CHOOSING A METHOD FOR POVERTY MAPPING

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Foreword

Poverty and food security are heterogeneous phenomena in most countries; types and depth of poverty, measured in different ways, vary between and within countries and regions. Poverty mapping in its various forms involves techniques that permit sufficient disaggregation of a poverty measure to local administrative levels or small geographical units. All poverty-mapping techniques imply alternative schemes for weighting a particular poverty index, and may imply alternative poverty ranking of the chosen unit. The methods used vary from participatory poverty profiles to sophisticated econometric techniques; most are under continuing development. Each has different data requirements and implementation costs, and different advantages and disadvantages. Statistical error and possible bias are significant issues in poverty mapping.

With this publication, FAO seeks to explore the wide variety of tools available for poverty mapping. The purpose of this paper is to discuss poverty and food-security mapping in terms of relevance and available options for analysis, policy design and implementation in the rural sectors of developing countries. The paper presents and compares a large selection of poverty and food-security mapping methodologies in use, in order to provide some guidance as to their potential and appropriateness for different policy applications. Many of the methods analysed play a crucial role in targeting interventions, from rural anti poverty programs to allocation of public services to early warning systems. As such, this publication can assist practitioners in the formulation and implementation of poverty reduction, food security and sustainable development strategies, and in the monitoring of progress toward the achievement of various international commitments and goals within the framework of Food Insecurity and Vulnerability Information and Mapping Systems (FIVIMS) and the Millennium Assessment Programme.

The author finds that poverty mapping does not yet have a gold standard, partly because the context of poverty mapping is as varied as its applications. Thus the choice of a poverty-mapping methodology depends on a number of logical and legitimate considerations, such as objectives of the poverty mapping exercise, philosophical views on poverty, limits on data and analytical capacity and cost.

While practitioners should choose the most appropriate method for their purposes, the most disturbing problem with current poverty-mapping methods is the minimal attention paid to potential error and bias, and to the types or characteristics of the poor populations chosen by different methodologies. Given the lack of information regarding bias and error in most poverty-mapping methods, practitioners should proceed with full awareness of the pitfalls and uncertainties of their particular method. The robustness of the chosen method should if possible be evaluated in terms of component variables, outcome indicators and alternative methods. Further research is clearly needed in terms of comparing the statistical precision and practical outcomes of different methods. Evaluating the statistical properties of some methods may not be technically feasible, but recognizing the potential bias of each method in terms of the resulting poverty profile is an essential first step.

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Contents

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Abstract

Poverty and food security are heterogeneous phenomena in most countries; types and depth of poverty, measured in different ways, vary between and within countries and regions. Poverty mapping in its various forms involves techniques that permit sufficient disaggregation of a poverty measure to local administrative levels or small geographical units. All poverty-mapping techniques imply alternative schemes for weighting a particular poverty index, and may imply alternative poverty ranking of the chosen unit. The methods used vary from participatory poverty profiles to sophisticated econometric techniques; most are under continuing development. Each has different data requirements and implementation costs, and different advantages and disadvantages. Statistical error and possible bias are significant issues in poverty mapping.

The purpose of this paper is to discuss poverty and food-security mapping in terms of relevance and available options for analysis, policy design and implementation in the rural sectors of developing countries. The paper presents and compares the range of poverty and food-security mapping methodologies in use in order to provide guidance as to their potential and appropriateness in different policy applications. This is done by studying in detail a number of applications of poverty mapping to policy questions.

Résumé

La pauvreté et la sécurité alimentaire constituent, dans la plupart des pays, des phénomènes particulièrement hétérogènes. Mesurées selon diverses méthodes, elles varient toutes deux, de même que la gravité de la pauvreté entre et dans les pays, les régions ou autres unités géographiques ou administratives. La cartographie de la pauvreté, sous différentes formes, requiert l'utilisation de techniques permettant une ventilation suffisante des mesures de la pauvreté aux différents niveaux de l'administration locale ou des petites unités géographiques. Toutes les techniques de cartographie de la pauvreté impliquent la mise en oeuvre de différents types de mécanismes pour pondérer un indice donné de pauvreté et peut donner lieu à différents types de classement en fonction de la pauvreté de l'unité en question. Les méthodologies appliquées sont variées et vont des profils de pauvreté fondés sur la participation aux techniques économétriques de pointe, dont la plupart font l'objet d'un processus continu d'élaboration. Chacune pose différentes exigences en termes de données et de coûts opérationnels et présente des avantages et des désavantages sur le plan de la mise en oeuvre. Les questions des erreurs statistiques et des biais eventuels sont cruciales en matière de cartographie de la pauvreté.

Cette étude vise à analyser la pertinence et les options disponibles de la cartographie de la pauvreté et de la sécurité alimentaire aux fins de l'analyse et de la conception et application de mesures dans le secteur rural des pays en développement. On y présente et compare un vaste éventail de méthodologies alternatives actuellement utilisées en matière de cartographie de la pauvreté et de la sécurité alimentaire afin d'apporter certaines orientations quant aux possibilités et à la pertinence de ces méthodologies dans différents cas de figure, et ce moyennant l'examen approfondi d'un certain nombre d'applications de la cartographie de la pauvreté à l'action gouvernementale.

Resumen

La pobreza y la inseguridad alimentaria son realidades enormemente heterogéneas en la mayoría de los países. Estos dos aspectos y la magnitud de la pobreza, medidos en diversas formas, varían no sólo entre países, regiones u otras unidades administrativas y geográficas, sino también al interior de los mismos. La cartografía de la pobreza, en todas sus diversas formas, incluye técnicas que permiten un desglose suficiente de una medida de pobreza a nivel administrativo local o de pequeñas unidades geográficas. Todas las técnicas de cartografía de la pobreza consideran esquemas alternativos para ponderar un índice de pobreza en particular y pueden contemplar ordenamientos distintos según la pobreza de la unidad elegida. Las metodologías utilizadas son diversas, desde perfiles participativos de pobreza hasta complejas técnicas econométricas, y la mayoría está en continuo desarrollo. Cada una de ellas requiere datos y costos de implementación distintos, y su aplicación tiene ventajas y desventajas. Los temas de error estadístico y los posibles sesgos son problemas claves en la cartografía de la pobreza.

El objetivo de este documento es examinar la relevancia y las opciones de la cartografía de la pobreza y de la seguridad alimentaria en el análisis y en el diseño e implementación de políticas en el sector rural de los países en desarrollo. Presentamos y comparamos una gran selección de las metodologías alternativas de cartografía de la pobreza y de la inseguridad alimentaria que se utilizan, con el fin de proporcionar cierta orientación en lo que respecta a las posibilidades y adecuación de estas metodologías para las distintas políticas. Para este efecto, hemos hecho un estudio detallado de varias aplicaciones de cartografía de la pobreza a problemas en materia de políticas.

1. Introduction

Poverty and food security are highly heterogeneous phenomena in most countries; it is thus common to find wide spatial variability. Types and depth of poverty, measured in a range of different ways, vary between and within countries, regions and other geographic and administrative units. Spatial heterogeneity can develop for a variety of reasons such as differences in geography, history and ethnicity, access to markets, public services and infrastructure, and other aspects of public policy (see de Janvry and Sadoulet, 1997; Bloom and Sachs, 1998; Jalan and Ravallion, 2002). Heterogeneity in poverty and food security is, however, often hard to measure correctly with conventional analytical tools. The fundamental problem is obtaining data that permit measurement of poverty and food security at a level of disaggregation sufficient to capture the heterogeneity brought about by spatial variability.

The concept of mapping involves measuring the incidence of poverty and food security in some predetermined area. While the term "poverty" mapping has become ubiquitous in research and policy circles, an almost unlimited variety of poverty and food-security indicators can be mapped with the methods described in this paper. Although poverty and food security are not necessarily the same concept, the terms are used interchangeably in this paper, because the focus is on methods, not specific indicators.

Poverty and food-security mapping can take place at global, continental and regional levels, and includes subnational analysis and areas within countries. Global or regional mapping typically uses country-level or broad geographical variables. At subnational level, poverty mapping in its various forms involves techniques that permit sufficient disaggregation of a poverty measure to local administrative levels or small geographical units. It is based on a wide variety of possible criteria such as agro-ecological, land-use, livelihood and production-system parameters, in order to gauge spatial heterogeneity accurately by specific criteria. All poverty maps that aspire to national coverage require a census on which microanalysis can be based, either directly or by extrapolation. All poverty-mapping techniques imply alternative schemes for weighting a particular poverty index, and may imply alternative rankings by poverty of the chosen unit. Statistical error and possible bias are thus fundamental issues in poverty mapping, though most practitioners to date have remained unaware of these complications.

The purpose of this paper is to discuss poverty and food-security mapping in terms of relevance and available options for analysis, policy design and implementation in the rural sectors of developing countries. It will present and compare a large selection of poverty and food-security mapping methodologies in use, in order to provide some guidance as to their potential and appropriateness for different policy applications. The aim is to send some warning signals regarding the deceptive ease with which it is possible to construct colourful and informative poverty maps, when different methods or different data could lead to very different results. This is done by studying in detail a number of applications of poverty mapping to policy questions. The paper concludes by indicating areas where more research is necessary. The focus is primarily on the subnational level, where there has been a considerable amount of analytical activity over the last few years.

2. The relevance of spatial analysis

Mapping is defined for the purposes of this paper as spatial analysis of poverty and food security, in visual and econometric terms. Spatial determinants are important for understanding the distribution of assets that are fundamental for alleviating poverty and combating food insecurity; these include human capital such as health, education and technology, and social capital such as the ability to cooperate and social networks. Spatial analysis has most promise in the area of natural resources, because natural capital-asset holdings such as natural resource stocks, land quality and environmental quality are difficult to characterize with conventional variables, and are spatially distributed by definition. Infrastructure variables such as road density and quality, and access to labour, product and input markets also have an important spatial dimension.

Poverty mapping has two primary uses. The first is spatial identification of the poor, on which this paper concentrates. Poverty mapping has in many instances served to target social, agricultural, emergency, environmental and anti-poverty programmes. Poverty maps have been crossed with environmental and agricultural-system maps in order to use visual spatial analysis to discern correlations. Numerous examples will be provided in the paper; for further reference, Snel and Henninger (2002) provide detailed case studies of poverty-mapping applications.

The second use is to create, as a by-product, explanatory and dependent spatial variables for use in multivariate analysis in combination with recently developed tools that permit the spatial dimension to be incorporated in multivariate examination of poverty issues.

Different methodologies are used for locating food-insecure or poor people, and for evaluating determinants of poverty and food insecurity; these include econometric models, livelihood-systems analysis and participatory appraisals. In each case, poverty mapping is used to reveal the location of poor people and the location-related aspects of the identified determinants of poverty and food insecurity. In econometrics-based methodologies, this assessment generally takes place within a multivariate regression framework, though it can and should be complemented with other types of information. The livelihood approach uses in-country expert opinions to categorize households by asset structures and livelihood strategies, thus revealing the location and determinants of poverty. The participatory approach elicits self-generated definitions of poverty, and with it the location and determinants, from respondents in the population under study. These methodologies are likely to lead to different outcomes with regard to locations – that is, maps – and policy implications; few comparisons of the practical differences have been made, however.

Spatial analysis of poverty has been utilized in a number of policy and research applications ranging from targeting emergency food aid and anti-poverty programmes to assessments of the determinants of poverty and food insecurity, in addition to providing visual representations of spatial relationships between variables. These applications have been used by organizations ranging from national governments to non-governmental organizations (NGOs) and multilateral development organizations (see Henninger, 1998, and Snel and Henninger, 2002, for a review of many of these applications).[1] The methodologies utilized are diverse, ranging from participatory poverty profiles to sophisticated econometric techniques; most are under continuing development. Each has different data requirements and implementation costs, and different advantages and disadvantages.

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[1] Mapping efforts that are not directly tied to poverty or food security are not included, such as the FAO farming system and agro-ecological typologies, or the many environmental and production applications among the Consultative Group on International Agricultural Research (CGIAR) centres, though these may be relevant to combining with poverty-mapping exercises.

The uses and abuses of poverty mapping

Poverty mapping is essentially a tool; its functionality must therefore be seen and evaluated in light of the objectives for which it is put to use – the research and policy questions and hypotheses upon which it can shed light. Poverty mapping should be initiated with clear objectives in mind that will help to guide interpretation of the output and determine the appropriate methodology. Although poverty mapping can serve as a useful exploratory or directed tool in establishing and presenting the spatial relationship between a pair or series of indicators, it can lead to serious misinterpretation of causal relationships between variables. Poverty maps do not as a rule represent causal linkages so much as visual correlations; interpreting causality can thus lead to serious policy and analytical mistakes. In a multivariate regression framework, however, using appropriate econometric analysis techniques, variables derived from poverty mapping exercises can serve as determinants – or outcomes – of causal relationships. Some livelihood approaches also attempt to understand causal relationships.

The role of geographical information systems

Most types of poverty mapping increasingly depend on data generated by geographical information systems (GIS), where values are fixed to specific locations on a grid. The spatial location of poor people facilitates integration of data from sources such as satellites, censuses, household surveys, sectoral surveys, models and simulations for the analysis of the determinants and impacts of poverty. GIS techniques provide four functions in poverty mapping (see Bigman and Deichmann, 2000a):

- integration of multiple databases from different sources;
- analysis of spatial association between variables;
- inclusion of spatially generated explanatory variables into the multivariate analysis of the determinants of poverty, including natural capital and infrastructure, and access to public services and product and labour markets; disaggregated poverty measures can serve as an explanatory variable for other outcomes;
- policy comparison and formulation through dynamic mapping or monitoring.

Recent studies have stressed the importance of geography and spatial variables as determinants of poverty. Most of the recent voluminous research on poverty and food insecurity, however, has been surprisingly limited to rudimentary and one-dimensional characterizations of the roles of regions and access to different types of infrastructure, public services and product and labour markets. Many poverty-mapping exercises involve simply a ranking of areas by some poverty, food security or marginality indicator and have no need for maps except as communication tools. GIS techniques can be used to incorporate spatial analysis into the determinants of rural poverty or food insecurity, or into issues that are important for alleviating poverty and food insecurity. This could include the determinants of migration, participation in off-farm labour activities, product market participation, crop choice or technology adoption. One of the most common applications is to the analysis of the causal relationship between poverty and the environment, where few links have been found, often because of technical, estimation or data limitations (see Lipper, 2001).

3. Methods of poverty mapping

A variety of methods for spatial location of the poor have been put forward in the literature and in practice; most are under continuing development. In this section, the major methods in use around the globe will be described, and the context in which each has been employed.

Small-area estimation

Small-area estimation is a statistical technique that combines survey and census data to estimate welfare or other indicators for disaggregated geographical units such as municipalities or rural communities. Small-area estimation applies parameters from a predictive model to identical variables in a census or auxiliary database; the assumption is that the relationship defined by the model holds for the larger population as well as the original sample. This technique has been used by the United States government for planning and targeting purposes (Ghosh and Rao, 1994).

Small-area estimation has more recently been extended to developing countries for poverty mapping. Two principal methods have emerged. The first uses census data on household units. It was developed principally by staff at the World Bank and is the main methodology used and promoted by the Bank's new poverty-mapping group (World Bank, 2000). The second uses community-level averages instead of data on household units and has been employed by researchers at the World Bank and various centres of the CGIAR system. These econometric models are not causal: they do not seek to explain the determinants of poverty, but maximize precision in identifying the poor. This is an important distinction in terms of the kinds of explanatory variables that are utilized.

Household-level method

This method was developed in Hentschel *et al*. (2000) and Elbers, Lanjouw and Lanjouw (2001); it is presented in Deichmann (1999) and World Bank (2000), from which the following discussion is derived.

The method requires a minimum of two sets of data: household-level census data and a representative household survey corresponding approximately to the same period as the census. In Nicaragua, for example, poverty maps have been made using data from a 1995 population census and a 1998 Living Standards Measurement Study (LSMS) survey; in Ecuador, data from a 1990 population census were used with 1994 survey data. The maximum allowable time difference will vary by the rate of economic change in a given country. Most efforts have used a population census with data on household units; an agricultural census that includes basic demographic information could be used, such as the 1997 Chinese agricultural census or other sufficiently representative large-scale survey. Elbers *et al.* (2001) provide an example of small-area estimation in Brazil using a large-scale household survey instead of a population census; Minot and Baulch (2002a) use a 3 percent sample of the 1999 Vietnamese population and housing census. Efforts are currently underway to test the use of the standardized demographic and health surveys (DHS) on health and nutrition in small-area estimation (Macro International, 2002).

The first step is to estimate a model of consumption-based household welfare[2] using data from the household survey. This model should be estimated by statistically representative regions, or urban or rural areas, with explanatory variables limited to those found in both data sets.

The following equation is estimated using ordinary least squares:

$$\ln C = \zeta + \eta_1 X + \eta_2 V + \kappa \tag{1}$$

Where C is total per-capita consumption, or another food-security or poverty proxy, X is a matrix of household-level characteristics and V a matrix of geographical-level characteristics.

The resulting parameter estimates are applied to the census data. For each household, the estimated parameters from the regression are used to compute the probability of each household in the census living in poverty. Household-level results can then be aggregated by the geographical region concerned by taking the mean of the probabilities for the chosen geographical entities.

For each household, the household-level value of the explanatory variable is multiplied by the corresponding parameter estimate, which in this case gives a predicted value of the log of total per-capita consumption for each household in the study area. The estimated value of the benchmark indicator is then used to determine the probability of a household being food-insecure or poor in terms of a given threshold below which a household is food-insecure or poor whether based on consumption, caloric intake or anthropometric measures. Here:

(2) $F_{ij} = 1$ if $\ln C_{ij} < \ln z$;
$F_{ij} = 0$ otherwise

with the corollary in poverty analysis being the headcount index. Following Hentschel, *et al.* (2000) and using the model of consumption from equation (1) but with only one vector of explanatory variables for exposition purposes, the expected food-security status of household *i* is:

(3) $$E\left[F_i \mid X_i, \eta, \omega\right] = \Phi\left(\frac{\ln z - X_i'\eta}{\omega}\right)$$

where Φ is the cumulative standard normal distribution. This equation gives the probability that a household is food insecure. Estimates of $\hat{\eta}$ and $\hat{\omega}$ are obtained from the model of the benchmark indicator, providing the following estimator of the expected food insecurity of household *i* in the census:

(4) $$F_i^* = E\left[F_i \mid X = i, \hat{\eta}, \hat{\omega}\right] = \Phi\left(\frac{\ln z - X_i'\hat{\eta}}{\hat{\omega}}\right)$$

Regional food insecurity, F, is found with:

(5) $$F = \frac{1}{N}\sum_{i=1}^{N} F_i$$

[2] Other well-being or food security indicators may also be used.

where N is the number of households in a specific region or geographical unit. Expected food insecurity is found with:

$$(6)\qquad E[F \mid X, \eta, \omega] = \frac{1}{N}\sum_{i=1}^{N} E[F_i \mid X_i, \eta, \omega]$$

The incidence of food insecurity is calculated as the mean of the probability of households being food-insecure:[3]

$$(7)\qquad F^{*} = E[F \mid X, \hat{\eta}, \hat{\omega}] = \frac{1}{N}\sum_{i=1}^{N} \Phi\left(\frac{\ln z - X_i \hat{\eta}}{\hat{\omega}}\right)$$

F* can be calculated for different levels of food insecurity. Food-insecurity measures comparable to the depth and severity of poverty (Foster, Greer and Thorbecke, 1984) and any number of the standard poverty measures can be constructed.

Although the concept is straightforward, application in practice presents a number of econometric and computational challenges, including the large size of census data sets, non-normality, spatial autocorrelation and heteroscedasticity; these are discussed in detail in Elbers, Lanjouw and Lanjouw (2001). One virtue of this methodology is the relative ease of checking the reliability of estimates that are built into the programmes provided by the World Bank to national poverty-mapping analysts. The size of standard errors in these estimates depends largely on the degree of disaggregation sought and the explanatory power of the exogenous variables in the first-stage model. Demombynes *et al.* (2002), for example, show that relatively precise poverty estimates can be made at the third administrative level, which for Ecuador and Madagascar means approximately 1 000–2 000 households and for South Africa 20 000 households. The optimal degree of disaggregation will depend on:

- the purpose of the map;
- the sampling properties of the household data;
- trade-offs between the size of standard error and policy needs.

[3] Simply counting households with expected values below the food security line gives biased estimates of poverty rates as a result of inequality in the intra-household distribution.

The other virtue of this approach is that it has the institutional backing of the World Bank and a team of researchers concerned with developing methodology and training. It is the only method where statistical properties have been and continue to be thoroughly investigated.

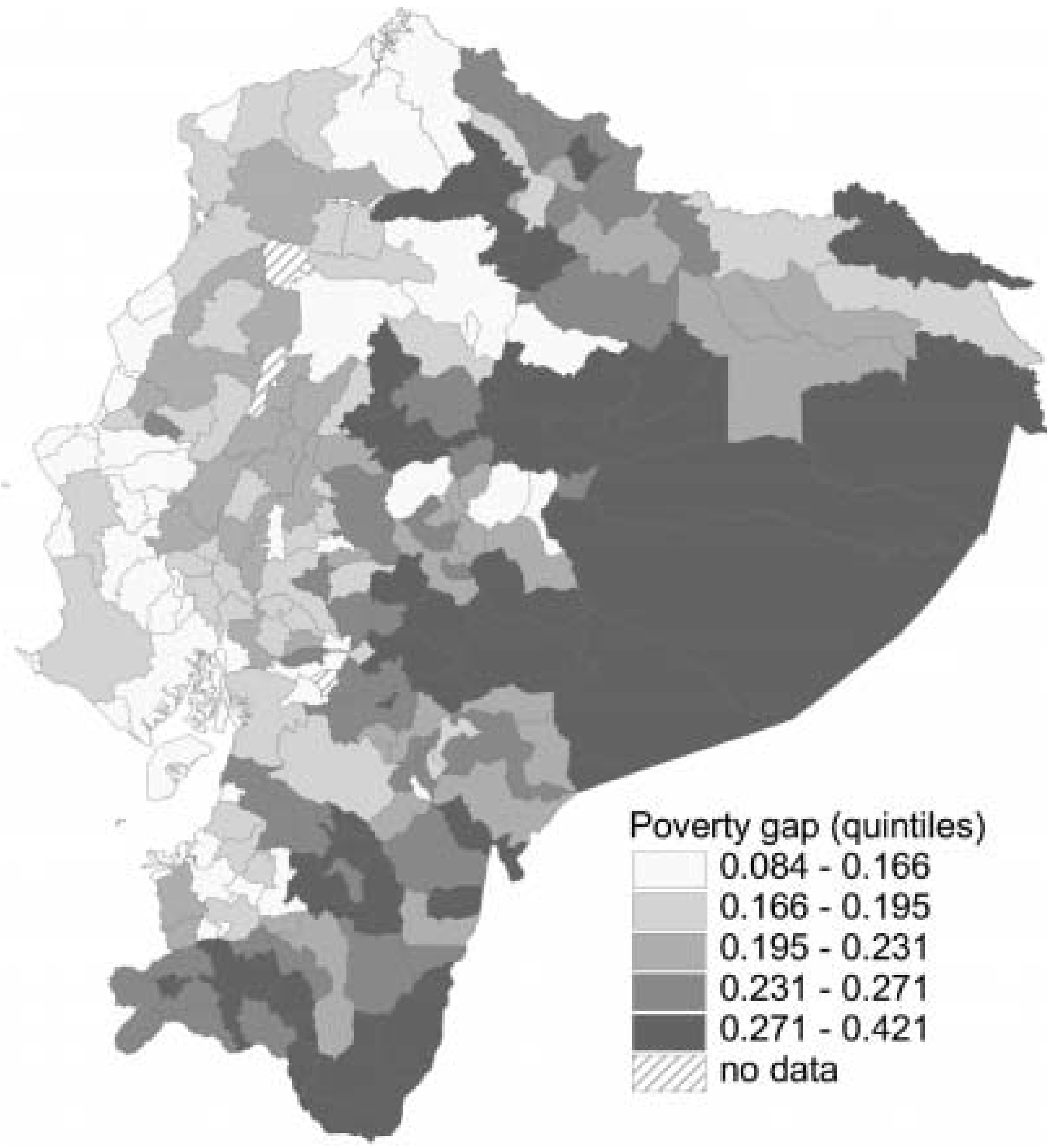
The Nicaraguan government and in particular the Fondo de Inversión Social de Emergencia (FISE), with support from the World Bank, have adopted and applied the household-unit data method for creating poverty maps for planning purposes and future targeted programmes such as the Red de Protección Social (RPS; Social Protection Network) anti-poverty programme (Government of Nicaragua, 2001). This method was pioneered in Ecuador (see Map 1) and has been used to create poverty maps for targeting and policy-making in Panama (World Bank, 2000) and South Africa (Alderman *et al.*, 2000); the World Bank and the International Food Policy Research Institute (IFPRI) are supporting efforts in Cambodia, Guatemala, Kazakhstan, Kenya, Madagascar, Malawi, Mozambique, United Republic of Tanzania, Uganda and Viet Nam (J. Lanjouw, personal communication, 2001; N. Minot, personal communication, 2001; S. Wood, personal communication, 2001; Snel and Henninger, 2002). In their case studies, Snel and Henninger (2002) provide detail on ways in which these poverty maps have been put to use in different countries.

Researchers from IFPRI are designing the national maps of Malawi and Mozambique with the aim of building a regional poverty map that could be expanded to include other East African countries. Such an effort means that the challenge of constructing comparable poverty lines and indices over two or more countries will have to be overcome. (T. Benson, personal communication, 2001; K. Simler, personal communication, 2001; S. Wood, personal communication, 2001.)

Community-level data method

An alternative small-area estimation method uses average values from disaggregated geographical units such as communities or small towns instead of household-unit data. This has the advantages that data requirements are less stringent and national statistical agencies may be more likely to release community averages on request; indeed, this data may be published. This is particularly important for researchers who, unlike the World Bank researchers, do not have institutional backing or resources to form formal collaborative arrangements with national statistical agencies. Apart from the difference in the scale of the predictive model, the two small-area estimation methods follow essentially the same steps. The first step is to estimate a model of consumption-based household welfare using the household survey data, as shown in equation 1. The resultant

Map 1
Ecuador poverty map, small-area estimation method



Source: U. Deichmann, personal communication, 2002.

parameters are then used to predict the expected level of well-being for communities.[4]

Predicted mean consumption in a community is not necessarily a good proxy for poverty, however, because poverty measures are functions of mean consumption and the distribution of consumption in a community. Bigman uses a Taylor expansion of the head count to obtain an expression for the measure of poverty as a function of mean consumption and spread parameters such as the standard error of the regression.

The expected head-count measure of poverty P_0 in a community j will be equal to:

$$(8) \qquad E(P_{0j}) = E(\text{Prob}\ [\ln y_{ij} < 0]) = E(A(-X_{ij}\eta/\psi_j))$$

where *lny* is the log of the level of consumption per adult in household *i*, X_{ij} is a matrix of individual and community level variables, A is the standard cumulative normal distribution and ψ_j is the standard error of u_j. X_{ij}, however, is not observed outside the household survey sample, and even within the sample the number of observations per community is usually too small. Estimates of the means of all variables in each community X_j are available, however. Since this expression is non-linear, X_j cannot be substituted for X_{ij}, though an approximation may be obtained using Taylor expansions.

This process relies on a series of assumptions. First, the variance around mean consumption within each village must be assumed to be constant. Second, in the consumption equation, the behavioural model inside and outside the household sample must be assumed to be constant. This may be a problem in a country where the geographical dimension is important and has not been taken into account in the sampling design. Within the sample, the problem can be addressed econometrically by testing the stability of the estimates between urban and rural areas, across regions or across other spatial units. Third, only limited information may be available at the community level for some variables, even in terms of means, which could lead to a problem of a missing variable.

This method has been frequently employed. Minot (2000) utilizes Viet Nam's 1994 agricultural census and the 1993 LSMS to create a national poverty map, relying on district-level averages to predict district-level poverty rates. Bigman *et al.* (2000) use a population census and household survey for a similar purpose in Burkina Faso. Bigman and Srinivasan (2001) likewise use a population census and household survey in India. Bigman and Huang (2000) have proposed a similar approach using data from the 1997 China agricultural census. Using data from Kenya, Bigman and Loevinsohn (1999) show how the community-

[4] The following discussion is based on Bigman *et al*. (2000).

level data method can be used in targeting agricultural research and development for poverty reduction. Godilano *et al.* (2000) have done preliminary work in linking disaggregated poverty incidence to environmental risk such as flooding and suitability for rice production in Bangladesh.

Easier access to data makes this method attractive, but the error associated with estimation for units of different sizes in terms of population has not been thoroughly investigated. To date, only one study, Minot and Baulch (2002b), has looked into the issue of how much precision is lost when using census data aggregated to community level or any other level. They find that the greater the disaggregation of the data, the more precise the estimates; errors in estimates based on census enumeration areas average approximately two percentage points. From another perspective, 98 percent of provincial poverty estimates had errors of less than five percentage points. Using census data aggregated to province level resulted in almost one third of provincial poverty estimates having errors of less than five percentage points. The study found that the magnitude of error varies with the estimated incidence of poverty, with error at its smallest when the poverty rate is close to zero, 50 percent and 100 percent. The authors conclude that the best option is to use household-level data; if it is unavailable, then community-level census data can be used to generate reasonably accurate poverty estimates.

Multivariate weighted basic-needs index

Various basic-needs indices are used for disaggregated poverty mapping. They differ among themselves in terms of the choice of variables and weighting schemes. This section focuses on an assortment of weighting schemes. Three are based on multivariate statistical techniques – principal components, factor analysis and ordinary least squares. The others have no weighting scheme; all components are valued equally.

Principal components

An alternative method of disaggregating poverty measures to the community level is that used by the Mexican Government. This methodology was first utilized to create a marginality index for policy-planning purposes and then as part of the targeting mechanism of the PROGRESA anti-poverty programme.[5] Localities were deemed eligible for the programme in terms of a ranking of the marginality

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5 See PROGRESA, 1998, CONAPO-PROGRESA, 1998, and Skoufias, Davis, and de la Vega, 2001.

index. Selection of households was then based on the results of a census administered in the communities.

This US$1 billion programme provides bimonthly cash transfers to over three million rural households, in exchange for which the children are sent to school and given medical examinations. The marginality index was developed using the method of principal components, based on seven community level variables from a combination of the 1990 and 1995 population census. In this case, four variables came from the 1995 *Conteo*, or population count:[6]

1. share of illiterate adults (persons over 14 years old) in the locality;
2. share of dwellings without water;
3. share of dwellings without drainage;
4. share of dwellings without electricity.

Three variables came from the 1990 population census:

1. average number of occupants per room;
2. share of dwellings with dirt floor;
3. share of population working in the primary sector.

The principal components statistical technique reduces a given number of variables by extracting linear combinations that best describe the variables, in this case transforming seven variables into one index. The first principal component, the linear combination capturing the greatest variance, can be converted into factor scores that serve as weights for the creation of the marginality index.[7] The marginality index was then divided into five groups based on the degree of marginality. The cutoff points were determined by the Dalenious-Hodges statistical procedure.[8]

Of 105 749 localities with a population greater than 50 individuals, only 74 994 – accounting for 97 percent of the population – had data on all seven variables. For the remaining 29 698 localities missing one or more of the seven variables, regression techniques were used to estimate the marginality index. A different equation was used to estimate the marginality index for 1 720 localities

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[6] For the first round of PROGRESA in 1996, the *Conteo* data was not yet available. All seven variables came from the 1990 census.

[7] For a description of this procedure, applied to poverty analysis, see Filmer and Pritchett (1998).

[8] For details of this application, see de la Vega (1994).

in Chiapas for which no data were collected in 1995 because of social unrest. Over 99 000 localities with fewer than two households, accounting for 585 944 inhabitants, or 0.64 percent of the population, were not included in the calculations. These households were initially excluded from the index and the programme.

For logistical, financial and programmatic reasons, the index was then crossed with other spatially based criteria – geographical location, distance between localities and access to health and school infrastructure – in order to determine inclusion in the programme. Data from other ministries were combined with GIS, and service zones were established by a process of characterizing localities according to their access to these services, taking into account the quality of roads when public services were not located in the same community. Another statistical routine was then used to choose household beneficiaries within these communities. The statistical properties of this index have not been determined. The sampling error associated with the marginality index is therefore not known. An evaluation of the PROGRESA method that compares the allocation of localities with a method similar to community-level small-area estimation is discussed in the section *Method matters*.

Principal components over time

FAO and Columbia University are using principal components in ongoing joint work to construct a poverty map for Costa Rica. The map is for use in analysing the relationship between poverty and deforestation over time. The principal components technique was chosen in preference to small-area estimation methods for two reasons: first, poverty maps were to be constructed over time for four decades, with one observation per decade, corresponding to deforestation data, but household-survey data are available only for the last two decades; second, it is feared that income data are biased.[9]

The principal-components methodology is similar to that used by PROGRESA, but in Costa Rica a comparable index over time was required. In order to construct time-series indices in the same scale, community-level averages at the district level were pooled over census years. Maps are constructed for each year, or for differences between censuses, to show which districts have improved most over time. The basic assumption made in pooling over time is that the impact of the included variables over the four decades is averaged.

[9] Community level small-area estimation will be used, however, to check the principal component results.

Change in the marginality index is thus limited to changes in the levels of variables, not changes in the relative importance or impact of each variable in determining the index. Changes in social or economic structure, for example, may alter the importance of education over the period 1963 to 2000, but these changes are averaged over the four decades (Cavatassi, Davis and Lipper, 2002).

Factor analysis

The South African government has created development indices based on factor analysis, a statistical technique similar to principal components. The primary purpose of factor analysis is to describe the relationships among many variables in terms of a few underlying but unobservable factors. Factor analysis is similar to principal-components analysis in that both are attempts to approximate the covariance matrix. Factor analysis, however, is more elaborate. The primary question it seeks to ask is whether data are consistent with some underlying structure (Johnson and Wichern, 1988). In factor analysis, sets of variables are grouped by their correlations; each group of variables represents a single underlying construct or factor. Although factor analysis does assist in identifying underlying factors represented by a set of variables, the method is subjective: the factors have to be interpreted to give them meaning. This interpretation relies on previous knowledge and intuition about underlying relationships.

Factor analysis with rotation was applied to 1996 population-census data in South Africa by Hirschowitz, Orkinand and Alberts (2000), with the aim of providing information for allocation of public development funds. The first component, interpreted as a household infrastructure index, explained 57 percent of the variance; the second component, interpreted as the household circumstances index, explained 17 percent of the variance. The variables in each factor can be seen in Table 1.

Creating the indices required the following steps. Variables were given equal weight in both indices, which was justifiable because all factor loadings were considered relatively high. In order to put variables into comparable units, each variable in each index was arranged from high to low values and then divided into three categories – high, medium and low development. Based on the value of each variable, each province is allocated to one of the categories. These are then summed for each province – with eight variables, the possible sums range from 8 to 24 – and adjusted by population size in order to provide a relative ranking of provinces by development.

TABLE 1
Factor analysis in South Africa. Loadings obtained by each variable

Variables	Infrastructure	Circumstances
Living in formal housing	.65	-.01
Access to electricity for lighting	.78	.07
Tap water inside the dwelling	.83	.12
A flush or chemical toilet	.84	.19
A telephone in dwelling or cellular phone	.77	.05
Refuse removal at least once a week	.74	.19
Level of education of household head	.60	.25
Monthly household expenditure	.84	-.08
Unemployment rate	.39	
Average household size	-.02	
Children under five years old	.05	

Source: Hirschowitz, Orkinand and Alberts, 2000.

Ordinary least squares

The Nicaraguan RPS anti-poverty programme used poverty mapping to target census segments for intervention. The pilot for this programme, which began in August 2000, currently reaches approximately 10 000 geographically targeted rural households in northern Nicaragua. The programme is similar to PROGRESA: in exchange for sending their children to school, being given health examinations and participating in public-health presentations, the woman heading a household receives a maximum of US$336 per year in cash transfers. In contrast to PROGRESA, all households in the census segments were included in the programme (Government of Nicaragua, 2000).

For programmatic reasons, the pilot was located in six municipalities in two northern departments. A marginality index was required to rank census segments for targeting purposes. The index was composed of four variables – household size, percentage of households without potable water, percentage of households without latrines and percentage of illiterate adults – which were weighted by the coefficients derived from ordinary least squares regression analysis of the determinants of extreme poverty, using household data and a larger group of variables (Arcia, 1999). No evaluation of this targeting method has been conducted. The ongoing expansion phase of the RPS will utilize poverty maps based on the household-unit level small-area estimation strategy.

Combination of qualitative information and secondary data

A number of organizations use various combinations of qualitative and secondary data to create poverty maps, focusing on food security rather than poverty. These instruments tend to focus on the determinants of food security, in most cases revolving around the concept of livelihood strategies, but collect and utilize data in different ways.

Primarily qualitative

Two variants of the livelihood approach are employed that use primary data in field vulnerability assessments. The first, the household-economy approach (HEA), developed by the Save the Children Fund in collaboration with the FAO Global Information and Early Warning System (GIEWS), has also been used by the World Food Programme (WFP) Vulnerability Analysis and Mapping System (VAM). The method has five steps (Seaman *et al.*, 2000; Bourdreau, 1998).

1. Define food-economy zones for a given region. A food economy-zone is defined as a geographical area where most households obtain food and cash income by a similar combination of economic activities.
2. In each zone, define different wealth categories. These are based on indicators of wealth identified by the people themselves, and thus relate only to categories in each zone.
3. Collect livelihood information on a typical household for a normal year in each of these categories.
4. Describe the economic context in which households live.
5. Use the above characterization as a baseline from which to hypothesize the possible impact of economic change on household income and food supply in each zone.

The main sources of data for constructing the food economy zones and livelihood strategies are rapid rural appraisal techniques, semi-structured group interviews and interviews with key informants, supplemented by secondary data. Since food-economy zones are based on geographical areas, vulnerability and risk maps can then be constructed.

The second variant is the vulnerable-group profiles developed by FAO as part of the Food Insecurity and Vulnerability Information and Mapping Systems (FIVIMS) initiative (Huddleston and Pittaluga, 2000), which identify mutually exclusive livelihood-strategy groups first through brainstorming sessions with experts. The primary source of livelihood typically serves as the principal means of classification. These groups are further refined through participatory fieldwork techniques and secondary data, and linked with geographical areas. Each profile contains information on the factors that influence livelihoods, including asset ownership and access, mediating factors such as laws, politics and culture, external factors such as demographics, the natural resource base and macroeconomic context, and vulnerability to economic and natural shocks. Emphasis is placed on understanding the determinants of food security or poverty. Group sizes are calculated, when possible using population-census data linked through occupation codes. Vulnerability maps are then constructed.

Primarily secondary

The "indicator" approach employed by the United States Agency for International Development (USAID) famine early-warning system (FEWS) – which is also geared to vulnerability assessment, though with a focus on identification of households rather than causality – is based mainly on secondary evidence, and less on field work (FEWS, 1999a). Stratification is by administrative unit and within administrative units, in some cases by household production strategies. These strategies may derive from information provided by NGOs, key informants or livelihood-system approaches such as HEA, described above. Food access and availability per person are then calculated at the administrative or group level (see FEWS, 1999b and 2000). These secondary data range from tables to statistical procedures to qualitative information when data are missing. Multiple vulnerability indicators are commonly combined into a single index with which areas and groups can be ranked. These indices are built using the following steps:

- determination of the primary dimensions of vulnerability such as agro-ecological, infrastructure, economic resources and coping ability;
- selection and transformation of comparable indicators;
- weighting of indicators, typically based on best judgment or expert opinion;
- ranking according to summed scores.

This information is linked to geographic area and thus is commonly included in vulnerability maps.

Statistical analysis of qualitative information combined with secondary data

This methodology can be combined with other statistical techniques. In a FEWS exercise in Malawi, for example, secondary information was collected from a variety of sources using statistical and conceptual-cluster analysis, and 154 geographical units, the extension planning area (EPA), were allocated to five "sphere of influence" clusters that best portrayed significant common factors influencing household food security behaviour. Such clusters are defined by the major factor influencing food-security decisions made by the majority of households in a given area. These included maize, mixed agriculture, large-estate influence, non-agricultural income-generating activity and urban influence. These methods parallel the HEA method described above (WFP, 1996; FEWS, 1997).

A principal-components analysis was then conducted on outcome indicators. The results produced three main components of vulnerability – poverty, food deficiency and malnutrition – which were mapped at the EPA level. A composite vulnerability tool was then constructed, based on the weighted distance of the three principal components in the EPAs. This index was eventually discarded, however, because of a perception that it condensed so much information as to be meaningless. Regression analysis by cluster was then used to discern which factors were associated with each of the three components, so that they could be used as policy levers. Finally, a time-series analysis of vulnerability was constructed, based on a regression analysis by cluster of the opinions of eight experts as to the evolution of vulnerability in 1992–1996.

Extrapolation of participatory approaches

Participatory assessments measure poverty in terms of local perceptions of poverty, which are identified and then extrapolated and quantified in order to construct regional poverty measures. Proponents argue that such a poverty measure is more comprehensive and represents the multidimensional nature of poverty and the processes that create and maintain it. With this indicator, poverty is defined locally in terms of perceptions of well-being and how neighbouring informants rank this perception. Utilization of this measure is thus limited to areas where people know about their neighbours, usually rural communities (Ravnborg, 1999).[10]

The process, described in Ravnborg (1999), is as follows. The number and location of communities in a chosen area are selected using a maximum-variation sampling strategy, taking into account factors that may explain expected variation in perceptions of well-being in the area of study. Following site selection, local perceptions are gathered in each site from community informants, who provide

[10] See Ravnborg (1999) for an application in Honduras, Narayan (1997) in Tanzania and Turk (2000) in Viet Nam.

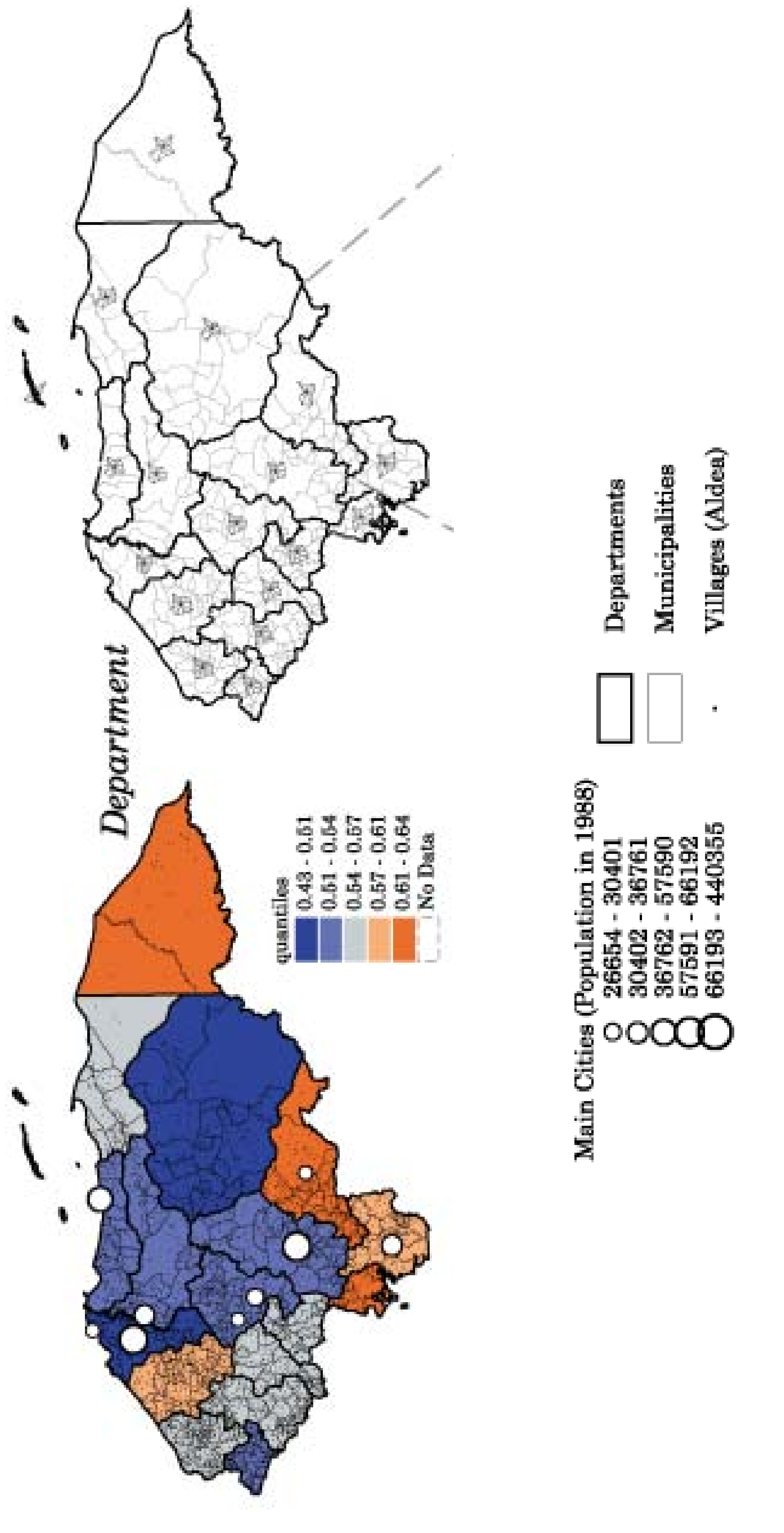
definitions of poverty and rank neighbours in terms of well-being. A well-being index is created and extrapolated to other communities in a region through a questionnaire put to a random sample of communities using standard sampling and survey procedures. At this point, the procedure resembles a classic proxy means analysis (Grosh and Baker, 1995), but instead of identifying key variables by multivariate regression, variables are identified by local informants and homogenized across sample sites. Leclerc, Nelson and Knapp (2000) compare Ravnborg's well-being index with a more traditional basic-needs index for the communities in the study area and find some correlation between the measures.

Leclerc, Nelson and Knapp (2000) extend the extrapolation of the Ravnborg index to the rest of the communities that make up rural Honduras. Using neural net software, artificial-intelligence techniques are utilized to link the 11 variables from the Ravnborg index to nine proxy variables from the most recent population and agricultural census and to calibrate the neural net on Ravnborg's original 12 communities. Once calibrated, the neural net is applied to the remaining rural Honduran villages for which data on all nine variables were available. In another paper, Leclerc (2002) directly matches 9 of the 11 variables from the Ravnborg index with the nine proxy census variables and computes village-level well-being indexes based on the average of well-being indexes for each household of a given village. The results of this exercise are shown in Maps 2A-D. The first column of maps refers to the well-being index under different levels of aggregation, while the second column of star plots corresponds to the average levels of the household variables from the census aggregated at the same levels.

Direct measurement of household-survey data

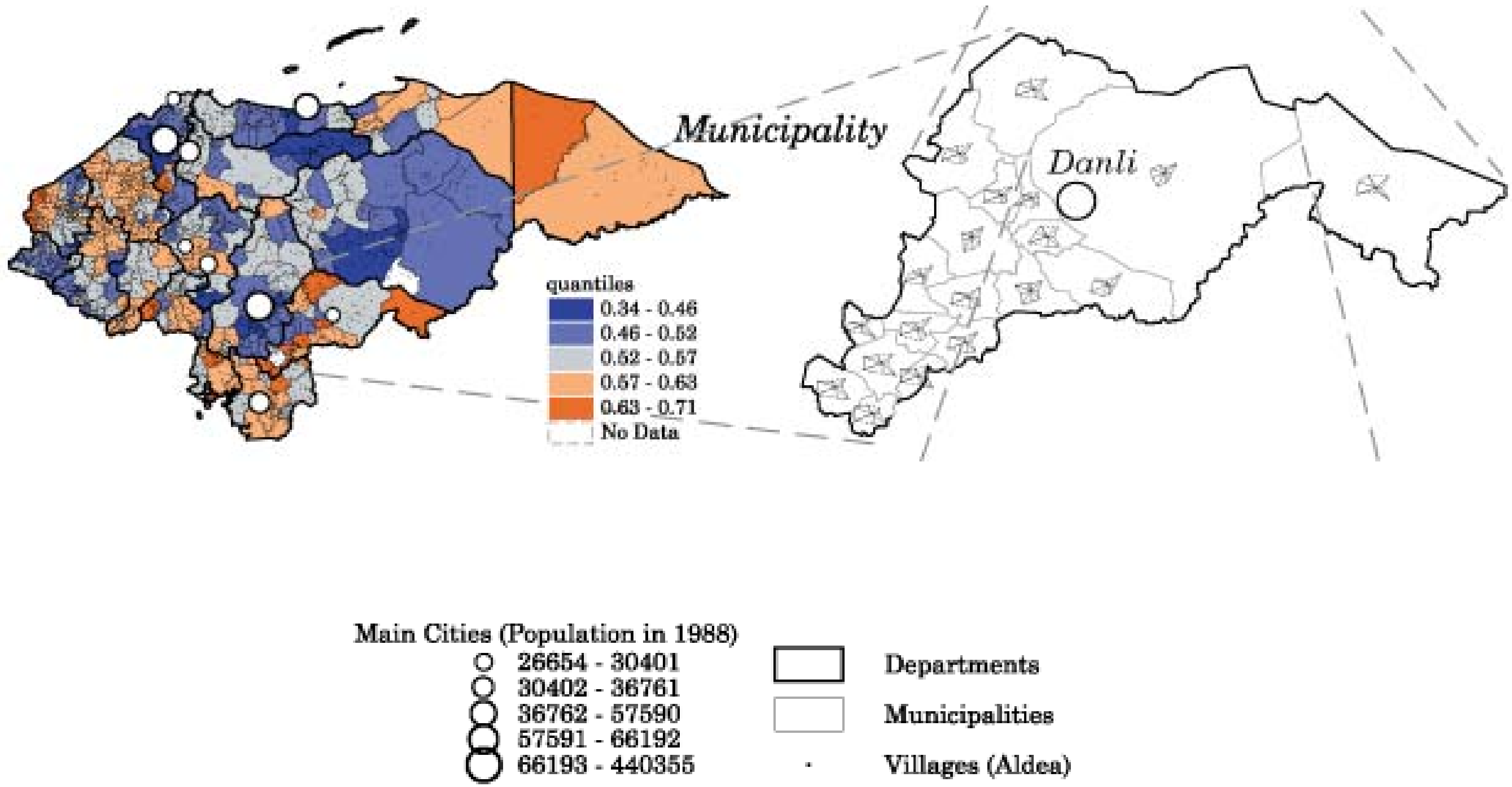
Survey data have served as the basis for a number of statistics-based poverty-mapping exercises, though their sampling properties sometimes present difficult statistical challenges. Household-survey data are often clustered and collected at too aggregate a level to be of much help in constructing disaggregated poverty maps; this is the origin of the development of small-area estimation strategies, discussed earlier. Many different kinds of survey data exist. Many countries have comprehensive household surveys with detailed consumption modules, such as the LSMS surveys described in the section on small-area estimation. Some surveys, such as the annual basic-grains survey in Nicaragua, are large and representative enough to serve as a census in small-area estimation. The light-monitoring survey (LMS) is shorter, collecting information on a series of socio-economic proxies, thus allowing a larger sample size. In comparison with LSMS, however, LMS is shown to be biased because of underestimation of

Map 2A
Honduras, participatory approach



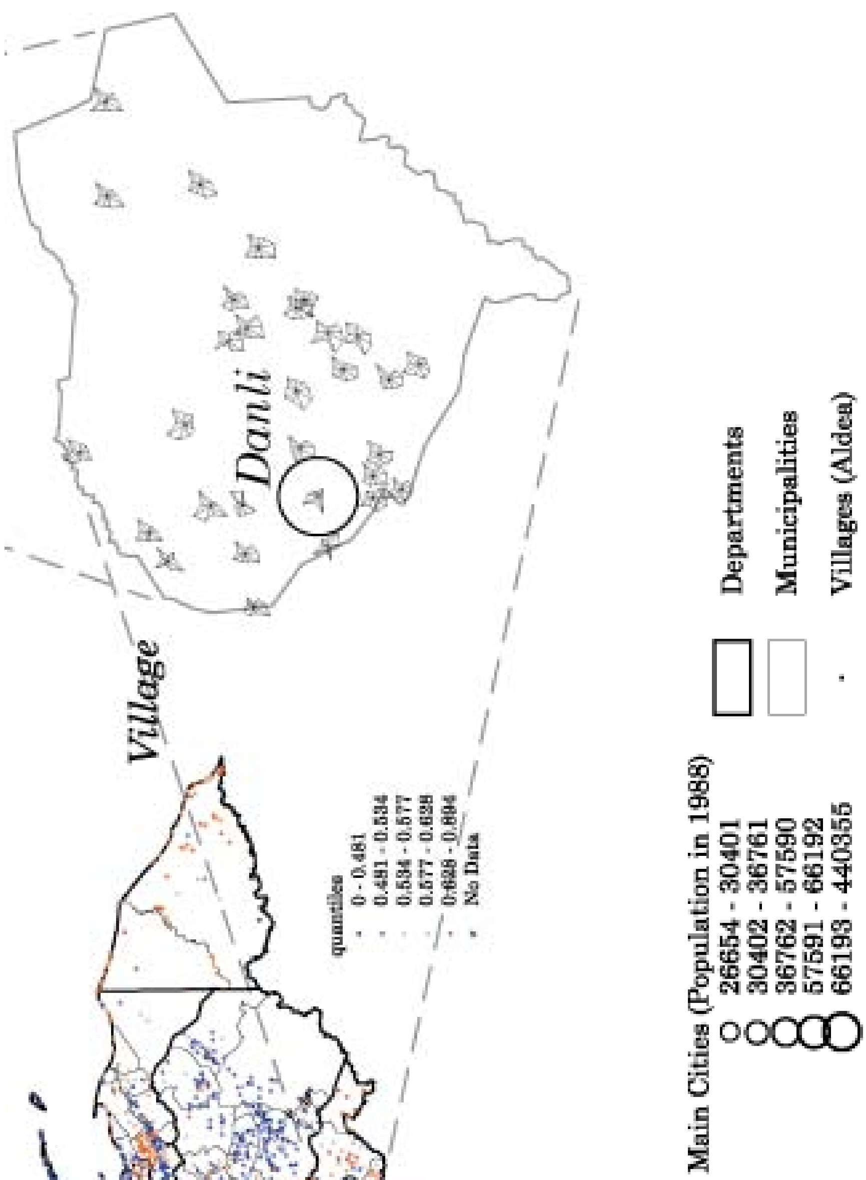
Source: Leclerc, 2002.

Map 2B
Honduras, participatory approach



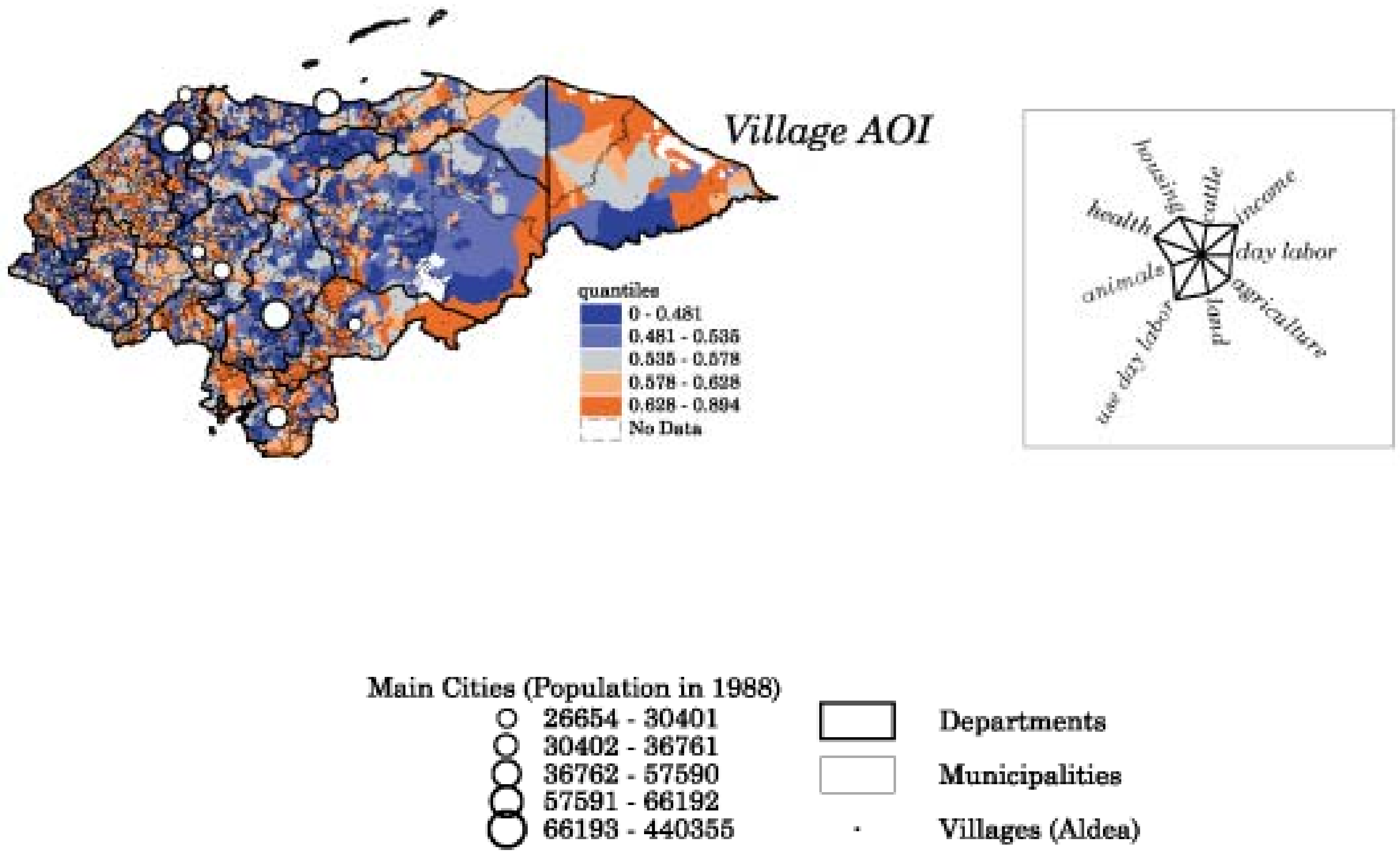
Source: Leclerc, 2002.

Map 2C
Honduras, participatory approach



Source: Leclerc, 2002.

Map 2D
Honduras, participatory approach



Source: Leclerc, 2002.

income/consumption. This results in bias in the magnitude of poverty and spatial distribution (Fofack, 2000).

Georeferenced household surveys have the potential to be re-aggregated into new units of analysis and thus help to create novel poverty maps; DHS on health and nutrition are an example. DHS does not include consumption, but proxies income by creating asset indices (Filmer and Pritchett, 1998). Henninger (1998), for example, describes how survey data were aggregated to new units of analysis – aridity zones – within which the distribution of anthropometric indicators was analysed. Macro International, the firm that carries out DHS, is starting to map a wealth index using data from the survey in Egypt (L. Montana, personal communication, 2001).

UNEP (1997) studied the relationship of rural poverty and land-use potential using DHS data from West Africa. DHS variables such as literacy, child mortality and school enrolment were used to build a human-development index (HDI) to serve as a proxy for poverty, which was then crossed with the aridity zones described above and land degradation. This information was then included in poverty maps for the West African region.

McGuire (2000), focusing on food security vulnerability instead of poverty, uses a composite HDI as well as principal components to analyse the relationship between food security and biophysical parameters. Spatial filtering techniques are then used to extend the correspondence of the DHS data from the first to the second administrative level. The HDI index, an arbitrarily weighted index composed of biophysical, educational, demographic, nutritional, health-access and income proxies, is then mapped at the second administrative level.

Rogers (2000) uses DHS data as an input in an impact evaluation of USAID programmes in Africa based on GIS techniques. The premise is that although the welfare estimates of these types of surveys are not representative at the cluster level, covariance analysis across clusters can be conducted provided that the estimates are unbiased. These cluster-welfare indicators serve as dependent variables and are linked through GIS with a series of explanatory variables.

Direct measurement of census data

Income data

Many countries collect information on income in population censuses. This information, typically based on only one or a few questions about cash income, has been used to create disaggregated poverty maps, without data from other sources. The Brazilian hunger map, for example, is based on direct measurement of household income reported in the 1991 population census. Household income was compared to a food-based extreme poverty line and a non-food moderate poverty line. The headcount index was then calculated for each municipality. Regional and state measures were based on a 1990 household survey (Peliano, 1993). Similar exercises have been conducted in South Africa and elsewhere. Some studies use direct measurement of census-based household income in multivariate analysis. Osgood and Lipper (2001), for example, link subnational proxies for poverty with soil-degradation measures in Ghana.

Recent analysis of South African data (Alderman *et al*., 2000), however, shows that census income variables, which are necessarily limited, given the extremely large number of observations collected, are systematically biased. Census income data under-represent levels of well-being as compared to expenditure data from a nationwide household survey, thus giving higher rates of poverty – almost 80 percent in this case. Differences were correlated with urban/rural location, suggesting that for rural households with a higher share of non-cash income, well-being is under-represented by census data. Census income data are thus a poor targeting tool in countries with a large share of non-monetarized or informal income.

Basic-needs index

A number of countries have used household-unit data from a census to create poverty maps based on basic-needs indices. In Honduras, for example, researchers from the Centro Internacional de Agricultura Tropical (CIAT) created a series of basic-needs indices for poverty-mapping purposes (Leclerc, Nelson and Knapp, 2000 and Leclerc, 2002). These were based on access to household-unit data from the 1988 population and housing census and the 1993 agricultural census. In basic-needs approaches, poverty is typically related to deprivation or lack of the goods and services necessary to sustain life. The indices are calculated at household level, then aggregated by geographical or administrative grouping by counting the fraction of the population in a particular basic-needs stratum. The process is the following: for each variable x, a minimum acceptable value x^* must be defined, which in this case is the corresponding national average value; cx is an indicator of failure in obtaining x^*. For household i, this is calculated as:

(X) $$cx_i \mid 14 \frac{x_i}{x^*}$$

which is normalized by maximum and minimum values over all households in order to allow comparison and aggregation among variables. Thus cx_i lies between –1 and 1.

Two aggregate indices were constructed for each household. The first included indices on small size and low quality of housing, lack of basic services and energy, lack of non-land assets and lack of education. The second was composed of the same indices, with the exception of education. Variables were weighted equally in almost all the individual indices that made up the aggregate indices, though different weights could be introduced. The two indices were aggregated to three levels: village, municipality and department. An administrative entity was considered poor if the proportion of poor households was greater than 0.4.

The Andean Network of Spatial Data (REDANDA) has brought together statistical agencies and universities in Bolivia, Columbia, Ecuador, Peru and Venezuela. They have created disaggregated municipal-level regional maps of development indicators from population-census data. This network achieved homogenization of standards among the five countries for the 2000 census, which will be jointly analysed in 2002–2003 (REDANDA, 2001).

In Brazil, 38 georeferenced variables including two composite indices from the 1970, 1980 and 1991 population censuses make up the Atlas of Human Development. The two composite indices, following United Nations Development Programme (UNDP) methodology, are the human-development index and the life-conditions index. The Atlas of Human Development has been a tremendous success as the basis for decision-making with regard to public investment and targeting of social programmes worth billions of dollars (Snel and Henninger, 2002).

Similarly, a basic-needs index based on 1993 census data was used by the Peruvian social fund (FONCODES) to distribute over US$500 million during the 1990s (Snel and Henninger, 2002).

Another project in Honduras developed and mapped a series of disaster-vulnerability indices by municipality, using census and other data sources. The indices had the following dimensions:

1. environmental: flood and landslide risk area;
2. population: total population at risk of flooding and landslide;
3. social: percentage of very poor people at risk;
4. infrastructure: roads and electricity lines at risk.

These indices were weighted and aggregated into an overall vulnerability index that allowed identification of municipalities for priority intervention (Segnestam, Winograd and Farrow, 2000).

Z scores

The Honduran Programa de Asignación Familiar, Fase 2 (PRAF-II), which began disbursements in 2001, is conceptually similar to PROGRESA and the Nicaraguan RPS. Beneficiaries receive US$58 per year per child for attendance at school, and another US$46 per year per family to cover the opportunity cost of complying with health-care attendance requirements. The programme provided funds to schools and health centres to improve the supply of services commensurate with increased demand (UCP-IFPRI, 2000).

Researchers at IFPRI who were assisting PRAF with design and development of the programme utilized yet another instrument for targeting. The second phase of PRAF was limited to the 80 poorest municipalities in the country, provided funds were available. Municipalities were selected on the basis of average height-for-age Z scores, which are the number of standard deviations from the mean. Height-for-age is considered a good indication of chronic malnutrition and thus serves as a proxy for poverty and food insecurity. Data were taken from the 1997 census of first-grade schoolchildren's height; Z scores were standardized by reversing on sex and age. Municipalities were ranked by Z scores and randomly allocated into three treatment and control groups for evaluation purposes.

4. Choosing is not a trivial decision

Most researchers and policy makers interested in using poverty maps, and even those developing poverty-mapping methodology, are unaware of this bewildering array of methods. Such a wealth of options, however, invites the question: Does it matter which method is chosen? The answer is an emphatic "yes", although one might suspect that most would prefer to remain ignorant rather than face an apparently impossible decision. The choice of method does matter; levels of disaggregation and drawing geographic boundaries matter; and the choice of indicator matters. All these elements can lead to a re-ranking of regions, communities or households, or lead to quite different policy conclusions. The fundamental problem is that little information exists on how much the choice of method matters, despite the fact that governments are spending billions of dollars a year, and millions of poor people either receive or are excluded from benefits as a result of these different poverty-mapping methods.

Method matters

The assertion that the choice of method matters should not be surprising. Different methodologies use different data sources, assumptions and statistical routines. Few comparisons or sensitivity analyses of the different methods have been carried out, however. This lack of information constitutes a gaping hole in the analytical foundation of the emerging poverty-mapping movement. Although sophisticated statistical advances have been made for a variety of methods, little information exists as to the practical implications of choosing one method or another. What kinds of poor people in which regions are favoured by one method or another?

One of the few comparative studies compares the PROGRESA principal-components method with a method similar to community level small-area estimation (Skoufias, Davis and de la Vega, 2001). A marginality index was calculated that combined data from a national-expenditure survey and a census, based on the predicted probability of being poor for each locality. As before, the index was separated into five groups based on Dalenious-Hodges. This classification is compared with the PROGRESA index using a 5x5 matrix, as shown in Table 2. Small-area estimation results in a stricter categorization of poverty, implying that the small-area estimation method would be more appropriate in cases where avoiding leakage – including the non-poor as beneficiaries – is more important than avoiding under-coverage – excluding the poor. The correlation between the two methods tends to break down in the middle of the marginality spectrum, the medium-poverty category, signifying that the PROGRESA index loses power of distinction as marginality becomes less abject. This result has important implications for expansion of the programme beyond the most marginal communities.

Some methods may be very robust and others quite sensitive to changes in the information included. Obviously, the more sensitive a measure is to small changes, the less confidence may be had in the results. An example of an extremely sensitive measure is the basic-needs method described earlier, employed with Honduras census data. Only a few variables are included in this index; in Maps 3A-D two indices are presented, distinguished by a single additional variable – educational attainment. The addition of this variable results in a re-ranking of marginality at all administrative levels.

TABLE 2
Categorization of marginality: PROGRESA versus small-area estimation

		Small area estimation						
		Very Low	*Low*	*Medium*	*High*	*Very High*	Total	%
PROGRESA	*Very Low*	**613**	3 473	3			4 089	5
	Low		**5 361**	250			5 611	7
	Medium		5 390	**7 088**	3		12 481	17
	High		83	15 819	**682**		16 584	22
	Very High			6 104	27 770	**2 357**	36 231	48
	Total	613	14 307	29 264	28 455	2 357	74 996	100
	%	1	19	39	38	3	100	

Source: Skoufias, Davis and de la Vega (2001).

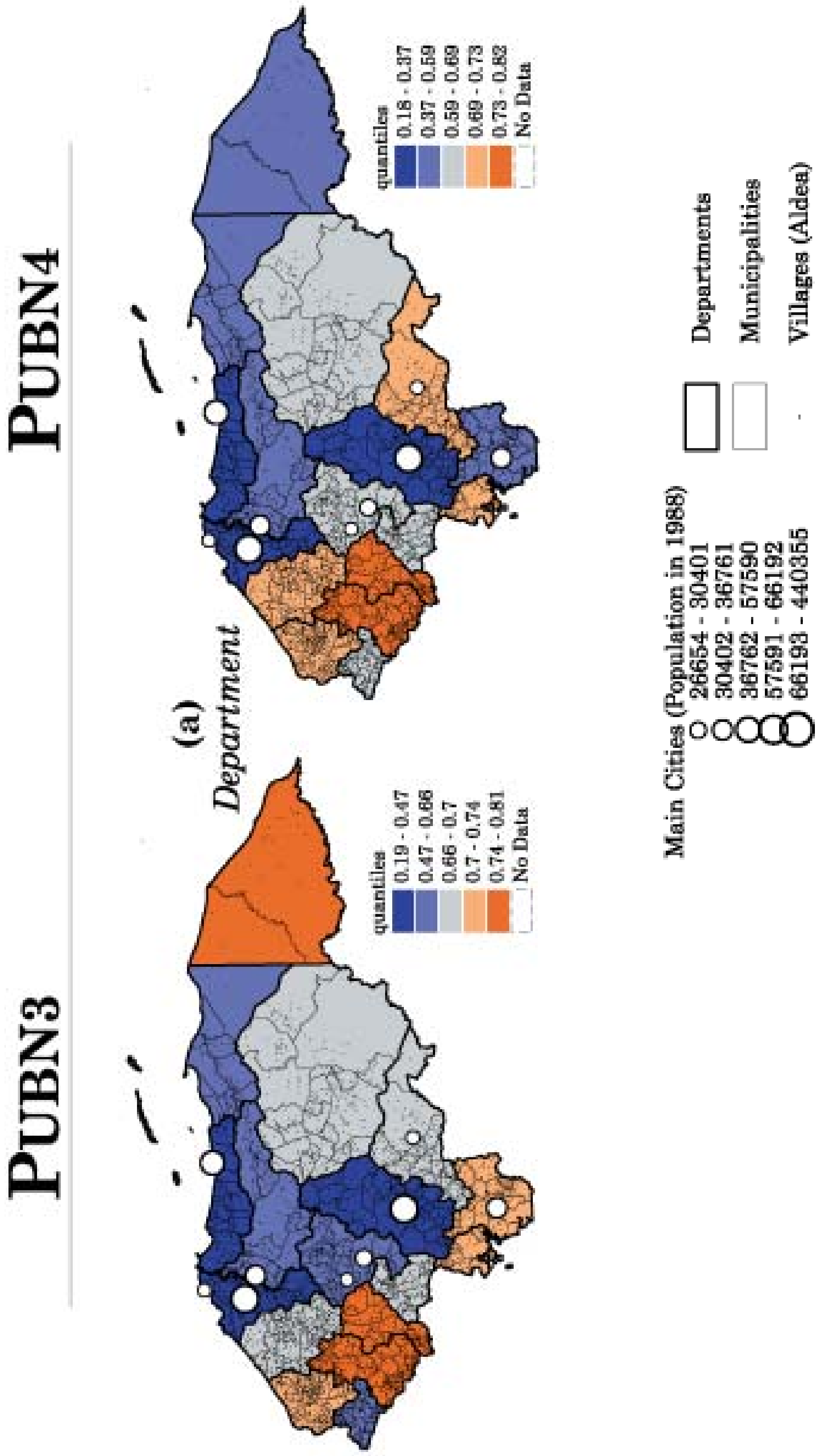
Levels of disaggregation and area shapes matter

Even simpler circumstances can have important impacts in terms of poverty rankings, such as changing the level of disaggregation as measured by geopolitical groupings. As shown in Map 3, the basic-needs index is presented at three levels of geopolitical disaggregation in Honduras; in Map 2 it is the participatory index. The results illustrate that choice of level of disaggregation has important policy implications. A given level of disaggregation in each index would lead to a different allocation of targeted resources. The apparent increased precision evident in the maps may thus be deceptive, because it is unclear what errors are associated with these measurements. Which level is appropriate?

Modifiable area unit problem

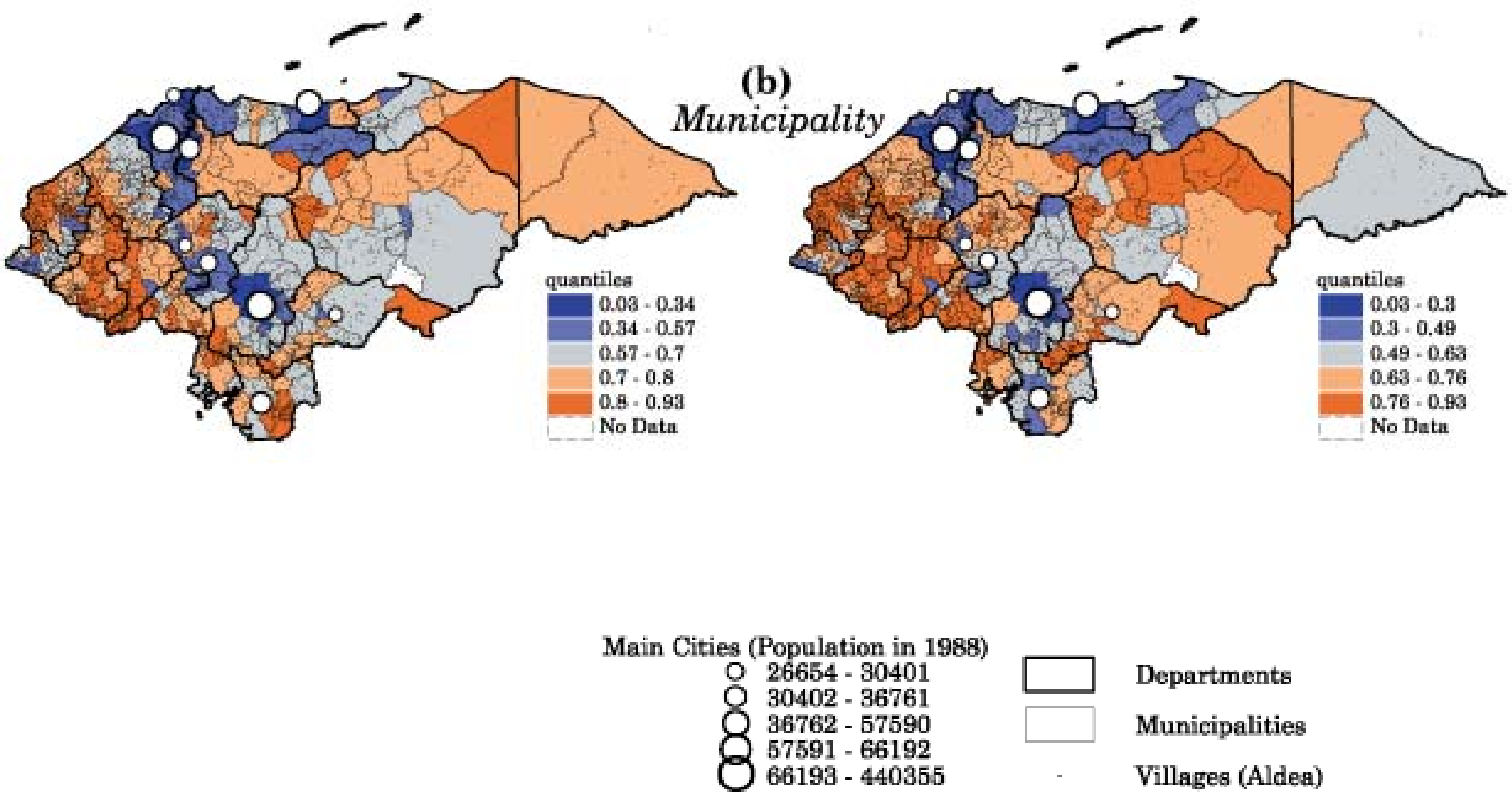
A major problem in spatial analysis is known as a modifiable area unit problem (MAUP). Units of area, whether administrative or political boundaries, agro-ecological zones or image pixels, are essentially arbitrary groupings, and the data within can be aggregated in an infinite number of ways (Nelson, 2001; Bigman and Deichmann, 2000a). This includes GIS-constructed data and any kind of spatially aggregated data such as censuses or household surveys. The practical implication is that alternative aggregations of the data may lead to different and conflicting results. In other words, the analysis soon becomes messy, and most practitioners would just as soon be ignorant of these awkward facts. This is true for simple visual correlation analysis as well as sophisticated econometric techniques. In terms of multivariate analysis, the relationship

Map 3A
Two indices: Honduras, basic-needs approach



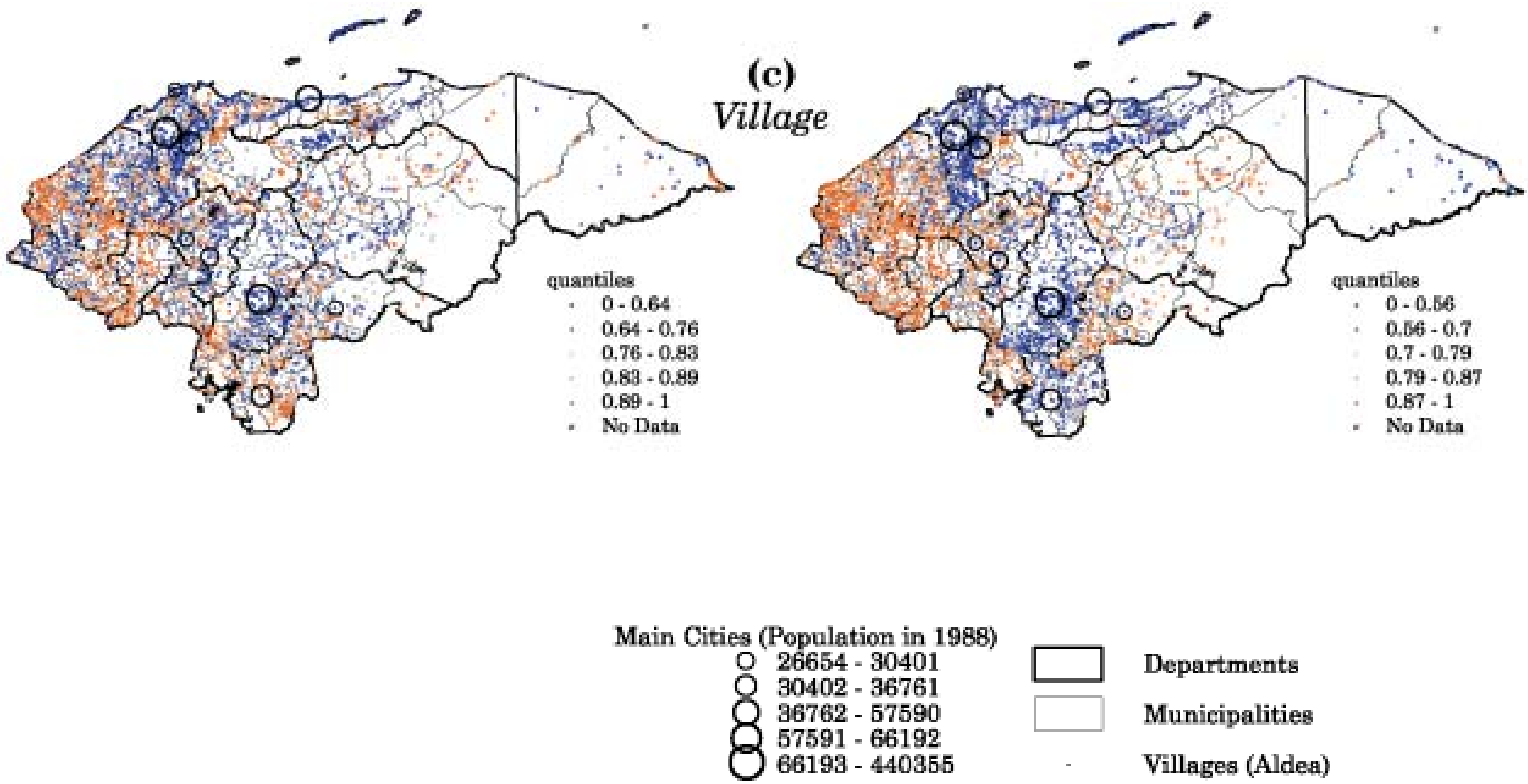
Source: Leclerc, 2002.

Map 3B
Two indices: Honduras, basic-needs approach



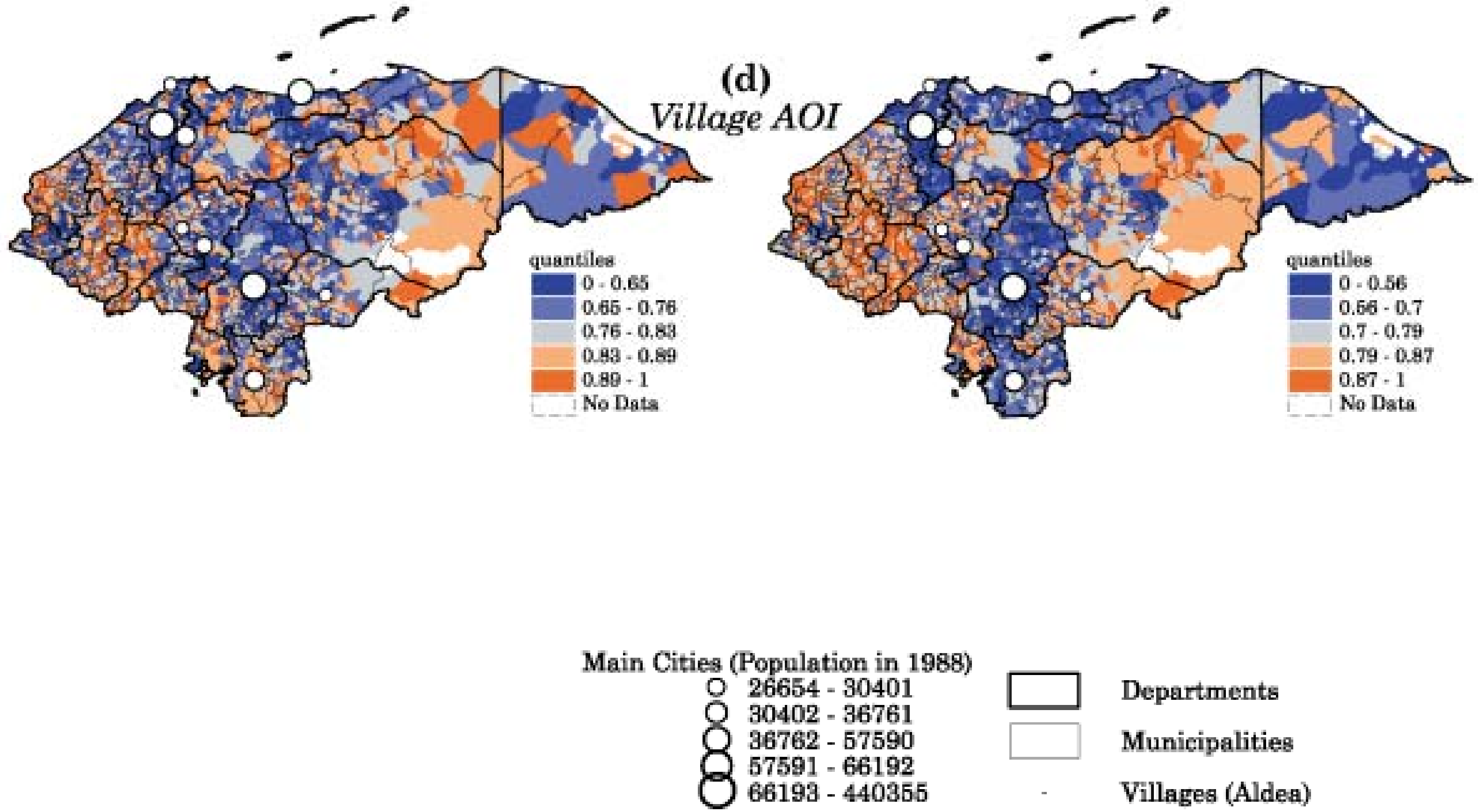
Source: Leclerc, 2002.

Map 3C
Two indices: Honduras, basic-needs approach



Source: Leclerc, 2002.

Map 3D
Two indices: Honduras, basic-needs approach



Source: Leclerc, 2002.

between dependent and independent variables may change over space in a manner that the analyst may not be able to determine *a priori*. Results can thus be purposely modified, or errors inadvertently made, through the process of aggregating data.

Nelson (2001) discusses a number of tools to minimize these effects. These include convolution filtering, in which a window moves over the data to produce a new data value, and different methods of zoning, including extending the concept of area units beyond preset administrative boundaries, or Euclidean distance to other measures such as time, accessibility, cost or energy that have more social or economic meaning. Nelson also explores a multivariate analytical technique, geographically weighted regression (GWR), which in combination with clustering techniques permits mapping of regression parameters and soundness of fit measures.[11] Rogers (2000) describes the process of reasoning in avoiding MAUP for the West African Spatial Analysis Prototype (WASAP) project and impact evaluation in Zaire.

Indicators matter

Alternative indicators

Few dispute the multidimensional nature of poverty and food security. Poverty mapping is by definition, however, about summarizing information in a few indicators, whether these are indices or single variables. A decision must therefore be made in each poverty-mapping application as to how to aggregate or how best to proxy food insecurity, and well-being in the case of poverty. While poverty and food insecurity are not necessarily the same phenomena, much overlap exists in terms of indicators.

Multiple indicators exist for poverty and food insecurity; there is an extensive literature on their strengths and weaknesses.[12] Discussion here will be kept to a minimum and will focus on household measures. The choice of indicator may respond to philosophical preconceptions – the view that self-chosen, participatory or basic-needs indices are inherently better than economic indicators – to data limitations, or it may be the result of reasoned analysis of a given context.

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11 The model and examples are discussed in detail in Nelson and Leclerc (2000).

12 See, for example, Ravallion (1992) and Maxwell (1999) for two among many on poverty measures, Maxwell and Frankenberger (1992), D. Maxwell (1996), S. Maxwell (1996) and Carletto (1997) for food security, and Henninger (1998) for a good review in the context of poverty mapping.

Analytical procedures range from statistical techniques to participatory studies in which poverty indicators are revealed by the population being studied. Information on most of these measures may be generated through surveys, secondary data, key informants/experts or a combination of these.

Poverty measures can be grouped into four major categories.

- **Economic**. These include monetary indicators of household well-being, particularly food and non-food consumption or expenditure and income. These measures are primarily used by economists, but many NGO and development agencies use a variety of consumption and income measures, including non-monetary proxies of household well-being such as ownership of productive assets or durables.
- **Social**. These include other non-monetary indicators of household well-being such as quality and access to education, health, other basic services, nutrition and social capital. These measures are sometimes grouped into basic-needs or composite development indices by agencies such as UNDP.
- **Demographic**. These indicators focus on the gender and age structure of households, as well as household size.
- **Vulnerability**. These indicators focus on the level of household exposure to shocks that can affect poverty status, such as environmental endowment and hazard, physical insecurity, political change and the diversification and riskiness of alternative livelihood strategies.

Food-insecurity measures can be similarly grouped into three categories.

- **Direct measures of consumption**. These indicators look at household or individual food intake, total and food expenditures and caloric acquisition.
- **Outcome indicators of nutritional status**. These indicators focus on anthropometric and micronutrient indicators.
- **Vulnerability**. This concept encompasses notions of access and availability, risk and uncertainty. Indicators include household access to assets, household size and composition, asset liquidity, crop and income diversification and food production at household level.

The choice of indicator matters

The choice of indicator certainly matters, for both poverty and food insecurity. Numerous studies have shown that at the subnational level, different indicators can lead to alternative poverty or food-insecurity rankings.[13] The choice of indicator thus has practical implications for results in terms of identifying the poor and their location. Care must be taken in poverty-mapping exercises not to assert *a priori* that one variable is better than another. It is far preferable to explore the trade-offs inherent in the choice of indicators: what assumptions must be made, and the practical implications in terms of costs, technical requirements, errors of exclusion and inclusion and the characteristics of the chosen population. While a full-scale comparison of the impact of alternative indicators in each exercise may not be feasible, all poverty-mapping efforts should at least justify or qualify the choice of poverty or food-security indicator.

5. How to choose a poverty map

The preceding discussion should make the potential practitioner somewhat nervous about the choice of methodology. It is in practice difficult and impractical for all practitioners to test alternative methods. Poverty mapping is carried out by a variety of institutions and individuals, ranging from government ministries to NGOs to individual academic researchers. Each may have different ideas and analytical and financial capacity with which to carry out the exercise. Five elements or constraints taken together guide and justify the choice of a poverty-mapping methodology: the purpose or objective of the exercise, the poverty philosophy of a practitioner or institution, data availability, analytical capacity and cost.

Purpose

Practitioners may have one or several objectives when planning and carrying out a poverty-mapping exercise. These may range from targeting specific small or large interventions, building a map to convey a political message or constructing inputs for a correlation or multivariate analysis. Each of these objectives may dictate a particular methodology. Interventions require greater precision and specific indicators, because the welfare of thousands, even millions, of people in a country depends on this measurement. Research and maps for

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13 See, for example, Glewwe and van der Gaag (1988), Baker and Grosh (1994), Carletto and Davis (2000), Hentschel *et al*. (2000), Skoufias, Davis and de la Vega (2001) and Leclerc, Nelson and Knapp (2000).

communication can tolerate greater levels of error and thus do not face this particular constraint. The purpose of a poverty map is thus linked directly to the issue of bias and error, though practitioners may be unaware that they are making this decision or trade-off.

Philosophy

Practitioners may have a range of philosophical beliefs that influence the choice of methodology. These beliefs are often associated with professional disciplines or institutional characteristics. Economists generally prefer consumption-based welfare measures and methods based on econometric analysis; they thus prefer the two small-area estimation methods, which were developed by economists. Sociologists and anthropologists are generally suspicious of poverty characterizations generated by quantitative survey data; they prefer case studies, rapid rural appraisals and participatory approaches. NGOs tend to prefer the latter techniques, which are more suited to the work and interventions they carry out. National statistical institutes have traditionally relied on statistical measures that have little economic meaning, such as principal-component and factor analysis, which are often used to create different types of indices. This is not surprising, because national statistical institutes have traditionally been staffed by statisticians. The great variety among the methods described in Section 3 stems largely from these professional and institutional beliefs.

In poverty analysis, however, these traditional preferences have recently begun to break down. Interagency cooperation in a number of countries has fostered openness at national statistical institutes for implementing other types of methodology. This is particularly evident in the diffusion of the World Bank's small-area estimation methodology, which has been accepted in an increasing number of countries. Much of this acceptance can be attributed to a commitment by the World Bank poverty-mapping group to in-country training and production of poverty maps, and to provision of user-friendly statistical instruments designed to utilize data already collected by national statistical agencies. Conversely, given the scarcity of consistent consumption or income data in many countries, and the cost of collection, economists have experimented with asset-based poverty indices based on statistical techniques such as principal components.[14]

[14] See, for example, Filmer and Pritchett (1998).

Data availability

Different types of data constitute the basic inputs into poverty mapping. Data availability is thus a fundamental constraint in choosing a poverty-mapping method. This constraint has two levels: the existence of data, and access to existing data. Many methodologies depend on the existence of data derived from extremely expensive collection efforts such as a population census and national household surveys. Few poverty-mapping exercises can justify such a level of expense for this single use, so in marketing its small-area estimation technique, probably the most data-intensive methodology, the World Bank wisely argues that their method serves to utilize data that already exist. But many countries do not have contemporaneous census and household-survey data, which constitutes a major problem for small-area estimation methodologies. Such databases are expensive to collect, so they are not repeated very frequently. When combining databases, practitioners are thus faced with problems of timing between databases; at some point, after a certain number of years, the databases are no longer compatible.

Other methodologies described in Section 3 require collection of primary data, and may combine this with whatever else is available. Methodologies that combine qualitative with secondary data are relatively inexpensive to implement and thus are less constrained by data availability. Because statistical rigour is less important, practitioners take advantage of existing data and fill the gaps with their own fieldwork. Participatory methods create their own data, but the formalization of the participatory method described in Section 3 requires a more formal and thus more expensive data-collection effort.

Obtaining access to existing data constitutes a barrier for a number of poverty-mapping methodologies. The household-level unit census data required for the World Bank small-area estimation method is perhaps the most sensitive type of information, and many countries are rightly reluctant to provide it to outside institutions and researchers. The World Bank poverty-mapping group has had great success in obtaining access to this information, primarily because of its policy of conducting all analysis in-country in collaboration with national analysts. Not all international organizations or NGOs and few individuals have similar resources and influence with which to obtain the same access, however, which limits use of the World Bank small-area estimation method by other practitioners.

Community-level averages from census data are more readily available, often on the Internet, which makes the alternative small-area estimation method more attractive for general use. For the same reason, practitioners working on small budgets will be drawn to those methodologies for which data are more readily available, be they marginality indices, direct measurement of census data or other secondary sources.

Subnational accessibility data such as access to health and education facilities and infrastructure and transport and travel time have proved useful in Mexico (PROGRESA, 1998) and Burkina Faso (Bigman *et al.*, 2000) as inputs into targeting anti-poverty programmes and visual correlation with poverty and food insecurity (see Henninger, 1998, for many examples). They can play a very important role as explanatory variables in the multivariate analysis of the determinants of poverty and food insecurity, though this has yet to become common practice. Availability of this type of data varies widely by country, however, and must be taken into consideration in terms of the design and selection of empirical studies.[15]

A major problem is that data are still weak on the environmental aspect, particularly for single-country subnational poverty studies. Few in-depth environmental surveys collect information typically found in household surveys – a search must be made for those notable exceptions – and although some kind of subnational poverty data are usually available, it is often not comparable with the environmental surveys, or it is not geo-referenced. Many global data sets may not be appropriate for use in subnational studies, particularly in medium-sized or small countries, because they do not capture in-country variation and are thus insufficient for establishing relations between these variables and the outcomes of interest. These include, for example, the FAO farming-systems typology and the GLASOD soil-degradation database.

Analytical capacity

Analytical capacity is another constraint. The poverty-mapping methods presented in Section 3 imply a wide range of analytical demands. The World Bank poverty-mapping group, for example, has expended great effort in making the sophisticated econometric small-area estimation model as standard and user-friendly as possible, but it still requires a certain level of statistical and econometric understanding to implement and interpret. Methods that employ statistical techniques that are more traditional in the sense that they form part of a professional statistician's training may be much more appealing; examples are

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[15] See Nelson *et al.* (2000) for a description of constructing these types of variables in Honduras, and Bigman and Deichmann (2000b) for discussion and examples relating to Madagascar.

principal components or factor analysis. Most statistical agencies are staffed by statisticians, as discussed earlier, and the application of econometric techniques favoured by economists is not always straightforward or easily understood. For smaller-scale practitioners such as NGOs, which depend on qualitative work, lack of basic training in statistics or econometrics tends to exclude more quantitative methods from the outset.

Cost

Cost represents the final and usually overriding constraint. Basically, the more sophisticated the analysis, and the more data to be collected, the more expensive the exercise becomes. Cost includes time spent obtaining, understanding and analysing data. Governments planning to use poverty maps to guide policy interventions should obviously invest in analytical and data infrastructure and then choose the technique which best fits their objectives and philosophical perspective. Researchers at the computer with limited funds may be restricted to what they can find on the Internet.

6. CONCLUSION

Anything can be mapped, from census data to highly sophisticated small-area estimation to expert opinion. But how good is the map? How can a poor poverty-mapping method be avoided? This is a particularly pernicious problem, given that it may be a number of years before the quality of a particular method is evident. Poverty mapping does not yet have a gold standard, partly because the context of poverty mapping is as varied as its applications. The choice of a poverty-mapping methodology therefore depends on a number of logical and legitimate considerations, discussed in Section 5, such as objectives, philosophical views on poverty, limits on data and analytical capacity and cost.

Practitioners should choose the most appropriate method for their purposes. The most disturbing problem with current poverty-mapping methods, however, is the minimal attention paid to potential error and bias, and to the types or characteristics of the poor populations chosen by different methodologies. Only two methods have made a serious attempt to gauge the importance of statistical error: the two small-area estimation methods, which provide indicators as to the error associated with increasing levels of disaggregation. Other methods, such as that used by PROGRESA, make poverty characterizations of communities as small as 50 households without specifying the statistical power of these characterizations. But data limitations often force simple solutions, such as direct census measures. In these cases, there must be an awareness of bias.

There is no evidence that methods that put themselves forward as a gold standard, particularly the World Bank small-area estimation method, result in the best poverty mapping. Indeed, there has been little study of the differences in terms of practical outcomes, error and bias between small-area estimation and other methods. Theoretically and philosophically, small-area estimation may be the best poverty-mapping method based on a consumption-based welfare indicator, but we cannot assert more then this. Alderman *et al*. (2000) argue that all poverty mapping comes down to appropriate weighting of a poverty index. Small-area estimation is essentially weighting an index using a multivariate regression model, and thus should compare favourably to ad hoc weights. But what about weights based on other statistical routines, or expert opinion?

Ultimately, given the lack of information regarding bias and error in most poverty-mapping methods, practitioners should proceed with full awareness of the pitfalls and uncertainties of their particular method. The robustness of the chosen method should if possible be evaluated in terms of component variables, outcome indicators and alternative methods. Further research is clearly needed in terms of comparing the statistical precision and practical outcomes of different methods. Evaluating the statistical properties of some methods may not be technically feasible, but recognizing the potential bias of each method in terms of the resulting poverty profile is an essential first step.

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