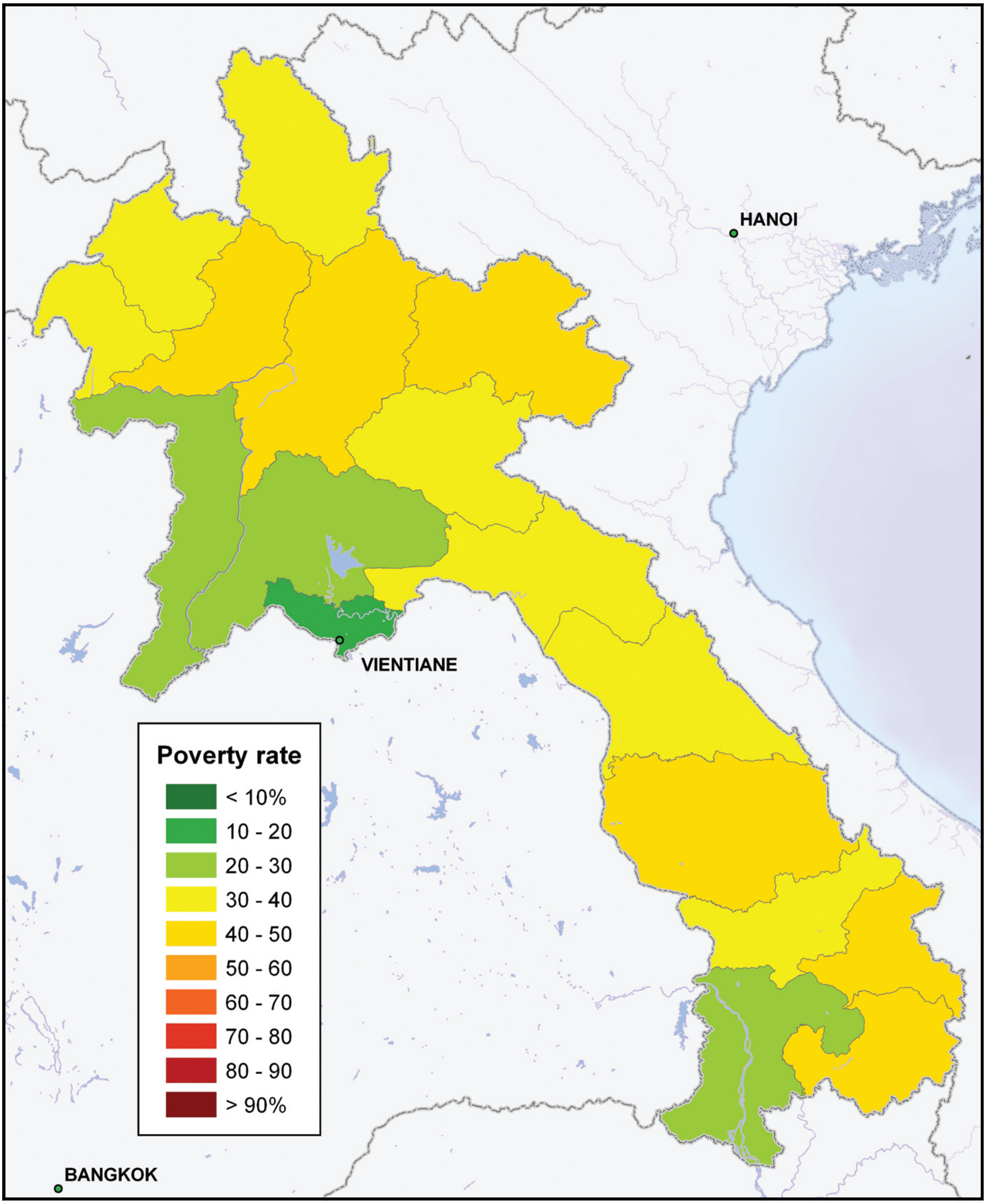
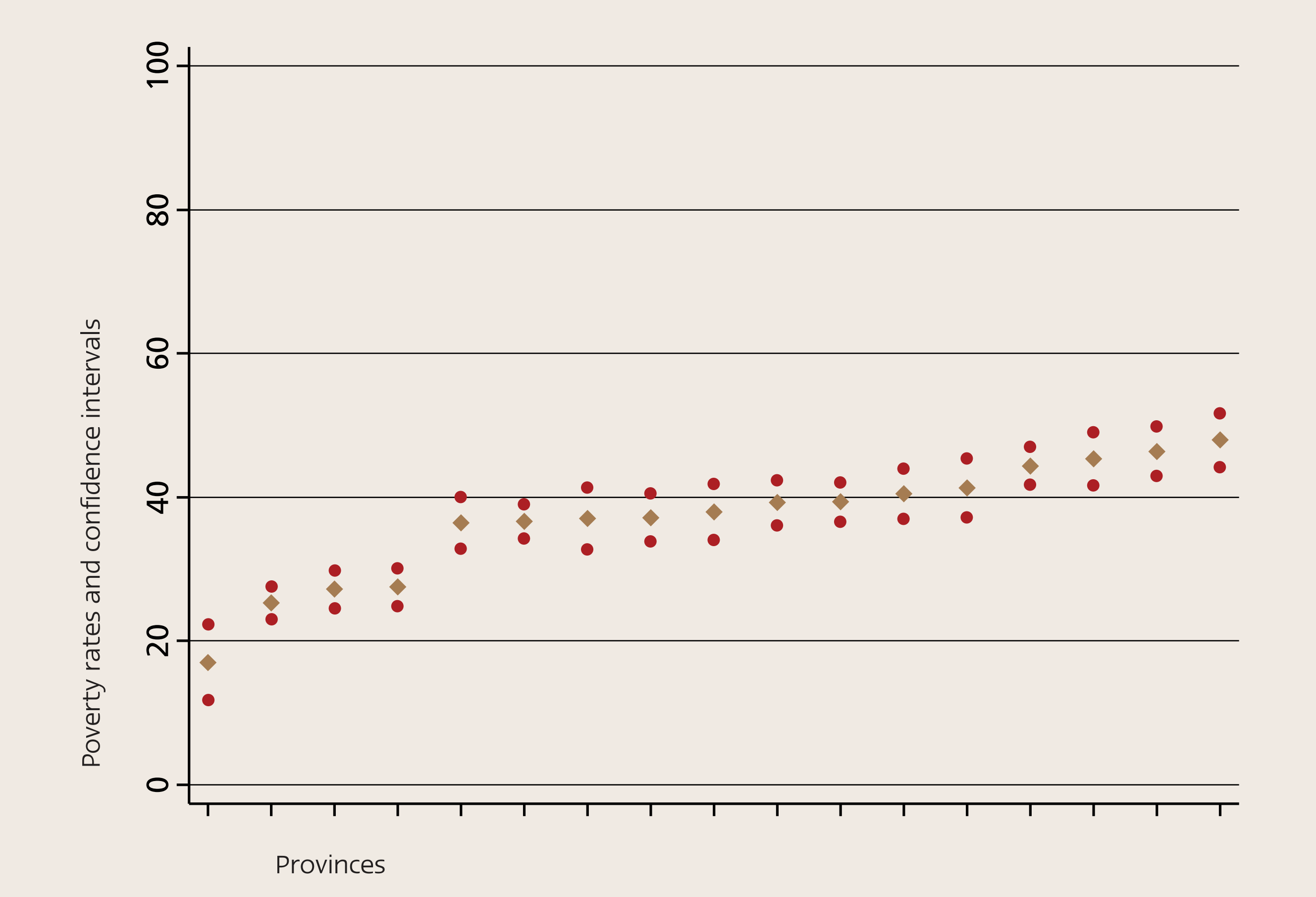


Figure 4. Provincial poverty rates and confidence intervals



From the table, we see that the poverty rate ranges from 17 percent in Vientiane Capital City to about 48 percent in Sekong province. Other provinces with high poverty rates include Attapeu and Savannakhet in the south and Oudomxay in the north.

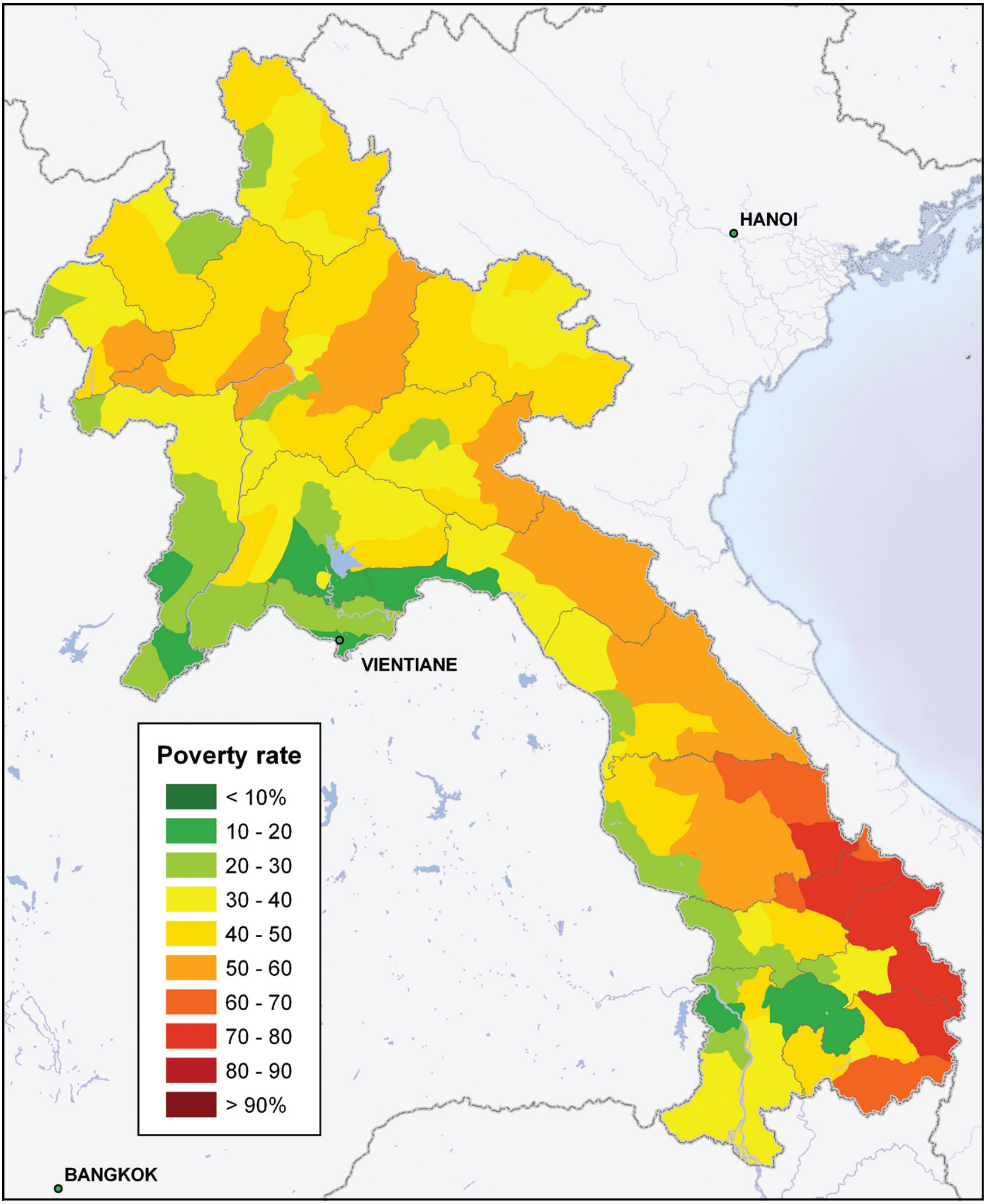
Table 6 also provides a comparison of the reliability of the provincial poverty estimates. Even though the LECS III was not designed to be representative at the provincial level, it is worth noting that the estimates derived directly from the LECS III are for several provinces relatively close to the estimates generated using the small-area estimation method, though for a number of other provinces the estimates differ by more than 10 percentage points. The standard errors of the small-area estimation are, however, typically much smaller than those of the LECS estimates.

Figure 3 maps the provincial poverty estimates, with the poorest areas coloured in orange and the least poor areas coloured dark green. These results illustrate our finding that poverty is greatest in the northeast and the southeast, particularly in the provinces along the eastern border with Vietnam.

While the poverty map at the provincial level is useful for identifying the broad spatial patterns of poverty, Table 7 provides additional detail, including the standard errors of the poverty estimates and the urban and rural poverty rates for each province. In all 17 provinces, the rural poverty rate is higher than the urban poverty rate. In fact, while the rural poverty rate ranges from 21 percent to 53 percent, the urban poverty rates are all less than 30 percent.

The poverty rates and their respective confidence

Figure 5. Map of the incidence of poverty (P_0) of each district



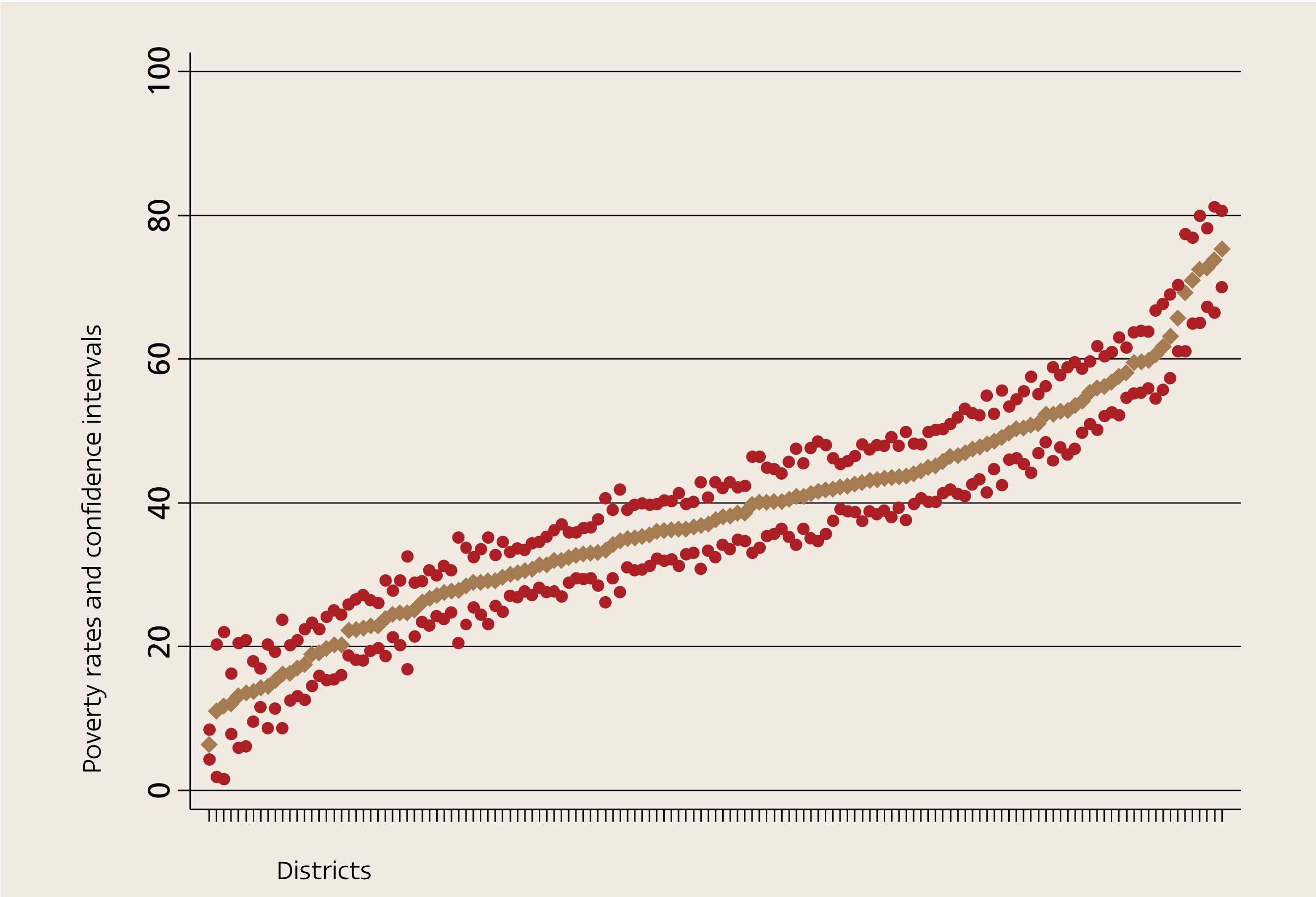
intervals for the 17 provinces (in order from the least to the most poor) are shown in Figure 4. The diamond-shaped markers are the provincial poverty estimates, while the dots above and below each estimate are the upper and lower limits of the 95 percent confidence interval. This graph shows that most (13) of the provinces have poverty rates in the range of 36 to 48 percent. There is just one province with a poverty rate below 20 percent, and three others have rates in the range of 25-28 percent. Across provinces, the 95 percent confidence interval ranges from ±2.3 percentage points to ±5.3 percentage points, with the average confidence interval being ±3.4. Half the provinces have confidence intervals between ±2.7 and ±3.8 percentage points (this is the inter-quartile range). Vientiane Capital City has the widest confidence interval (±5.3 percentage points), reflecting the greater diversity of incomes in the capital city.

One important implication of these standard errors is that if two provinces have poverty rates that differ by less than say 3.5 percentage points there is a good chance that the difference is not statistically significant. For example, if province A has a poverty rate of 36 percent and province B has a rate of 40 percent, in general we cannot say that province B is poorer than province A. As a general rule, two poverty rates must differ by at least 6-8 percentage points to give us confidence that the difference is statistically significant.

District poverty rates (P_0)

The poverty mapping method can also be used to generate poverty estimates for each of the 139 districts in the Lao PDR. The spatial patterns in the incidence of poverty at district level can be seen

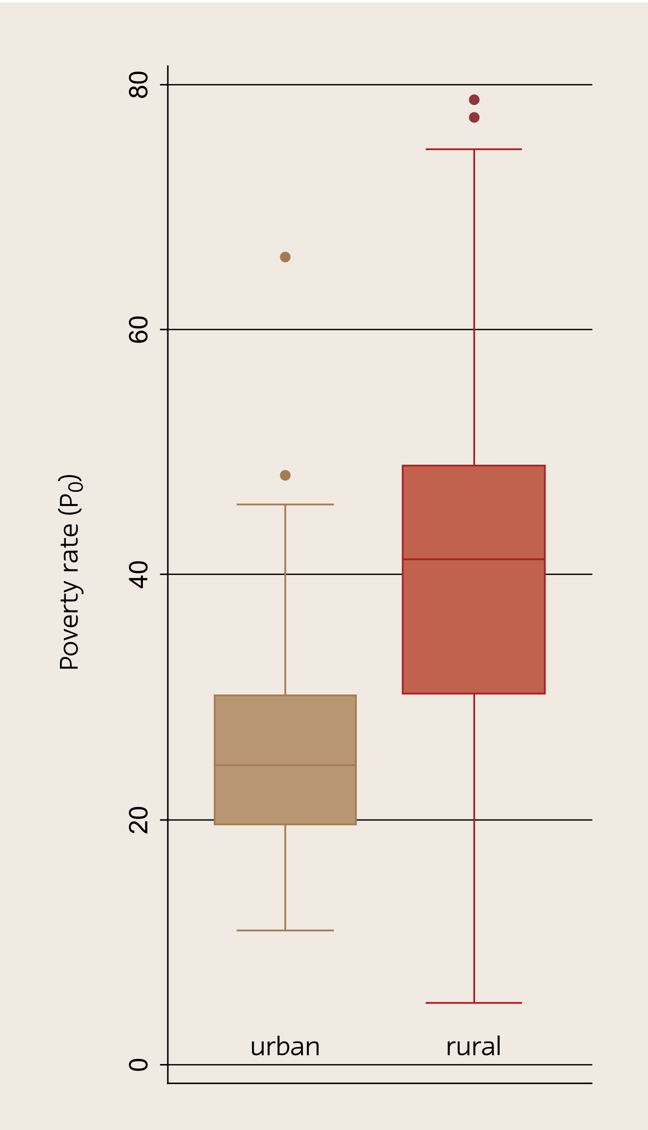
Figure 6. District poverty rates and confidence intervals



in Figure 5. The district-level poverty map shows considerably more detail than the provincial poverty map. For example, in the provincial map, the provinces of Vientiane and Xayabury both appear as one bright-green block, implying a poverty rate in the range of 20-30 percent.

The district map, however, shows that the poverty rate varies widely within these two provinces of Vientiane and Xayabury; being under 20 percent in some of their south-eastern parts (Boten and

Figure 7. Distribution of district-level poverty rates in urban and rural areas



Thongmixai districts in Xayabury, and Thourakho, Keo-Oudom, Phonghong and Hinheup districts in Vientiane province), and over 40 percent in Met and Hom districts of Vientiane province.

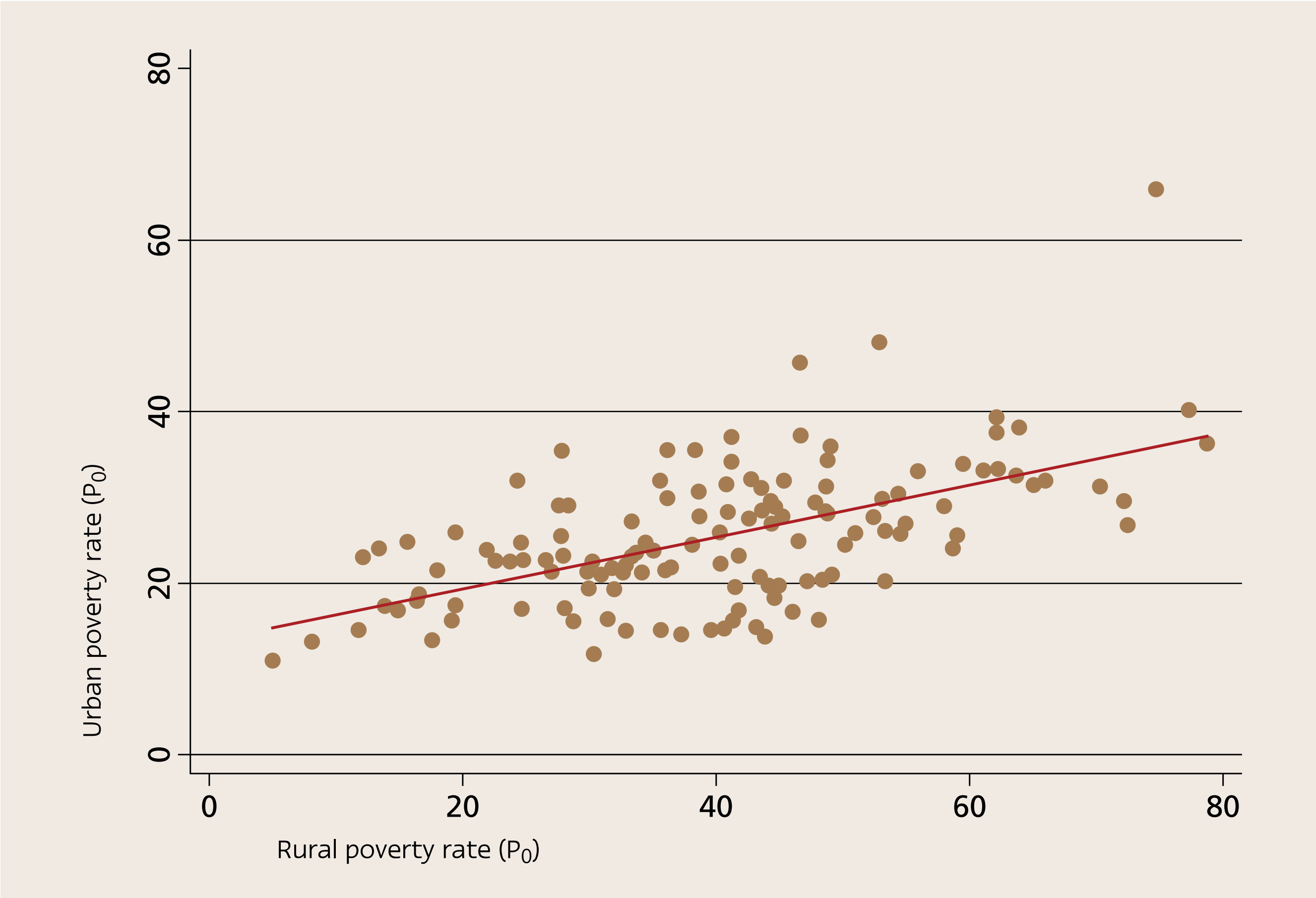
Similarly, the provincial map indicates that almost all of the central part of the Lao PDR is coloured yellow, implying poverty rates in the 30-40 percent range. In contrast, the district map provides a more differentiated picture. It shows that the poverty rate in the Mekong plain is generally less than 30 percent, but the rates in the more mountainous parts are typically greater than 50 percent, and even above 60 percent for some districts. Two districts in this region have poverty rates over 70 percent, both on the Vietnamese border: Ta-Oy district in Saravane and Nong district in Savannakhet. The district map also reveals variations in the incidence of poverty in other parts of the country that remain hidden in the provincial map.

The 95 percent confidence intervals for the district-level poverty rates are shown in Figure 6. As in Figure 4, the centre line made up of brown diamonds represents the estimates of the district poverty rates, while the dots above and below are the upper and lower 95 percent confidence limits. The district-level confidence intervals range from ±2.1 to ±10.2 percentage points, with an average value of ±4.8 percentage points. Half of the districts have confidence intervals between ±3.9 and ±5.6 percentage points (this is the inter-quartile range).

In general, the confidence intervals for district poverty rates are somewhat larger than those of provincial poverty rates, for which the average was ±3.4 percent. This is normal, as there are fewer households per district than there are in the provinces. Nevertheless, the number of households per district in the sample is still relatively large: only 2 of the 139 districts have fewer than 1,000 households in our sample of the Census data, while 85 percent of them have more than 2,000 households.

Figure 7 shows the distribution of district-level poverty rates in urban and rural areas using a box-and-whisker plot. The bottom and top of the box represent the 25th and 75th percentiles, while the

Figure 8. Urban poverty and rural poverty by district



line in the middle represents the median. The outer horizontal lines indicate the 5th and 95th percentiles. This figure shows that half of the urban district poverty rates are between 20 and 30 percent, while half of all rural district poverty rates fall between 32 and 49 percent.

As shown in Figure 8, there is a weak positive correlation (R^2=0.32) between the urban poverty rate in a district and the rural poverty rate in the same district.

Village poverty rates (P_0)

The poverty mapping method can also be applied to generate estimates of the incidence of poverty (P_0) for each of the 10,467 villages in the Lao PDR. It is important to use these results with caution because the small number of households in some villages means that the poverty estimates are not reliable for these villages. The reliability of the village poverty estimates is further discussed below.

The spatial patterns in village poverty rates are shown in Figure 9. This map provides a high level of detail in the spatial distribution of poverty, a considerable increase in information content compared to the district poverty map. For example, in Luangprabang province, the village poverty map reveals, besides the green areas along the Mekong River and in and around Luangprabang town, a green stretch in the orange and red areas, marking the lower Nam Ou valley (which also coincides with the first section of the main road connecting

Figure 9. Map of the incidence of poverty (P_0) for each village

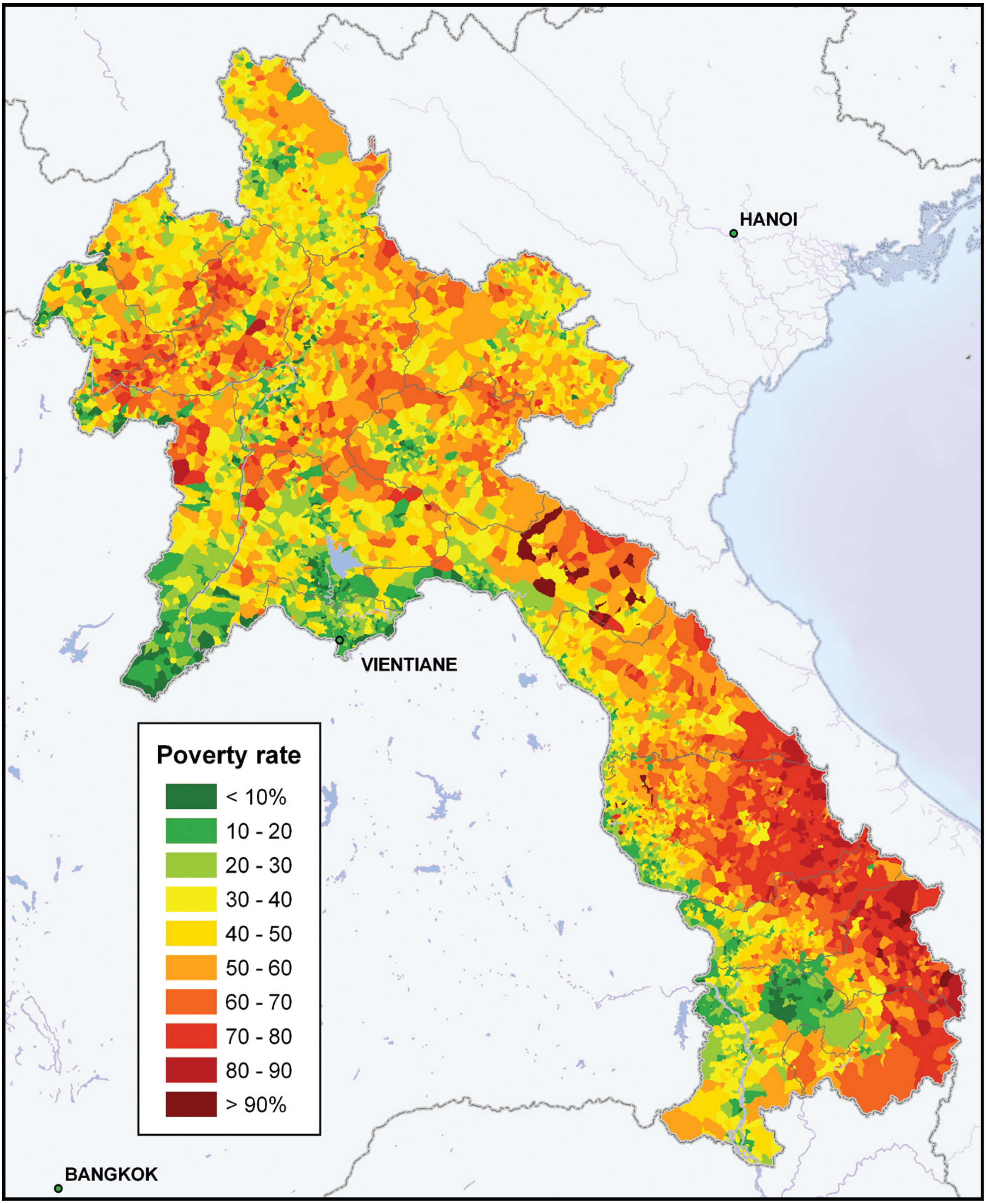
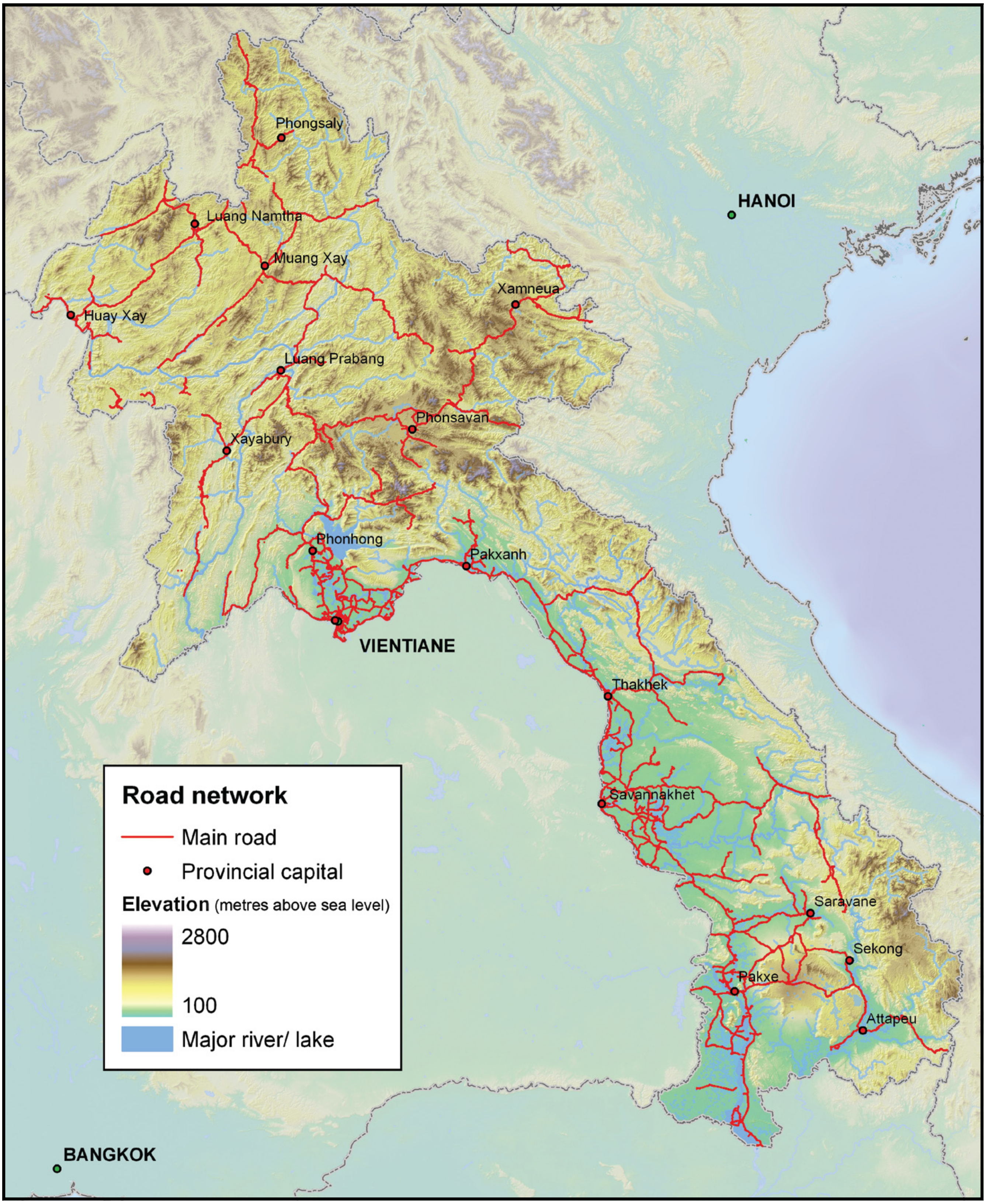


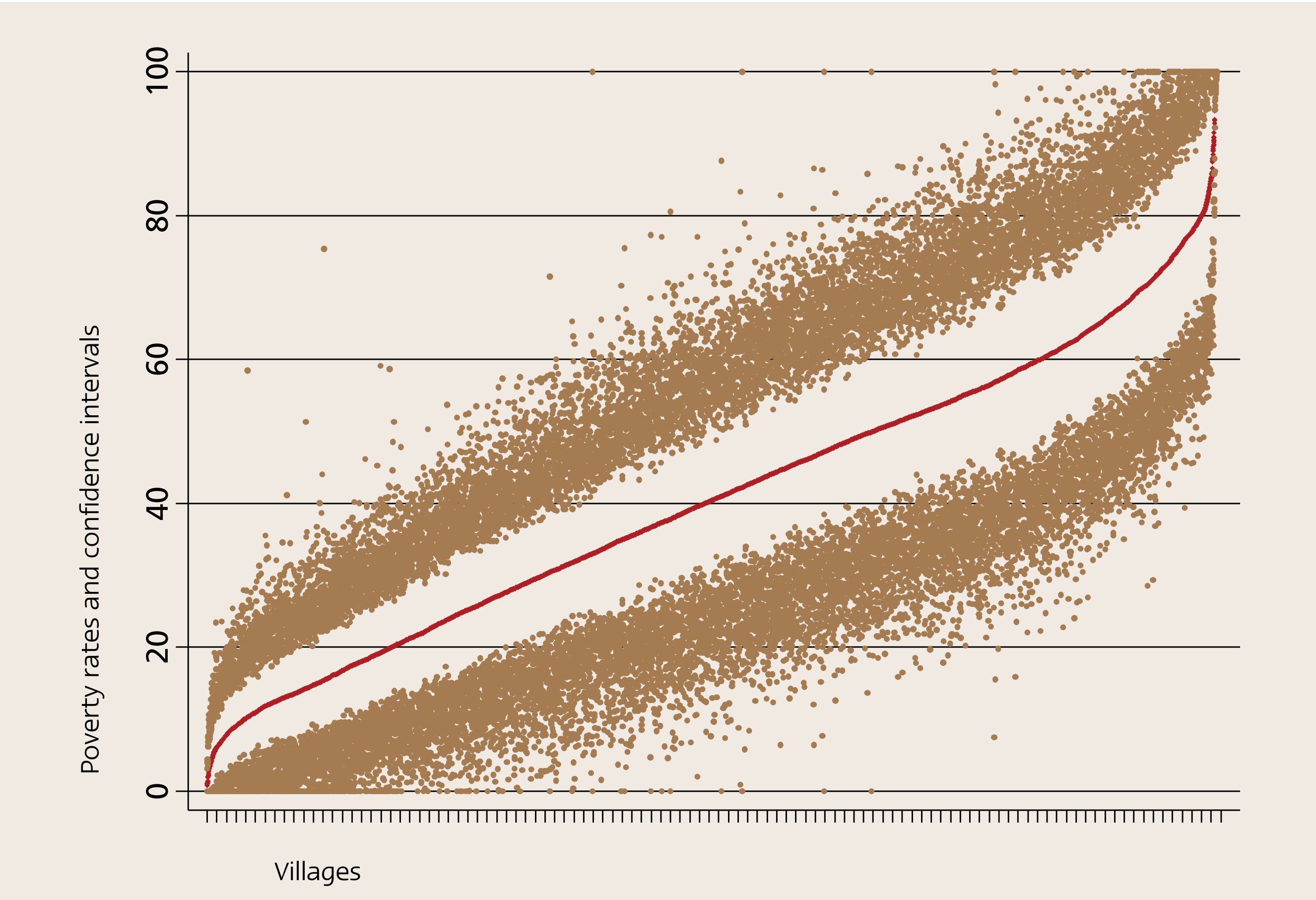
Figure 10. Map of the road network and the main towns



Luangprabang and Oudomxay) (Figure 10) - areas with relatively low incidence of poverty surrounded by mountainous areas with much higher poverty rates. Villages near the rivers often benefit from the flat land, the year-round availability of irrigation water and from transportation provided by the river, all of which reduce poverty rates. In addition, many urban areas in and around the district and provincial towns of the northern mountainous provinces, show relatively low poverty rates. This is particularly clear for Phongsaly town, for Muang Sing town in northern Luangnamtha province and Phonsavan town in Xiengkhuang province. Such local patterns only become visible when moving from the aggregated district poverty estimates to those at the village level.

The influence of the road network is visible in some places, particularly in the northern part of the country. Figure 10 shows the road network and main towns. For example, in the village poverty map there is a line of green villages between Vientiane and Luangprabang, and to a lesser extent between Luangprabang and Xayabury, and then further on to Paklay in Xayabury province. This corresponds to the path of the highway connecting those towns. This may reflect the impact of market access on poverty rates (cf. Section 4). Similarly, the greenish line running from the centre of Huaphanh province towards the border with Vietnam marks the path of the road from Xamneua town to Viengxay and the border with Vietnam, probably indicating the positive impact of the border trade on the local population. The road from Oudomxay town to the Mekong River harbour in Pak Beng is clearly visible, running southwest from Oudomxay in a fairly

Figure 11. Village poverty rates and confidence intervals



straight line towards the Mekong River.

In the southern part of the country, besides the green areas along the Mekong River valley, villages with lower poverty rates stretch along the road connecting the National Road No 13 in the Mekong River valley with Laksao and the border crossing to Vietnam, a transit route running west-east through Borikhamxay province, which serves as an important channel for trade between the two countries.

The village poverty map illustrates even more clearly that the villages in the south-central Mekong corridor have lower poverty rates, while the upland regions along the Vietnamese border have much higher poverty rates. One exception to this pattern is the Boloven Plateau. The lower poverty rates in this region possibly reflect the good agricultural conditions there, with fertile brown basalt soils and favourable climatic conditions.

Besides the agricultural benefits of the lowland river plain, the proximity to the border with Thailand is likely to have a poverty reducing effect. This is particularly visible in the north-eastern parts of the Lao PDR, where villages along the Thai border are better off than villages along the Mekong River and other inland villages. While this is true for most border villages in Oudomxay province, the benefits of border trade appear particularly strong in the south of the province of Xayabury, which has some of the lowest rural poverty rates in the country. This area was one of the first border regions in the country's recent history to engage in intensive border trade with Thailand.

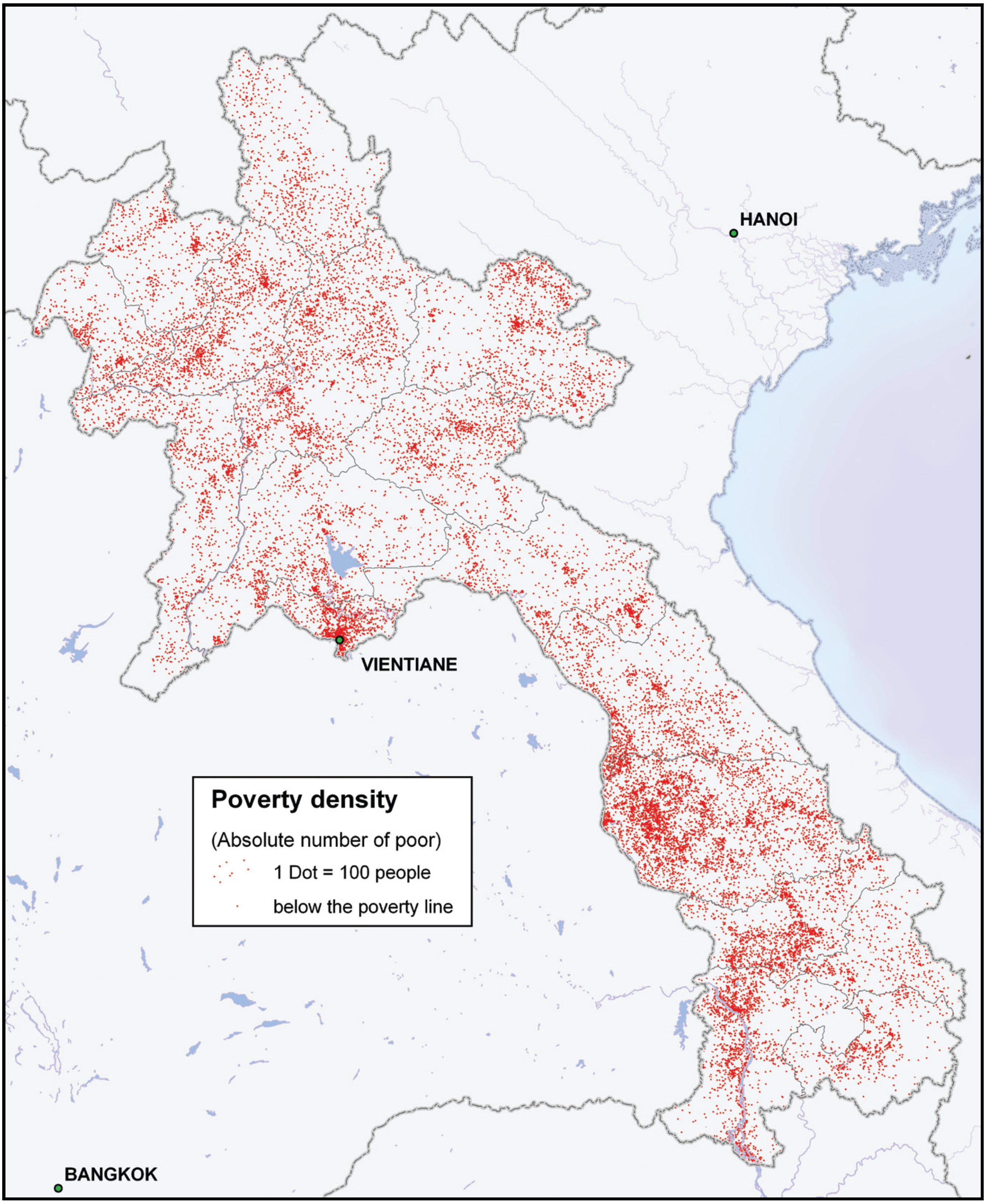
The south-central mountains along the border with Vietnam, on the other hand, exhibit some of the poorest areas in the Lao PDR. In particular, the eastern parts of Attapeu, Sekong, Saravane, Savannakhet and the south-eastern parts of Khammuane provinces are shaded red to dark red on the map, indicating poverty rates over 70 percent. The high incidence of poverty in this region is probably due to the fact that this is one of the least accessible parts of the Lao PDR, and the acidic soils and rugged terrain make it difficult to practice intensive agriculture. Moreover, this region is also adjacent to one of the poorest regions of Vietnam (Epprecht and Heinimann, 2004; Minot *et al.,* 2006).

As mentioned earlier, the village level estimates of poverty must be interpreted with great caution. Many of the villages have a very small number of households, leading to rather high margins of error in the poverty estimates. As shown in Figure 11, the 95 percent confidence intervals for village level poverty estimates range from less than ±1 percentage point to as high as ±75 percentage points, the average being ±16.5 percentage points. Half of the villages have confidence intervals between ±12 and ±20 percentage points. This means that only one-quarter of the villages have confidence intervals of less than ±12 percentage points. By comparison, none of the province level confidence intervals were greater than ±12 percentage points and none of the district level confidence intervals were this large. The large confidence intervals are not surprising considering the small size of many of the villages; the number of sample households in the villages ranges from as few as three households to as many as 639 households. The mean size of the villages is less than 70 sample households, and over 80 percent of all the villages have less than 100 sample households. Clearly, the village estimates of poverty must be used very cautiously, taking into account the size of the confidence intervals. In most cases, the estimated poverty rates for individual villages are quite rough. However, the colour shading of the map only differentiates the 10-percentage-point intervals for each village (for example, 20-30 percent). Nevertheless it can still be used to identify the spatial patterns in poverty. While the poverty estimations for individual villages should be treated with caution, it is still worth noting how coherent the spatial patterns of poverty are across the country.

Poverty density

The three maps presented in Figure 3, Figure 5 and Figure 9 show the incidence of poverty, defined as the percentage of the population living below the poverty line. Another way to look at the spatial

Figure 12. Map of the density of poverty



distribution of poverty is to examine the poverty density, defined as the number of poor people living in a given area, or the spatial distribution of the absolute number of poor people. By multiplying the village level poverty rates by the population in each village, we can estimate the number of poor people living in each village, a number that is represented by the number of dots in that village[11]. Figure 12 shows the poverty density in the Lao PDR, where each dot represents 500 poor people.

At a first glance it might be somewhat surprising to find that a high density of poor people is found in areas that have a low poverty rate, while areas with a high poverty rate often have only a relatively small total number of poor people per given area. This is because the areas with the highest poverty rate tend to be remote and sparsely populated areas, and the lower population density more than offsets the higher percentage of the population that is poor. Nevertheless, high incidences of poverty do coincide with relatively high densities of poverty, particularly in mountainous parts of Oudomxay, and, somewhat surprisingly, along National Road No 9 connecting Savannakhet town with Lao Bao on the border with Vietnam. Overall, however, most poor people live in more densely populated lowland areas along the Mekong corridor, in and around Vientiane Capital City and other urban areas of the country.

An important implication of Figure 12 is that if all poverty alleviation efforts are concentrated in the areas where the poverty rate is the highest, including the southeast, most of the poor will be excluded from the benefits of these programs. The implications of this map are discussed in Section 6.

3.3 Spatial patterns in other measures of poverty

The previous section explores the spatial patterns in the incidence of poverty, also called P_0. There are other measures of poverty that have useful properties. The depth of poverty (P_1), also called the poverty gap, takes into account not just how many people are poor, but how poor they are, on average. In fact, the depth of poverty is equal to the proportion of the population that is poor multiplied by the percentage gap between the poverty line and the average per capita expenditure of the poor. The severity of poverty (P_2), also called the poverty gap squared, takes into account not just how poor the poor are, on average, but also the distribution of income among them (see Section A.2 of the Annex for more details).

At the national level, the estimated value of the depth of poverty (P_1) is 0.102, implying that the average poor person has a level of per capita expenditure that is about 29 percent below the poverty line[12]. The estimated value of the severity of poverty (P_2) at the national level is 0.041. Figure 13 shows the district level maps of the depth of poverty (P_1) and the severity of poverty (P_2), presented side-by-side to make comparison easier. We can see that the spatial patterns in P_1 and P_2 are quite similar to each other and similar to the spatial pattern of P_0 (see Figure 5). In all three

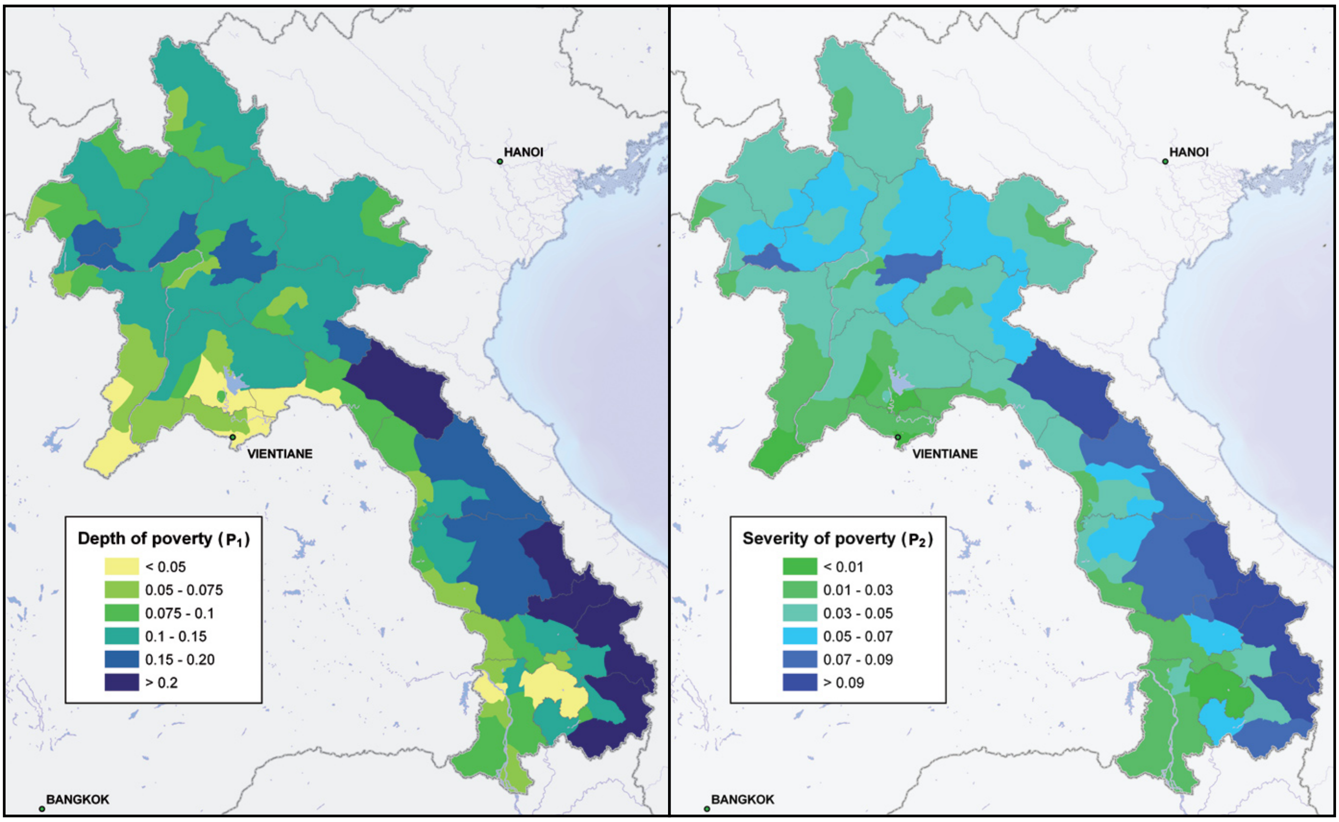
[11] We do not have information on the geographic distribution of households within each village, so the dots are distributed randomly within each village polygon.

[12] $P_1=P_0 \cdot G$, where G is the gap between the poverty line and the average per capita expenditure of poor people, expressed as a proportion of the poverty line. Since $P_0 = 0.347$ and $P_1 = 0.102$, $G = 0.294$.

maps, poverty is greatest in the southeast and the central mountainous areas along the border with Vietnam, as well as in parts of Luangprabang and Oudomxay provinces. Poverty is intermediate in much of the north of the Lao PDR, and it is lowest in the large urban areas, as well as in the southern part of Xayabury province, the Boloven Plateau, and along the south-central Mekong corridor.

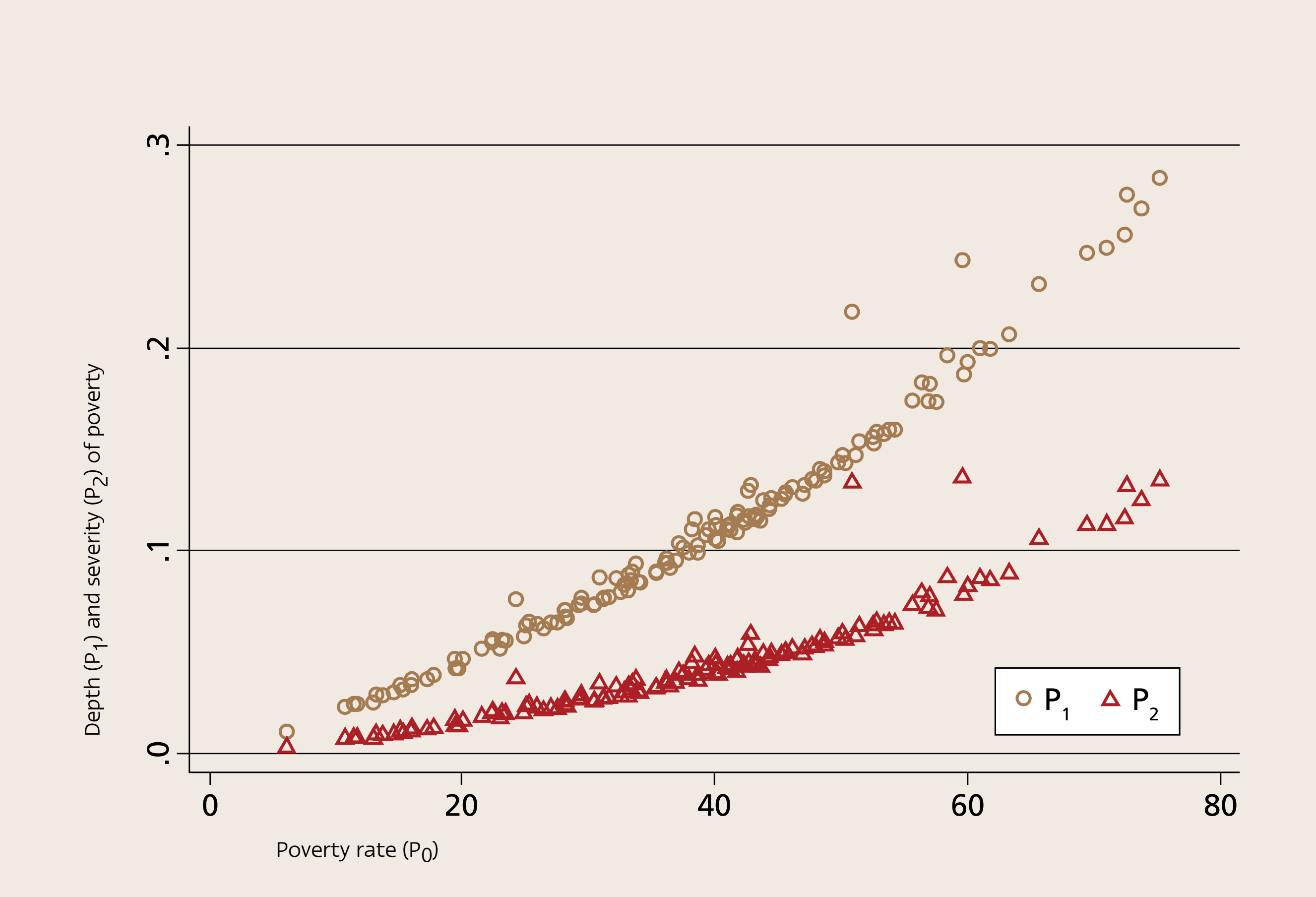
Figure 14 plots the depth of poverty (P_1) and the severity of poverty (P_2) on the vertical axis with the incidence of poverty (P_0) on the horizontal axis, with each point representing one district. As the incidence of poverty rises, the depth and severity of poverty also rise. The correlation between the poverty measures is quite strong[13]. The fact that the P_1 line curves upwards as P_0 increases implies that, as the poverty rate rises, the percentage gap between the poverty line and the per capita expenditure of the average poor households increases as well.

Figure 13. Maps of the depth of poverty (P_1) and severity of poverty (P_2) for each district



[13] A quadratic trend line based on P_0 has an R^2 of 0.97 in the case of P_1 and 0.91 in the case of P_2.

Figure 14. Depth of poverty (P_1) and severity of poverty (P_2) as a function of the incidence of poverty (P_0) in each district



3.4 Spatial patterns in inequality

As discussed in Section 2.4, the small-area estimation method is most commonly used to estimate the incidence of poverty (poverty mapping), but it can also be used to estimate the level of inequality for small areas. While poverty measures focus on those below the poverty line, inequality measures look at the welfare distribution of an entire population or particular segments of it. In this analysis, we focus on three commonly used measures of inequality: the Gini coefficient, the Theil L index of inequality, and the Theil T index of inequality. The two Theil indices are also part of a class of Generalized Entropy measures, and are sometimes labelled GE(0) and GE(1).

Table 8 provides estimates of these three measures of inequality at the national level, as well as for different sub-populations, along with the respective estimated total populations, povertyrates and average per capita expenditures for reference.

The Gini coefficient is a measure of inequality which varies between 0 (when everyone has the

Table 8. Comparison of poverty and inequality estimates for population sub-groups

	Population (approximate)	Poverty rate (P_0)	Average per capita expenditure (kip/month[14])	Inequality		
				Gini	Theil L	Theil T
National	5,490,792	0.34	140,721	0.33	0.19	0.19
By urban/rural residence						
Urban	1,435,412	0.20	208,641	0.32	0.17	0.17
Rural	4,055,381	0.38	116,581	0.29	0.14	0.14
By ethnicity						
Tai-Kadai	3,352,856	0.26	160,924	0.32	0.17	0.18
Mon-Khmer	1,280,016	0.51	101,797	0.30	0.14	0.15
Tibeto-Burman & Hmong-Mien	626,273	0.44	114,833	0.30	0.15	0.16
other ethnic groups	231,647	0.40	132,177	0.34	0.20	0.21
By agro-ecological region						
Vientiane Plain	832,989	0.16	211,983	0.31	0.16	0.17
Mekong Corridor	1,870,584	0.33	132,691	0.31	0.16	0.17
Northern Lowlands	1,123,031	0.28	135,333	0.31	0.16	0.16
Northern Midlands	690,169	0.46	120,295	0.31	0.17	0.17
Northern Highlands	537,700	0.42	121,274	0.32	0.17	0.18
South-Central Lowlands	257,616	0.60	90,830	0.29	0.14	0.15
South-Central Midlands	28,670	0.65	78,277	0.30	0.15	0.16
South-Central Highlands	23,731	0.75	70,296	0.28	0.13	0.14
Boloven Plateau	126,302	0.15	158,339	0.27	0.12	0.12

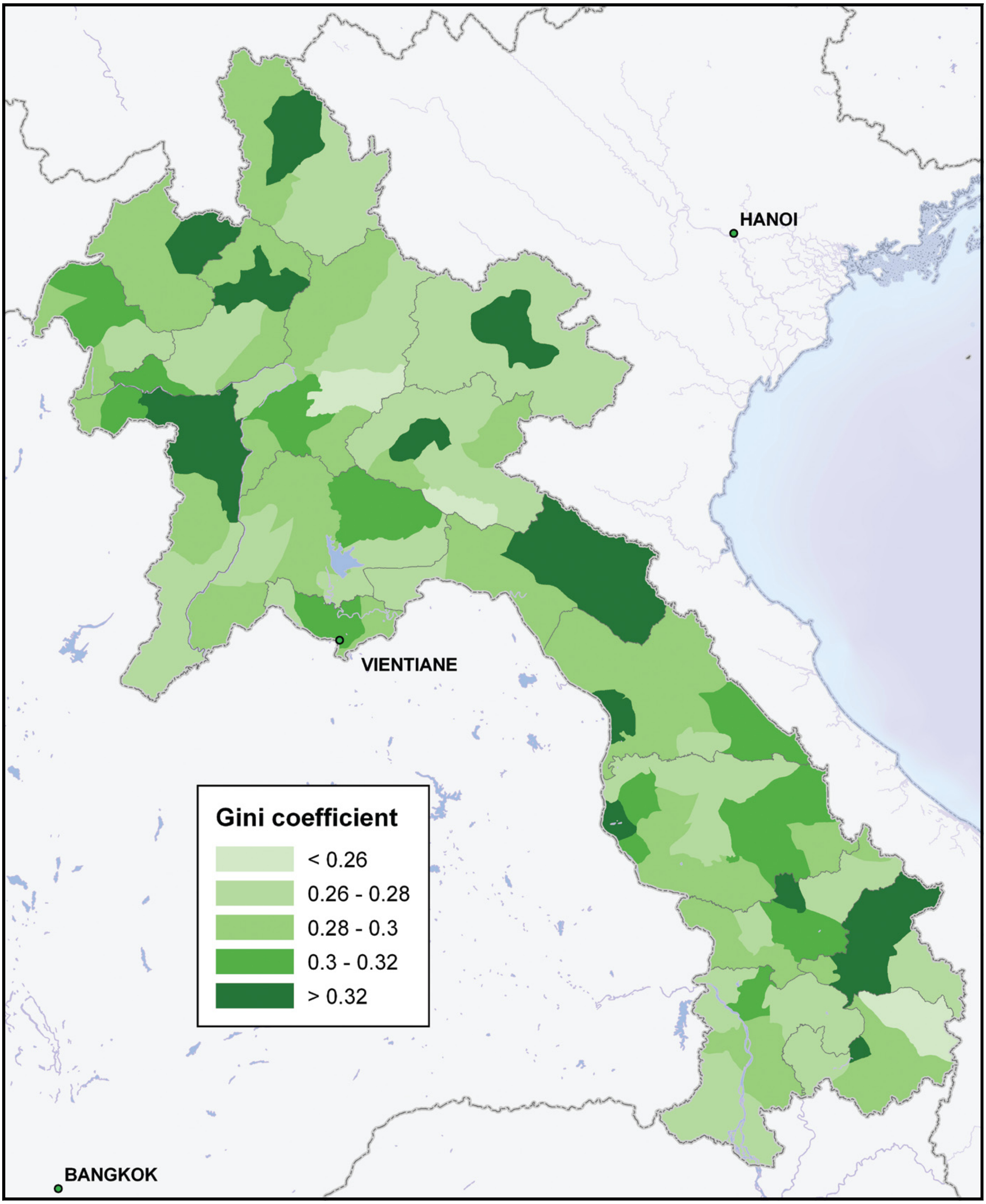
same expenditure or income) and 1 (when one household earns all the income). Thus, a higher Gini coefficient implies more inequality. The equation used to calculate the Gini index is given in A.3 of the Annex. For most developing countries, Gini coefficients range between 0.3 and 0.6. According to our analysis, the national Gini coefficient is 0.333, indicating a relatively low degree of inequality in per capita expenditure. As expected, the Gini coefficient for rural areas (0.291) is slightly lower than that for urban areas, which is 0.318.

The Theil L index varies between 0 (absolute equality) and infinity (absolute inequality), although it is unusual for it to exceed 1. Like the Gini coefficient, a higher Theil index implies a more unequal distribution of expenditures (or incomes). However, the Theil L gives more weight to the bottom of the distribution, thus giving greater weight to the distribution of expenditure among the poor than does either the Theil T index or the Gini coefficient.

The Theil T index varies between 0 and log (N), where N is the population. Unlike the Theil L index, the Theil T index gives equal weight to all parts of the distribution. The equations used to calculate the two Theil indices are given in Section A.3 of the

[14] In 2003 one US$ corresponded in average to about 7900 kip.

Figure 15. Map of inequality as measured by the Gini coefficient



Annex. Both Theil indices were estimated at 0.19 at the national level, and 0.17 and 0.14 in urban and rural areas, respectively.

We also calculated the Gini coefficient and the two Theil indices for the broad categories of Lao ethno-linguistic families commonly used in the Lao PDR: the Tai-Kadai, the Mon-Khmer, and the Hmong-Mien and Tibeto-Burman ethno-linguistic families, plus one category for all other ethnicities that are not indigenous to the Lao PDR (mainly relatively recent immigrants from other countries). Table 8 provides an overview of the estimates for the different groups. Even though these groups exhibit different poverty rates, ranging from 26 percent for the Tai-Kadai to 51 percent for the Mon-Khmer, the estimates of inequality are remarkably similar. The highest levels of inequality were estimated for the group comprising all the non-indigenous ethnicities in the Lao PDR, indicated by a Gini coefficient of 0.34, or the Theil L and T indices of 0.20 and 0.21 respectively. This is not surprising, as this group is likely to be the most heterogeneous in terms of the individuals' socio-economic backgrounds. Among the three "Lao" groups, the inequality estimates are slightly higher for the Tai-Kadai, which, as mentioned, is also the group with the lowest poverty rate. The Tai-Kadai makes up the bulk of the urban population, where inequalities tend to be somewhat higher.

Table 8 also provides estimates of inequality by agro-ecological region. Again, the Gini coefficients, as well as the two Theil indices, are remarkably similar for the different regions, despite the great differences in welfare levels among the populations of those regions indicated by the respective poverty rates (P_0). In fact, the two lowest Gini coefficients were estimated for the poorest and for the richest regions: the south-central highlands, with a poverty rate of 75 percent, and the adjacent

Figure 16. Maps of inequality as measured by the Theil L and Theil T indices

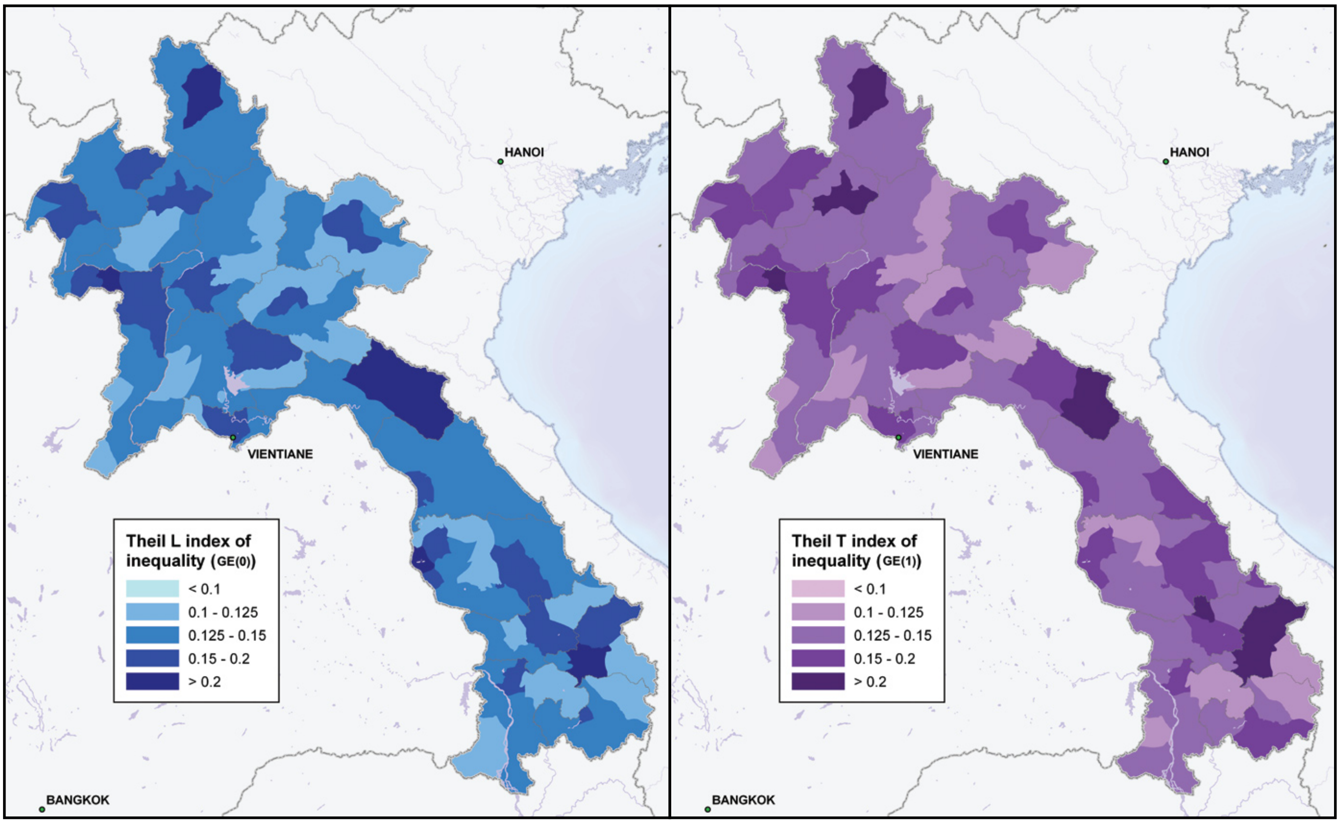
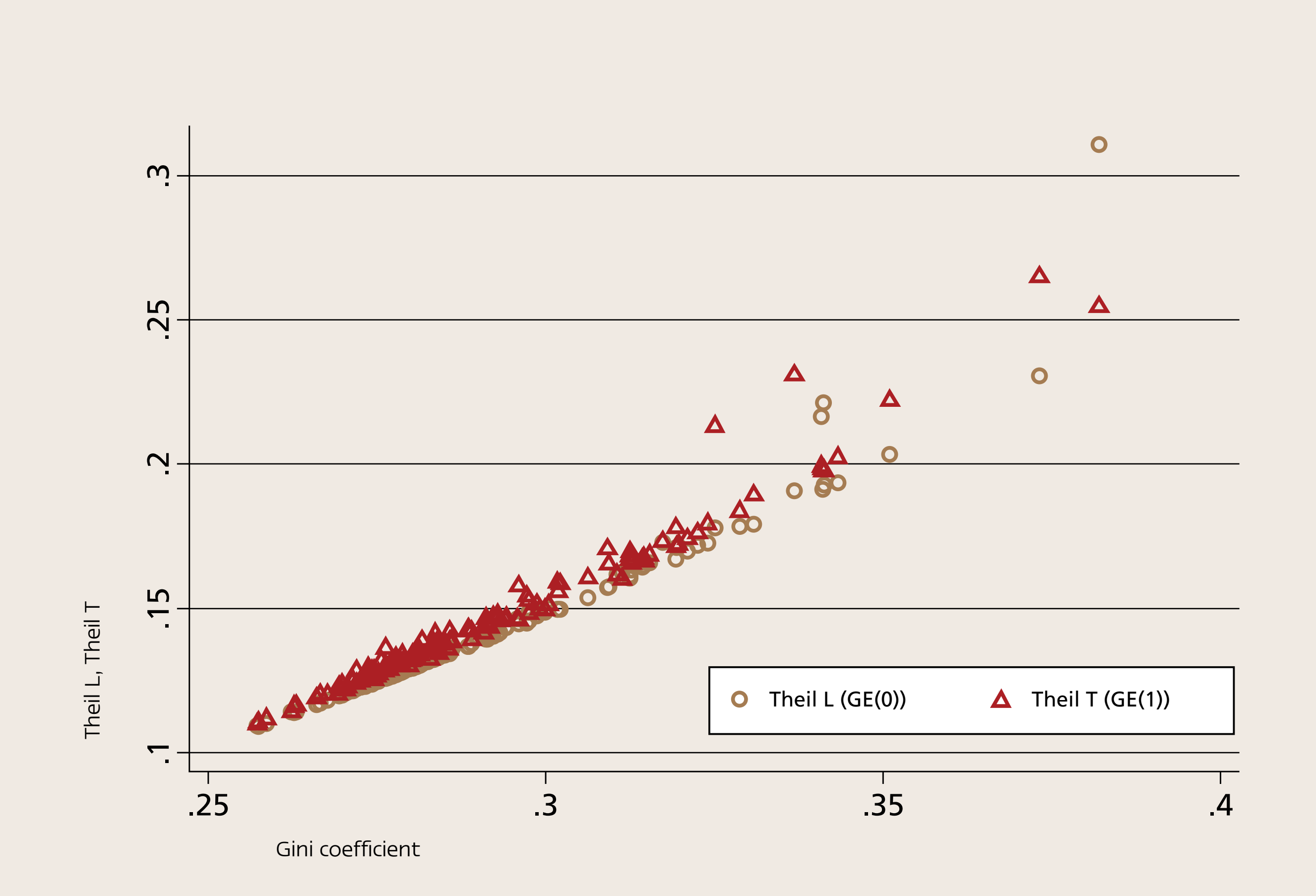


Figure 17. Theil indices of inequality as a function of the Gini coefficient for each district



Boloven Plateau, with a poverty rate of only 15 percent, both have a Gini coefficient of below 0.3 (0.28 and 0.27 respectively). Both Theil indices reflect the same pattern. In general, inequality tends to be slightly higher in the northern regions compared to those of the south.

Like other measures of inequality, the Gini coefficient tends to be smaller for smaller groups, such as provinces or districts, than for the nation as a whole. This is because households in a small area are likely to be more similar to each other than to households across the entire country. Figure 15 shows the level of inequality in per capita expenditure as measured by the Gini coefficient at the district level. The areas with the least inequality (shaded in lightest green) include the highland areas in Attapeu, Luangprabang and Xiengkhuang provinces, while the greatest levels of expenditure inequalities are found in districts that include both provincial and district towns, as well as in the surrounding urban areas; the comparatively high levels of inequalities in those districts are therefore largely a reflection of urban-rural welfare differences, seen in the village level poverty map (Figure 9). Apart from this, inequality is relatively high in the upland districts of Khamkeut and Viengthong in Borikhamxay province, as well as in the Karum district of Sekong province.

It is not surprising that there is a welfare gap between urban areas and the surrounding rural villages, since urban areas have some of the richest households in the country as well as recent immigrants and others whose income is barely higher than that in rural areas. However, the reasons for the comparatively high inequalities in the upland areas of Borikhamxay and Sekong provinces are less obvious. As can be seen in the village poverty map (Figure 9), these areas have a few villages with unusually high poverty rates, as well as a couple of villages with relatively low poverty rates.

It is also interesting to note that many of the better-off rural areas have rather low levels of inequality. Although these areas tend to be characterised by intensive irrigated agriculture and by a large percentage of the population depending on agriculture, and a relatively uniform agricultural potential of the irrigated farm land, one could also have expected that greater commercial opportunities (particularly in proximity to the Thai border) would result in greater inequalities among the population there. The fact that this appears not to be the case implies that the majority of the population manages to benefit rather equally from the opportunities presented.

The district-level maps of inequality as measured by the Theil L and the Theil T indices are shown in Figure 16. Despite their different underpinnings, the maps of inequality using the two Theil indices give similar results to the map using the Gini coefficient.

Figure 17 shows the relationship between the three measures of inequality, where each dot represents one district. This graph indicates that there is a linear relationship between the Gini coefficient on the one hand, and the two Theil indices on the other, and that the correlation is quite close. For the relationship between the Gini coefficient and the Theil L index, $R^2 = 0.94$, while in the relationship between the Gini coefficient and the Theil T index, $R^2 = 0.96$. This helps to explain why the three inequality maps are quite similar.

Decomposing inequality

In the preceding chapters, poverty rates and inequality levels have been calculated and interpreted for the different sub-populations, such as urban-rural and lowland, midland and highland Lao ethnic groups, and by different administrative levels. Considerable differences in poverty rates as well as those in expenditure inequalities have been identified among the different sub-populations. For socio-economic pro-poor planning purposes, it can be of interest to know how much of the overall inequality is due to differences in mean per

Table 9. Decomposition of inequality into between- and within- components

Sub-population (# of sub-groups)	Variable	Total inequality at national level GE(0)	Maximum potential *between*-group inequality	Between-component of total/max. potential	Within-component
Urban-rural	Value of index	0.185	0.063	0.036	0.149
(2)	Share of total/ maximum	100%		19% / 57%	81%
Agro-ecological	Value of index	0.185	0.090	0.024	0.161
region (9)	Share of total/ maximum	100%		13% / 26%	87%
Province	Value of index	0.185	0.094	0.021	0.164
(17)	Share of total/ maximum	100%		11% / 22%	89%
District	Value of index	0.185	0.099	0.038	0.147
(139)	Share of total/ maximum	100%		21% / 38%	79%
Village	Value of index	0.185	0.092	0.066	0.119
(10467)	Share of total/ maximum	100%		36% / 73%	64%
Ethnicity	Value of index	0.185	0.063	0.019	0.165
(4)	Share of total/ maximum	100%		10% / 30%	90%

capita expenditure *between* the sub-groups, and how much is due to variation in per capita expenditure *within* each sub-group.

Unlike the Gini coefficient, the Theil L and T indices of inequality can be precisely decomposed into such *between* and *within* components for any mutually exclusive grouping (Shorrocks, 1984). For example, the Theil index for all of the Lao PDR is equal to the weighted average of the provincial indices (the "*within*-province" component) plus the Theil index of the inequality in provincial average expenditures (the "*between*-province" component). The *between*-province component refers to what inequality would be if everyone inside a province had the same expenditure as the provincial mean, while the *within*-province component takes into account inequality *within* provinces but excludes inequality of provincial averages.

The technique has widely been applied (see for example Datt and Walker, 2004; Elbers *et al.,* 2004; Shorrocks and Wan, 2005). We applied the decomposition techniques to the inequality data for the following sub-groups: agro-ecological regions, main ethnic grouping, urban and rural areas, and the three levels of administrative units. Because of the close relationship between the Theil L and T indices, we present here the results of the Theil L decomposition only. Table 9 lists the different types of sub-groups in the first column.

The sizes of the *between*- and *within*-group components depend on the number of sub-groups – the greater the number of sub-groups, the larger the *between* component. This is confirmed by various empirical studies (for example Elbers *et al.,* 2005; Cheng, 1996; Shorrocks and Wan, 2005). The sub-group decomposition for the Lao PDR exhibits the same pattern for progressively higher spatial disaggregation of the administrative units, from 17 provinces to over 10,000 villages (see Table 9).

The *between* component of the urban-rural decomposition is relatively high at 25 percent, given that the number of sub-groups is only two. This is not surprising given the considerable difference between high inequalities in the smaller urban population compared to the low inequalities in the much larger rural population described earlier. Similar patterns are found in other countries (for example Shorrocks and Wan, 2005).

The *between* components for the decomposition along ethnic lines, as well as by agro-ecological region, are both much smaller than for the urban-rural decomposition, despite the distinctive differences in expenditures among the different ethnic groups, and agro-ecological regions. This is possibly due to the smaller relative differences in mean per capita expenditure, to the relative difference in sub-group sizes[15], and to the inverse relationship between the size of the sub-groups and the respective inequality levels.

Clearly, the size of the *between* and *within* shares depend on a number of factors, which makes these decomposition results hard to interpret. Elbers *et al.,* (2005) therefore proposed an alternative, measure of the *between* component that provides a complementary source of information to the conventional assessment of the *between* group component. Rather than using the total observed inequality as the denominator of the conventional *between*-ratio, which Elbers *et al.,* (2005) argue is quite an extreme bench mark, an alternative benchmark of the "maximum *between*-group inequality that could be obtained if the number of groups and their sizes were restricted to the same as of the numerator" (Elbers *et al.,* p6, 2005), was suggested. This measure normalises by the number of sub-groups and their relative sizes, and so can be better compared across settings (Elbers *et al.,* 2005).

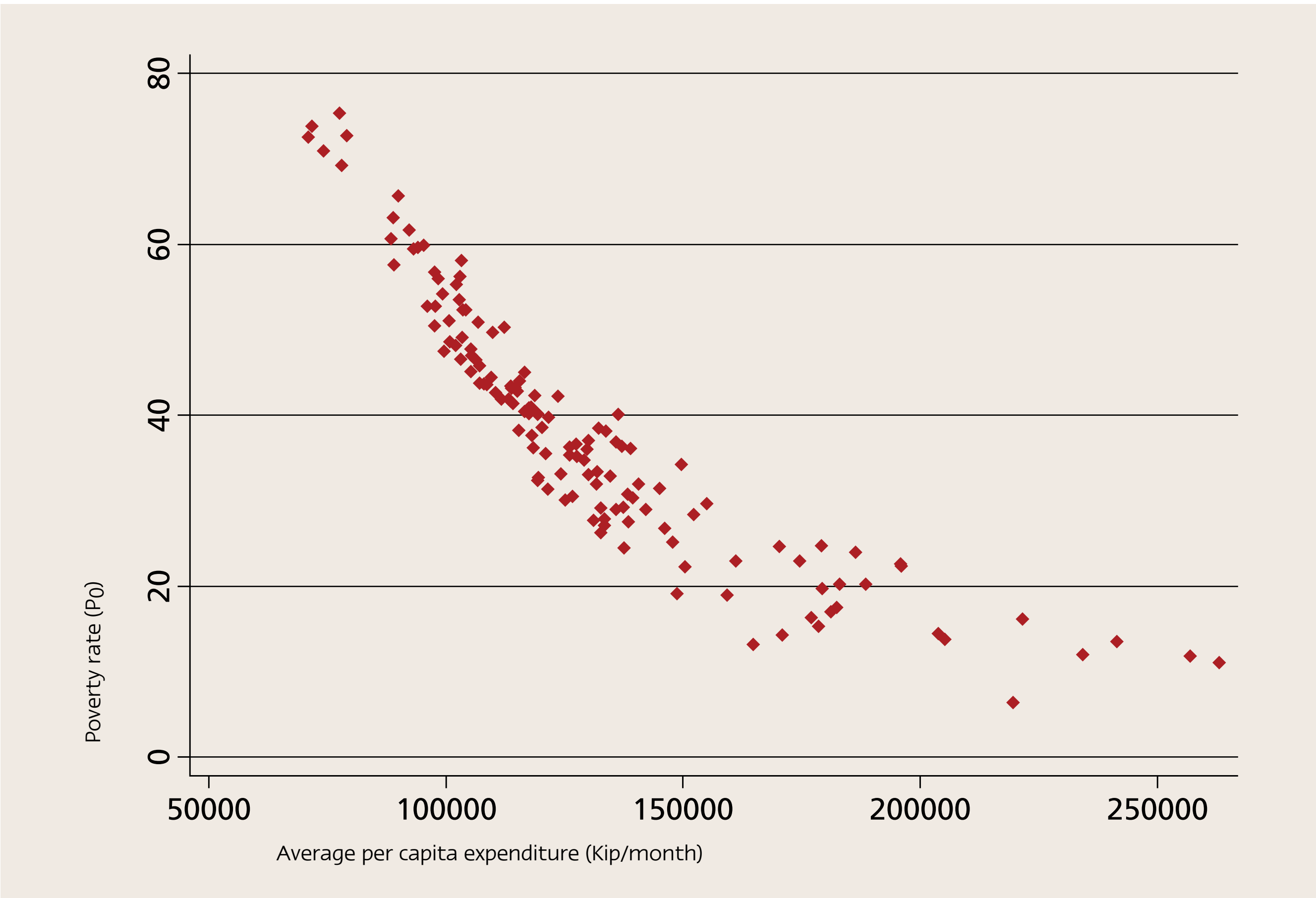
We calculated the maximum attainable *between*-group inequality by using the current income

[15] The urban population is almost three times smaller than the rural population while the Tai-Kadai population is about 1.75 times smaller than the Mon-Khmer, Hmong-Mien and Tibeto-Burman populations together.

distribution, the relative sizes of the sub-groups, and what has been termed the "pecking order" (Elbers *et al.,* 2005). We then sorted the groups by mean per capita expenditure, and redistributed the individual per capita household expenditure values among the households in such a way that all the lowest per capita household expenditures are assigned to the households of the sub-group with the lowest mean per capita household expenditure, the next lowest values to the sub-group with the second lowest mean per capita expenditure, and so on, up to the highest per capita expenditures to the households of the sub-group with the highest mean per capita expenditure. Using this data set with the redistributed household per capita expenditure, we calculated the *between*-group inequality, which is the maximum *between* group inequality that can be obtained given the current overall expenditure distribution, the numbers and relative sizes of the groups, and the original "pecking order".

The fourth column in Table 9 lists the respective maximum attainable *between* component, and the alternative between shares, that is the share of the observed between inequality of the maximum possible *between*-group inequality in the right part of the fifth column. Naturally, the alternative *between*-group measure is always higher than the conventional measure. However, as shown in Table 9, the correlation between the two different measures of *between*-group inequality shares is limited: while the increases in the *between*-group components in progressively higher spatial disaggregation of the administrative units are similar between the two measures, the differences are

Figure 18. Poverty rate (P_0) as a function of per capita expenditure



more pronounced particularly for the urban-rural decomposition, but also in the decompositions by ethnicity. It is worth noting, however, that inequality between villages reaches almost three quarters of the maximum possible inequality between villages, given the observed income distribution among households.

The observed inequality between urban and rural areas accounts for almost 60 percent of the maximum possible inequality between the two population sub-groups, while it reaches 30 percent for the ethnicity decomposition. These shares are about three times higher than the conventionally measured between-group shares, indicating comparatively strong between group inequalities, given the present overall expenditure distribution.

Relationships between income, poverty, and inequality

Sections 3.2 to 3.4 examined the spatial patterns in poverty and inequality. In this section, we examine the relationship among poverty, inequality, the degree of urbanization, and average per capita expenditure at the district level. In order to reduce the number of variables and because of the close correlation among poverty measures, we will use P_0 to represent poverty. Similarly, because all three inequality measures are closely correlated, we will use the Gini coefficient to represent inequality.

In Figure 18, we plot the poverty rate (P_0) as a function of the district-average of per capita expenditure, where each dot represents a district.

Figure 19. Gini coefficient of inequality as a function of per capita expenditure

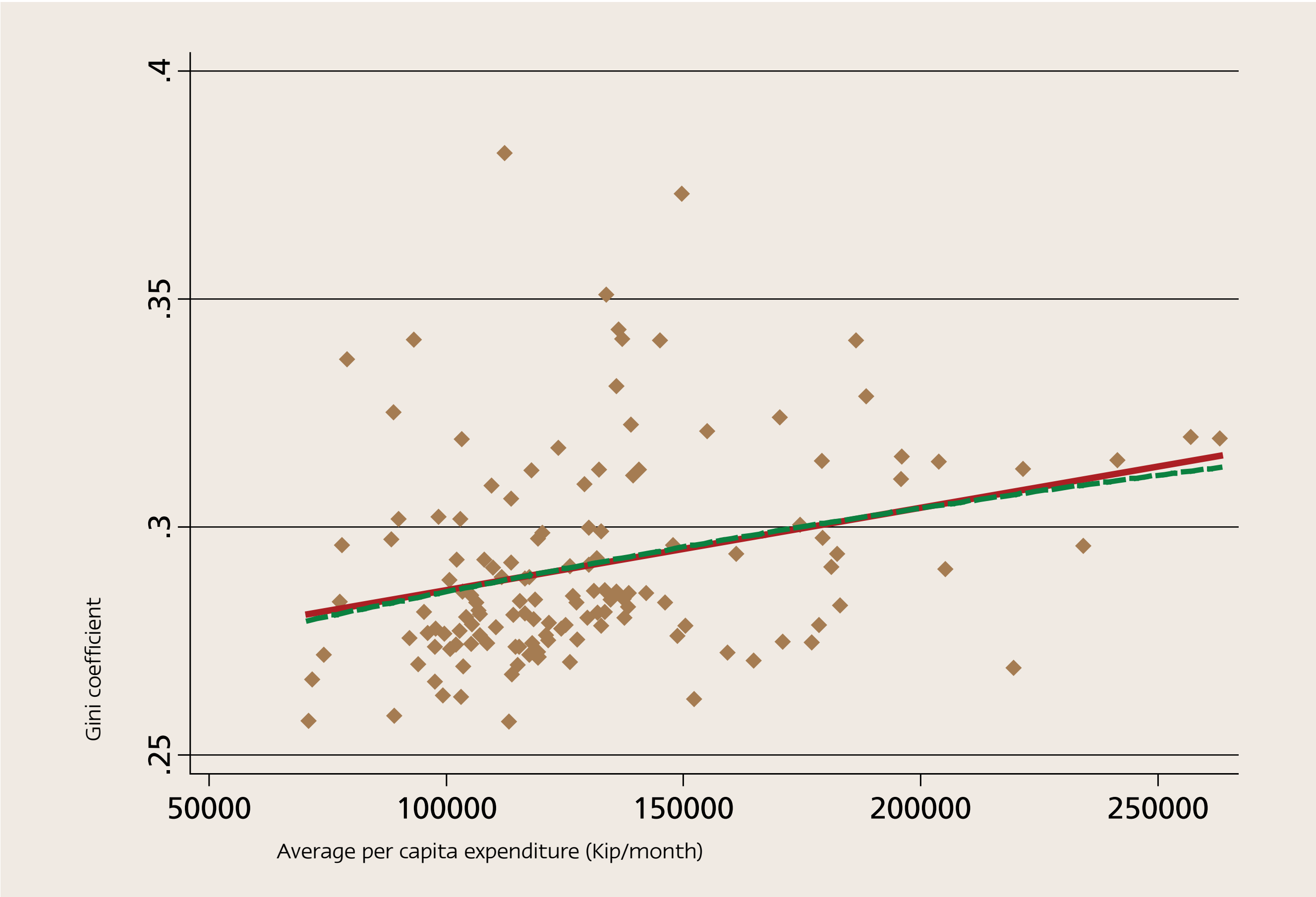
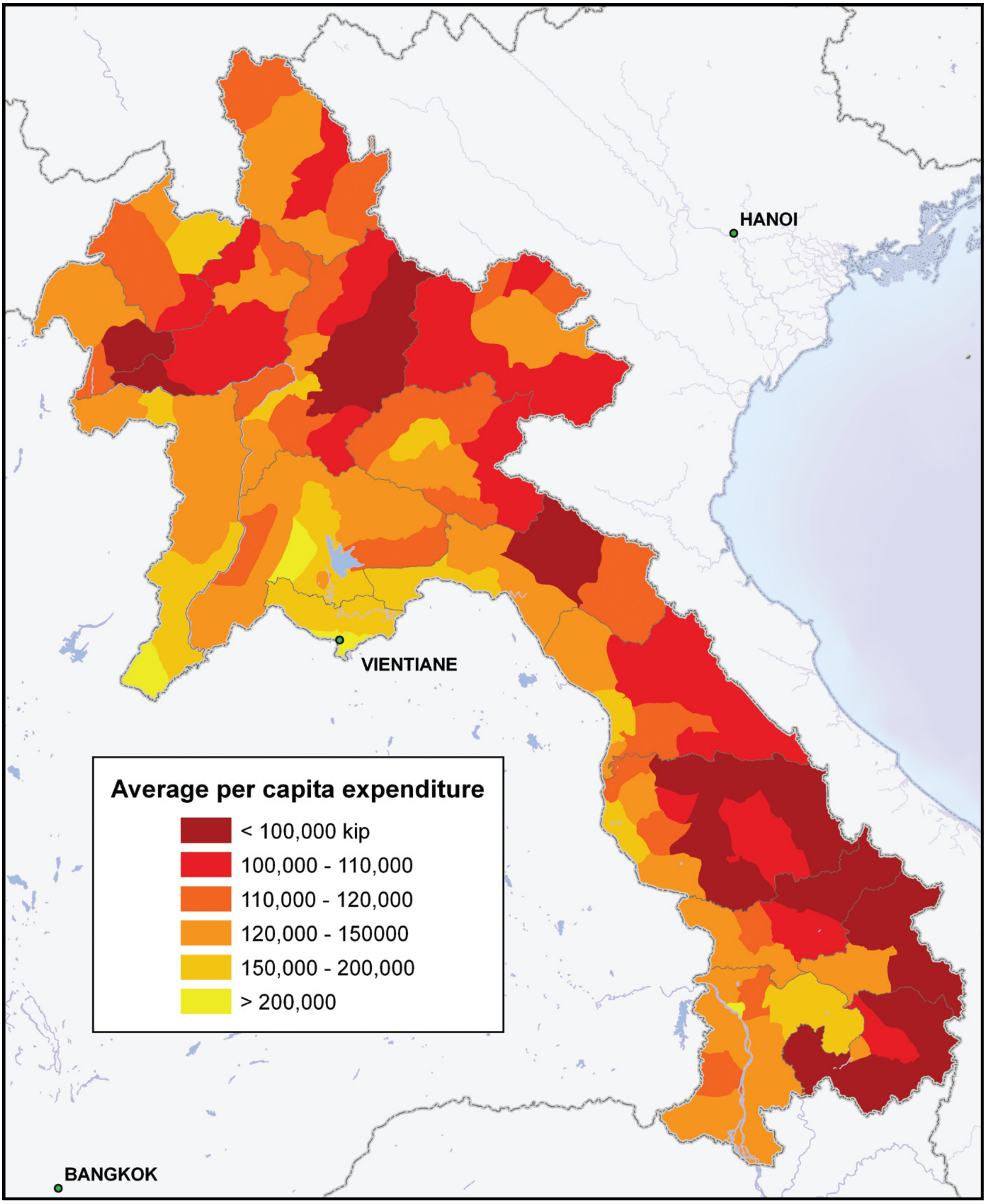


Figure 20. Map of per capita expenditure

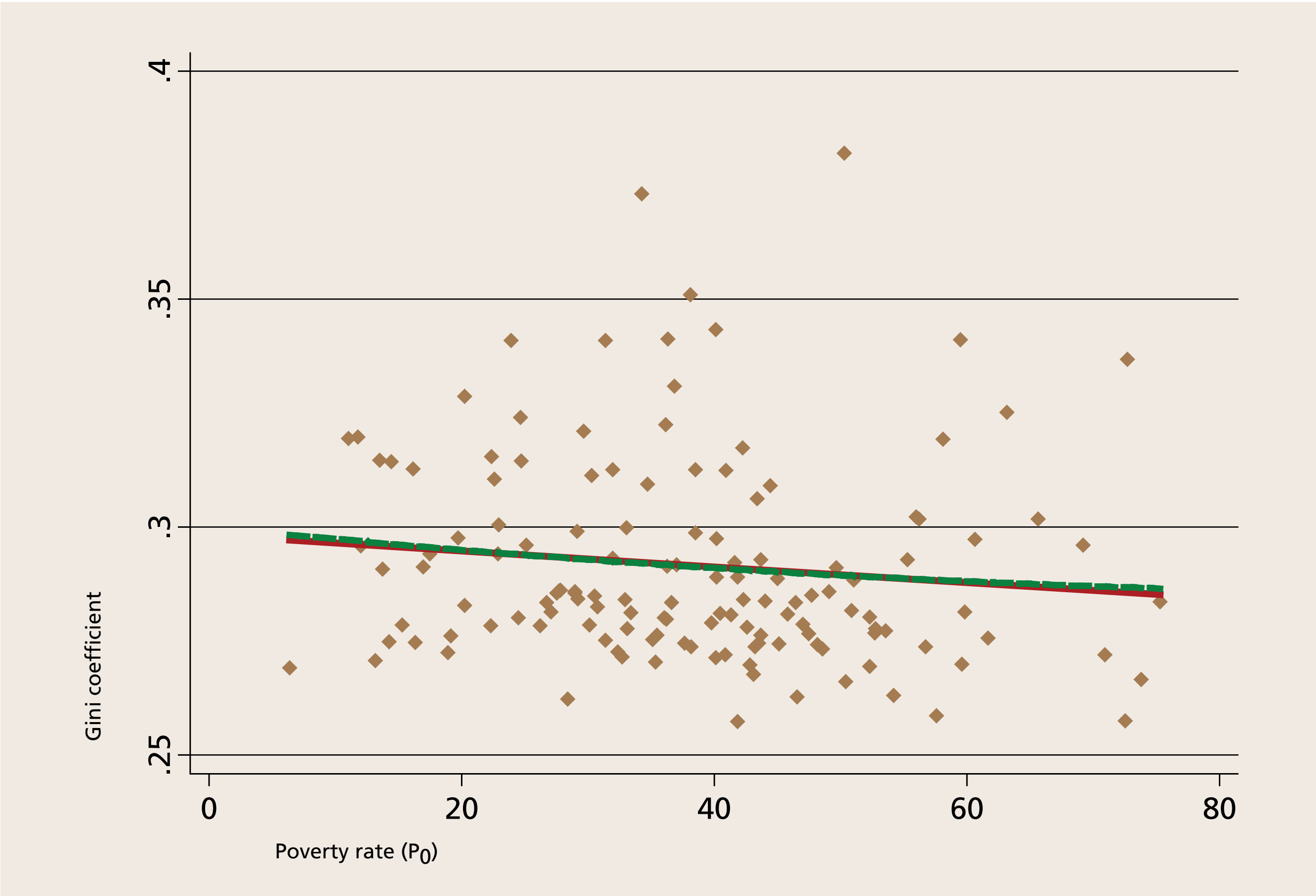


We expect that as per capita expenditure rises, the poverty rate will fall. Nonetheless, it is surprising how closely the poverty rate depends on the average per capita expenditure of the district. Particularly among the poorer districts, the relationship between the two variables is quite close. A quadratic trend-line explains 67 percent of the variation in poverty. This suggests that the incidence of poverty in a district is to some extent a function of the average level of per capita expenditure in the district. Likewise, the degree of inequality within a district plays a minor role in determining the poverty rate.

Figure 19 shows the relationship between the Gini coefficient and the average per capita expenditure of the district. It is widely believed in the Lao PDR and other countries that as incomes rise, the gap between the poor and rich widens. The data presented here confirm that view to some degree. The linear trend line shown on the graph indicates an increase in the Gini coefficient from 0.28 to 0.31 as per capita expenditure rises from 75 thousand kip/month to 250 thousand kip/month. This may be part of the pattern found in international data in which at low-levels of income, higher income is associated with higher inequality, but at some point further increases in income tend to reduce inequality. This inverted-U pattern is called the Kuznets curve. Since the Lao PDR is a low-income country, the Kuznets curve would predict a positive relationship between income and inequality over time and across districts.

But the relationship between inequality and per capita expenditure in Figure 19 is not a

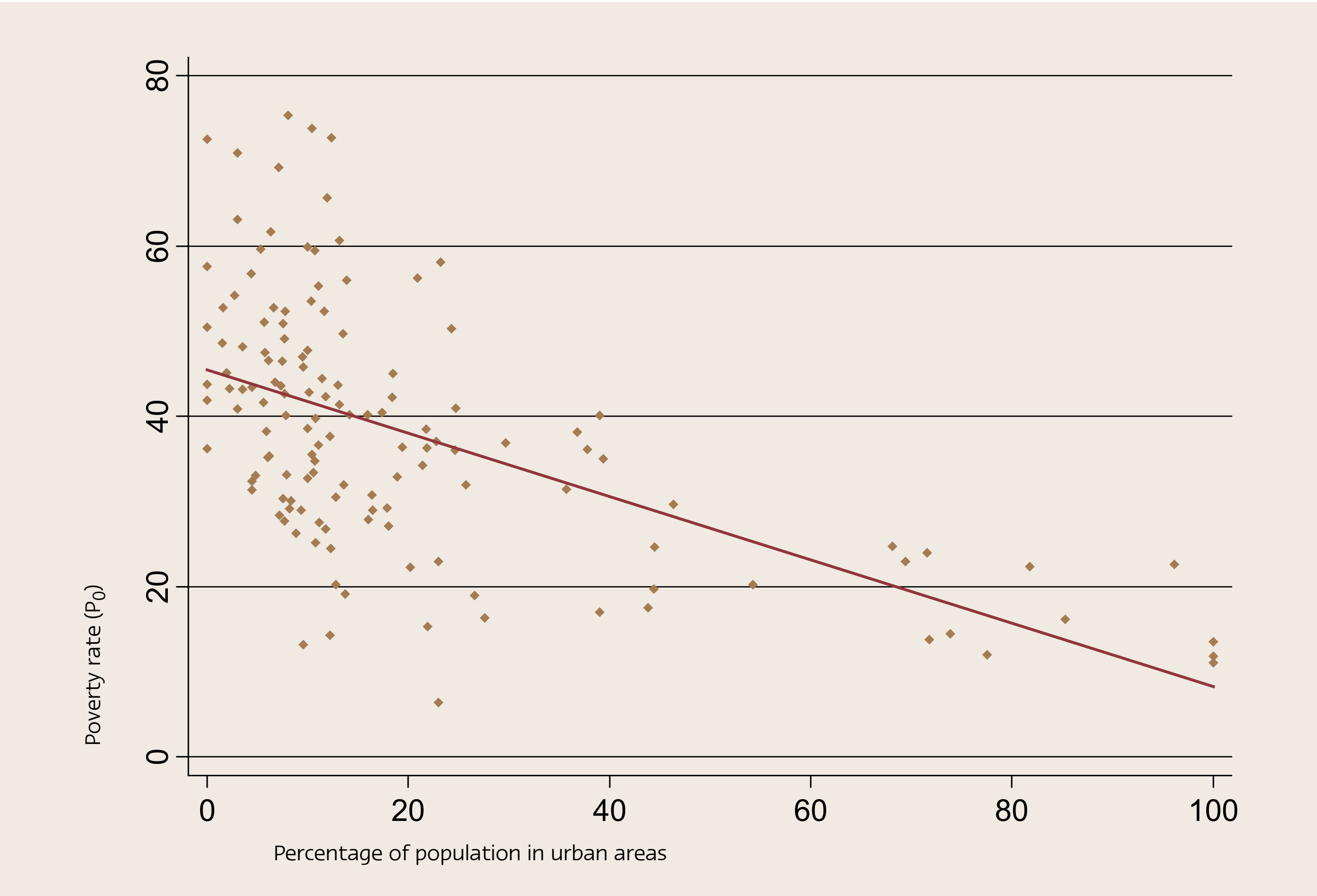
Figure 21. Gini coefficient of inequality as a function of the poverty rate (P_0)



simple positive relationship. Many low-income districts also have a high level of inequality. In fact, the districts with the highest levels of inequality tend to be the relatively poor districts with per capita expenditure below 150 thousand kip/month (Figure 20). Furthermore, low-income districts have a wider range of levels of inequality, while high-income districts seem to converge toward a Gini coefficient of around 0.3.

The relationship between poverty (P_0) and inequality (the Gini coefficient) is shown in Figure 21. There appears to be no obvious pattern in this relationship. The linear and the quadratic trend lines both do not support the idea of a linear or quadratic (curved) relationship. In other words, contrary to expectations, the level of inequality is roughly the same in poor districts and better off districts. Rural poverty rates exceed urban poverty rates in almost every country where they have been studied. Indeed, this pattern has been confirmed for the Lao PDR by various surveys (for example, see Engvall *et al.,* 2005; World Bank, 2005). Using small-area estimation methods, however, we can examine the poverty rates for many urban and rural districts to provide a more detailed picture of the relationship between the degree of urbanisation and poverty. Figure 22 shows the relationship across districts between the proportion of the population living in urban areas and the poverty rate (P_0), along with a linear trend line. The graph clearly indicates that there is an apparent negative relationship; most largely rural districts have poverty rates in the range of 25-75 percent, while most mainly urban districts have poverty rates of less than 25 percent.

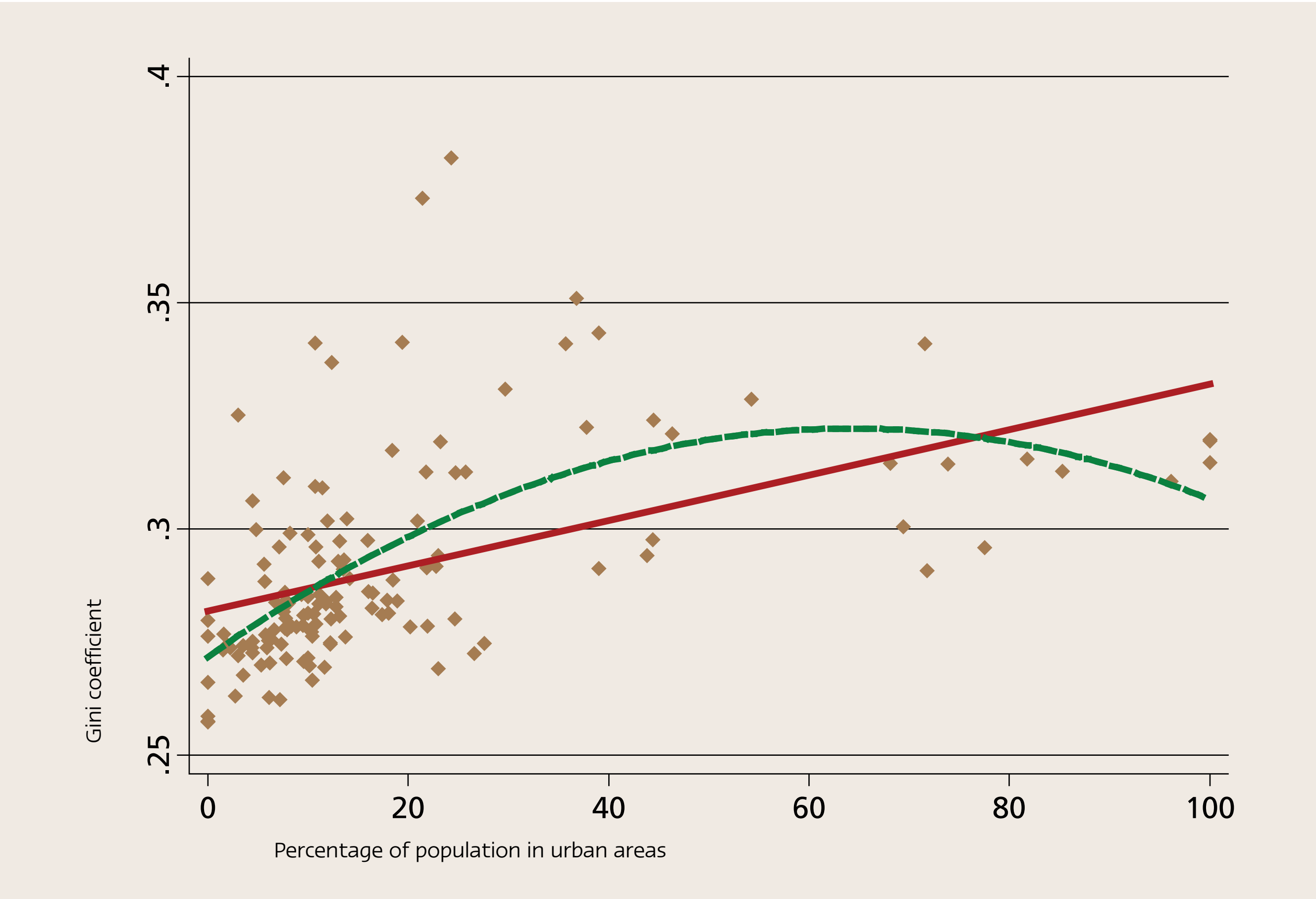
Figure 22. Poverty rate (P_0) as a function of the share of the population in urban areas



At the same time, it is interesting to note the wide range of poverty rates among rural districts. Several dozens of districts have a mainly rural population and poverty rates almost as low as urban districts. This suggests that under some circumstances, poverty can be significantly reduced in rural areas. Based on the maps presented earlier, it is clear that many of these "rich" rural districts are in the south-western region of the north of the Lao PDR and on the Boloven Plateau which both benefit from the access to fertile and relatively flat land, and international commodity markets.

The relationship between the degree of urbanisation and inequality is quite different. As shown in Figure 23, inequality (as measured by the Gini coefficient) is quite low for districts that are almost entirely rural, and it is medium for districts that are almost entirely urban. The districts with the highest level of inequality are those that combine urban and rural populations, with the urban share of the population being in the range of 20 to 40 percent. These results confirm the common view that urban areas have more inequality than rural areas (indicated by the linear trend line), but it suggests that the pattern is more complicated in that districts with both rural and urban populations have the highest inequality (quadratic trend line). Given the welfare differences between urban and rural areas within a single district, visualised for instance in Figure 7 and Figure 9, this is not surprising. The quadratic trend line shows that inequality is at its highest when the urban share is about 60 percent.

Figure 23. Gini coefficient of inequality as a function of the share of the population in urban areas



3.5 Poverty estimates compared to other geographic estimates of well-being

To assess the validity of our estimates of poverty from another angle, we compare in this section the estimates of the incidence of poverty (P_0) derived from our application of the small-area estimation method to other spatially disaggregated measures of welfare available. As mentioned earlier, there is still a lack of such information in the Lao PDR. Despite the many differences in the definitions of poverty and the data collection methods, we compared our estimates to the classification of the country's districts according to poverty levels, which was produced by DOS as a planning tool for the implementation of the National Growth and Poverty Eradication Strategy (NGPES) (Lao People's Democratic Republic, 2004). We then compared our estimates to the results of a village level vulnerability and food insecurity study done by the Vulnerability Analysis and Mapping (VAM) Unit of the World Food Programme (WFP) Office in the Lao PDR (United Nations World Food Programme, 2004).

Since neither the DOS district poverty classification nor the WFP vulnerability analysis report any actual poverty rates or rates of vulnerable households (although the DOS classification is based largely on village poverty rates), but instead result in a relative ranking of the districts or villages, we focus here on a comparison of the respective spatial patterns. Since poverty rate figures depend on a chosen poverty line, and given the wide range of views on how to construct a poverty line, there is little to be gained from debates over the "true" poverty rate. A focus on the spatial patterns in welfare distribution resulting from different approaches in some sense 'normalises' those results, and makes them more comparable with each other.

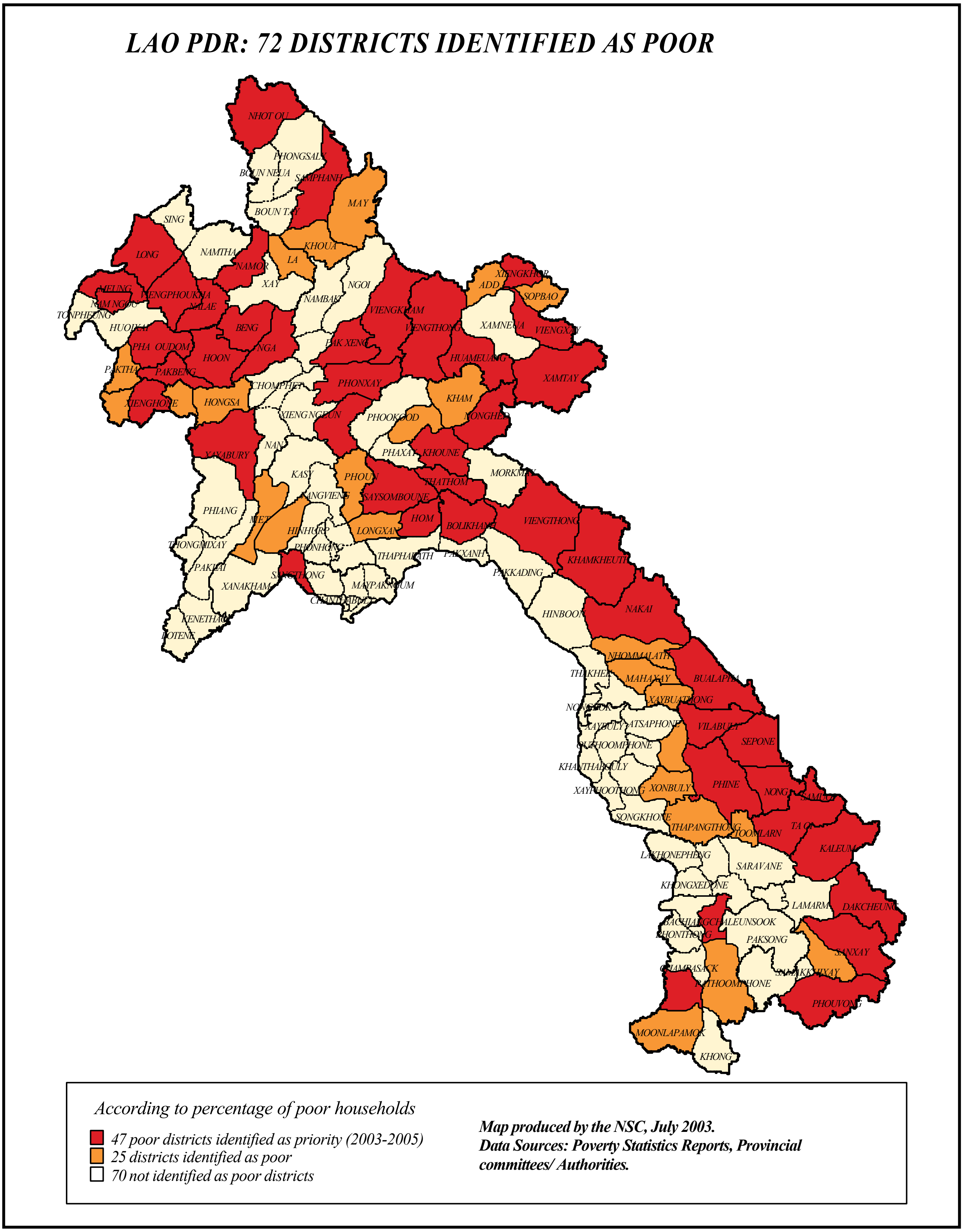
DOS district poverty classification

As mentioned, the two district poverty maps compared here are based on different approaches. Although both assess district poverty levels at a similar time period (the DOS map is based on data collected in 2001/02, and our estimates are based on LECS III of 2003 and the Population Census data of 2005), the definitions of poverty are different. Our definition of poverty uses the welfare indicator of the value of per capita consumption expenditure, including the value of subsistence food production and the imputed rental value of owner occupied housing. In contrast, DOS uses a broader definition based on a set of household, village and district level indicators of basic minimum needs as its welfare indicator. Poverty was defined at the household, village, district and provincial levels based on a set of criteria. For example, household welfare depends on adequacy in food, clothing, housing, schooling, health care and income. Based on the resulting indicator, the Government of the Lao PDR identified 47 poor priority districts and 25 poor districts out of a total of 139 districts in its NGPES (Lao People's Democratic Republic, 2004). In 39 of these first priority districts, at least 50 percent of the households are poor according to the household poverty criteria.

Figure 24 maps those first and secondary priority poor districts. Comparing this map to our map of district poverty rates (Figure 5), the general spatial patterns are rather similar, with most districts in the mountainous parts of the southern Lao PDR along the border with Vietnam being identified as first priority districts, and some areas of the northern uplands being poor, too. Indeed, almost all first priority districts appear orange or red in our map, indicating that at least 50 percent of the households are poor. Equally, most secondary priority districts appear yellow or orange in our map, indicating poverty rates of 30 to 60 percent.

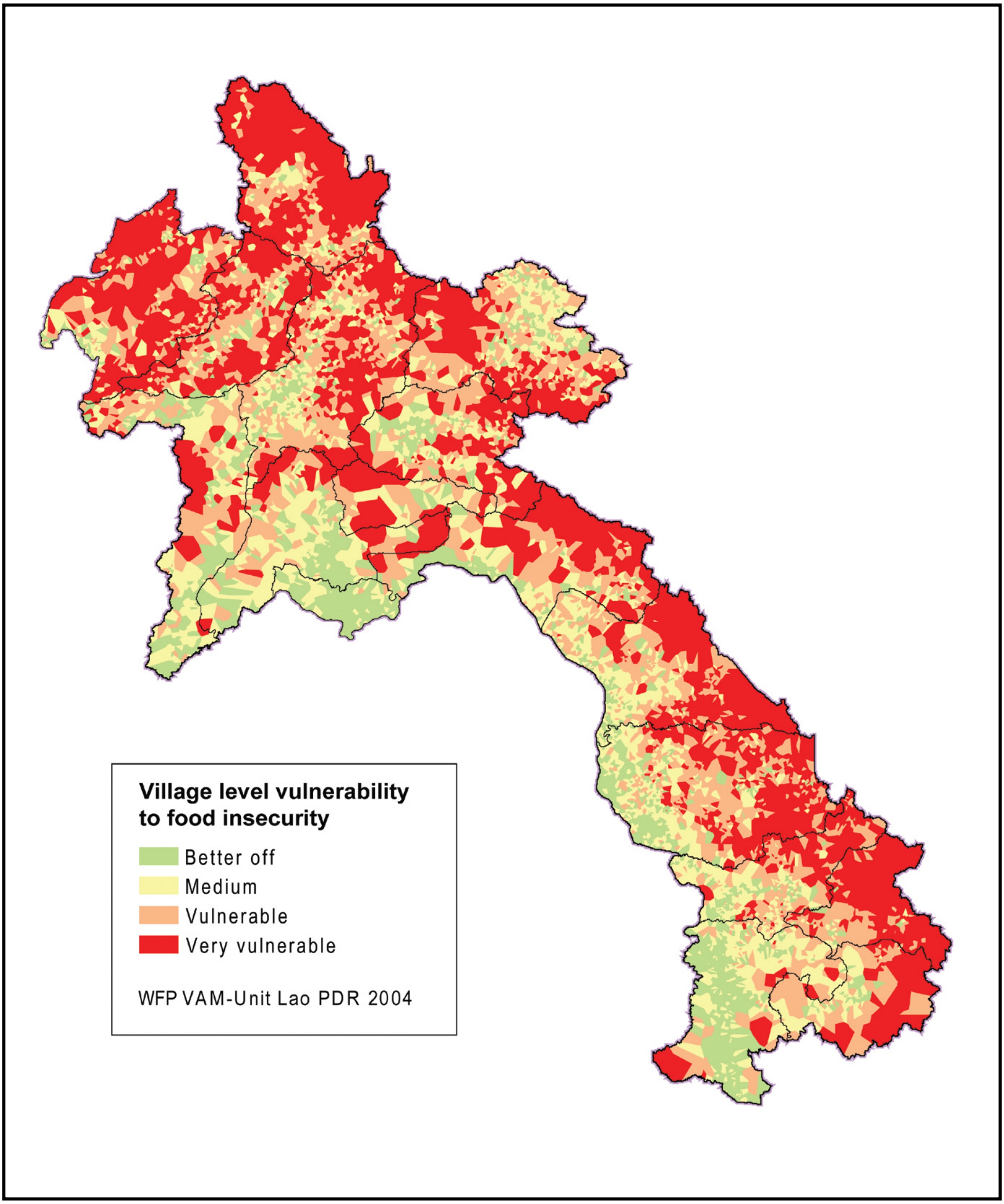
A closer look at the two maps, though, reveals a few cases where the estimates are very different. Sangthong district in Vientiane Capital City, Pek

Figure 24. DOS district poverty map



Source: Lao People's Democratic Republic, 2004.

Figure 25. Map of village-level vulnerability to food insecurity



Source: United Nations World Food Programme (WFP), 2004 district in Xiengkhuang province and Khop district in Bokeo province have relatively low poverty rates according to our estimates, but are classified as first and secondary priority districts using the DOS method. Conversely, there are two districts that have a poverty rate of just over 50 percent in our estimates, but were not classified as priority districts in the DOS map: namely Mok-Mai district in Xiengkhuang province and Atsaphon district in Savannakhet province. Nevertheless, the rather good agreement of the two maps, despite the very different methodologies, is reassuring. Although the NGPES emphasises that the poverty reporting and assessment system is still in its infancy in the Lao PDR, our results certainly add credibility to the DOS map.

WFP vulnerability and food insecurity analysis

An alternative source of spatially highly disaggregated information on welfare is the World Food Programme (WFP) Vulnerability and Food Insecurity Analysis (United Nations World Food Programme, 2004). Although certainly closely related, vulnerability and food insecurity are not the same as poverty. Furthermore, the methodology used to produce the vulnerability map is very different from the small-area estimation method used in this study. The vulnerability and food insecurity index is based on a principle component analysis of a variety of indicators considered representative of food security that were derived from the Population Census 1995 and the Agricultural Census 1997/98. Nevertheless, in view of the scarcity of spatial information on welfare aspects in the Lao PDR, here we take a comparative look at the village vulnerability and food insecurity WFP map (Figure 25) and our map of village-level poverty incidence (Figure 9). Again, the overall patterns of welfare distribution in the Lao PDR correspond well: vulnerability and food insecurity tends to be greatest in villages with a high poverty rate. This agreement between the two maps is particularly strong in the southern part of the Lao PDR. In the northern part, the agreement between the two maps is still reasonably good, although the differences are more obvious in the south. Many villages in the far north (particularly in Phongsaly and Luangnamtha provinces) are classified as very vulnerable, while the corresponding villages' poverty rates are not as high as in the southern 'very vulnerable' villages, although this can also be partly an artifact of the fewer classes used in the WFP map. Perhaps the biggest differences between the two maps can be found in the northern part of Xayabury province, where most villages of Hongsa and Ngeun districts are classified as not very vulnerable, but have poverty rates of around 50 percent.

However, it is reassuring that despite the differences in conceptual approach, indicator definition, methodology and data sources, the two results agree with each other very well. Vulnerability and food insecurity in the Lao PDR appear therefore to be closely related to household welfare.

SECTION 4:

GEOGRAPHIC DETERMINANTS OF POVERTY

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GEOGRAPHIC DETERMINANTS OF POVERTY

The poverty maps presented in Section 3 show considerable geographic variation among provinces, districts and villages in the Lao PDR. In particular, the incidence of poverty is highest in the upland areas of the Lao PDR bordering Vietnam and lowest in urban centres, fertile lowland plains, and along parts of the Thai border. This section uses the village-level poverty estimates described in Section 3 to investigate the extent to which geographic variables may have an effect on the incidence of poverty in a village.

4.1 Geographic factors

Table 10 lists a number of geographic factors that may help to explain the spatial patterns of poverty in the Lao PDR, but which are unlikely to be affected themselves by the level of poverty in a given village. For example, environmental factors such as rainfall or topography may influence poverty, but they are not influenced by poverty. The only variable group where there may be some reverse causation is accessibility, measured in travel time to urban areas and rivers. Such potentially endogenous variables may both influence poverty and be influenced by it (at least in the long run). For example, areas with low poverty rates may attract more (private) investments in markets, and transport infrastructure is determined at least in part by the level of economic activity, so that a low poverty rate may influence the density of markets and roads in the long run. The rather low level of economic activity

Table 10. Environmental factors that may affect poverty rate

Variables	Expected relationship to poverty		
Elevation	Higher elevation	→	higher poverty
Roughness	Rougher terrain	→	higher poverty
Slope	Steeper slopes	→	higher poverty
Soil Suitability	Less suitable soils	→	higher poverty
Mean annual temperature	Lower temperatures	→	higher poverty
Temperature variability	Not known		
Annual temperature extremes	Greater temperature extreme	→	higher poverty
Annual rainfall	Not known		
Rainfall seasonality	Not known		
Length of growing period (LGP)	Shorter growing period	→	higher poverty
Accessibility to towns and rivers	Better access	→	lower poverty

in most of the rural parts of the Lao PDR until fairly recently, however, implies that rural infrastructure development is not likely to have been directly affected by welfare levels in a given area. We therefore consider those measures of accessibility, which are very strongly influenced by the local terrain, as exogenous variables. The right-side column of Table 10 shows the expected relationship between each variable and poverty.

In order to carry out a regression analysis, the agro-climatic factors in Table 10 must be expressed as specific variables. Section A.6 of the Annex provides an overview of the variables prepared for the analysis. Due to strong collinearity among several independent variables, a sub-set of the full list was chosen for the regression analysis[16]. Furthermore, variables with insignificant coefficients were omitted from the final models. The individual models are discussed in the remainder of this chapter.

Using a Chow test, we determined that the coefficients explaining urban and rural poverty were significantly different from each other, indicating that separate urban and rural models would be preferable. For example, we expect soil suitability, rainfall and temperature to matter more in rural areas, where the majority of households depend on agriculture as their main source of income. We therefore estimate separate models for urban and rural areas.

4.2 Estimation issues

Figure 9 indicates that, poverty rates in nearby villages are likely to be similar to one another, so it is important to pay attention to the structure of spatial dependence in our data. Failure to do so can result in inconsistent or biased estimates of the impact of different geographic variables. The spatial econometrics literature makes a distinction between two types of spatial dependence:

i. Spatial error dependence, in which unobserved explanatory variables are correlated over space. An example of this would occur if, because of provincial policies and budgets, the quality of local health care were similar across all districts in a province but different across provinces. When there is spatial error dependence, ordinary least squares regression coefficients will be unbiased but not efficient (the standard errors will be larger than they would have been if all information had been used).
ii. Spatial lag dependence, in which the dependent variable in one area is directly affected by the values of the dependent variable in nearby areas. An example would be if the poverty rate in one area were directly affected by poverty in nearby districts. When there is spatial lag dependence, ordinary least squares regression coefficients are biased and inconsistent.

Whenever spatial error or spatial lag dependence is indicated, special types of regression models need to be applied. In the case of spatial error dependence, the spatial error model is appropriate, whereas in the case of spatial lag dependence, the spatial lag model is used[17]. In both cases, the researcher must specify the structure of spatial

[16] Elevation, for instance, was closely correlated to annual mean temperature (with a Pearson correlation coefficient of above 0.9); further investigation showed a higher explanatory power of the temperature variable, so that the variable on elevation was dropped.

[17] See Anselin (1988) for a description of these models.

weights describing the neighbourhood relationship of observations to each other. The resulting weight matrix defines the functional form of the weights as a function of distance or contiguousness of neighbouring observations.

Our estimation strategy was as follows. First, we estimated an ordinary least square (OLS) model. Second, we performed tests for the two types of spatial dependence. Third, based on the results of the spatial dependency tests, we used either the spatial error or the spatial lag model to re-estimate the model using maximum likelihood (ML). Based on a visual inspection of the spatial patterns, we adopted second-order queen contiguity weights. First-order queen contiguity means that one takes into account the potential influence of all surrounding villages that have a common border or vertex with the village of interest, similar to the movement of the queen in chess (Anselin, 1988). Our second-order queen weights take into account all adjacent villages as well as villages adjacent to those villages[18].

4.3 National model of rural poverty

Table 11 shows the results of the tests which were conducted for spatial dependence when an ordinary least squares model was estimated with the rural village-level poverty rate as the dependent variable and a set of environmental variables as the explanatory variables (Table 12). As discussed above, second-order cumulative queen contiguity weights were used to perform this test[19]. Both the Moran's and the Lagrange multiplier test statistic reject the null hypothesis of no spatial dependence. The much larger Lagrange multiplier in the spatial error model indicates that this type of spatial dependence is more likely (see Section A.5 of the Annex for more information on these tests). We therefore proceeded to estimate a spatial error model to analyse the determinants of rural poverty.

Table 11. Diagnostic tests for spatial dependence in urban poverty

Test	Statistic	df	p-value
Spatial error model:			
Moran's I	141.02	0.51	0.000
Robust Lagrange multiplier	4051.30	1	0.000
Spatial lag model:			
Robust Lagrange multiplier	333.42	1	0.000

Table 12 shows the results of regressing village-level rural poverty rates on the selected set of environmental variables using a spatial error model. The rural model consists of 11 explanatory variables, plus eight interaction terms with the village road access variable. The Pseudo R^2 is 0.69, indicating that the model "explains" the data fairly well. The spatial lag coefficient (λ) is positive, large (close to 1.0), and statistically significant. This suggests that the error terms of nearby villages are strongly and positively correlated with each other (see equation 17 for the interpretation of λ). In other words, the similarity of the poverty rates in neighbouring villages suggests that there are

[18] In order to be able to calculate contiguity of the villages, we divided the area of the country into Thiessen polygons around each village GPS point. Thiessen polygons are delineated at the equidistance between two nearest points.

[19] We carried out the analysis with other commonly used forms of contiguity weighting, and the results were similar.

spatial factors not included in the model that affect poverty. Possible examples include the quality of local governance, security, cultural factors, and variation in climate or soil that are not picked up by our indicators.

Of the 19 coefficients, 14 are statistically significant at the 1 percent level. It may seem surprising that, for instance, soil suitability was not statistically significant (and was therefore not included in the final model), but this may be because slope and climatic variables are included in the model. In other words, soil suitability in the Lao PDR might be determined largely by slope and rainfall.

The two slope variables (share of flat land and share of land with gentle slopes) are both statistically significant. Since the omitted category is sloping land (more than 7.5 percent slope), these results indicate that villages with a large area of

Table 12. Spatial error model of the geographic determinants of rural poverty

Rural spatial error model				
Mean of dependents	0.433688	# of observations	9178	
S.D. of dependents	0.189638	# of variables	20	
Lag coeff. (Lambda λ)	0.887993	df	9158	
Pseudo R^2	0.688312	Log likelihood	7207.376387	
Sigma-square	0.011209	AIC	-14374.8	
S.E. regression	0.105873	Schwarz crit.	-14232.3	
Variable	Coefficient	Std. error	z-value	
Standard deviation of elevation	0.00176	0.00312	0.56	
% flat area	-0.00174	0.00013	-13.23	***
% gently undulating area	-0.00080	0.00016	-5.13	***
Mean annual temperature	-0.00034	0.00020	-1.71	*
Annual temperature range	-0.00316	0.00055	-5.78	***
Annual rainfall	-0.00011	0.00002	-5.34	***
Seasonality of rainfall	0.00609	0.00114	5.36	***
Travel time to major rivers	0.00492	0.00093	5.29	***
Travel time to urban areas	0.00093	0.00084	1.12	
Length of growing period (LGP)	0.00169	0.00051	3.31	***
Village has road access	-0.91597	0.15926	-5.75	***
Village road access * Std. dev. elevation	0.01322	0.00406	3.26	***
Village road access * Mean ann. temp.	0.00088	0.00017	5.25	***
Village road access * Ann. temp. range	0.00049	0.00026	1.91	*
Village road access * Ann. rainfall	-0.00002	0.00001	-1.94	*
Village road access * Rain seasonality	0.00283	0.00079	3.58	***
Village road access * Time to major river	0.00273	0.00114	2.38	**
Village road access * Time to urban areas	0.00288	0.00087	3.32	***
Village road access * LGP	0.00140	0.00035	4.04	***
Lambda (λ)	0.88836	0.00779	114.03	***
Constant	0.47418	0.23717	2.00	**

flat or near-flat land will have lower poverty rates than those with sloping lands. This is not surprising given the difficulties of cultivating and irrigating sloping land, as well as problems associated with soil degradation on steep land.

The analysis includes three accessibility variables: travel time to major rivers, travel time to urban areas, and the binary variable indicating whether or not the village has road access. All three variables are statistically significant, although the travel time to towns is significant only for villages with road access. The positive coefficient means that the rural poverty rate is higher in villages with greater travel times to urban areas and to major rivers. Lower poverty in closer proximity to towns possibly reflects the benefits of better access to the various services typically provided in towns, including access to markets. The pro-poor effect of living closer to large rivers includes better access to irrigation water and possibly better access to fertile land with alluvial soils along the major rivers. The latter might be an effect not captured by the soil suitability variable, which is, as mentioned, not significant in our national rural analysis.

Among all the different variables in our model, the village road access variable has by far the strongest influence: taking into account the effect of the interaction terms[20], the model indicates that having road access to the village decreases the village poverty rate by 19 percentage points, holding other factors constant. On the one hand, this highlights the value of building roads to villages in terms of poverty reduction. Presumably, roads allow farmers to sell their crop surpluses at better prices, buy inputs and consumer goods at lower prices, and perhaps earn wage income in other parts of the country. On the other hand, these results suggest that, in the meantime, anti-poverty programs need to reach villages without roads to be effective.

The interaction terms indicate that the benefits of having a road to the village are smaller if the village is hilly (as indicated by the standard deviation of altitude), if the average temperature is high, if rainfall is highly seasonal, if the village is far from a major river, if the village is far from an urban area, or if the village has a long growing season. Some of these results suggest that good agricultural growing conditions have a more positive effect on standards of living if at the same time roads are available to provide a market outlet.

Among the four climatic variables, three are statistically significant at the 1 percent level, and one (annual temperature mean) is significant only at the ten percent level. The negative sign of the annual rainfall coefficient indicates that high annual rainfall is associated with lower poverty rates, whereas greater rainfall seasonality is linked to higher poverty rates. The annual mean temperature is negatively related to village poverty rates, indicating that areas with higher annual temperatures tend to have lower poverty rates, a pattern that may reflect the highland-lowland differences in climate and welfare. Other temperature variable coefficients are less conclusive. The relationship between temperature variability and poverty is not significant, and, it is not immediately obvious why annual temperature range, measuring temperature extremes over the year, is negatively related to poverty.

The coefficient of the length of growing period (LGP) is significantly greater than zero, suggesting that a longer growing period relates to higher poverty rates, particularly in rural villages with road access. At first, the reason for this is not immediately apparent. However, if the spatial distribution of LGP and poverty patterns in the Lao PDR are considered it becomes clearer; the mountainous parts in the south have a longer growing period than most of the rest of the Lao PDR, an area that coincides spatially with the highest

[20] The influence of village-level road access can be calculated as follows. If the interaction variables are V_i and the interaction coefficients are B_i, then the effect of road access on poverty is the road access coefficient plus the sum of (B_iV_i). Standard practice is to use the mean values of the V_i.

[21] If the explanatory variables in a regression equation are affected by the dependent variable, then coefficients estimated with ordinary least squares regression will be biased and will not reflect the effect of changes in the explanatory variable on the dependent variable.

poverty rates of the country (see Figure 26). Therefore, the theoretical climatic limitations defining the LGP are not the limiting factors in those areas, but rather other factors such as terrain and soil quality (which, however, does not come out significantly in our model).

Having developed this model of rural poverty, we then tested to see if the inclusion of any variables describing the basic demographic characteristics would increase the explanatory power of the models. In theory, adding such variables may cause problems of simultaneity[21]. The addition of three variables describing the share of the population below the age of 5, between the ages of 5 and 15, and the percentage of the population aged over 60, to the rural poverty model increases the explanatory power (R^2) by about 10 percentage points. Adding dummy variables for the nine agro-ecological regions of the Lao PDR, on the other hand, increases the explanatory power of the rural model by less than one percentage point despite the individual and joint significance of these variables. This leads us to the following conclusions:

a. While the agro-ecological regions provide significant, but comparatively little additional information to the model about the environmental settings in the different parts of the Lao PDR, the selected environmental variables manage to describe the agro-ecological differences across the country reasonably well.
b. The inclusion of just three basic demographic variables manages to increase the explanatory power of the model significantly. Demographic factors are playing a significant role as determinants of poverty.
c. The remaining 'unexplained' portion of the variation in rural poverty is likely to be due to mainly socio-economic aspects, rather than to environmental characteristics.

Based on the finding that dummy variables for the nine agro-ecological regions are all significant in the models, we will analyse in the next section the spatial variation in the coefficients of this rural model (see Section 5).

It is no surprise that agro-climatic variables affect rural poverty. Poverty in rural areas is closely related to agricultural productivity and market access. The climate, slope and soil quality all have direct effects on agricultural productivity. Similarly, travel costs to towns and cities is one (admittedly crude) indicator of market access, which affects not only the choice of agricultural products that make sense to produce, but also the prices farmers receive for their output and the prices they pay for inputs. But it is somewhat surprising that these variables explain a rather high percentage of the variation in rural poverty across villages.

4.4 National model of urban poverty

As with rural poverty, we first tested for the type of spatial dependence when an unrestricted ordinary least squares model is estimated with the village-level urban poverty rate as the dependent variable and the environmental variables the explanatory variables. We used a set of independent variables very similar to those used for the rural models, with the exception of the variable measuring accessibility to urban areas, for which we

Table 13. Diagnostic tests for spatial dependence in urban poverty

Test	Statistic	df	p-value
Spatial error model:			
Moran's I	28.448	0.46	0.000
Robust Lagrange multiplier	475.10	1	0.000
Spatial lag model:			
Robust Lagrange multiplier	0.1	1	0.650

substituted 'accessibility to urban areas' with 'accessibility to urban areas with a population of at least 5,000 people'[22]. Table 13 shows the results of the diagnostic tests for spatial dependence (second-order cumulative queen contiguity weights were used to perform this test). The results from the tests are rather conclusive: for the urban model, there is very clear evidence for preferring the spatial error rather than the spatial lag model.

The model of village-level urban poverty gives a relatively good fit with the observed patterns in urban poverty, though the fit is not as good as that for rural poverty (see Table 14). This indicates that urban poverty is somewhat harder to explain with geographic variables alone than is rural poverty, which is what one would expect. That environmental factors have a significant influence on urban welfare, however, is rather surprising.

Indeed, seven out of our nine explanatory variables have coefficients that are statistically significant at the one percent level, and one is significant at the five percent level. Although none of the rainfall variables were significant in the urban model, the coefficient of mean annual temperature is significantly positively related to poverty, indicating that urban areas with higher temperatures tend to have higher poverty rates, a pattern opposite to that found for rural areas. Annual temperature variability is also positively related to poverty, although a greater annual temperature range relates to lower levels of urban poverty, a finding that largely corresponds to the results of the rural model.

While these climatic influences on urban poverty are less easy to explain, the coefficients of terrain and accessibility are more easily explainable: both higher terrain roughness and a lower proportion

Table 14. Spatial error model of the geographic determinants of urban poverty

Urban spatial error model				
Mean of dependents	0.212676	# of observations	1279	
S.D. of dependents	0.093399	# of variables	10	
Lag coeff. (Lambda λ)	0.627752	Df	1269	
Pseudo R^2	0.547121	Log likelihood	1660.174	
Sigma-square	0.003951	AIC	-3300.35	
S.E. regression	0.062854	Schwarz crit.	-3248.81	
Variable	**Coefficient**	**Std. error**	**z-value**	
Std. elevation	0.00753	0.00407	1.85	*
% flat	-0.00072	0.00020	-3.59	***
% gently undulating	0.00067	0.00029	2.33	**
Mean ann. temperature	0.00211	0.00032	6.64	***
Std. temperature	0.00005	0.00001	3.64	***
Ann. temperature range	-0.00104	0.00031	-3.38	***
Acc. to major river	0.00472	0.00094	5.01	***
Acc. to urban areas pop. >5k	0.00226	0.00079	2.85	***
Acc. to urban areas pop. > 50k	0.00231	0.00089	2.58	***
Lambda (λ)	0.62775	0.02270	27.66	***
Constant	-0.27185	0.09286	-2.93	***

[22] The variable on rural road access and the respective interaction terms are not applicable in the urban model.

of flat land are related to higher urban poverty. And greater proximity to major rivers, towns of a population of at least 5,000 people, and to large towns with a population of 50,000 and more, all relate to lower urban poverty. The latter two imply that larger towns tend to have lower poverty rates compared to smaller urban places. This is in contrast to the rural model, where distance to major towns with a population of over 50,000 was not significant. This indicates that living close to large centres of demand is more important to producers of non-agricultural products and services than for rural agricultural producers. It may also mean that services available in larger towns only are of greater relevance to residents in small towns than to rural households.

The two most typical agro-ecological variables of LGP and soil suitability are both not significant in our urban poverty model.

The explanatory power of the model also improves when adding variables to control for basic demographic characteristics, as well as when adding dummy variables for the regions. While the addition of three basic demographic variables improves the model performance by ten percentage points, adding region dummies only adds about one percentage point of explanatory power. Again, this implies that our environmental variables describe reasonably well the environmental variation across the country that directly influences urban welfare, and the unexplained variation is likely to be due to socio-economic aspects not reflected in our models.

It is no surprise that there is a close link between environmental aspects and those industries and services which drive urban productivity. In urban areas the clustering of industry, patterns of employment and availability of complementary infrastructure are crucial. Nevertheless, the fact that many environmental variables have a significant influence on urban poverty in the Lao PDR possibly reflects the strong linkages between the economic activities in urban areas and the agricultural conditions in surrounding rural areas.

SECTION 5:

SPATIAL VARIATION IN THE DETERMINANTS OF RURAL POVERTY

SECTION 5:
SPATIAL VARIATION IN THE DETERMINANTS OF RURAL POVERTY

Section 4 described the results of an analysis of the linkages between the spatial distribution of poverty and some agro-ecological and market access variables based on "global" regression models. These models are "global" in the sense that they describe the relationship between poverty and geographic variables in the Lao PDR as a whole. In other words, the global model assumes that the relationships described by the coefficients apply in the same way across the country.

However, one would expect these relationships to be dependent on location and therefore to vary over space. Indeed, an almost universal feature of spatial data is the variation in relationships over space – a phenomenon generally referred to as spatial non-stationarity or spatial drift. The problems of spatial non-stationarity and of spatial dependence are closely related; the error terms of global regression models will show spatial auto correlation if applied to data with spatially varying relationships, since the global model can only describe universal relationships.

This section presents the results of an analysis of the spatial variation in relationships between rural poverty as the dependent variable and a set of agro-ecological and accessibility variables as the independent variables. We tried, for example, to explore if the influence of rough terrain exerts an equal constraint across the country, or if the pro-poor effect of a village with road access is stronger in some parts of the country than in others. We applied a spatially-weighted local regression model to this analysis. Based on the hypothesis that the nearer things are to each other then the closer is their relationship, the local spatially-weighted regression models were specified so that separate regressions were estimated for each village, using all the observations, but decreasing importance was given to those observations at an increasing distance from the respective regression location. In a society with considerable socio-cultural differences between high and low land communities we would expect vertical distance (altitude) to matter more than horizontal distance. For example, a highland village A on the northern slope of a valley could be expected to be more similar to another highland village B on the southern slopes of the same valley than to the lowland village C in the bottom of the valley between the two upland villages.

Although the horizontal distance between A and B is greater than the distances between A and C and between B and C, we expect A and B to be more similar than either of those two to C, based on their similar altitude. We therefore applied a spatially weighted model which takes into account both the horizontal and the vertical distances, with individual distance decay functions for both weight components (see Annex, Section A.5 for a description of the weighting scheme).

5.1 Spatially weighted model of rural poverty

The village-level estimates of rural poverty (P_0), as the dependent variable, are regressed on the same explanatory variables as used in the rural model presented in Section 4.3. The spatial distributions of the

Table 15. Significance of spatial variations in parameter estimates

Variable	P-Value	
Std. elevation	0.060	*
% flat	0.000	***
% gently undulating	0.000	***
Mean ann. temperature	0.000	***
Ann. temperature range	0.000	***
Ann. rainfall	0.000	***
Rain seasonality	0.000	***
Travel time to major rivers	0.000	***
Travel time to urban areas	0.000	***
Length of growing period (LGP)	0.000	***
Village has road access	0.000	***
Village road access * Std. elevation	0.080	*
Village road access * Mean ann. temp.	0.000	***
Village road access * Ann. temp. range	0.000	***
Village road access * Ann. rainfall	0.000	***
Village road access * Rain seasonality	0.000	***
Village road access * Time to major river	0.040	**
Village road access * Time to urban areas	0.100	
Village road access * LGP	0.000	***

Note: *** significant at the 1 percent level,
** significant at the 5 percent level
* significant at the 10 percent level.

values of the individual variables (excluding the interaction terms) are shown in Figure 26[23].

We estimated the regression parameters for each village, taking into account all other observations (villages), but with decreasing weight with increasing vertical and horizontal distances. The regression points are those locations for which the local parameters are estimated (the village GPS points), and from which the other observations are weighted with decreasing weight the further away (horizontally and vertically) they are. For the calculation of the spatial weights for the local regression models, we applied a vertical bandwidth of 20m and a horizontal one of 300km[24] to the distance decay function (see Annex, Section A.5)[25]. We used ordinary least square (OLS) models in this analysis. Spatial dependency issues discussed in the previous chapter are minimized by the local spatially weighted nature of the applied model, where spatial auto correlation is largely accounted for by allowing the regression parameters to vary over space, rather than by including a spatial error term. Indeed, instead of attempting to control for spatial dependencies, the spatially weighted analysis models observed the spatial dependencies.

Significance tests based on Monte Carlo simulations, where the spatial distribution of the observations are randomised and the local models re-estimated in 100 permutations, were used to test whether the observed spatial variations in parameter estimates were due to random variations or whether they reflect true spatial differences. The tests indicated significant spatial variation of the coefficients for all variables except for one interaction term (see Table 15), implying that a local spatially weighted model has the ability to describe the observed relationships better, underlining the validity of the applied local regression model.

Table 16 summarises the means and ranges of the local coefficients estimated by the spatially weighted models, together with the respective coefficients of the global models, estimated using ordinary least squares (OLS) for better comparison, as well as the maximum likelihood (ML) spatial error models, as presented in Chapter 4. Figure 27 shows the spatial

[23] The values for each village are depicted using Thiessen polygons, whereby the polygon area of each village is delineated at the equidistance between two adjacent/closest village GPS points.

[24] The east-west extent of the northern Lao PDR, and the north-south extent of the southern Lao PDR, both are approximately 600km.

[25] While there are numerous ways of identifying the 'optimal' bandwidth (see e.g. Fotheringham *et al.*, 2002) for a discussion of different criteria for eliciting bandwidth), we used an iterative process aiming at a bandwidth combination that maximizes the number of significant variables in local regressions across space.

Table 16. Summary results of local parameter estimates

	Global coefficients		Global coefficients			
Variable	ML spatial error	OLS	Mean	Std. Dev.	Min	Max
Std. Elevation	0.00176	-0.0057	-0.00425	0.00684	-0.01955	0.01616
% flat	-0.00174	-0.0016	-0.00113	0.00059	-0.00353	-0.00012
% gently undulating	-0.00080	-0.0001	0.00024	0.00148	-0.00238	0.00240
Mean ann. temperature	-0.00034	0.0009	-0.00071	0.00144	-0.00323	0.00199
Ann. temperature range	-0.00316	-0.0014	-0.00004	0.00131	-0.00414	0.00249
Ann. Rainfall	-0.00011	0.0000	-0.00009	0.00004	-0.00031	0.00000
Rain seasonality	0.00609	0.0000	0.00233	0.00098	-0.00025	0.00724
Travel time to major rivers	0.00492	0.0120	0.00968	0.00235	0.00370	0.01310
Travel time to urban areas	0.00093	0.0067	0.00565	0.00185	0.00163	0.00894
Length of growing period (LGP)	0.00169	0.0023	0.00265	0.00105	0.00039	0.00405
Village has road access	-0.91597	-1.4304	-0.82246	1.07735	-5.89888	0.58680
Vill. road access * Std. elevation	0.01322	0.0355	0.02513	0.00943	0.00989	0.04586
Vill. road access * Mean ann. temp.	0.00088	0.0017	0.00107	0.00110	-0.00135	0.00381
Vill. road access * Ann. temp. range	0.00049	-0.0004	-0.00020	0.00120	-0.00230	0.00476
Vill. road access * Ann. rainfall	-0.00002	-0.0001	-0.00003	0.00010	-0.00046	0.00023
Vill. road access * Rain seasonality	0.00283	0.0079	0.00429	0.00425	-0.00151	0.02788
Vill. road access * Time to rivers	0.00273	0.0037	0.00745	0.00176	0.00197	0.01199
Vill. road access * Time to towns	0.00288	0.0003	0.00093	0.00124	-0.00165	0.00636
Vill. road access * LGP	0.00140	0.0026	0.00024	0.00291	-0.00408	0.01363
R^2	0.68831 [25]	0.8920	0.90452	0.01719	0.85628	0.93668

Note: Coefficients in italics are not significant at the 10% level in the global model.

distribution of those local regression coefficients for each of the 19 explanatory variables. Although the general trend of the local coefficients corresponds largely to the coefficients of the global models, considerable spatial variation in local coefficient strength can be identified for almost all of the variables, and many of them have rather large ranges, often even including sign changes. Bluish shades represent positive relationships, and reddish shades are used for negative coefficients, with darker colours indicating the stronger coefficients. The strengths and signs of the individual variable's local coefficients are further discussed below.

Figure 28 depicts the spatial patterns of the significance of the local coefficients. Most of the variables' coefficients are significant (often at the 1 percent level) in large parts of the country, with smaller areas where the local coefficients are not significant. The map in the upper right of Figure 28 shows the local R^2 values obtained from the local regression analysis. The values of the local R^2 are mostly above the global score of a comparable global OLS model (0.892)[26], whereby the upland areas are generally

[26] The local OLS R^2 cannot directly be compared to the Pseudo R^2 of the global spatial error model presented in Section 4, which is based on a ML model.

better described by the local model than are the lowland regions. The local model performs 'only' equally, or slightly poorer compared to the global model mainly in the northern lowlands of the Lao PDR, indicated by the yellow areas on the map. This might indicate areas where important determinants of poverty might be missing from our model. The better performance of the local model in the uplands, however, is not too surprising, since one would expect agro-ecological and other variables, for example market access to have a stronger influence on human welfare in environmentally more difficult areas than in more accessible and less mountainous areas.

Turning now to the discussion of the individual local coefficients of the independent variables, we can identify several patterns. The top most row of maps in Figure 27 illustrates the spatial distribution of the local coefficients of our variables describing the relief: terrain roughness, and the percentage of flat and undulating land surrounding the village. Roughness is almost exclusively significant for villages with road access, since villages in rougher terrain tend to be poorer. Although this pattern is not significant in the south of the Lao PDR it is strongest in the uplands and the highlands. The proportion of flat land, on the other hand, is negatively related to poverty, and is strongest in the uplands and the highlands of the north and the south, indicating that the availability of flat land tends to have the strongest pro-poor effect in areas where flat land is particularly scarce. That this effect is particularly strong in the south is, however, likely to be, to some extent, an artifact of the spatial constellation there, where poor rugged upland areas are relatively close to the rich and fairly flat upland areas of the Boloven Plateau. Interestingly, the proportion of gently undulating land is positively related to the incidence of village-level poverty incidence in the south – except for the Boloven Plateau and the highest mountain areas in the southeast, and negatively in the north.

The middle row of maps in Figure 27 depicts the spatial patterns of the local coefficients of our climatic variables. Annual mean temperature is positively related to the incidence of poverty in the northeast, where higher poverty incidences tend to be associated with higher temperatures. It is also positively related in the central and southern parts of the country, but only in those villages with road access.

The annual temperature range, measuring the annual temperature extremes, is negatively related to poverty incidence in central Lao PDR and in the southern uplands, and positively in the southern lowlands and in the northern uplands. Greater temperature extremes appear to reduce poverty in the central and southern uplands, while this appears to be a limiting factor in the north. As for precipitation, in general, the more the better, but the less seasonal is its annual distribution, the better it is with regard to poverty. Both of these patterns are most pronounced in the southern part of the Lao PDR.

The local coefficients of the variables representing aspects of accessibility are depicted in the maps in the bottom row. As one would expect, travel time to towns is positively related to poverty incidence, implying that higher poverty rates are found in areas more remote from urban areas. This pattern is strongest in southern Lao PDR. Accessibility to major rivers is also particularly strongly related to the local incidence of poverty in the southern midlands and highlands, whereby higher access costs (greater distance) to large rivers corresponds to areas with higher poverty rates.

As in the global model, the length of growing period (LGP) is, somewhat unexpectedly, positively related to poverty incidence; the longer the growing period, the higher the poverty incidence. This unexpected outcome is most pronounced in the south. It is, however, significantly negatively related to poverty incidence in the northern villages with road access.

Spatial patterns in relationships between poverty and agro-ecological and market access variables show considerable variations over space. While some variables might be important positive contributors to poverty in one area, the same variables could have no, or even a negative effect, on poverty in other areas. A spatially explicit analysis approach helps to reveal local particularities that otherwise would not be obvious. Such information can be valuable for pro-poor policies that are differentiated by location.

Figure 26. Maps of the spatial distribution of the values of the dependent and independent variables

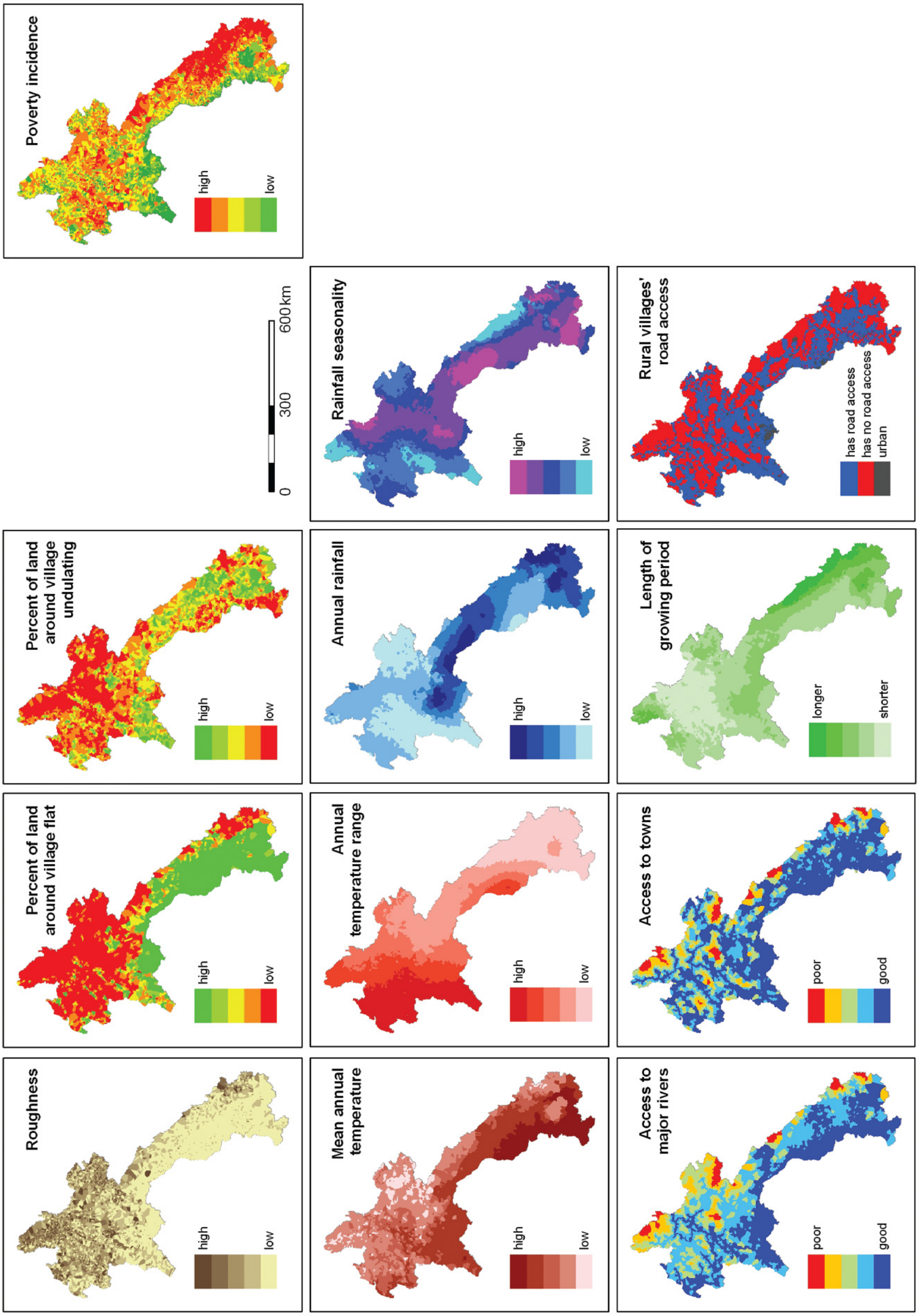


Figure 27. Maps of the spatial distribution of the local coefficients of the independent variables

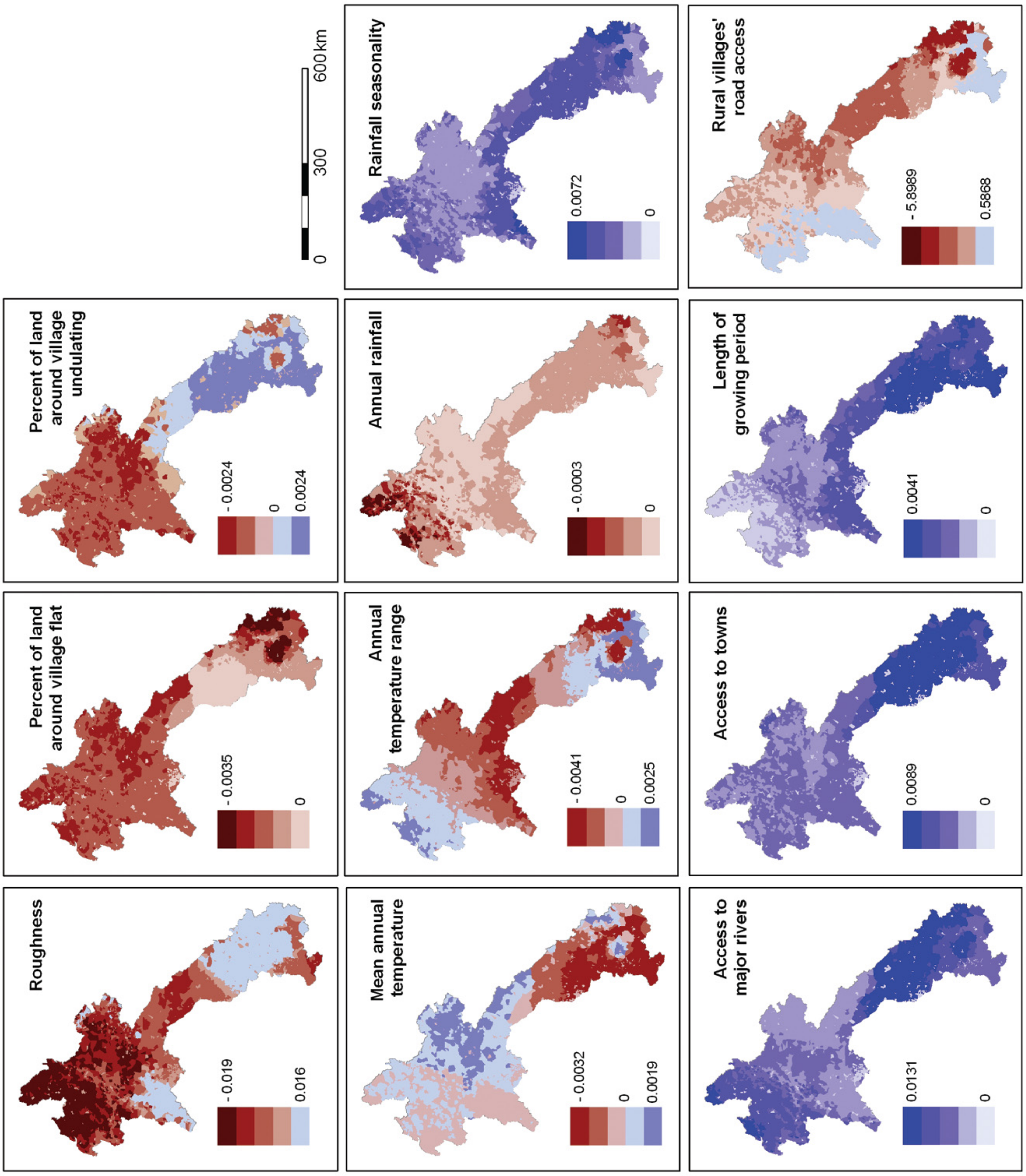


Figure 27. Maps of the spatial distribution of the local coefficients of the independent variables (cont.)

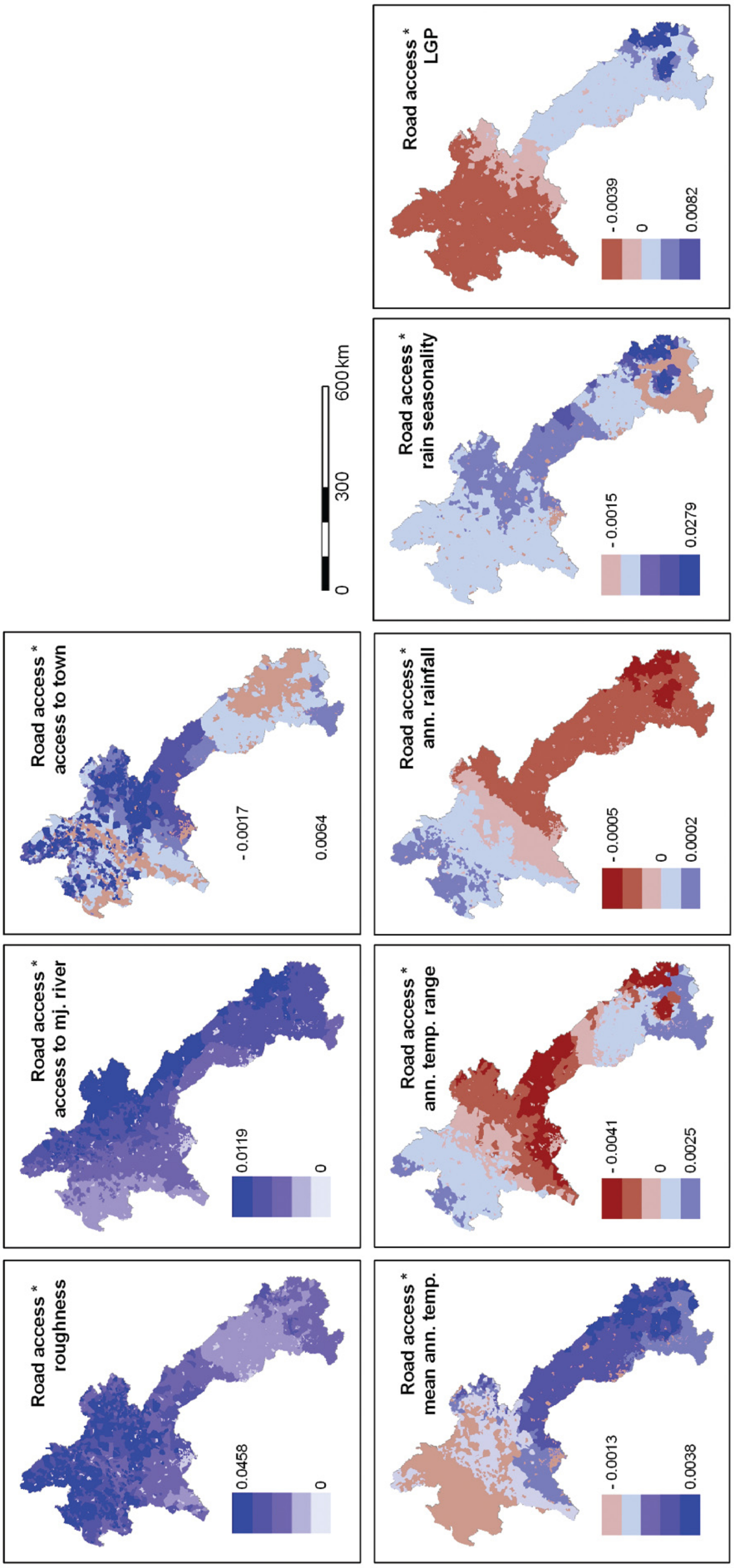


Figure 28. Maps of the spatial distribution of the local coefficients' significance (P>|t|), and the local model performance (local R²)

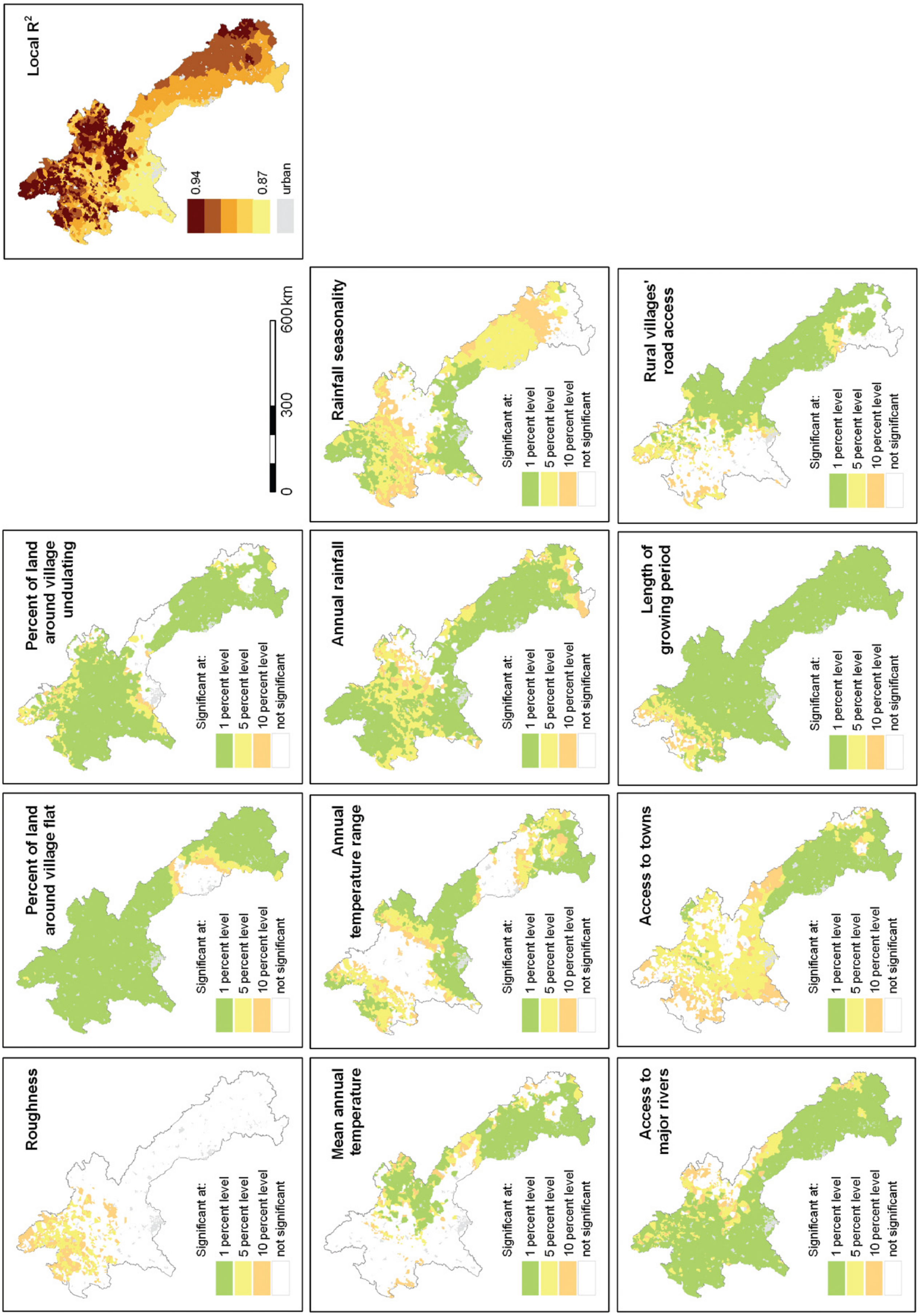
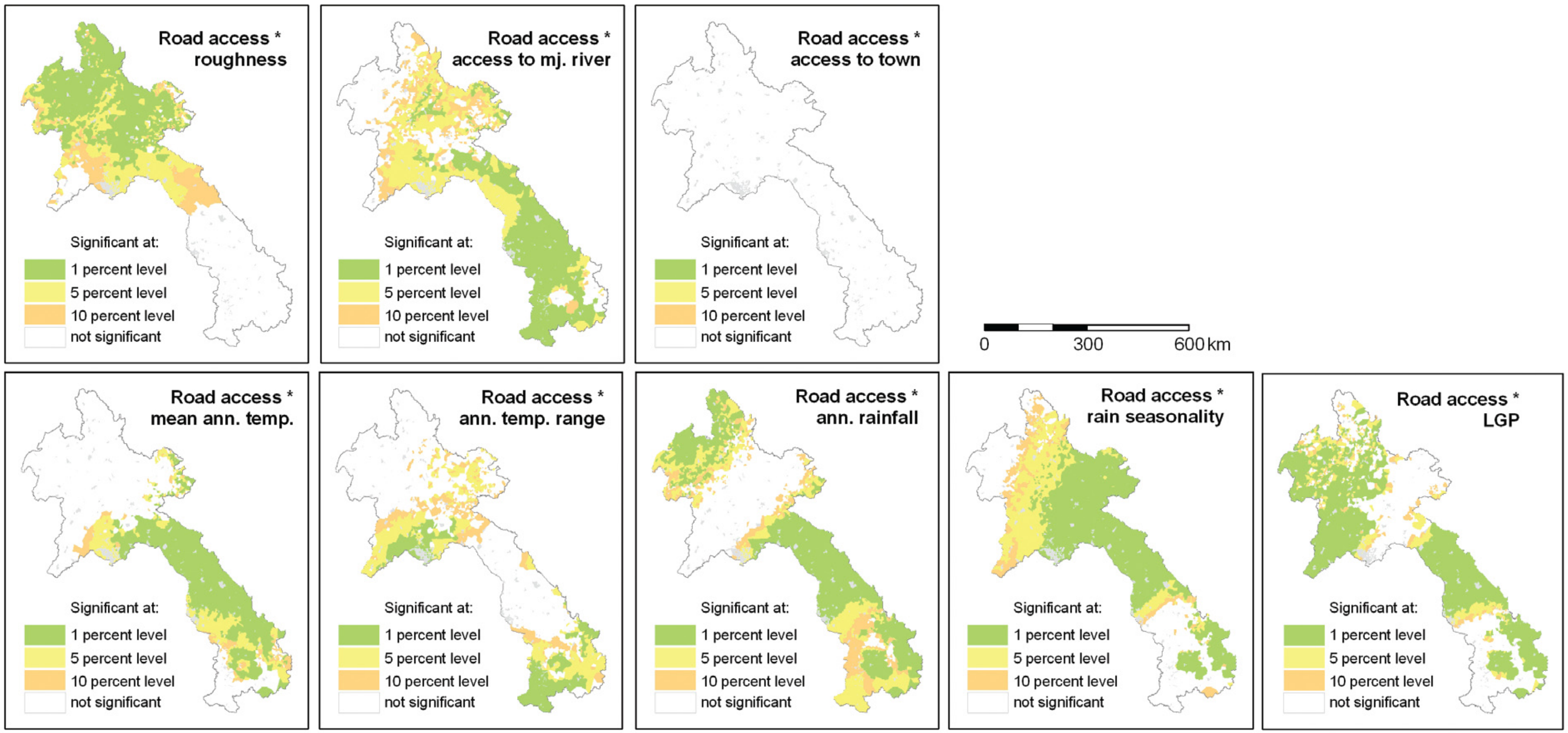


Figure 28. Maps of the spatial distribution of the local coefficients' significance (P>|t|), and the local model performance (local R^2) (cont.)



SECTION 6:

SUMMARY & CONCLUSION

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SUMMARY & CONCLUSION

This concluding chapter is divided into four sections. Section 6.1 provides a brief descriptive summary of the objectives, methods, and results of this report, and Section 6.2 draws a number of general conclusions. Although the main purpose of this study was to generate information on the patterns of poverty and inequality rather than address specific policy issues, Section 6.3 explores some of the implications of the findings for socio-economic policies and development programs. Finally, since the report raises as many questions as it answers, Section 6.4 describes some avenues for future research related to poverty and inequality in the Lao PDR.

6.1 Summary

Background and methods

Information on the spatial distribution of poverty and inequality is crucial as it assists policy makers and program designers by shedding light on the causes of poverty and so facilitating efforts to target poverty alleviation programs to the poorest regions. Information on the spatial patterns of poverty is particularly important in the Lao PDR because of the large regional disparities within the country and the government's strong commitment to the goal of reducing poverty and eliminating hunger.

Various household surveys carried out by the Department of Statistics (DOS) (formerly the National Statistics Centre (NSC)) provide information on the incidence of poverty at the regional and provincial levels, but these surveys cannot generate district or village level poverty estimates. DOS produces a list of the poorest districts ("priority districts") based on data collected from its officers in the field, but there are concerns regarding the criteria and methods used.

The objectives of this study therefore were 1) to explore the spatial distribution of poverty and inequality in the Lao PDR at the highest possible spatial resolution by applying small-area estimation methods to the national data sets, 2) to study the effect of agro-climatic variables and market access on poverty at the village level, and 3) to demonstrate the potential for new methods, including the small-area estimation method, to generate information of use to policy makers and development practitioners in the Lao PDR.

The small-area estimation method combines household survey data and census data to estimate a variable of interest (often poverty) for small areas such as districts. In the Lao PDR, data from the 2002/03 Lao Expenditure and Consumption Survey (LECS III) were used to estimate an equation describing the relationship between per capita expenditure and various household characteristics. The equation was then applied to data on those same household characteristics from the 2005 Population and Housing Census, generating poverty estimates for each household in the Census. These results were then aggregated to generate estimates of poverty and inequality at the village, district, and province level.

The study also examines the geographic determinants of poverty through spatial regression analysis. The dependent variable is the village-level poverty rate, while the explanatory variables include variables representing topography, soil, climate, and market access. Using spatially-weighted local regression models, we analysed the variation of the influence of those geographic determinants on poverty.

Spatial patterns in poverty and inequality

In the first stage of the analysis, an econometric model of per capita expenditure was estimated for urban and rural households using the 2002/03 LECS data. It has been shown that per capita expenditure is significantly related to household size and composition, education of the head of household and the spouse, housing characteristics, type of cooking fuel, type of toilet and place of residence (cf. Table 2 and Table 3). In general, the models explain a little more than one third of the variation in per capita expenditure in urban areas and about 43 percent of that variation in rural areas.

With regard to the spatial patterns in the incidence of poverty, the findings can be summarised as follows (cf. Figures 3, 5, and 9):

- Poverty rates (P_0) are highest in the south-central midlands and highlands along the border with Vietnam, as well as in the eastern parts of the lowlands of the south-central part of the Lao PDR. Somewhat lower poverty rates, but still above the national average, are found among people living in the northern mountains.
- Poverty rates are intermediate in the Mekong corridor and the northern lowlands.
- Poverty rates are the lowest in the Boloven Plateau and on the Vientiane Plain.
- Urban poverty rates are consistently much lower than rural poverty rates.
- The map of village-level poverty reveals the effect of mountains and even of roads on poverty rates.
- Regions in the vicinity of international borders seem to be influenced by the welfare or poverty of neighbouring countries.
- There is a relatively good correlation between these poverty estimates and other estimates of welfare in the Lao PDR.

The confidence intervals for the province and district level poverty estimates are reasonable; half the provinces have confidence intervals between ±2.7 and ±3.8 percentage points (cf. Figure 4), while half the districts have intervals between ±3.9 and ±5.6 percentage points (cf. Figure 6). However, the confidence intervals for poverty at the village level are wider, indicating less reliable estimates; half the villages have confidence intervals between ±12 and ±20 percentage points (cf. Figure 11). In other words the presented results may not be very reliable when looking at individual villages. Rather, the village level poverty estimates should be used to observe the very revealing and often detailed spatial patterns across the country (cf. Figure 9).

Two other poverty measures, the depth of poverty (P_1) and the severity of poverty (P_2), were estimated at the district level. These two measures were highly correlated with the incidence of poverty (P_0), resulting in very similar poverty maps.

The map of the density of poverty (the number of poor people per unit of area) reveals that the density of poverty is greatest where the incidence of poverty is lowest (cf. Figure 12). The regions with the highest poverty rates - the south-central midlands and highlands - are so sparsely populated that the number of poor people living there is relatively small. In contrast, the more densely populated cities and the Mekong corridor account for a greater absolute number of poor people despite their lower poverty rates.

This study also generated district level estimates of three measures of inequality in per capita expenditure: the Gini coefficient (cf. Figure 15), the Theil L index, and the Theil T index (cf. Figure 16). We can summarise the results as follows:

- The three measures of inequality were very highly correlated.
- Inequality was greatest in the urban areas and

- in the northern highlands.
- Inequality was the lowest in the poor south-central highlands and in the relatively well-off Boloven Plateau.
- Almost 90 percent of the inequality was within provinces rather than between provinces.
- About four-fifths of the inequality was within districts rather than between districts.

Examining the relationships among poverty, inequality, per capita expenditure, and the degree of urbanisation at the district level, the study found that:

- The district level poverty rate and average per capita expenditure in the district correlated with per capita expenditure explaining about 67 percent of the variation in inequality across districts.
- In general, higher per capita expenditure was associated with higher inequality, but some poorer districts also had very high levels of inequality.
- As the share of the population living in urban areas rises, the poverty rate declines.
- As the share of the population living in urban areas rises, the level of inequality rises up to a point, after which further urbanisation is associated with lower inequality. In other words, the districts with the highest levels of inequality are those with both urban and rural populations.

Geographic determinants of poverty

This analysis explored the geographic determinants of rural and urban poverty using spatial regression analysis (cf. Section 4). The dependent variable was the village-level incidence of poverty (P_0), and the explanatory variables included a wide range of variables: elevation, slope, soil suitability, rainfall, temperature, and distance to towns and cities. Separate models were used to estimate urban and rural poverty.

The following factors were positively linked to rural poverty: terrain roughness, rain seasonality, travel time to major rivers and to urban areas, as well as surprisingly the climatically potential length of the agricultural growing period (cf. Table 12). Availability of flatland, annual rainfall and annual temperature range are negatively related to the incidence of poverty at the village level. Mean annual temperature, temperature variability, travel time to a town of at least 50,000 inhabitants, and (surprisingly) soil suitability do not have statistically significant effects.

The urban model with the same explanatory variables had a much lower fit. This implies that urban poverty is much less affected by agro-climatic conditions and market access than rural poverty. Urban poverty was positively associated with terrain roughness, mean annual temperature, temperature variability, annual rainfall, travel time to major rivers, to towns of at least 5,000 inhabitants, and to cities with at least 50,000 inhabitants (cf. Table 14). Urban poverty was negatively associated with availability of flat land, annual temperature range, and rainfall seasonality. Soil suitability and the climatically potential length of the agricultural growing period were not significantly related to urban poverty

Spatial variation in the determinants of poverty

The nature of how agro-climatic and market access variables are related to poverty varies over space. This study applied a spatially weighted local regression analysis to explore the geographic variation in the relationships to the incidence of poverty of 13 explanatory variables (cf. Section 5).

The results of the analysis highlighted two points. Firstly, there were significant variations in the way that individual explanatory variables were related to poverty. In areas where poverty rates were comparatively low and agricultural production had already been intensified, the roughness of terrain was closely correlated to high poverty rates. Conversely, in remote uplands with rough relief the availability of flat lands played an important role in explaining lower poverty rates. Travel time to towns had the strongest positive association to poverty in those areas where poverty rates were lowest, and agricultural production was most intensive. Secondly, a model that allows for spatial variations in relationships better describes the complex relationship between poverty and the environment. The results of the analysis suggested that almost everywhere the local measures of goodness-of-fit were higher than the fit achieved by the global model, and that there were great differences over space in how the model was able to replicate the data. Generally, areas with rougher terrain achieved a better fit in the model, suggesting that agro-ecological conditions had a stronger influence on human welfare in those areas than in areas where environmental conditions were less difficult.

6.2 Conclusions

The spatial distribution of the poverty rates estimated in this study agree well with the district poverty classification produced by DOS, and also with the spatial patterns of the village vulnerability and food insecurity index developed by WFP. Although these two studies used different welfare definitions and different data, and different methods of data collection and analysis, it is reassuring that there is a good correlation among the various welfare measures estimated by the different methods.

Using the small-area estimation technique, it was possible, though, to show one important difference, which we did not perceive from DOS or WFP data: *Poverty in the south is generally much more accentuated than in many parts of the northern highlands.*

Poverty rates across districts and villages vary widely. One of the striking aspects of the poverty maps generated by this study is the accentuated disparities between districts and between villages. In some districts, particularly remote districts in the upland areas, over 70 percent of the population lives below the poverty line. In others, particularly in or near the larger urban centres, less than 15 percent of the population is poor (cf. Figure 9).

In spite of the wide variation in poverty rates across the country, the level of inequality is relatively low. One might expect a country with such wide variations in poverty to have a high degree of inequality, but the level of inequality in Lao PDR is relatively low by international standards (cf. Figure 15).

Inequality is not restricted to better developed areas such as urban and commercial farming areas. It is widely believed that in the Lao PDR (and in other developing countries) inequality is primarily associated with urban areas and rural areas characterized by commercial agriculture. This is based on the idea that inequality is the by-product of economic growth, as some households take advantage of new market opportunities and earn incomes much higher than average. Our findings confirm that inequality is greater in urban areas than in rural areas, but we also find that inequality can be comparatively higher in rural areas, even in areas characterized by sparse population and semi-subsistence farming (cf. Section 3.4).

Average per capita expenditures rather than inequality explain poverty of a district. Sixty-seven percent of the variation in district-level poverty rates can be explained by differences in average per capita expenditure, with differences in inequality accounting for just about one percent. The explanation is that inequality does not vary much from one district to another.

Most poor people live in the less poor areas. The density of poor people is lowest in areas with the highest poverty rate (such as the rural upland areas), while the poverty density is highest in areas with low poverty rates (such as cities and rural lowland areas of the Mekong corridor) (cf. Figure 9 and Figure 12). The absolute number of poor people that live in areas with high poverty rates is relatively low because the population density in these areas is also low. By contrast, most of the rural poor live in the lowland areas of the Mekong corridor. Although these areas have relatively low poverty rates compared to other rural areas, the population density ensures that most of the poor live in the Mekong corridor.

Agro-ecological factors and access to markets explain many of the differences in poverty of rural villages. While it is not surprising that agro-climatic factors and market access explain some of the variation in village level rural poverty, it is somewhat surprising that they explain a significant proportion of the variation (cf. Table 12). In contrast, considerably less of the variation in urban poverty can be explained by these factors (cf. Table 13).

6.3 Implications for policy and programs

The main objective of this study is to examine spatial patterns in poverty and inequality, with the idea that this information is useful for targeting poverty alleviation programs. The study was not designed to assess specific policy options for reducing poverty. The results do, however, provide some indirect implications for policy and programs. In this section, we discuss some of these.

Knowing where the poor are

First and foremost, this study provides for the first time detailed information on the spatial distribution of poverty. Careful attention should be given to this information when targeting poverty alleviation programs. Not only do the results provide information on the distribution of poverty in the Lao PDR, but they also provide information on the accuracy of these estimates. In addition, by generating information on alternative poverty measures, they allow program designers to target assistance to districts with the greatest depth or severity of poverty.

Assistance to poor areas or to poor people?

If most poor people live in less poor areas, what are the implications for targeting poverty alleviation programs? In particular, should poverty alleviation programs concentrate their efforts on areas with the greatest poverty density? The answers depend on the type of poverty alleviation program, as discussed below.

Some programs are relatively untargeted and lift the income of all households in an area. Examples of such programs might be better roads, better health care and financial support to local government. Assuming the program has a fixed cost per inhabitant, the program will have a greater effect on poverty if it is concentrated on poor areas. In these areas, a higher percentage of the population is poor so a higher percentage of the beneficiaries will be poor. In this way, the government achieves more poverty reduction per dollar spent. This is certainly true if the goal is to reduce the depth of poverty (P_1) and it is probably true if the goal is to reduce the incidence of poverty (P_0).

Other programs are targeted at poor households (e.g. income transfers, food for work, or social service fee exemptions). Areas with a high poverty density tend to coincide with a high general population density. Therefore, in those areas where many poor people live, there are also a large number of non-poor (such as in the Mekong corridor of the Lao PDR). Household-targeted poverty alleviation programs are therefore likely to be more appropriate in such areas. Although household targeting is typically more costly than areal targeting, the gains from excluding non-poor households from receiving poverty assistance are greater the more non-poor households there are in a given area, which in the Lao PDR tends to be the case in more densely populated areas.

Of course, these guidelines assume the cost of the development intervention is constant in per capita terms, implying that the cost is not affected by population density. Some programs, such as electrification and extension, will cost more in per capita terms in low-density areas. Other programs, particularly land-intensive programs such as roads and parks, may be more expensive in a high-density area.

Does geography make upland development impossible?

The analysis of the geographic determinants of poverty reveals that a significant proportion of the variation in rural poverty at the village level can be explained by a small number of agro-climatic and market access variables (cf. Section 4). This finding is somewhat troubling because it is not possible to design policy interventions that directly influence the agro-climatic variables. These results might be interpreted as saying that those living in villages with steep slopes and poor soils are caught in spatial poverty traps from which it is difficult to escape.

We are less pessimistic about these findings. First, market access can be influenced by public investment and policy. Although the government cannot reduce the actual distance to cities, it can reduce travel time and travel costs which are probably the relevant variables. Of course, roads will also allow goods (such as rice) produced more cheaply elsewhere to enter the region and compete with local production. But trade theory suggests that the aggregate impact on the region will be positive, and the results presented here indicate it will be positive even in terms of reducing poverty.

Moreover, in an analysis of the geographical distribution of the Lao population, the Socio-Economic Atlas of the Lao PDR (Messerli *et al.,* 2008) has revealed that more than 90 percent of the Lao people live within a day trip from the nearest district capital. If this surprisingly good accessibility can be transformed into true market access by supporting and stimulating the economic and public service functions of district capitals, the potential for poverty alleviation could be considerable.

In addition, geography is only a limiting factor in poverty reduction to the extent that people are not able to migrate. To the extent that migrants are able to raise their living standards without negatively affecting others, migration can be an effective tool in reducing poverty. The implication is that the government should not exclude migration as a possible development strategy, particularly for districts that are severely constrained by agro-ecological factors. Relaxing some of the restrictions on migration would allow people from agro-climatically constrained areas to raise their incomes and reduce poverty. Although migrants from rural areas to the cities tend to be initially poorer than their urban neighbours, thus contributing to a more visible increase in the number of urban poor and urban inequality, the relevant question is whether the standard of living of the migrants is better than it would be if they had not migrated.

Finally, it is important to avoid the idea that geography will prevent any development in disadvantaged areas. Other studies have shown that economic growth and poverty reduction have occurred even in disadvantaged regions such as the northern uplands (NSC *et al.,* 2006). The fact that agro-climatic factors are good predictors of poverty rates across districts at one point in time does not mean that they are good predictors of poverty over time for a given district.

Growth vs. equity

In the Lao PDR, as elsewhere, there is a debate between those who support policies and programs to reduce poverty through direct assistance to poor people and those who support policies and programs to increase economic growth as a strategy to raise the poor out of poverty. This study finds that almost two thirds (67 percent) of the variation in district-level poverty rates can be explained by differences in district-level average per capita expenditure. Certainly, it is possible to reduce district-level poverty by reducing inequality, but in practice this is not what distinguishes high and low poverty districts in the Lao PDR. If this cross-sectional pattern reflects the changes that occur over time, then the implication is that poverty reduction occurs largely as a result of broad-based economic growth rather than improvements in income distribution. In conclusion, growth-oriented development interventions seem to be a promising opportunity for the future as long as they do not ignore the who and the where of beneficiaries.

6.4 Implications for future research

Poverty at the household level can be explained fairly well based on simple household characteristics. 43 percent of the variation in rural household per capita expenditure, and 36 percent of urban household per capita expenditure can be explained using household characteristics from the Census questionnaire (cf. Table 2). These variables cover household size and composition, education, housing characteristics, fuel use, toilet facilities, ownership of consumer durables, and place of residence. A questionnaire focused on the characteristics which distinguish poor from non-poor households should be able to predict expenditures even better. This suggests the potential for the development of a short survey (or a set of indicators to be included in larger surveys) focused on those household characteristics proven to be associated with expenditure or income. This could be used for poverty monitoring, project evaluations, or household-level targeting. This is needed to identify and build consensus around the best predictors of poverty and verify that the targeting based on these predictors would be reasonably accurate.

Small-area estimation is a valuable tool for understanding the spatial distribution of poverty and inequality. The results presented in this book suggest that there is considerable potential for using small-area estimation methods and census data to obtain a better understanding of the spatial patterns in poverty and inequality. Census data provides the level of disaggregation which will be increasingly necessary for spatially disaggregated policy analysis and decentralization.

However, small-area estimation cannot easily be used to update poverty maps. Although small-area estimation is valuable for generating poverty maps and other information about the spatial distribution of poverty and inequality, it is probable that it cannot be used to generate district and village poverty estimates for the whole of the Lao PDR on an annual basis. If the analysis uses population census data in the second stage, it can only be updated every ten years. Data from the agricultural census could be used to update the estimates of rural poverty every five years, provided the questionnaires can be adapted as mentioned above. Annual household surveys, such as those carried out by DOS, can only help update the prediction equation, not the poverty estimates themselves.

Small-area estimation can also be applied to the study of the spatial distribution of nutrition, commercial agriculture, or any other variable that can be predicted based on household characteristics. Although this report applies small-area estimation methods to study the spatial patterns in poverty and inequality, the method could be used to explore spatial patterns in other variables of interest.

For example, if caloric malnutrition or micro-nutrient deficiencies can be predicted using household characteristics in a nutrition survey, the results could be applied to the census data to produce detailed information on the spatial distribution of those problems. Similarly, other variables such as the degree of income diversification, vulnerability to weather related shocks, or involvement in commercial agricultural production could be mapped in a similar way if they can be predicted with at least moderate accuracy by household characteristics in the census data. Another possible application is to use small area estimation methods to examine poverty and inequality among groups of households that are too small to be studied with conventional household surveys, such as the disabled, specific ethnic groups, widows, or marginalised occupational groups.

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ANNEX:

POVERTY MAPPING METHODS

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A.1 Methods to estimate the incidence of poverty (P_0)

As mentioned in Section 2, the poverty mapping method (also called small-area estimation) can be divided into three stages. These three stages are described below.

Stage 0: Identifying household characteristics in both the LECS and the Census

The first step was to compare the questionnaires of the 2002/03 Lao Expenditure and Consumption Survey and the 2005 Population and Housing Census to identify household characteristics found in both

Table 17. Household characteristics in both the Census and the LECS

	Question number	
Household characteristic	2005 Census	2002/03 LECS
Household size (number of people)	Pt B, Q1	Pt I, Q1
Proportion of household members aged 0-5 years	Pt B, Q4	Pt I, Q5
Proportion of household members aged 5-10 years	Pt B, Q4	Pt I, Q5
Proportion of household members aged 10-20 years	Pt B, Q4	Pt I, Q5
Proportion of household members aged 20-60 years	Pt B, Q4	Pt I, Q5
Proportion of household members over 60 years (elderly)	Pt B, Q4	Pt I, Q5
Age of head of household	Pt B, Q4	Pt I, Q5
Whether or not the head of household is a female	Pt B, Q2,3	Pt I, Q2, Q3
Ethnic origin	Pt B, Q8	Pt I, Q8
Highest level of education completed by head	Pt C,Q11-13	Pt III, Q3, Q12
Highest level of education completed by spouse	Pt C,Q11-13	Pt III, Q3, Q12
Type of roof	Pt I, Q26	Pt IX,Q4
Type of walls	Pt I, Q27	Pt IX,Q3
Type of floor	Pt I, Q28	Pt IX,Q5
Size of living area	Pt I, Q30	Pt IX,Q7
Main source of drinking water	Pt I, Q31	Pt IX,Q8,Q10
Type of toilet	Pt I, Q32	Pt IX, Q12
Type of source of energy for cooking	Pt I, Q33	Pt IX, Q14
Region of residence	Pt A	Cover page
Village level variables		

Source: Questionnaires for 2002/03 LECS and 2005 Population and Housing Census surveys that could be used as poverty indicators. In addition to comparing the questionnaires, it is necessary to compare the values of the variables to ensure that they are in fact describing the same characteristics. Based on this comparison, 18 household characteristics were selected for inclusion in the poverty mapping analysis (see Table 17).

Some household characteristics are categorical and, for regression analysis, must be represented by a number of dummy (binary) variables. For example, the main source of drinking water is a categorical variable, but for the regression analysis it must be represented by separate dummy variables for each type of water source: indoor tap, outdoor tap, covered well, uncovered well, and so on. Thus, the 18 household characteristics are represented in the regression analysis by 61 variables.

Stage 1: Estimating per capita expenditure with a household survey

As mentioned above, Stage 1 of the poverty mapping method involves using the household survey data and regression analysis to estimate household welfare as a function of household characteristics. In this study, we use real per capita consumption expenditure from the 2002/03 LECS as the measure of household welfare. The explanatory variables are the 18 household characteristics described above, represented by 103 variables. Economic theory provides no guidance on the functional form, but generally a log-linear function is used:

$$In\,(y_i) = X_i' b + e_i \tag{1}$$

where y_i is the real per capita consumption expenditure of household i, X_i' is a 1xk vector of household characteristics of household i, β is a kx1 vector of estimated coefficients, and ϵ_i is a random disturbance term distributed as N(0,σ). Because our main interest is predicting the value of $ln(y)$ rather than assessing the impact of each explanatory variable, we are not concerned about the possible endogeneity of some of the explanatory variables. Hentshcel *et al.,* (2000) show that the probability that household i with characteristics X_i is poor can be expressed as:

$$E[P_i \mid X_i, \beta, \sigma^2] = \Phi\left[\frac{In\,z - X_i'\beta}{\sigma}\right] \tag{2}$$

where P_i is a variable taking a value of 1 if the household is poor and 0 otherwise, z is the "overall poverty line," and Φ is the cumulative standard normal function. If the predicted log per capita expenditure $(X_i'\beta)$ is equal to the log of the poverty line $(ln(z))$, then the term in brackets is zero and the predicted probability that the household is poor is 50 percent. A lower predicted expenditure would imply a positive term in brackets and a higher probability that it is poor, while a higher predicted expenditure would imply a probability less than 50 percent.

Stage 2: Applying regression results to the census data

In Stage 2 of the standard poverty mapping method, the estimated regression coefficients from the first step are combined with census data on the same household characteristics to predict the probability that each household in the Census is poor. This is accomplished by inserting the household characteristics for household i from the census, X_i^c, into equation 2. The expected probability that household i is poor can be calculated as follows:

$$E[P_i \mid X_i^c, \beta, \sigma^2] = \Phi\left[\frac{In\, z - X_i^c \beta}{\sigma}\right] \tag{3}$$

This estimate is not very accurate for an individual household, but it becomes more accurate when aggregated over many households. For a given area (such as a district or province), Hentschel *et al.,* (2000) show that the proportion of the population living in households that are below the poverty line is estimated as the mean of the probabilities that individual households are poor:

$$E[P \mid X^c, \beta, \sigma^2] = \sum_{i=1}^{N} \frac{m_i}{M} \Phi\left[\frac{In\, z - X_i^c \beta}{\sigma}\right] \tag{4}$$

where m_i is the size of household i, M is the total population of the area in question, N is the number of households, and X is an N x k matrix of household characteristics. The advantage of using the Census data, of course, is that the large number of households allows estimation of poverty headcount ratios for geographic units much smaller than would be possible with the LECS data.

Provided that a) the error term is homoskedastic, b) there is no spatial auto-correlation, and c) the full Census data are used, the variance of the estimated poverty headcount ratio can be calculated as follows:

$$var(P^*) = \left(\frac{\partial P^*}{\partial \hat{\beta}}\right)' var(\hat{\beta}) \frac{\partial P^*}{\partial \hat{\beta}} + \left(\frac{\partial P^*}{\partial \hat{\sigma}^2}\right)^2 \frac{2\hat{\sigma}^4}{n-k-1} + \sum_{i=1}^{N} \frac{m_i^2 P_i^*(1-P_i^*)}{M^2} \tag{5}$$

where n is the sample size in the regression model. Thus, n, k, and σ^2 are from the regression analysis, while m_i, M, and N are obtained from the census data. The partial derivatives of P^* with respect to the estimated parameters can be calculated as follows:

$$\frac{\partial P^*}{\partial \hat{\beta}_j} = \sum_{i=1}^{N} \frac{m_i}{M} \left(\frac{-x_{ij}}{\hat{\sigma}}\right) \phi\left(\frac{In\, z - X_i' \hat{\beta}}{\hat{\sigma}}\right) \tag{6}$$

$$\frac{\partial P^*}{\partial \hat{\sigma}^2} = -\frac{1}{2} \sum_{i=1}^{N} \frac{m_i}{M} \left(\frac{In\, z - X_i' \hat{\beta}}{\hat{\sigma}^3}\right) \phi\left(\frac{In\, z - X_i' \hat{\beta}}{\hat{\sigma}}\right) \tag{7}$$

The first two terms in equation 5 represent the “model error”, which comes from the fact that there is some uncertainty regarding the true value of β and σ in the regression analysis. This uncertainty is measured by the estimated covariance matrix of β and the estimated variance of σ^2, as well the effect of this variation on P^*. The third term in equation 5 measures the “idiosyncratic error” which is related to the fact that, even if β and σ are measured exactly, household-specific factors will cause the actual expenditure to differ from predicted expenditure. These equations are described in more detail in Hentschel *et al.,* (2000) and Elbers *et al.,* (2003).

As noted above, equation 5 is valid only if the full Census data are available for the second stage of the mapping procedure. In this study, we use a 75 percent sample of the Census data in the second stage, so equation 5 must be modified as follows:

$$var(P^*) = \left(\frac{\partial P^*}{\partial \hat{\beta}}\right)' var(\hat{\beta}) \frac{\partial P^*}{\partial \hat{\beta}} + \left(\frac{\partial P^*}{\partial \hat{\sigma}^2}\right) \frac{2\hat{\sigma}^4}{n-k-1} + \sum_{i=1}^{N} \frac{m_i^2 P_i^*(1-P_i^2)}{M^2} + V_s \tag{8}$$

where V_s represents the variance associated with the sampling error in the Census, taking into account the design of the sample. In this study, we rely on the statistical software Stata to calculate the variance associated with the sampling error, taking into account the design of the sample[27].

In order to compare poverty headcount ratios in different regions or provinces, it is convenient to calculate the variance of the difference between two estimates of poverty. Hentschel *et al.,* (2000, footnote 17) provide an expression for the case when full Census data are used. Here we extend the expression to include the variance associated with sampling error:

$$var(P_1 - P_2) = \left(\frac{\partial P_1 - P_2}{\partial \hat{\beta}}\right)' var(\hat{\beta})\left(\frac{\partial P_1 - P_2}{\partial \hat{\beta}}\right) + \left(\frac{\partial P_1 - P_2}{\partial \hat{\sigma}^2}\right)^2 \frac{2\hat{\sigma}^4}{n-k-1}$$
$$+ V_i(P_1) + V_i(P_2) + V_s(P_1) + V_s(P_2) - 2cov_2(P_1, P_2) \quad (9)$$

where $V_i(P_r)$ is the idiosyncratic variance of the poverty estimate for region r (the third term in equation 5), $V_s(Pr)$ is the sampling variance of the poverty estimate for region r, and $cov_s(P_1,P_2)$ is the covariance in the poverty estimates for regions 1 and 2 associated with sampling error.

A.2 Methods to estimate other measures of poverty

The methods described above allow one to estimate the incidence of poverty, defined as the proportion of people below the poverty line. This measure, sometimes labelled P_0, is a member of a class of poverty measures identified by Foster, Greer, and Thorbecke (1984). These poverty measures can be expressed as follows:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{M}\left[\frac{z - y_i}{z}\right]^\alpha \quad (10)$$

where z is the poverty line
y_i is income (or expenditure) of person i in a poor household
N is the number of people in the population,
M is the number of people in poor households

Different values of α in equation 10 give different poverty measures. When α=0, this formula gives the incidence of poverty. This is because the term in brackets is always one, so the summation gives us the total number of people in poor households, which, when divided by N, gives us the proportion of people living in poor households. When α=1, it gives a measure called the depth of poverty (or the poverty gap). P_1 takes into account not just how many people are poor, but how poor they are on average. It is equal to

[27] This is accomplished with the "svymean" command. Stata calculates a linear approximation (a first-order Taylor expansion) of the sampling error variance based on information on the strata, the primary sampling unit, and the weighting factors. See StataCorp (2001, Volume 4, svymean) for more information

the incidence of poverty (P_0) multiplied by the average percentage gap between the poverty line and the income of the poor. When α=2, this equation gives a measure called the severity of poverty (or squared poverty gap). P_2 takes into account not just how many people are poor and how poor they are, but also the degree of income inequality among poor households. It is equal to the incidence of poverty (P_0) multiplied by the average squared percentage gap between the poverty line and the income of the poor.

The poverty mapping method described in Section A.1 provides a method for estimating the proportion of people below a given poverty line, z, but does not provide any information on the distribution of income among the poor, for which it is necessary to calculate P_1 and P_2. We can use the poverty mapping method to estimate P_1 and P_2 by noting that z does not have to be the poverty line. We can estimate the cumulative distribution of the population by level of per capita expenditure by running the poverty mapping calculations repeatedly for different values of z. More specifically, we use the following steps:

1. Select 1,000 levels[28] of per capita expenditure, divided evenly along the range of per capita expenditure from the poorest household to the richest household;
2. Set z equal to the lowest of these 1,000 levels (call this z_1), run the poverty mapping calculations to calculate the proportion of the population with per capita expenditure below z_1;
3. Then repeat step 2 setting z equal to each of the other 999 expenditure levels (z_2 to z_{100}), storing the values of z_i and the proportion of the population below z_i in a file for further analysis.

As z_i rises from its lowest level to its highest level, the proportion of people with per capita expenditure below z_i rises from 0 to 100 percent. Thus, these results trace out the cumulative distribution of the population by per capita expenditure[29].

This information can be used to calculate the values of P_1 and P_2. In the gap between each pair of z's (z_i and z_{i+1}), we know the average per capita expenditure and the proportion of people with per capita expenditures in that range. Thus, each pair of z's that are below the poverty line can be used to represent one value of y_i in equation 10, taking into account the number of households with per capita expenditure in that range.

A.3 Methods to estimate measures of inequality

In this context, inequality measures describe the degree of variation in per capita expenditure across households. Perfect equality would describe the case where all households have the same level of per capita

[28] The use of 1,000 levels is arbitrary. The larger the number of levels, the more accurate is the estimation of the cumulative distribution and hence, the more accurate are the estimates of P_1 and P_2. Of course, increasing the number of levels also increases the computational burden and time to run the program.

[29] Strictly speaking, we know only the range of per capita expenditures in this group of households and we assume that the average is $(z_i + z_{i+1})/2$. But if we choose a large number of z's, the difference between z_i and z_{i+1} will be small, so the error in making this assumption will also be small.

expenditure, while perfect inequality would refer to the situation in which one household accounts for all the expenditure and others have none.

In this analysis, we calculate three of the more common measures of inequality: the Gini coefficient, the Theil L index of inequality, and the Theil T index of inequality. The latter two measures are also part of a class of "general entropy" measures of inequality, so that the Theil L index is also called GE(0) and the Theil T index is also called GE(1).

The Gini coefficient is based on the Lorenz curve, which describes the cumulative distribution of income (or expenditure) as a function of the cumulative distribution of households. More specifically, the Gini coefficient is the area above the Lorenz curve and below the diagonal 45 degree line divided by the area under the diagonal line. When we have information about the proportion of people below different levels of per capita expenditure, the Gini coefficient can be approximated as follows:

$$Gini = 2\sum_{i=1}^{N}\left[\left(\frac{1}{2}(P_i + P_{i+1}) - \frac{1}{2}(X_i + X_{i+1})\right)(P_{i+1} - P_i)\right] \tag{11}$$

where P_i is the cumulative share of the population for interval i and X_i is the cumulative share of expenditure for interval i. The first term in the large parentheses is the "height" of each slice, from the diagonal line down to the Lorenz curve, while the last term in small parentheses is the "width" of each slice. The Gini coefficient ranges from 0 (perfect equality) to 1 (perfect inequality).

The Theil L index of inequality is calculated as follows:

$$Theil\ L = GE(0) = \frac{1}{N}\sum_{i=1}^{N} In\left(\frac{\bar{y}}{y_i}\right) \tag{12}$$

where N is the number of households, $\bar{y}$ is the average per capita expenditure, and y_i is the per capita expenditure of household i. The Theil L index ranges from 0 (perfect equality) to infinity (perfect inequality). This inequality measure gives greater weight to the bottom end of the distribution. This implies that it gives greater weight to the distribution of expenditure among the poor than either the Gini coefficient or the Theil T index of inequality.

The Theil T index of inequality is calculated as:

$$Theil\ T = GE(1) = \frac{1}{N}\sum_{i=1}^{N} \frac{y_i}{\bar{y}} In\left(\frac{y_i}{\bar{y}}\right) \tag{13}$$

where the variables are defined as in equation 12. The Theil T index ranges from 0 (perfect equality) to $ln(N)$ (perfect inequality). This inequality measure gives equal weight to all parts of the distribution.

In order to calculate inequality measures, we use the three steps described in Section A.2 to generate the cumulative distribution of households by per capita expenditure. To estimate the Gini coefficient, we calculate the cumulative distribution of expenditure from the values of z_i and the cumulative proportion of the population from the values of P for each z_i. These can be used in equation 11 to calculate the Gini coefficient.

As in the calculation of P_1 and P_2, the two Theil indices of inequality are calculated by using each pair of $z's$ to represent one value of y_i. As described above, between each pair of $z's$ (z_i and z_{i+1}), we know the average per capita expenditure and the proportion of people with per capita expenditure in that range. This information allows us to apply equations 12 and 13 to calculate the Theil indices of inequality.

Inequality decomposition

A generalized entropy inequality index such as GE(0) can be decomposed for mutually exclusive population sub-groups into a within component $GE(0)_w$ and a between component $GE(0)_b$. Both sum up to the inequality of the total population: $GE(0)_t = GE(0)_w + GE(0)_b$ (Shorrocks, 1984). The within component takes the following form:

$$GE(0)_W = \sum_k \frac{N_k}{N} GE(0)_k \tag{14}$$

and the between component can be written as follows:

$$GE(0)_B = \frac{1}{N} \sum_{i=1}^{N} In\left(\frac{\bar{y}}{\bar{y}_k}\right) \tag{15}$$

where k are the sub-groups with a number of households of N_k. $GE(0)_k$ denotes the sub-group inequality index and $\bar{y}_k$ is the mean expenditure of the population sub-group.

The share of the *between*-group component of total inequality is often surprisingly small, and depends on a number of factors, making comparisons across settings difficult. As an alternative assessment of the importance of inequality between specific population sub-groups, we also compare the observed between-group inequality with the maximum possible inequality between those groups. Following Elbers *et al.,* (2005), we calculate the maximum possible between-group inequalities as an alternative denominator, through redistributing household per capita expenditure to the sub-groups in order to achieve this maximum. To do that, all the lowest per capita expenditures are assigned to the households of the sub-group with the lowest mean per capita expenditure, the next lowest per capita expenditures to the households of the sub-group with the second lowest mean per capita expenditure, and so forth. Hence, the size and number of the population sub-groups, the relative ranking of mean expenditure of the sub-groups, as well as the overall expenditure distribution remain unchanged. Only the expenditures of the total population are redistributed among the sub-groups as unequal as possible. The observed between component is then normalized by the calculated maximum possible between component.

A.4 Limitations of the analysis

Three qualifications need to be made regarding the implementation of the poverty mapping method in the Lao PDR. First, as in all poverty mapping analyses, the requirement that all variables be in both the survey and the census constrains the number of variables that can be used to predict per capita expenditure. In particular, many of the explanatory variables are related to assets so they have a lagged relationship with per capita expenditure. Ideally, it would be good to include variables that change with short-term fluctuations in per capita expenditure, such as food consumption patterns, but this information is not available in the census. However, as shown in Section 3.1, the explanatory power of our Stage 1 regression models is relatively good, providing some reassurance on this issue.

Second, the regression analysis in Stage 1 does not explicitly take into account heteroskedasticity (differences in the variance of the dependent variable across the sample). On the other hand, by expressing the dependent variable (per capita expenditure) as a logarithm, we reduce the degree of heteroskedasticity. In addition, we carry out the regression analysis with the *"svyreg"* command in Stata, which takes into account stratification and clustering in the sample in calculating the standard errors of the estimates. It does this by using the Huber/White/sandwich estimator of standard errors, which is robust to heteroskedasticity. The estimated coefficients are not biased, but they are "inefficient" in that they do not use all possible information (see StataCorp, 2001, Volume 4 *"svyreg"*).

Third, the Stage 1 regression coefficients do not take into account spatial autocorrelation. Spatial autocorrelation exists when either the dependent variable (or the error term) of the regression in a households in the LECS is correlated with the dependent variable (or error term) in nearby households. If the *error terms* are correlated, the coefficients are unbiased but inefficient. This would be the case if some other factors (such as distance to a major city) were excluded from the regression model and were spatially correlated. For example, all the households near a city might have negative error terms (predicted expenditure is less than actual expenditure). On the other hand, if the dependent variable in one household is directly affected by the value of a nearby household, then the estimated regression coefficients will be biased. One type of spatial autocorrelation is correlation among households in a sample cluster, sometimes called location effects (spatial autocorrelation is discussed in more detail in Section A.5).

To reduce spatial autocorrelation, Elbers *et al.,* (2003) recommends incorporating community-level variables in the Stage 1 regression model. These variables could be obtained by calculating community-level means of the household-variables or by using geographic information systems (GIS) analysis to generate geographic variables representing climate, topography, or degree of market access. Although our analysis indicates the presence of some spatial autocorrelation, we were not able to eliminate it by including community-level variables in the regression analysis (more detail is given in Section 3.1). Furthermore, we were constrained from using geographic variables in the Stage 1 regression analysis because we plan to examine the geographic determinants of poverty at a later stage. We were concerned that including geographic variables in the Stage 1 model could exaggerate the strength of the relationship between (estimated) poverty and the geographic variables in the later analysis.

A.5 Methods used in evaluating the geographic determinants of poverty

This section describes the methods used to analyse the geographic determinants of poverty. This analysis, sometimes called "Stage 3", involves spatial regression analysis of poverty as a function of variables representing agro-climatic characteristics and market access. Because the dependent variable in this analysis is, itself, an imputed value, special care must be taken in interpreting the results, but Elbers *et al.,* (2004) show that the basic results are essentially the same as they would be with a "true" measure of poverty.

Global spatial regression analysis

This section describes the global spatial regression analysis, where "global" refers to the fact that the models assume that the relationship between poverty and geographic variables is the same across the country. The dependent variable is the village-level estimate of poverty obtained from Stage 2 of the poverty mapping analysis described in Section A.1. The independent variables are listed in Table 18, whereby the variables below the dotted line are those used in some sub-models.

As discussed in Section 4.2, one of the problems with carrying out regression analysis on spatial relationships is that there is likely to be spatial autocorrelation in the data. In general spatial autocorrelation means that variables in one location are affected by the value of that variable in neighbouring locations. There are two ways this problem can manifest itself.

Spatial lag dependence refers to a situation in which the dependent variable in one location is affected by the dependent variable in nearby locations. For example, if the dependent variable is income or poverty, it is probable that the level of economic activity in one location is directly affected by the level of economic activity in neighbouring locations through migration, trade, or investment linkages. The spatial lag dependence model can be written as follows:

$$y_i = \sigma \sum_{j \neq i} w_{ij} y_j + X_i \beta + \varepsilon_i \qquad (16)$$

where y_i is the dependent variable for location i,
σ is the spatial autoregressive coefficient,
w_{ij} is the spatial weight reflecting the proximity of i and j,
y_j is the dependent variable for location j,
X_i is a row vector of explanatory variables for location i,
β is a column vector of coefficients, and
ε_i is the error term for location i.

The spatial weights matrix, w, describes the degree of proximity between each pair of spatial observations. Usually it is a binary variable based on whether the two locations are contiguous or a continuous variable based on some function of the distance between the two locations. If the regression analysis is carried out without adjustment for spatial lag dependence, the estimated coefficients will be biased and inconsistent (Anselin, 1988).

The second type of problem that may occur is spatial error dependence, in which the error term in one location is correlated with the error terms in nearby locations. This can occur if there are variables that are not included in the regression model but do have an effect on the dependent variable and they are spatially correlated. For example, the quality of local government affects income and poverty but is difficult to include in a regression model. Because the quality of local government is likely to be spatially correlated (all towns in a state are affected by the quality of state government), the error term in each location is likely to be correlated with those in nearby locations. This model can be written as follows:

$$y_i = X_i\beta + \varepsilon_i \text{ with } \varepsilon_i = \lambda \sum_{j \neq i} w_{ij}\varepsilon_j + u_i \qquad (17)$$

where y_i is the dependent variable for location i,
X_i is a row vector of explanatory variables for location i,
β is a column vector of coefficients,
ε_i is the error term for location i,
λ is the spatial error autoregressive coefficient,
w_{ij} is the spatial weight reflecting the proximity of i and j, and
u_i is the uncorrelated portion of the error term for location i.

In this case, using ordinary least squares to estimate the model does not yield biased coefficients, but the estimates of the coefficient are not efficient and the standard t and F tests will produce misleading inference (Anselin, 1988).

In order to test for the presence of spatial autocorrelation, Moran's I is frequently used:

$$Moran's\ I = (x - \mu)'W(x - \mu) / (x - \mu)'(x - \mu) \qquad (18)$$

where x is a column vector of the variable of interest,
μ is the mean of x, and
W is the weighting matrix.

Table 18. Explanatory variables used in spatial regression analysis

Variable	Description
Std. elevation	Standard deviation of elevation in 3km radius of village centre point
% flat	% Slope 0-2% in 3km radius of village centre point
% gently undulating	% Slope 2-7.5% in 3km radius of village centre point
Mean ann. temp	Annual mean temperature
Std. temp	Temperature seasonality (standard deviation *100)
Ann. range temp	Temperature annual range
Ann. rain	Man annual precipitation
Seasonality rain	Precipitation seasonality (coefficient of variation)
Acc. to major river	Travel time to major river
Acc. to urban areas	Travel time to towns
Acc. to urban areas pop. > 50k	Travel time to towns with a population of > 50,000
Soil suitability	General soil suitability for agriculture
Length of growing period (LGP)	Annual length of agricultural growing period (LGP)
Village type	urban; rural with road access; rural without road access
Age groups	% of population: 0-5 years old; 6-15 years old; > 60 years old
Agro-ecological regions	Vientiane plain; northern lowlands; northern midlands; northern highlands; south-central lowlands; south-central midlands; south-central highlands; Boloven plateau

This statistic is simply the correlation coefficient between x at one point in space and the weighted average of the values of x nearby. In order to test whether there is spatial lag dependence or spatial error dependence, the Lagrange multiplier is used to test the statistical significance of the spatial autocorrelation coefficient (λ) in the two models. Anselin (1988) shows that the model in which the coefficient (λ) is larger is more likely to be the appropriate model.

In this study, we estimate the district level poverty rates (P_0) as a function of the spatial variables listed in Table 18. A Chow test indicates that the coefficients to predict urban poverty differ significantly from the coefficients to predict rural poverty. Thus, we carry out the regression analysis separately for urban and rural areas.

The weighting matrix was generated using the inverse distance between the geographic centres of the two districts. In other words the value of w_{ij} is equal to the inverse of the distance between the centre of district i and the centre of district j.

A Lagrange multiplier test is used to test for the statistical significance of σ and λ, which indicates the need to use the spatial dependence lag model or the spatial error dependence model, respectively. Often with spatial regression models, both parameters are statistically significant, and the normal procedure is to adopt the model that yields the higher value of the Lagrange multiplier.

The analysis was carried out using the Geodata Analysis software 'GeoDa', developed as a beta version by the Spatial Analysis Lab, University of Illinois, and is available for download from https://geoda.uiuc.edu.

Local spatial regression analysis

The global model described above assumes that the relationship between poverty and the geographic factors is the same across the country. Local spatial regression analysis does not make this assumption and examines spatial variations in the relationship between poverty and geographic factors. We use a "moving window" regression framework in which numerous regression models are estimated, each cantered on a "regression point" and including other observations with decreasing weight the further away they are from the respective regression point. Coefficient estimates are generated for each regression point (see Fotheringham *et al.,* 2002).

A model based on geographically weighted regression (GWR) techniques, where observations within the local regression window are weighted according to the distance to the regression point, was applied (Brunsdon *et al.,* 1996). Observations closer to the regression point X_i receive more weight than data of observations further away. The weighted regression window is then 'moved' to the next regression point, until all points have been covered.

Since this method is based on a conventional regression framework, the technique will produce the standard regression output for each regression point. The regression coefficients vary from one observation to another because they are based on a local regression that includes observations in the vicinity. This allows the regression output (including coefficients and R^2) to be mapped, showing their variation over space. This makes this technique particularly useful for analysing relationships in spatial data.

The standard global regression model can be written as:

$$y_i = X_i^{'}\beta + \varepsilon_i \tag{19}$$

where y_i is the dependent variable,
$X_i^{'}$ is a row vector of explanatory variables for location i,
β is a column vector of coefficients, and
ε_i is the error term.

This model can be extended to a local regression model as follows:

$$y_i = X_i^{'}\beta_i + \varepsilon_i \tag{20}$$

where β_i is a column vector of coefficients specific to location i.

In this local regression model, we are interested in giving higher weights to observations that are likely to be socio-economically more similar to the observations at the regression point. We assume that communities dwelling at similar altitude and in closer horizontal proximity are more similar to each other than to communities residing at very different elevation levels and far apart from each other. For each local regression at an individual regression point i, the observations are therefore weighted depending on the horizontal, as well as on the vertical distances from the regression point to the observation j.

Using projected x and y coordinates of the observations' location, we calculate horizontal Euclidean distances dh_{ij} from the local regression point x_i to each observation x_j which we used to calculate the individual horizontal importance weight component wh_{ij} for each observation x_j. To determine the corresponding vertical weight component wv_{ij}, the absolute elevation differences dvij from each regression point x_i to every observation x_j are calculated and used to determine the vertical importance weight components. The horizontal and the vertical importance weight components wh_{ij} and wv_{ij} , both ranging from 0 to 1, are then multiplied with each other in order to create a single importance weight w_{ij} for each observation.

While both weights components are calculated using the same Gaussian distance decay function, different bandwidths rh and rv are being applied for the horizontal and vertical weighting function, resulting in different distance-based weighting decays in x, y and z direction.

The distance decay function applied in this analysis can be written as follows:

$$w_{ij} = exp\left[-\frac{1}{2}\frac{d_{ij}}{rh}\right]^2 * exp\left[-\frac{1}{2}\frac{d_{ij}}{rv}\right]^2 \tag{21}$$

where w_{ij} is the weight at regression point i for observation j,
d_{ij} is is the distance from regression point i to observation j,
r is the bandwidth or the radius of influence around each observation,
h is the horizontal component, and
v is the vertical component.

Based on the assumption that a specific distance difference in a horizontal direction implies different changes in livelihood patterns (and thus in household characteristics and expenditure patterns) than does the same distance difference in a vertical direction, individual optimal bandwidths rh and rv for the horizontal and the vertical components of the weighting function were evaluated. The optimal bandwidths rh and rv for the horizontal and the vertical weighting components were identified through a series of regression iterations, aiming at maximizing the number of significant independent variables in local regressions across space.

Finally, we assess whether a local model really describes relationships better than a global model; Fotheringham *et al.,* (2002) proposed a Monte Carlo test of whether spatial variations in the estimated coefficients are statistically significant. The test involves randomly adjusting the geographic location of the observations numerous times, running a GWR on each, and then comparing statistically the parameter estimates for the randomly distributed observations with the parameter estimates of the actual geographic distribution.

The analysis was carried out in Stata, using the software's 'importance weights' option for the local weights in the local regressions.

A.6 List of variables developed for spatial regression analysis

Table 19 lists all the variables prepared for the spatial regression analysis, of which a selection was used in the final models (see Table 18).

Table 19. Variables prepared for spatial regression analysis

Variable
Village-level poverty rate (dependent variable)
Village type (urban; rural with road access; rural without road access)
% of population 0-5 years old
% of population 6-15 years old
% of population 45-60 years old
% of population over 60 years old
Agro-ecological regions:
Vientiane plain
Northern lowlands
Northern midlands
Northern highlands
South-central lowlands
South-central midlands
South-central highlands
Boloven plateau

Table 19. Variables prepared for spatial regression analysis (cont.)

Variable
Agricultural soil suitability
Annual length of agricultural growing period (LGP)
Elevation
Standard deviation of elevation in 3km radius of village centre point
Roughness in 500m radius of village centre point
Roughness in 3km radius of village centre point
Mean slope in 500m radius of village centre point
Mean slope in 3km radius of village centre point
% Slope 0-2% in 3km radius of village centre point
% Slope 2-7.5% in 3km radius of village centre point
% Slope 7.5-15% in 3km radius of village centre point
% Slope 15-25% in 3km radius of village centre point
% Slope >25% in 3km radius of village centre point
Travel time to main roads
Travel time to Mekong river
Travel time to major river
Travel time to towns
Travel time towns with a population of > 1,000
Travel time towns with a population of > 5,000
Travel time to towns with a population of > 10,000
Travel time to towns with a population of > 25,000
Travel time to towns with a population of > 50,000
Annual mean temperature
Mean diurnal range (P2 = mean of monthly (max temp - min temp))
Isothermality (P2/P7) * 100
Temperature seasonality (standard deviation *100)
Maximum temperature of warmest month
Minimum temperature of coldest month
Temperature annual range (P7)
Mean temperature of wettest quarter
Mean temperature of driest quarter
Mean temperature of warmest quarter
Mean temperature of coldest quarter
Annual precipitation
Precipitation of wettest month
Precipitation of driest month
Precipitation seasonality (coefficient of variation)
Precipitation of wettest quarter
Precipitation of driest quarter

About this book

This study presents estimates of various measures of poverty and inequality in the Lao PDR at a high level of spatial disaggregation. Highly detailed information on the spatial distribution of welfare across the country has been developed through the application of small-area estimation techniques on a combination of information from the 2003 Lao Expenditure and Consumption Survey and from the 2005 Population and Housing Census. The analysis confirms that poverty incidence tends to be highest in mountainous areas, and further reveals that the poorest areas are found in the mountains of the southern part of the country. Nevertheless, the greatest numbers of poor people live in the lowland areas of the Mekong River corridor, where the population density is much higher than that of the sparsely populated upland areas. An analysis of various geographic factors, including access to markets, reveals that both accessibility and agro-climatic variables are able to explain to a large extent the differences in rural poverty rates, and indicates that poverty in the remote areas is linked to low agricultural potential and lack of market access. Improved access to markets, however, has the strongest pro-poor effect in areas where poverty rates are lowest, and agricultural production is most intensive. Since many poverty alleviation programs of the Lao PDR are geographically targeted, the results from this study can serve as an important source of information in order to improve the targeting of these programs by making use of more precise estimates of poverty at the district and village level.

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Swiss National Centre of Competence in Research (NCCR) North-South
Hallerstrasse 10, 3012 Bern, Switzerland
T: +41 31 631 52 72; E: nccr-north-south@cde.unibe.ch; www.north-south.ch

International Food Policy Research Institute (IFPRI)
2033 K Street, N.W., Washington, D.C. 20006-1002, U.S.A.
T: +1 202 862 5600; E: ifpri@cgiar.org; www.ifpri.org

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