Is it possible to avoid a lemon?
Reflections on choosing a poverty mapping method

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ABSTRACT

Poverty and food security in most countries are highly heterogeneous phenomena. Both types and depth of poverty, measured in a variety of ways, vary between and within countries, regions or other geographic and administrative units. Poverty mapping in all its various forms involves techniques which 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 rankings by poverty of the chosen unit. The methodologies utilized are diverse, from participatory poverty profiles to sophisticated econometric techniques, and most are under continuing development. Each of these has different data requirements and implementation costs, and different advantages and disadvantages in their use. The themes of statistical error and possible bias are key issues in poverty mapping.

The purpose of this paper is to discuss the relevance of and options in poverty and food security mapping for analysis and policy design and implementation in the rural sector of developing countries. We present and compare a large selection of the alternative poverty and food security mapping methodologies in use, in order to provide some guidance as to the possibilities and appropriateness of these methodologies for different policy applications. We do this by studying in detail a number of applications of poverty mapping to policy questions.

1. Introduction[1]

Poverty and food security in most countries are highly heterogeneous phenomena, making it common to find wide spatial variability. Both types and depth of poverty, measured in a variety of ways, vary between and within countries, regions or other geographic and administrative units. Spatial heterogeneity can develop for a variety of reasons, including differences in geography, history, ethnicity, and access to markets and public services, infrastructure, and other facets of public policy (see, for example, Bloom and Sachs, 1998, Jalan and Ravallion, 2000, or de Janvry and Sadoulet, 1997). Heterogeneity in poverty and food security is often hard to measure correctly, however, with conventional analytical tools. The key problem is obtaining data which permits the measurement of poverty and food security at a level of disaggregation sufficient to capture the heterogeneity brought on by spatial variability.

The concept of mapping involves measuring the incidence of poverty and food security by 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 since here the focus is on methods, not specific indicators.

Poverty and food security mapping can take place at a variety of levels ranging from the globe to continents and regions, to subnational analysis and specific areas within countries. Global or regional mapping typically uses country level or broad geographic based variables. At the subnational level, poverty mapping in all its various forms involves techniques which permit sufficient disaggregation of a poverty measure to local administrative levels, or small geographical units based on a wide variety of possible criteria (e.g. agroecological, land use, livelihood or production system parameters), in order to accurately gauge spatial heterogeneity by a specific criteria. All poverty maps that aspire to national coverage require a census with which to exploit directly or extrapolate micro analysis. All poverty mapping techniques imply alternative schemes for weighting a particular poverty index, and may imply alternative rankings by poverty of the chosen unit. Thus the themes of statistical error and possible bias are key issues in poverty mapping, though most practitioners to date have remained blissfully ignorant of these complications.

The purpose of this paper is to discuss the relevance of and options in poverty and food security mapping for analysis and policy design and implementation in the rural sector of developing countries. We will present and compare a large selection of the alternative poverty and food security mapping methodologies in use, in order to provide some guidance as to the possibilities and appropriateness of these methodologies for different policy

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applications. The goal is to send some warning signals regarding the deceptively relative ease with which it is possible to construct colorful and informative poverty maps, when different methods or different data could lead to very different results. We do this through studying in detail a number of applications of poverty mapping to policy questions. We conclude by pointing out where more research is necessary. Our focus is primarily at the subnational level, where a spate of analytical activity has blossomed over the last few years.

2. The relevance of spatial analysis

Mapping, for the purposes of this paper, is defined as the spatial analysis of poverty and food security, both visually and econometrically. Spatial determinants are important for understanding the distribution of assets key to poverty alleviation and combating food insecurity, including human capital (health and education, technology) and social capital (ability to cooperate, social networks). It is particularly in the area of natural resources where spatial analysis has most promise, as natural capital asset holdings (including natural resource stocks, land quality, and environmental quality) are difficult to characterize with conventional variables, and by definition are spatially distributed. Similarly, infrastructure variables, such as road density and quality, and access to labor, product, and input markets also have an important spatial dimension.

Poverty mapping has two primary uses. First, the spatial identification of the poor, the use on which we concentrate in this paper. In many instances poverty mapping has served to target social, agricultural, emergency, environmental and anti-poverty programs. Poverty maps have also been crossed with environmental and agricultural systems maps in order to use visual spatial analysis to discern a correlation. Numerous examples will be provided throughout the paper, and for further reference Snel and Henninger (2002) provide detailed case studies of poverty mapping applications.

Second, as a byproduct, poverty mapping serves to create both explanatory and dependent spatial variables use in multivariate analysis in combination with recently developed tools which permit the explicit incorporation of spatial dimension in multivariate examination of poverty issues.

Different methodologies are used for locating the food insecure or poor, and/or evaluating the determinants of poverty and food insecurity, such as econometric models, livelihood systems analysis, and participatory appraisals. In each case, poverty mapping is used to reveal the location of the poor and/or the locational aspects of the identified determinants of poverty and food insecurity. Within the more 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 uncovering 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 likely lead to different locational outcomes (maps) and policy implications, but few comparisons of the practical differences have been made.

The spatial analysis of poverty has been utilized in a number of policy and research applications. Beyond a visual representation of spatial relationships between variables, these range from the targeting of emergency food aid and anti-poverty programs to assessments of the determinants of poverty and food insecurity. These applications have been used by organizations ranging from NGOs and multilateral development organizations to national governments (see Henninger (1998) and Snel and Henninger (2002) for a review of many of these applications).[2] The methodologies utilized are diverse, from participatory poverty profiles to sophisticated econometric techniques, and most are under continuing development. Each has different data requirements and implementation costs, and different advantages and disadvantages in their use.

2.1 The uses and abuses of poverty mapping

Poverty mapping is, at essence, a tool, and thus its functionality must be seen and evaluated in light of the objectives for which it is put to use, that is, the research and policy questions and hypotheses upon which it can shed light. Poverty mapping should be initiated with clear objectives in mind, which will help guide interpretation of the output and determine the appropriate methodology to utilize. While 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 also lead to serious misinterpretation of causal relationships between variables. In general poverty maps do not represent causal linkages but rather visual correlations, and interpreting causality can 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 of the livelihood approaches also attempt to understand casual relationships.

2.2 The role of GIS

Most types of poverty mapping increasingly depend on geographical information system (GIS) generated data, where values are fixed to specific locations on a grid. The spatial location of the poor facilitates integration of data from various sources such as satellites, census, household surveys, sectoral surveys, and models and simulations for the analysis of the determinants and impacts of poverty. GIS techniques provide four functions in poverty mapping[3]:

- The integration of multiple databases from different sources.
- Analysis of spatial association between variables.
- The inclusion of spatially generated explanatory variables into the multivariate analysis of the determinants of poverty, including natural capital, infrastructure, and access to public services, and product and labor markets. Disaggregated poverty measures can also 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. But surprisingly, most of the recent voluminous research on poverty and food insecurity has not gone beyond only very rudimentary and one dimensional characterizations of the role of regions and access to different types of infrastructure, public

[2] We do not include mapping efforts which are not directly tied to poverty or food security, such as the FAO farming system and agro ecological typologies or the many environmental and production applications among the CG centers, though these may be relevant to combining with poverty mapping exercises.
[3] See, for example, discussion in Bigman and Deichmann (2000a).

services, and product and labor markets. Many poverty mapping exercises involve simply a ranking of areas by some poverty, food security, or marginality indicator, and have no real 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 which are important for alleviating poverty and food insecurity. This could include the determinants of migration, participation in off farm labor activities, product market participation, crop choice, or technology adoption. One of the most common applications is the analysis of the causal relationship between poverty and the environment, where to date few links have been found, often due to technical, estimation, or data limitations (see review in Lipper, 2000).

3. Poverty mapping methods

A variety of methods for the spatial location of the poor have been put forward in the literature and in practice, and most are under continuing development. In this section we shall describe the major methods in use around the globe, and show in what context each has been employed.

3.1 Small area estimation

Small area estimation is a statistical technique which combines survey and census data to estimate welfare or other indicators for disaggregated geographic 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, assuming that the relationship defined by the model holds for the larger population as well as from the original sample. This technique has been used by the U.S. government for planning and targeting purposes (Riely and Anselin, 1995; Ghosh and Rao, 1994).

More recently, small area estimation has been extended to use in developing countries for poverty mapping. Two principal methods have emerged. The first, using household unit level data from a census, has been developed principally by staff at the World Bank and is the principal methodology utilized and promoted by the Bank's new poverty mapping group (World Bank, 2000). The second uses community level averages instead of household unit level data, and has been employed by researchers at both the World Bank and various centers of the CG system. As employed here these econometric models are not casual; they do not seek to explain the determinants of poverty but rather maximize the precision of identifying the poor. This is an important distinction in terms of the kinds of explanatory variables that are utilized.

3.1.1 Household unit level method

This method has been developed in Hentschel, *et al*, (2000) and Elbers, Lanjouw and Lanjouw (2001), and is also presented in World Bank (2000) and Deichmann (1999), from which the following discussion is derived. The method requires two sets of data at a minimum: household level census data and a representative household survey corresponding approximately to the same time period as the census. For example, in Nicaragua poverty maps have been built using 1995 population census data and a 1998 LSMS survey, and in Ecuador 1990 population census 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 household unit data, but an agricultural census which includes basic demographic information, such as the 1997 Chinese agricultural census, or any other large scale survey for that matter with sufficient level of representativity, could also be used. Elbers, et al (2001) provide an example in Brazil of doing small area estimation with a large scale household survey instead of a population census, and Minot and Baulch (2002a) use a three 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 as well (Macro International, 2002).

The first step is to estimate a model of consumption based household welfare[4] using the household survey data. This model should be estimated by statistically representative regions or areas (such as urban/rural), with explanatory variables limited to those found in both data sets.

The following equation is estimated using ordinary least squares,

(1) $$\ln C = \alpha + \beta_1 X + \beta_2 V + \varepsilon$$

Where C is total per capita consumption (or another food security or poverty proxy), X is a matrix of household 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 of interest by taking the mean of the probabilities for the chosen geographical entities.

Specifically, 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, for a given threshold below which a household is food insecure or poor, whether based on consumption, caloric intake, or anthropometric measures, the probability of a household being food insecure or poor. Here,

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

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) $$E(F_i / X_i, \beta, \sigma) = \Phi\left[\frac{\ln z - X_i'\beta}{\sigma}\right]$$

where Φ is the cumulative standard normal distribution. This equation gives the probability that a household is food insecure. From the model of the benchmark indicator estimates of $\hat{\beta}$

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

and $\hat{\sigma}$ are obtained, providing the following estimator of the expected food insecurity of household *i* in the census

$$F_i^* = E\left(F_i / X = i, \hat{\beta}, \hat{\sigma}\right) = \Phi\left[\frac{\ln z - X_i'\hat{\beta}}{\hat{\sigma}}\right] \tag{4}$$

Regional food insecurity, F, is found with

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

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

$$E\left(F / X, \beta, \sigma\right) = \frac{1}{N}\sum_{i=1}^{N} E\left(F_i / X_i, \beta, \sigma\right) \tag{6}$$

The incidence of food insecurity is calculated as the mean of the households' probability of being food insecure,[5]

$$F^* = E\left(F / X, \hat{\beta}, \hat{\sigma}\right) = \frac{1}{N}\sum_{i=1}^{N} \Phi\left[\frac{\ln z - X_i'\hat{\beta}}{\hat{\sigma}}\right] \tag{7}$$

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) can also be constructed, as well as any number of the standard poverty measures.

While 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, which are discussed in detail in Elbers, Lanjouw and Lanjouw (2001). One virtue of this methodology is the relative ease with which to check the reliability of estimates which are built into the programs the World Bank provides to national poverty mapping analysts. The size of standard errors in these estimates depends in large part on the degree of disaggregation sought, as well as the explanatory power of the exogenous variables in the first stage model. For example, Demombynes, et al (2002) show that relatively precise poverty estimates can be made at the third administrative level, which for Ecuador and Madagascar imply approximately 1000-2000 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
- Tradeoffs between the size of standard error and policy needs.

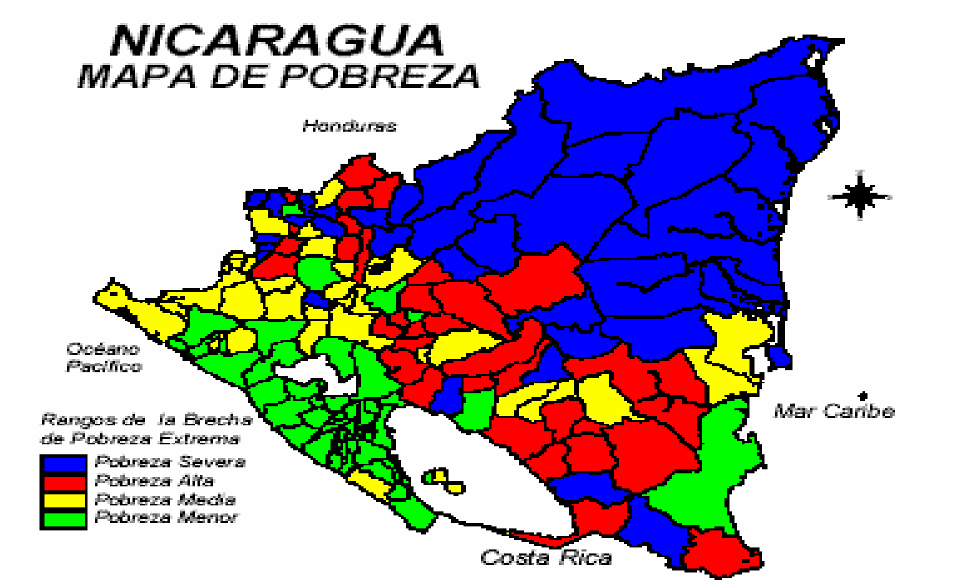
[5] Simply counting households with expected values below the food security line gives biased estimates of poverty rates, due to inequality in the intrahousehold distribution.

The other virtue of this approach is that it has the institutional backing of the World Bank, and a team of researchers associated 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), has adopted and applied the household level unit data method with support from the World Bank, for creating poverty maps for planning purposes and future targeted programs, such as the Red de Protección Social (Social Protection Network) anti-poverty program (see Map 1 and results in Government of Nicaragua, 2001). This method was pioneered in Ecuador and has also been used to create poverty maps for targeting and policy making in Panama (World Bank, 2000) and South Africa (Alderman, et al. 2000), while the World Bank and IFPRI are supporting efforts in a number of other countries including Madagascar, Vietnam, Guatemala, Madagascar, Malawi, Mozambique, Tanzania, Kenya, Uganda, Cambodia, and Kazakhstan (Minot, 2001; Lanjouw, 2001; Wood, 2001; and Snel and Henninger, 2002). In their case studies Snel and Henninger (2002) provide detail on how these poverty maps have been put to use in different countries.

Further, researchers from IFPRI are designing the national maps of Malawi and Mozambique with an eye towards building a regional poverty map, which could possibly expand to include other East African countries. Such an effort will require overcoming the challenge of constructing comparable poverty lines and indices over two or more countries (Wood, 2001; Benson, 2001; and Simler, 2001).

Map 1. Nicaragua poverty map, small area estimation method



Source: Government of Nicaragua, 2001

3.1.2 Community level data method

An alternative small area estimation method involves using average values from disaggregated geographical units, such as communities or small towns, instead of household unit level data. This has the advantage of less stringent data requirements; national statistical agencies may be more likely to release community averages upon request; indeed, this data may be published. This is particularly important for researchers who do not have the institutional backing or resources, as do the World Bank researchers, to form formal collaborative arrangements with national statistical agencies. Besides the difference in scale of the predictive model, the two small area estimation methods follow essentially the same steps. Again, the first step is to estimate a model of consumption based household welfare using the household survey data, as shown in equation 1. Second, the resultant parameters are used to predict the expected level of well-being for communities.[6]

Predicted mean consumption in a community is not necessarily a good proxy for poverty, however, since poverty measures are functions of both 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:

$$E(P_{0j}) = E(\text{Prob}\,[\ln y_{ij} < 0]) = E(\Phi(-X_{ij}\beta/\rho_j)) \tag{8}$$

where lny is the log of the level of consumption per adult in household i, X_{ij} a matrix of individual and community level variables, Φ is the standard cumulative normal distribution and ρ_j 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. However, estimates of the means of all variables in each community X_j are available. 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 constant. Second, in the consumption equation the behavioral model inside and outside the household sample must be assumed 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, this 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, leading to a possible missing variable problem.

This method has been employed frequently. Minot (1998) utilizes Vietnam'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 to similar ends 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 the 1997 China Agricultural Census data. Using data from Kenya, Bigman and Loevinsohn (1999) show how the community 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 (flooding) and suitability for rice production in Bangladesh

While easier access to data makes this method attractive, the error associated with estimation for different sized (in terms of population) units has not been thoroughly investigated. Only

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[6] The following discussion is based on Bigman, et al (2000).

one study to date, Minot and Baulch (2002b), has looked into the issue of how much precision is lost when using community level (or aggregated to any level) census data. They find that the greater the disaggregation of the data, the more precision in the estimates, with the errors in estimates based on census enumeration areas averaging around two percentage points. From another perspective, 98 percent of provincial poverty estimates had errors of less then five percentage points. Using census data aggregated to the province level resulted in almost one third of provincial poverty estimates had errors of less then five percentage points. They find 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 while the best option is to use household level unit data, if unavailable then community level census data can be used to generate reasonably accurate poverty estimates.

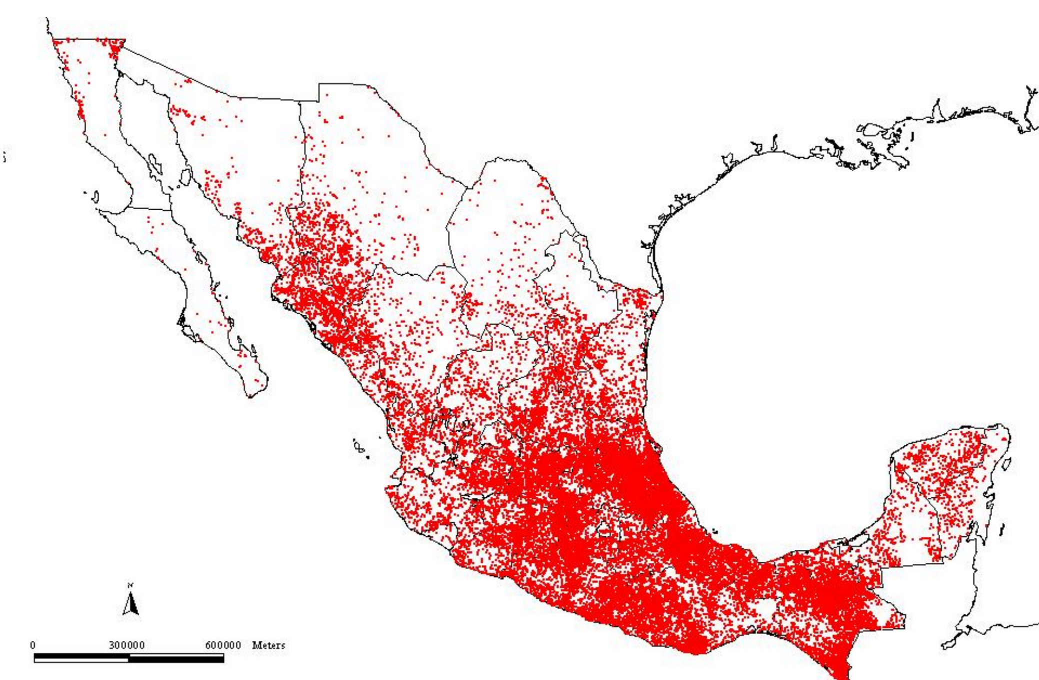
3.2 Multivariate weighted basic needs index

A variety of basic needs indices are used for disaggregated poverty mapping. They differ among themselves based on the choice of variables and weighting schemes. In this section we focus on an assortment of weighting schemes. Three are based on multivariate statistical techniques—principal components, factor analysis, and ordinary least squares. The remaining have no weighting scheme; all components are valued equally.

3.2.1 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 specifically as part of the targeting mechanism of the PROGRESA anti-poverty program.[7] Localities were deemed eligible for the program based on a ranking of the marginality index. Households were then selected based on the results of a census administered in these communities.

Map 2. Marginal localities in Mexico, principal components



[7] See PROGRESA, 1998; CONAPO-PROGRESA, 1998; and Skoufias, Davis, and de la Vega, 2001.

This $700 million program provides bimonthly cash transfers to over three million rural households, who in exchange send their children to school and receive medical exams. 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 "Population Count," or *Conteo*:[8]

1. Share of illiterate adults (> 14 years) in the locality
2. Share of dwellings without water
3. Share of dwellings without drainage systems
4. Share of dwellings without electricity

Three variables came from the 1990 population census:

5. Average number of occupants per room
6. Share of dwellings with dirt floor
7. Share of population working in the primary sector

Principal components is a statistical technique for reducing a given number of variables by extracting linear combinations which best describe these variables, in this case transforming seven variables into one index. The first principle component, the linear combination capturing the greatest variance, can be converted into factor scores, which serve as weights for the creation of the marginality index.[9] 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.[10]

Of 105,749 localities with a population greater than 50 individuals, only 74,994 (comprising 97 percent of the total 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 in Chiapas for whom no data was collected in 1995 due to social unrest. Not included in the calculations were over 99,000 localities with less than two households, comprising a population in of 585,944, or .64 percent of the population. These households were initially excluded from the index and the program. Map 2 indicates the geographical distribution of marginal localities in Mexico.

For logistical, financial, and programmatic reasons, the index was then crossed with other spatially based criteria—geographic location, distance between localities, and access to health and school infrastructure in order to determine final selection into the program. Combining data from other ministries with GIS, service zones were established, by which localities were characterized by their access to these required services, taking into account the quality of roads when public services were not located in the same community. Another statistical routine was used to then choose household beneficiaries within these communities. The statistical properties of this index have not been determined. Thus the sampling error associated with the marginality index is not known. An evaluation of the PROGRESA method compared the allocation of localities with a method similar to community level small area estimation is discussed in Section 4.1.

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

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

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

3.2.2 *Principal components over time*

Principal components is also being used in work under progress, jointly by the FAO and Columbia University, to construct a poverty map for Costa Rica. The objective of this map is for use in analyzing the relationship between poverty and deforestation over time. Principal components was chosen over small area estimation methods for two reasons. First, poverty maps were to be constructed over time for four decades (one observation per decade, corresponding to deforestation data), and household survey data are available only for the last two decades. Second, income data is feared biased.[11]

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

3.2.3 *Factor analysis*

The South African government has created development indices based on factor analysis, a statistical technique which is 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. However, factor analysis is more elaborate and the primary question it seeks to ask is whether the data are consistent with some underlying structure (Johnson and Wichern, 1988). Factor analysis groups sets of variables by their correlations and each group of variables represents a single underlying construct or factor. While factor analysis does assist in identifying underlying factors represented by a set of variables, the method is subjective and requires interpretation of the factors to give them meaning. This interpretation relies on previous knowledge and intuition about underlying relationships.

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

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 a 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	.45
average household size	-.02	.90
# children under the age of five years	.05	.80

Source: Hirschowitz, et al, 2000.

Factor analysis with rotation was applied to 1996 population census data in South Africa by Hirschowitz, et al, (2000) with the goal of providing information for allocation of public development funds. The first component, interpreted as a household infrastructure index, explained 57 percent of the variance, while 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 actual indices required the following steps. In both indices variables were given equal weight, which was justified by the analysts in that all factor loadings were considered relatively high. In order to put variables into comparable units, in each index each variable was arranged from high to low values, and then divided into three categories—high, medium, and low development. Based on the value of each particular variable, each province is allocated to one of these categories. These are then summed up for each province (with eight variables, the possible sums range from eight to 24), and adjusted by population size, in order to provide a relative ranking of provinces by development.

3.2.4 Ordinary Least Squares

The Nicaraguan Red de Protección Social (RPS) anti-poverty program also used poverty mapping to target census segments for intervention. The pilot for this program, which began operations in August, 2000, currently reaches approximately 10,000 geographically targeted rural households located in northern Nicaragua. This program is similar to PROGRESA; in exchange for sending their children to school, receiving health exams, and participating in public health presentations, the female head of household receives a maximum of $336 in cash transfers per year. In contrast to PROGRESA, all households in the census segments were included in the program (Government of Nicaragua, 2000).

For programmatic reasons, the pilot was located in six municipalities in two northern departments. A marginality index was required in order 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 expansion phase of the RPS currently underway will utilize poverty maps based on the household unit level small area estimation strategy.

3.3 Combination of qualitative information and secondary data

A number of organizations use a variety of combinations of qualitative and secondary data to create poverty maps, with a focus more on food security then poverty. These types of instruments also 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.

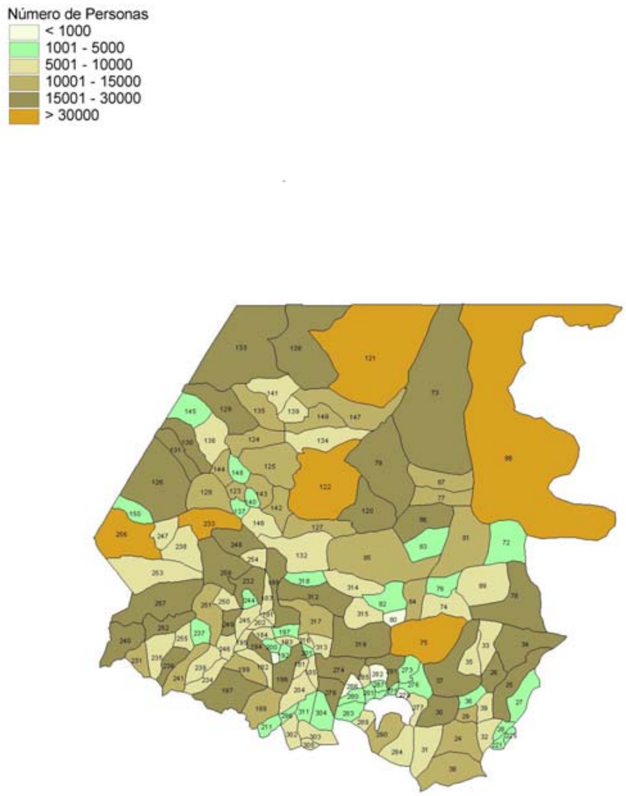
3.3.1 Primarily qualitative

Two variants of the livelihood approach are employed using primary data in field vulnerability assessments. The first, the Household Economy Approach (HEA) developed by Save the Children Fund in collaboration with the FAO Global Information and Early Warning System (GIEWS), has also been used by the 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 their food and cash income by approximately the same combination of economic activities.
2. Within each zone, define different wealth categories. These categories use indicators of wealth identified by the people themselves, and thus are relative 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 key data sources 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.

Map 3. Number of food insecure vulnerable small producers, Western Highlands of Guatemala, vulnerability group profiles



Source: Huddleston and Pittaluga, 2000

Second, the vulnerable group profiles developed by the FAO as part of the FIVIMS initiative (Huddleston and Pittaluga, 2000) identify mutually exclusive livelihood strategy groups first, through brainstorming sessions with experts. Typically the primary source of livelihood serves as the key 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 (laws, politics and culture); external factors (demographic, natural resource base, macroeconomic context); and vulnerability to economic and natural shocks. An emphasis is placed on understanding the determinants of food security or poverty. Calculations are made as to the size of the groups, when possible using population census data linked through occupation codes, and vulnerability maps are then constructed. An example from a recent analysis of the Western Highlands of Guatemala can be seen in Map 3.

3.3.2 Primarily secondary

The "indicator" approach employed by the Famine Early Warning System (FEWS) of USAID, also geared to vulnerability assessment though with more of a focus on identification of households then causality, is based primarily on secondary evidence, with less direct 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 the HEA described above. Food access and availability per person are then calculated at the administrative or group level (see FEWS, 1999b and 2000). The collection of this secondary data ranges from tables to statistical procedures to qualitative information when data is missing. Multiple vulnerability indicators are commonly combined into a single index with which areas and groups can be ranked. These indices are built with the following steps.

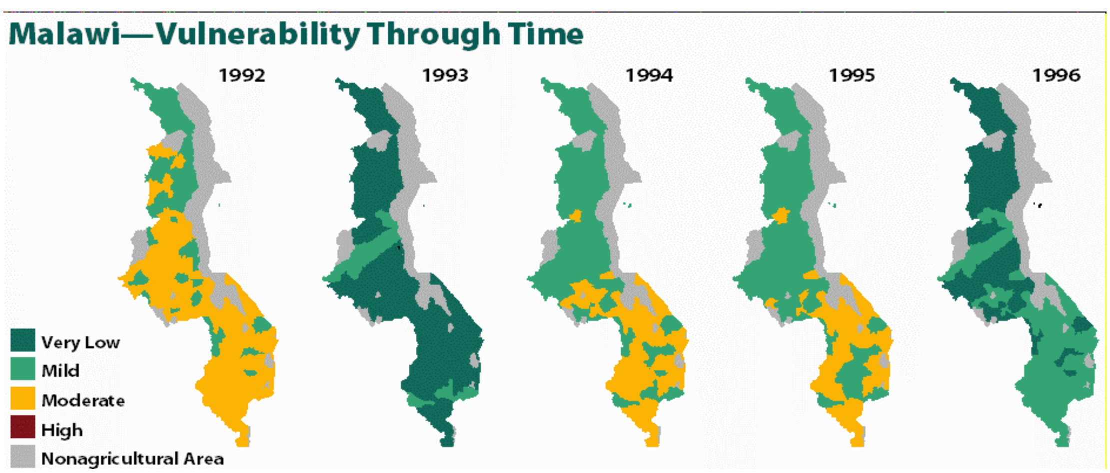
- Determination of the primary dimensions of vulnerability (agroecological, infrastructure, economic resources, coping ability, etc)
- Selection and transformation of comparable indicators
- Weighting of indicators (typically based on best judgment or expert opinion)
- Ranking according to summed scores.

This information is linked to geographic area and thus is commonly put into vulnerability maps.

3.3.3 Statistical analysis of qualitative information combined with secondary data

This methodology can also be combined with other statistical techniques. For example, after collecting secondary information from a variety of sources, a FEWS exercise in Malawi, using both statistical and conceptual cluster analysis, allocated 154 geographical units (Extension Planning Area, or EPA) to five "sphere of influence" clusters which best portrayed common significant factors influencing household food security behavior. The 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 influenced, (non agricultural) income generating activity, and urban influenced. These methods parallel the HEA method described above (WFP, et al, 1996, and FEWS, 1997).

Map 4. Malawi food security vulnerability over time, regression on expert opinion



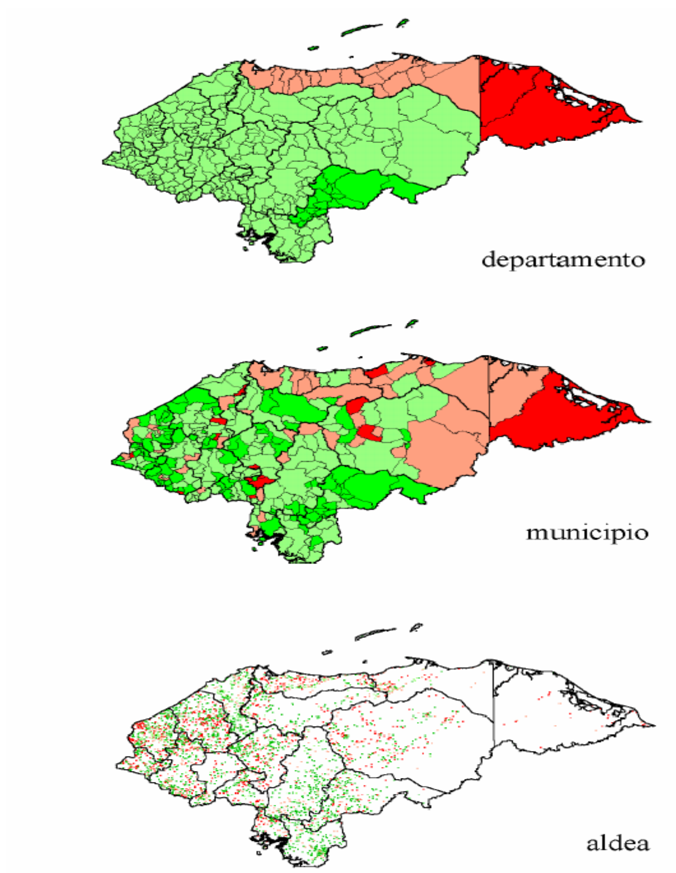
Source: FEWS, 1997

Principal components was then conducted on outcome indicators, with the results producing 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 in the EPAs of the three principal components, but this index was eventually discarded due to the perception that it condensed so much information as to be meaningless. Regression analysis, by cluster, was then used to discern which factors are associated with each of the three components in order for use as policy levers. Finally, a time series analysis of vulnerability was constructed based on a regression analysis, again by cluster, of the opinions of eight experts as to the evolution of vulnerability in 1992-1996. This can be seen in Map 4. Which goes to show you can map anything!!

3.4 Extrapolation of participatory approaches

Participatory assessments measure poverty based on local perceptions of poverty. These local perceptions 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 poverty's multidimensional nature and the processes which create and maintain poverty. With this indicator, poverty is defined locally, based on perception of well being and how neighbor informants rank this perception. Thus the utilization of this measure is limited to areas where people are knowledgeable about their neighbors, most typically rural communities (Ravnborg, 1999a).[12]

Map 5. Honduras, participatory approach



(Source: Leclerc, et al, 2000)

[12] See Ravnborg (1999a) for an application in Honduras, Narayan (1997) in Tanzania, and Turk (2000) in Vietnam.

The process is as follows, as described in Ravnborg (1999a). The number and location of communities in a chosen area are selected based on a maximum variation sampling strategy, taking into account those factors which may explain expected variation in well being perceptions in the area of study. Following site selection, local perceptions are gathered from community informants in each site who provide definitions of poverty and rank neighbors in terms of well being. A well being index is created and extrapolated to other communities in a region using a questionnaire applied 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 the identification of key variables by multivariate regression, they are identified by local informants and homogenized across sample sites. Leclerc, et al (2000) compares Ravnborg's well being index to a more traditional basic needs index for the communities within the study area (discussed below in Section 4.6.2), and finds some correlation between the measures.

Leclerc, et al (2000) then further extends the extrapolation of the Ravnborg index to the rest of the communities that make up rural Honduras. Using neural net software, they employ artificial intelligence techniques to link the 11 variables from the Ravnborg index to nine proxy variables from the most recent population and agricultural census, and 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. The results can be found in Map 5.

3.5 Direct measurement of household survey data

Survey data has served as the basis for a number of statistical-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, which is the origin of the development of the small area estimation strategies discussed earlier. Many different kinds of survey data exist. A large number of 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 (or representative) enough to serve the role of a census in small area estimation. The Light Monitoring Survey (LMS) is shorter, collecting information on a series of socioeconomic proxies, thus allowing a larger sample size. But in comparison with LSMS the LMS is shown to be biased due to underestimation of income/consumption. The result is not only bias in the magnitude of poverty but also spatial distribution (Fofack, 2000).

Georeferenced household surveys, such as the standardized Demographic and Health Surveys (DHS) on health and nutrition have the potential to be re aggregated into new units of analysis and thus help create novel poverty maps. The DHS does not include consumption but instead proxies income with the creation of asset indices (Filmer and Pritchett, 1998). Henninger (1998) for example describes how the survey data was aggregated to new units of analysis—aridity zones—within which the distribution of anthropometric indicators was analyzed. Macro International, the firm that carries out the DHS, is also beginning efforts to map a wealth index using data from the survey in Egypt (Montana, 2001).

GRID Arendal (1996) studied the relationship of rural poverty and land use potential using DHS data from West Africa. In this case, DHS variables such as literacy, child mortality, school enrollment, etc were used to build a Human Development Index (HDI) to serve as a proxy for poverty, which are then crossed with the same aridity zones as described above, as well as land degradation. This data was then placed into poverty maps for the West African region.

McGuire (2000), looking specifically at food security vulnerability instead of poverty, uses a composite HDI as well as principal components to analyze the relationship between food security and biophysical parameters. Next, McGuire uses spatial filtering techniques to extend the representativity of the DHS data from the first to the second administrative level. The HDI index, essentially an arbitrarily weighted index composed of biophysical, education, demographic, nutrition, 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 programs in Africa based on GIS techniques. The premise is that while the welfare estimates of these types of surveys are not representative at the cluster level, as long as the estimates are unbiased, covariance analysis across clusters can be conducted. These cluster welfare indicators serve as dependent variables, and are linked via GIS with a series of explanatory variables.

3.6 Direct measurement of census data

3.6.1 Income data

Many countries collect information on income in the population census. This information, typically based on only one or a few questions on cash income, has then been used directly to create disaggregated poverty maps without reliance on other data sources. For example, the Brazilian hunger map is based on the direct measurement of household income reported in the 1991 population census. Household level income was compared to both a food-based extreme poverty line and a food-non food moderate poverty line. The headcount index was then calculated for each municipality. Regional and state level 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. For example, Osgood and Lipper (2000) link subnational proxies for poverty with soil degradation measures in Ghana.

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

3.6.2 Basic needs index

A number of countries have used household level unit data from a census to create poverty maps based on basic needs indices. For example, in Honduras, CIAT researchers created a series of basic needs indices for poverty mapping purposes (Leclerc, et al, 2000). These were based on access to household level unit data from both the 1988 Population and Housing Census and the 1993 Agricultural Census. As typical with basic needs approaches, poverty is related to deprivation, or a lack of a minimal level of goods and services necessary to sustain life. The indices are calculated at the household level, then aggregated by any geographical or administrative grouping by counting the fraction of the population in a particular basic needs strata. 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) $$cx_i = 1 - \frac{x_i}{x^*}$$

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.

For each household two aggregate indices were constructed. The first included indices on lack of housing size and quality; 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. In almost all of the individual indices making up the aggregate indices, variables were weighted equally, though differing 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 households considered poor was less then .4.

Second, the Andean Network of Spatial Data (REDANDA) has brought together statistical agencies and universities in five countries (Bolivia, Columbia, Ecuador, Peru, and Venezuela) who have created disaggregated regional maps, at the municipal level, of development indicators from population census data. This network achieved homogenization of standards between the five countries for the 2000 census, which will be analyzed in a coordinated fashion in 2002-2003 (REDANDA, 2001).

Third, in Brazil 38 georeferenced variables, including two composite indices, from the 1970, 1980, and 1991 population census make up the Atlas of Human Development. The two composite indices follow UNDP methodology: the Human Development Index and the Life Conditions Index. The Atlas of Human Development has been a tremendous success in terms of serving as the basis for public investment decision making and targeting of social programs worth billions of dollars (Snel and Henninger, 2002). Fourth, similarly, a basic needs index based on 1993 census data was used by the Peruvian Social fund (FONCODES) to distribute over $500 million during the 1990s (Snel and Henninger, 2002).

Fifth, another project developed and mapped by municipality in Honduras a series of disaster vulnerability indices 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 (percent of very poor at risk), and
4. infrastructure (roads and electricity lines at risk)

In turn these indices were weighted and aggregated into an overall vulnerability index which allowed identification of municipalities for priority intervention (Segnestam, et al, 2000).

3.6.3 Z scores

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

Researchers at IFPRI who were assisting PRAF staff with the design and development of the program utilized yet another instrument for targeting the program. Given availability of funds, the second phase of PRAF was limited to the 80 poorest municipalities in the country. Municipalities were selected based on 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 both poverty and food insecurity. Data was taken from the 1997 First Grade School Children Height Census, and Z scores were standardized by reversing on sex and age. After municipalities were ranked by Z scores, they were 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 begs the question, however: does it matter which method is chosen? While one suspect that most would prefer to remain ignorant and not face a seemingly impossible decision, the answer is an emphatic yes—the choice of method matters, the level of disaggregation and the drawing of geographic boundaries matters, and the choice of indicator matters. All three of these elements can lead to a reranking of regions, communities, or households, or lead to quite different policy conclusions. The key problem is that little information exists on how much it matters, despite the fact that governments are spending billions of dollars a year, and millions of poor and not so poor either receive or are excluded from benefits, based on these different poverty mapping methods.

4.1 Method matters

The assertion that the choice of a method matters should not be surprising. Different methodologies use different sources of data, assumptions, and statistical routines. Few comparisons or sensitivity analysis, however, have been carried out between the different methodologies. This lack of information constitutes a gaping hole in the analytical foundation of the emerging poverty mapping "movement;" while quite 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 kind of poor, located in which regions, are favored 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). Combining a national expenditure survey and census data, a marginality index was calculated 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 5 X 5 matrix, as seen in Table 2. The small area estimation results in a stricter categorization of poverty, implying that the small area estimation method would be more appropriate if avoiding leakage (including the non poor as beneficiaries) is more important than avoiding undercoverage (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 program beyond the most marginal communities.

Table 2. Categorization of marginality: PROGRESA versus small area estimation

		Small area estimation						
		Very Low	*Low*	*Medium*	*High*	*Very High*	Total	Percent
PROGRESA	*Very Low*	**613**	3473	3			4089	5
	Low		**5361**	250			5611	7
	Medium		5390	**7088**	3		12481	17
	High		83	15819	**682**		16584	22
	Very High			6104	27770	**2357**	36231	48
	Total	613	14307	29264	28455	2357	74996	100
	Percent	1	19	39	38	3	100	

Source: Skoufias, Davis, and de la Vega, 2001

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 to be held in the results. An example of an extremely sensitive measure is the basic needs method described in Section 3.6.2, as employed with Honduras census data. Only a few variables are included in this index, and in Map 6 two indices are presented, distinguished only by an additional variable—education. The addition of this variable results in a reranking of marginality at all administrative levels.

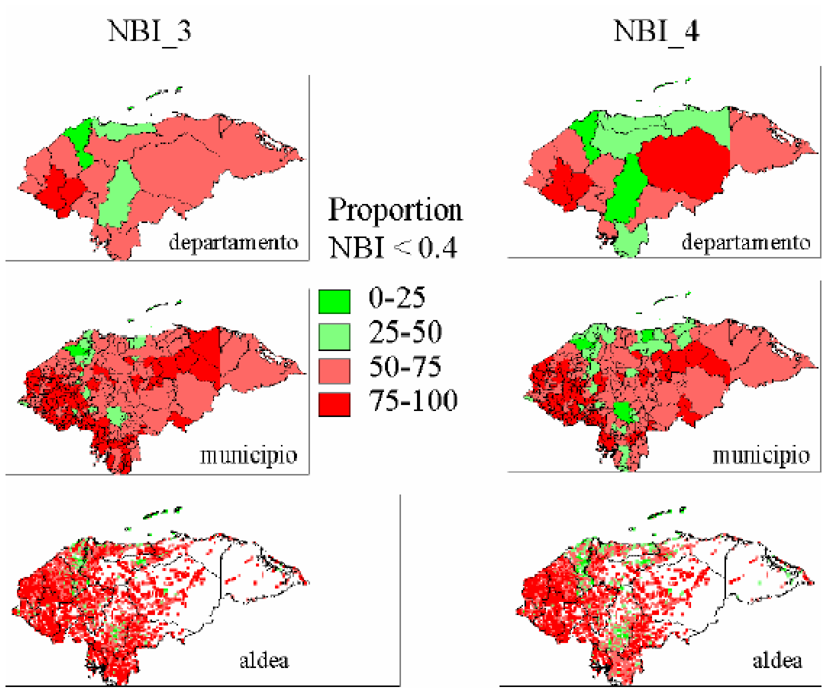
4.2 Level of disaggregation and shape of areas matters

Even more simple circumstances, such as changing the level of disaggregation as measured by geopolitical groupings, can have important impacts in terms of poverty rankings. Again looking at Map 6 the basic needs index is presented at three levels of geopolitical disaggregation in Honduras, and in Map 5 the participatory index. The results illustrate that choice of level of disaggregation has important policy implications. Within each index a given level of disaggregation would lead to a different allocation of targeted resources. The apparent increased precision evident in the maps may thus be deceptive, as it is unclear what errors are associated with these measurements. Which level is appropriate?

4.2.1 MAUP

One key problem in spatial analysis is known as the Modifiable Areal Unit Problem (MAUP). Areal units, whether administrative or political boundaries, agroecological zones, or image pixels are essentially arbitrary groupings and the data within can be aggregated in an infinite number of ways (Nelson, 2001 and Bigman and Deichmann, 2000a). This includes not only GIS constructed data, but any kind of spatially aggregated data, such as census or household surveys. The practical implication is that, for example, alternative aggregations of the data may lead to different and conflicting results. In other words, the analysis gets messy quick, and most practitioners would just as soon be ignorant of these unpleasantries. This is true for simple visual correlation analysis as well as sophisticated econometric techniques. In terms of multivariate analysis, the relationship between dependent and independent variables may change over space in a manner that the analyst may not be able to determine *a priori*. Thus results can be modified purposely—or errors made inadvertently—through the process of aggregating data.

Map 6. Two indices, Honduras, basic needs approach



Source: Leclerc, et al, 2000

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 zonification, including extending the concept of areal units beyond preset administrative boundaries or Euclidean distance to other measures such as time, accessibility, cost or energy, which 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 goodness of fit measures.[13] Rogers (2000) describes the process of reasoning in avoiding MAUP for the WASAP Project in rural West Africa and impact evaluation in Zaire.

4.3 Indicators matter

4.3.1 Alternative indicators

While few dispute the multidimensional nature of poverty and food security, poverty mapping by definition is about summarizing information in a few indicators, whether these are indices or single variables. Thus a decision must be made in each poverty mapping application on

[13] The model and examples are discussed in detail in Nelson and Leclerc, 2000.

how to aggregate or how to best 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 both poverty and food insecurity, as well as a long and storied literature on their respective strength and weaknesses.[14] As such we will keep our discussion here to a minimum and focus on household measures. The choice of indicator may respond to philosophical preconceptions (beliefs that self chosen, participatory or basic needs indices are inherently better then economic indicators), to data limitations, or as the result of reasoned analysis of a given context. Analytical procedures range from statistical techniques to participatory studies where poverty indicators are revealed by the population being studied. Similarly, information on most of these measures may be generated either 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 also use a variety of consumption and or income measures. These also include non monetary proxies of household well being, such 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 such agencies 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 exposure of households to shocks which can affect poverty status, such as environmental endowment and hazard, physical insecurity, political change, and the diversification and riskiness of alternative livelihood strategies.

Similarly, food insecurity measures can be 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, as well as risk and uncertainty. Indicators include household access to assets, household size and composition, asset liquidity, crop and income diversification, and food production at a household level.

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[14] 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.

4.3.2 *The choice of indicator matters*

For both poverty and food insecurity, the choice of indicator matters. Numerous studies have shown that at the subnational level different indicators can lead to alternative poverty or food insecurity rankings.[15] Thus the choice of indicator has very practical implications for results in terms of determining who the poor are and where they are located. Poverty mapping exercises should be careful not to assert a priori that one variable is better than another, but rather to explore the tradeoffs inherent in the choice of indicators: what assumptions one must make, and what are 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, at the very least all poverty mapping efforts should justify or qualify the choice of poverty or food security indicator.

5. So how does one choose a poverty map?

The preceding discussion should make the potential practitioner somewhat nervous about his/her choice of methodology. In practice it is indeed difficult and impractical for all practitioners to test alternate methods. Poverty mapping is carried out by a variety of institutions and individuals, ranging from government ministries to NGO to lonely 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. These include the purpose or objective of the exercise; the poverty philosophy of a particular practitioner or institution; data availability; analytical capacity; and cost.

5.1 Purpose/objective

Practitioners may have one of a variety of objectives when planning and carrying out their poverty mapping exercise. These may range from targeting specific small or large interventions or building a map to convey a political message, to constructing inputs for a correlation or multivariate analysis. Each of these objectives may dictate a specific methodology. Interventions require greater precision and perhaps specific indicators as the welfare of thousands, even millions, of people in a given country depend on this measurement. Research and maps for communication can tolerate greater levels of error and thus do not face this particular constraint. Thus the purpose of a poverty map is linked directly to the issue of bias and error, though practitioners may be unaware that they are making this decision or tradeoff.

5.2 Philosophy

Practitioners may have a range of philosophical beliefs (or prejudices) which influence the choice of methodology. These beliefs are often associated with professional disciplines and/or institutional characteristics. Economists generally prefer consumption based welfare measures, and methods based on econometric analysis, and thus are enamored with the two small area estimation methods (which were developed by economists). Sociologists and anthropologists are generally suspicious of poverty characterizations generated by quantitative

[15] See, for example, Glewwe and Gaag (1988), Baker and Grosh (1994), Carletto and Davis (2000), Hentschel, et al (2000), Skoufias, Davis, and de la Vega (2001), and Leclerc, et al (2000).

survey data, and thus prefer case study, rapid rural appraisal, and participatory approaches. NGOs also tend to prefer the latter techniques, which appeal more intuitively to the type of work and interventions they carry out. National statistical institutes traditionally have relied on statistical measures somewhat devoid of economic meaning, such as principal component and factor analysis, which are often used to create different types of indices. This is not surprising, as national statistical institutes traditionally have been staffed by statisticians. The great variety among methods described in Section 3 stem in large part from these professional and institutional beliefs.

Within poverty analysis however, these traditional preferences recently have begun to break down. Inter agency cooperation in a number of countries has fostered openness at national statistical institutes for implementing other types of methodologies. This is particularly evident in the diffusion of the World Bank's small area estimation methodology, which as we saw above has been accepted in a 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 the provision of relatively easy to use statistical instruments designed to utilize data already collected by the national statistical agency. Conversely, given the paucity 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.[16]

5.3 Data availability

Different types of data constitute the basic inputs into poverty mapping, making data availability a key 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 expertise for this single use, so wisely the World Bank in marketing its small area estimation technique, arguably the most data intensive methodology, argues that their method serves to utilize data which already exist. But many countries do not have contemporaneous census and household survey data, which constitutes a major problem for small area estimation methodologies. Since these databases are expensive to collect, 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 become no longer compatible.

Other methodologies described in Section 3 imply primary data collection and may combine this with whatever else is available. These methodologies, combining qualitative with secondary data, are relatively inexpensive to implement and thus are less constrained by data availability. Since statistical rigor is less important, practitioners take advantage of already existing data, and fill in the gaps with their own fieldwork. Participatory methods also 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 already 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 data, and many countries are rightly reluctant to provide such data to outside institutions and researchers. The World

[16] See for example, Filmer and Pritchett, 1998.

Bank poverty mapping group has had great success in obtaining access to this data, primarily due to its policy of conducting all analysis in country in conjunction with national analysts. However, not all international organizations or NGOs and few individuals have similar resources and clout with which to obtain the same access, thus limiting the use of the World Bank small area estimation method by other practitioners.

Community level averages from census data are more readily available, indeed often sitting on the Internet, making 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 is 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 facility location and infrastructure, as well as transport and travel time, for example, have proven very useful in Mexico (PROGRESA, 1998) and Burkina Faso (Bigman, et al, 2000), as inputs into the targeting of anti-poverty programs and in the visual correlation with poverty and food insecurity (see Henninger, 1998 for many examples). They also 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 catch on as common practice. The 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.[17]

A key problem is that data is still weak on the environmental side, particularly for single country subnational poverty studies. Few in depth environmental surveys collect information typically found in household surveys (though we must search for those notable exceptions), and while some kind of subnational poverty data is usually available, it is often not comparable with the environmental surveys, or is not georeferenced. Many global data sets may not be appropriate for use in subnational studies, particularly in medium or smaller sized countries, as they do not capture in country variation and thus are 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.

5.4 Analytical capacity

Analytical capacity represents another constraint. The poverty mapping methods presented in Section 3 imply a wide range of analytical demands. For example, while the World Bank poverty mapping group has expended great effort in making the rather sophisticated econometric small area estimation model as standard and easy to use as possible, it still requires a certain level of statistical and/or econometric understanding to implement and interpret. Methods which employ more traditional statistical techniques (in the sense that they traditionally form part of a professional statistician's—but not economist's—training) such as principal components or factor analysis may be much more appealing. Most statistical agencies are staffed by statisticians, as we discussed earlier, and the application of econometric techniques favored by economists is not always straightforward and easily understood. For smaller scale practitioners such as NGOs, who depend on qualitative work, lack of basic training in statistics or econometric tends to exclude more quantitative methods from the outset.

[17] See Nelson, et al (2001) for a description of constructing these types of variables in Honduras, and Bigman and Deichmann (2000b) for discussion and examples on Madagascar.

5.5 Cost

Finally, cost represents the final and most often overriding constraint. Basically, the more sophisticated the analysis, and the more data to be collected, the more expensive. Cost includes time spent obtaining and understanding data, and then analyzing. Governments planning to use poverty maps to guide policy interventions should obviously invest in analytic and data infrastructure, and then choose the technique which best fits their objectives and philosophical perspective. Researchers stuck behind a computer with limited funds may be restricted to what they can get off the Internet.

6. Conclusion

Anything can be mapped, from census data, to highly sophisticated small area estimation, to expert opinion. But how good is any of it? How does one avoid a poor poverty mapping method, a lemon? This is particularly pernicious problem given that it may be a number of years expost when realization of the quality of a specific method is evident. Poverty mapping does not yet have a gold standard, in part 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, discussed in Section 5, such as the objective of the 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 played to potential error and bias, and beyond statistical concepts to the types or characteristics of the poor 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 on communities as small as fifty households with no specification of the statistical power of these characterizations. But data limitations often force simple solutions, such as direct census measures. In these cases, one must be aware of biases.

For those methods that put themselves forward as a gold standard—particularly the World Bank small area estimation method—we have no evidence that it results in the "best" poverty map. Indeed, little study has been made of what are 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 boils 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 favorably 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 cognizant of the pitfalls and uncertainty of their particular method. If possible, the robustness of the chosen method should be evaluated in terms of component variables, outcome indicators, and, if possible, alternative methods. Further research is clearly needed in terms of comparing the statistical precision and practical outcomes between methods. While evaluating the statistical properties of some methods may be technically unfeasible, recognizing the potential bias of each method in terms of the resulting poverty profile should constitute a necessary first step.

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