Figure 4.3. Poverty Index at Village Level

Source: Data from Province of Houet, Department of Karangasso-Vigue.

sampling frame of the PS survey. To evaluate the program, its outcomes are compared with an untargeted uniform transfer scheme, in which all the individuals in the country receive an equal transfer. The targeted program
is designed to include only 30 percent of the population, by setting the poverty line accordingly.\textsuperscript{17}

Selection of the villages targeted by the program is as follows. All the villages in the sample are first ranked according to the estimated levels of poverty. The villages are selected for targeting starting from the poorest village until (at least) 30 percent of the population is being included in the program.\textsuperscript{18} With village-level targeting using the predicted poverty levels per community, the undercoverage is 56 percent and the leakage is slightly over 50 percent. By design, the undercoverage of the untargeted transfers is zero, but the leakage is high. For the untargeted program, the leakage, namely the share of the non-poor covered by the program (in the total population) is 70 percent (since the poverty line has been set so that 30 percent of the population are poor). The targeted program reduces leakage by 20 percent, but this is achieved by a program that leaves more than 50 percent of the poor uncovered.

Conclusion

Geographical targeting of anti-poverty programs can effectively reach the poor while keeping the costs of such programs in check in countries where the information on individual households is incomplete or unavailable and a practical individual or household targeting is therefore not possible. By identifying the geographical areas in which the poor concentrate, these programs can reduce the leakage to the non-poor so that, compared with a non-targeted program, a larger share of the poor population can be reached with a given budget. However, in most countries where geographical targeting is applied, the target areas are the region, the state, or the entire rural area. Although targeting even at these levels can offer considerable savings compared with a non-targeted program, they necessarily involve substantial leakage to non-poor households that reside in the target areas. Narrow targeting at the level of the community or the administrative department may offer a more effective alternative of reaching the poor, reduce leakage, and lower the costs in countries or regions where the communities are relatively homogeneous in terms of the standard of living of their population. Narrow targeting can be effective when poverty tends to be concentrated in a relatively small number of villages and urban communities. It is often more effective than other methods of targeting because it requires relatively low costs to administer the programs. In addition, by relying primarily on the local authorities, narrow targeting has the potential of ensuring that a larger portion of the benefits will reach the target population.

This chapter presents a methodology of using data from a wide variety of different sources to establish criteria for targeting poverty-alleviation programs at the levels of the village, the urban community, or the local
administrative department, and illustrates its application for Burkina Faso. The methodology is based on the construction of a detailed database with information collected from a large number of sources and brought together at the village level as a GIS. Data on the population were collected from several socioeconomic and demographic surveys as well as the population census; data on the road infrastructure, public facilities, and the location of central towns and markets were collected from several government ministries and public administrations; and agro-climatic data were collected from local and international research institutes. An econometric analysis was then conducted with the data of the household survey to identify the variables that best explain the households' consumption levels. The explanatory variables in this analysis included important characteristics of the community—such as the distance to the urban center and the public facilities, the quality of the access road, and the agro-climatic conditions—together with key characteristics of the households in that community—such as literacy levels or dependency ratios. The explanatory variables at the household level were selected so that their mean values per community were available for the majority of the communities in Burkina Faso and not only those covered by the household survey. This made it possible to use the model that has been estimated in the regression analysis with the data of the PS to predict the incidence of poverty in all the villages outside the PS sample, and thereby identify the spatial distribution of poverty at the community level.

In the present analysis for Burkina Faso, constraints on the availability and quality of the data led to considerable prediction errors and prevented us from using the complete ordering of the villages according to their incidence of poverty as was predicted by the econometric analysis. We used a simple method to reduce the impact of these errors by dividing the villages into several categories and focusing only on the categories of the poorest and the least poor villages. Indeed, practical considerations in the application of anti-poverty programs and tight budget constraints are likely to reduce the use of complete ordering. Instead, poverty alleviation programs are likely to focus on villages at the lower end of the distribution, and cost-recovery programs are likely to focus on the villages at the higher end. The limited availability of georeferenced data and the low quality of the data currently available reduced the predictive power of our econometric analysis, and further work would be necessary to augment and improve the stock of relevant data.

Targeting poverty alleviation or cost-recovery programs at lower-level administrative areas of the village or the department have other advantages as well. First, budget constraints are likely to restrict programs that are targeted on larger geographical areas of regions or states, and, as a result, the errors of inclusion and exclusion are likely to be quite high. Targeting on
smaller geographical areas can, with the same budget constraints, reach many more of the country’s poor. Second, lower-level targeting is likely to include villages and districts in all regions or states and thus be less divisive and contentious on ethnic, social, or political grounds. Third, whereas the differences in the incidence of poverty between regions are primarily due to differences in their agro-climatic conditions, differences in the incidence of poverty between villages within the same region often reflect past biases in policies that led to differences in the quality of their access road or their public services; targeting future policies in light of these criteria can remedy these past biases.

Notes

David Bigman was at the World Bank while this work was done and is currently at ISNAR; Stefan Dercon is at the Catholic University of Leuven, Belgium, and at Oxford University—Centre for the Study of African Economies; Michel Lambotte is at I-Mage, Mons, Belgium; Dominique Guillaume was at the Catholic University of Leuven, Belgium, and at Oxford University—Centre for the Study of African Economies while this work was done and is currently at the International Monetary Fund (IMF). This chapter does not necessarily represent the views of the IMF or its board of directors.

1. For simulated examples from Latin America, see Baker and Grosh (1994).
2. See also Besley and Kanbur (1991), pp. 69–90.
3. These programs may also provide incentives to households to move to the targeted areas, thereby defeating the purpose of the program and raising its costs.
4. Due to data limitations discussed below, the complete data set necessary for the predictions was available only for 3,871 out of the country’s 6,821 villages.
5. Simple nutritional adult equivalent scales were used, using 0.7 for a child 5 to 15 years old and 0.3 for younger children. Each adult counted as one.
6. For a poor person, therefore: \( y_j \leq 1 \), or \( \ln y_j < 0 \).
7. Note that the within-village variance of consumption can be written as:

\[
E[(Y_j - E(Y_j))^2] = E[(b'X_{ij} - b'X_j)^2] + s_j^2
\]

in which \( Y_j \) is the mean level of consumption in the village. In other words, the variance of consumption is the sum of the squared deviation of predicted household consumption from predicted mean consumption per village and the village-level variance of the prediction model.

8. Hentschel and others (1998) use this property to predict regional poverty from census data.

9. Examples are Glewwe and Kanaan (1989), or Coulombe and McKay (1996). Glewwe (1991) has a useful discussion on the justification for including particular
variables in this type of approach. We will return to the problems related to this specification below.

10. The regression was weighted with individual sampling weights derived from the original sampling frame used by the World Bank/INSD.

11. Pooling tests convincingly rejected running one national regression.

12. The Breusch-Pagan LM test convincingly reject homoskedasticity (see table 4.5a). The Glesjer (1965) test indicates that in both urban and rural areas, the null hypothesis of multiplicative heteroscedasticity cannot be rejected at the 1 percent level.

13. Note that the variables describing the literacy of adults in the households also include the household head.

14. Note that this also requires that the same program-placing rule is used both outside and inside the sample. Since the sample is nationally representative, this may be an appropriate assumption.

15. There are other sources of endogeneity. For example, our approach assumed that location is not a choice variable. Migration is therefore not explicitly considered, requiring further care in the interpretation of the results.

16. This statistic is distributed a Chi-square with two degrees of freedom and the normality hypothesis had to be rejected at 0.997 probability. One should note, however, that the Jarque-Bera test is not robust to the presence of heteroskedasticity, which could not be rejected by the Breusch-Pagan LM test and the Glesjer test. We are not aware of a test of normality in the presence of heteroskedasticity, but the high value of the Jarque-Bera statistic suggest that it is highly probable that the residuals are not distributed normally.

17. The simulation thus sets the poverty line at a lower level than in the previous section of this chapter (“Estimating Poverty within the Sample”).

18. Further details, including on the inter-regional distribution of leakage and undercoverage, is given in a longer, working paper version of this paper (Bigman and others 1999).

References


Applying Household Expenditure Survey Data to Improve Poverty Targeting: The Case of Ghana

Hippolyte Fofack

Household surveys, which have traditionally provided the basis for poverty studies and the design of targeted programs, are conducted rather infrequently. The frequency of these surveys was originally planned at five-year intervals; over the past decade, however, very few countries in the developing world have followed this course in their statistical program and analysis plan. This irregularity has made it difficult to assess the effects of macroeconomic reforms on poverty and income inequality in the short and medium term. The major constraint in conducting household surveys more regularly and frequently is their high cost, which is increasingly difficult to meet in the context of limited budget.

The need to have reliable poverty maps to assess changes in poverty and allocate scarce resources to the most needy is fully recognized by policymakers.1 To regularly update these maps, several surveys have been designed and proposed as short-term alternatives to integrated surveys. These alternatives are generally defined as light monitoring surveys (LMS), because they are a subset of much broader comprehensive surveys and are designed to provide quick and regular identification of groups on which targeted interventions should be focused. These broader surveys include Rapid Appraisal methods (see Narayan and Srinivasan 1994) and Priority Surveys (PS) (see Marchant and Grootaert 1991). More comprehensive surveys include Living Standards Measurement Surveys (LSMS) (see Grosh and Glewwe 1998) and Integrated Surveys (IS) (see Delaine and others1992).
Integrated Surveys and the similar Living Standards Measurement Surveys are broad in scope and were specifically designed for integrated poverty analysis; they are known to be more appropriate for policy analysis (see Ravallion and Gaurav 1993, Ravallion 1996, and Deininger and Squire 1996). More specifically, the IS and LSMS questionnaires are more comprehensive than other surveys (Demery and others 1992); they provide extensive information on household income, credit, and savings; household enterprise; valuation of durable, productive, and financial assets; agricultural livestock; food processing and consumption of own produce; food and non-food consumption; and other expenditures. The turnaround time is particularly long for these surveys, since the enumeration is spread over a year, with multiple visits to households in order to capture seasonality. Reduction in nonsampling errors is achieved through low recall periods. However, a much smaller sample size is recommended for IS and LSMS surveys to contain the costs and limit the time lag between data collection and production of results for policy analysis. This constitutes a major constraint on both the application of the survey for poverty analysis in a country's different geographic areas, and also for geographical targeting, because the sample size at the subregional level is too small to provide the minimum data required for sound inference.

Light monitoring surveys in contrast are administered very quickly and are less broad in the scope of data collected, but much broader in terms of geographical coverage. Their questionnaires are designed to collect information to construct key socioeconomic indicators and are much shorter. Moreover, unlike integrated surveys, LMS instruments collect a limited set of information on single visits to households, and can neither capture seasonality of consumption pattern nor provide an accurate estimate of consumption and income. However, from the design standpoint, a short questionnaire and a single visit to households reduces the time allocated to data collection, and allows for a larger sample size with a better representation of the different geographical areas.

The limited coverage of expenditure items in LMS does have some major drawbacks for policy analysis. Short questionnaires focus data collection of household expenses on a few sets of goods, and consumption aggregates based on subsets are likely to provide total expenditure estimates that are lower than estimates from more integrated type surveys (see Deaton and Grosh 1998). Moreover, it is highly unlikely that underestimation of total consumption will be uniform across households, causing a simple shift in the Engel curve, and thus preserving the ranking for policy analysis. Rather, the degree of bias in estimating household expenditure aggregates varies significantly across households and regions, in part because changes over time and regional differences in consumption patterns, which are determinants of the overall distribution of income and expenditure, are not taken
into account. The representation of distributions of income and expenditure under integrated and light monitoring surveys differ significantly.

Despite the differences between integrated surveys and LMS, and evidence that the latter might provide inaccurate estimates of aggregated expenditure, LMS instruments have been used extensively as tools for policy design. Particularly in Sub-Saharan African countries, major recommendations made in Poverty Assessments are drawn from these surveys (see World Bank 1997). This chapter shows that welfare indicators estimated from LMS are biased, and the bias affects not only representation of the magnitude of poverty, but also its apparent spatial distribution. Dispersal rates are not maintained under the LMS design, in part because household per capita expenditure, which is the basis for targeting, underestimates aggregate expenditure and may yield inaccurate poverty maps. Any targeted program based on LMS might cause leakage in income transfer schemes. In the past, attempts have been made to circumvent these limitations and provide more accurate welfare estimates for improved policy analysis in the absence of appropriate data. These include proxy means tests (see Ravallion 1989, Ravallion and Gaurav 1993, and Grosh and Baker 1995) and combining household surveys for optimal household ranking (see Fofack 1997).

The objective of this chapter is to investigate how comprehensive surveys can be combined with LMS to improve geographical targeting, achieve efficient transfers for poverty alleviation, and improve inference on welfare measures drawn from LMS. The paper is organized as follows. The next section ("Limits of Light Monitoring Surveys as Instruments for Targeting") assesses the limits of LMS when they are used for poverty analysis. In particular, it is shown that poverty maps constructed from these surveys do not reflect the spatial distribution of poverty. A method for designing more efficient targeted schemes that combines comprehensive surveys and LMS to derive poverty predictors for imputing consumption is proposed in the section titled "Estimating Total Expenditure for Improved Targeting." Results and policy implications of the proposed method on targeting and poverty mapping are assessed in the section titled "Results and Implications for Geographical Targeting." In particular, it is shown that imputing consumption significantly reduces the error of inclusion and improves inferences about welfare drawn from LMS. The final section provides some concluding remarks.

Limits of Light Monitoring Surveys as Instruments for Targeting

This section looks at the implications of errors in measurement in poverty mapping when light monitoring surveys are used as a basis for poverty analysis. Error frequency and impact is ascertained by comparing welfare indicators estimated from LMS with the ones derived from the more com-
prehensive LSMS. In order to allow full comparability, we extract LMS-aggregated expenditure from LSMS. In that regard, this study can be viewed as a counterfactual experiment, since estimates of total expenditures are actually known, and the study aims at assessing the variation in poverty measures through cross-sectional analysis.

There are several benefits in adopting the construction described above when comparing these two surveys. In a country where both light monitoring and comprehensive surveys have been carried out, the absence of reliable regional price indices and national consumer price indices has been a major impediment for cross comparison. Therefore, adjusting for seasonality and changes over time, monitoring inflation is essential for cross comparison and trends analysis. Moreover, in addition to the implied seasonal variation, changes over time in the sampling frame and design make it difficult to assess the performance of these surveys in light of household welfare estimates. Under the method used here, comparisons are made on the same households for which expenditure aggregates have been suitably constructed under both the full LSMS assumption and hypothesized LMS assumption. There is no time lag in data collection between the two surveys, and errors in measurement associated with variation in the sampling design are completely eliminated because the comparisons are made on the same unit of analysis.

Distribution of Expenditure from LSMS and LMS

The present study is based on the last Ghana Living Standards Survey (the GLSS 3, conducted in 1992), which is similar to the standard LSMS survey. The GLSS 3 was the third round of a series of living standards surveys initiated in Ghana. This was a nationally representative household survey, based on the master sample of enumeration areas defined by the 1984 population census. The data collection was spread over a whole year. A high response rate was achieved, and this survey design provided a total sample size of about 4,500 households. GLSS 3 differs from the two previous rounds of household surveys carried out in Ghana because it collects data on all dimensions of household welfare and economic behavior. The sections on household income and expenditure are comprehensive and much more disaggregated than previously. Overall, estimates of this third round are considered more accurate (see GSS 1995), in part because they are based on much shorter bounded recall periods—seven recalls at two-day intervals in rural areas, and 10 recalls at three-day intervals in urban areas.

Although LSMS and IS surveys collect extended information on both household income and expenditure, the data on the latter variable are used as a measure of economic welfare. In part because nonsampling errors due to underreporting of income create large biases in reported household
income, there are strong theoretical reasons for the use of an expenditure variable (see Deaton and Muellbauer 1980). For this study, therefore, expenditure data is retained and serves as the basis for differentiating poor from non-poor households, for constructing poverty maps to design improved targeted programs.

Estimates of household total expenditure on food and non-food constructed from the GLSS 3 data uses six aggregates and seventeen sub-aggregates. These estimates account for all household expenses including total household expenditure on rent, with imputed rent calculated from owner-occupied, rent-free, or subsidized dwellings; consumption of home-produced food; and the value of wage income received by household members in the form of food. Other imputed expenditures include total wage income paid in kind to household members, the value of non-farm enterprise produce consumed by households itself, and the use value of durable goods. The value of remittances made by the household, and all other expenses, such as for education and household amenities, were also included in the overall total expenditure aggregates. Missing values and outliers were imputed on each variable (see GSS 1996). Since the survey was carried out over one year, all expenditure data were adjusted to take account of inflation over the survey period, and the monetary values are based on March 1992 prices. However, no adjustment for seasonal effects on household expenditure was made.

The aggregate total household expenditure is obtained by summing up across all household expenditure items, sub-aggregates, and aggregates on food and non-food items. We first sum across items and sub-aggregates to obtain intermediate values for expenditure aggregates at the household level, as shown in equation 5.1:

\[ S_k^h = \sum_{j=1}^{N} \lambda \delta_j^h p_j^h q_j^h \]  \hspace{1cm} (5.1)

where \( h \) stands for households varying from 1 to the total sample size, and \( j = 1, 2, \ldots, N \) is the total number of items. The total household expenditure for LSMS surveys is obtained by summing across expenditure aggregates, as shown in equation 5.2

\[ \hat{Y}_{LSMS}^h = \sum_{k=1}^{A} S_k^h = \sum_{k=1}^{A} \sum_{j=1}^{N} \lambda \delta_j^h p_j^h q_j^h \]  \hspace{1cm} (5.2)

where \( k = 1, 2, \ldots, A \) is the total number of sub-aggregates, and \( \hat{Y}_{LSMS}^h \) is the total household LSMS expenditure aggregates for a given household \( h \). \( p_j^h \) and \( q_j^h \) are price and quantity of item \( j \), the component of aggregate \( k \) consumed by a given household \( h \). The multiplicative factor \( \delta_j^h \) is the frequency
of purchase (recall period) of a given item within household \( h \), and \( \lambda \) is the seasonality factor or frequency of visits to the households.

Estimates of household total expenditure from LMS design are obtained by similar aggregation, except that the number of items and subaggregates are much smaller. The components of total household aggregated expenditure are selected following the recommendations of the standard PS, which suggest limiting the collection of expenditure data to key food items and a few non-food items (see Demery and others 1991). The total expenditure aggregate constructed for this experiment is based on three subaggregates: two non-food which include expenditure on education and health, and a food expenditure aggregate containing 10 key food items. The total household expenditure from the hypothesized PS is constructed by summing up across these three subaggregates, which of course have already been adjusted to account for inflation over time. The adjustment is necessary because the PS design recommends a single visit to the households, and inference on welfare is drawn assuming no seasonal variation in the consumption pattern. In fact, the relatively short time period devoted to data collection reduces the range of price fluctuations. Estimates of total household expenditure from the hypothesized PS can be provided by equation 5.3:

\[
\hat{Y}_{PS} = \sum_{k=1}^{A} S^h_k = \sum_{k=1}^{A} \sum_{j=1}^{N} S^h_{jk} P^h_{jk} Q_{jk}^h
\]

(5.3)

Note that in the PS estimate, the number of subaggregates is much smaller \((a < A)\), and the number of items is much smaller as well \((n < A)\). The seasonality factor \( \lambda \) does not appear in the PS aggregates because the data are collected in a single visit to households. Since the number of items and subaggregates is smaller in the PS design, this value is generally underestimated and one would expect the following ordering between the two constructed variables: \( Y_{PS}^h < Y_{PS}^h \). In the remaining of this chapter, these two variables are adjusted for the effects of household size to produce the household per capita expenditure data used for analysis.

Table 5.1 provides summary statistics relative to these two variables. Note that the variance of the distribution of total household per capita expenditure from LMS is relatively high, because the coefficient of variation of the LMS per capita expenditure is higher than the LSMS estimates across all regions, despite the fact that the PS mean per capita expenditure is uniformly smaller.

While the ratio of regional estimates of mean per capita expenditure to national estimates shows less variations in the LSMS design—the ratio oscillates around 1, indicating that these values do not differ markedly from the national estimate—large fluctuations are observed when these ratios are estimated from LMS. While the mean per capita expenditure in rural areas
Table 5.1 Summary Statistics Distribution of Per Capita Expenditure by Survey Type and across Region

<table>
<thead>
<tr>
<th>Regions</th>
<th>Priority survey</th>
<th></th>
<th>LSMS survey</th>
<th></th>
<th>t-test stat</th>
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<td>CV</td>
<td>Max</td>
<td>Share of national mean PCE</td>
<td>CV</td>
</tr>
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<td>181.3</td>
<td>698520</td>
<td>1.2097</td>
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<tr>
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<td>155.88</td>
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<td>Rural forest</td>
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<td>197760</td>
<td>1.0123</td>
<td>147.4</td>
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<td>0.9928</td>
<td>178.55</td>
</tr>
<tr>
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<td>150.81</td>
</tr>
<tr>
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<td>1.0869</td>
<td>157.68</td>
</tr>
<tr>
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<td>0.9569</td>
<td>166.1</td>
</tr>
<tr>
<td>National</td>
<td>—</td>
<td>278.5</td>
<td>698520</td>
<td>—</td>
<td>163.87</td>
</tr>
</tbody>
</table>

— Not available
* Comparison of the distributions of total expenditure from the two surveys.
Source: Author’s calculations.

represents approximately 95 percent of national mean per capita in the full GLSS 3 survey, the bias is more pronounced in the PS setting, where the mean per capita expenditure in rural areas represents only 52 percent of the national estimate. On the other hand, the mean per capita expenditure is much higher in urban areas, where it represents nearly twice the national estimate. In other words, the disparities between urban and rural areas are more pronounced in LMS. As a result, effective targeted programs for poverty alleviation drawn from LMS-based poverty maps are likely to require more resources than actually required to improve living standards in rural areas and reduce regional disparities.

Similar variations are observed in the regions when the regional mean per capita expenditure is expressed as a percentage of national mean estimates. The estimated mean per capita expenditure in Rural Coastal and Savannah regions are the lowest and represent about 50 percent of the LMS national estimate. On the average per capita expenditure, these two regions are the poorest in Ghana. However, the difference that exists between these regions does not show up in the PS design, especially in rural areas where important disparities are known to exist. In fact, while Savannah and Rural Coastal regions are both poor, poverty is more acute in the Savannah where the ratio of per capita household expenditure to national level estimates is the lowest in the GLSS 3 design (88 percent), and the magnitude of the difference between the two poorest regions is close to 12 percent.

Since the value of household total expenditure is based on few items, the downward bias in mean per capita expenditure is likely to cause the distri-
bution to shift to the left, which better reflects the low level of consumption reported. However, while the scope of items and subaggregates might explain large absolute difference between these two distributions—the LMS mean per capita expenditure is 17,678 cedis and represents less than 8 percent of LSMS estimate of 21,5185 cedis—the variation in the structure of these distributions, and the large urban/rural difference might be largely due to the nature of the consumption items in the overall aggregate. Although own consumption represents a large share of household consumption in rural areas, it is not accounted for in the total PS aggregate, partly because of low-level of monetisation of the rural economy, but also because the key consumption items are more tradable in urban areas.

Important variations are also observed in the overall distribution of income across income groups. The distribution of income across income group is not maintained in the LMS design, where the concentration of income tends to be much larger in the uppermost quintile, and substantially smaller in the lowest quintile—implying that the distribution of income is highly unequal in the PS survey. Figure 5.1 shows the distribution of household per capita expenditure across expenditure quintiles under the two designs. This figure shows the share of expenditure quintiles. Note that the distributions of income across income groups are significantly different in the two surveys. The bottom two expenditure quintiles (40 percent of

Figure 5.1 Distribution of Household Per Capita Expenditure by Quintile

Per capita expenditure share

![Graph showing distribution of household per capita expenditure by quintile.](source)

*Source: Author’s calculations.*
population) accounts for less than 8 percent of total expenditure declared in the PS; the LSMS estimates are over 20 percent. However, a reverse scenario is observed in the upper quintiles where expenditure shares are overestimated in the hypothesized PS design. These differences in distribution of income across income groups suggest that poverty maps constructed from LMS may not be accurate, partly because poverty maps are constructed from these distributions. Moreover, since ranking across expenditure quintiles is a mere reflection of individual welfare, a small income share in the income group is inversely proportional to the poverty rate in the group. The degree of inaccuracy is further illustrated by the scope of underestimation in the lowest quintile. LMS tends to overestimate the living standards of the non-poor and underestimate the living standards of the poor—the income share is relatively high in the upper quintile, and extremely low in the lowest quintile, suggesting that the poor might be even poorer than the data indicates.

Implications for Policy Analysis and Poverty Mapping

In the latest Ghana poverty profile (World Bank 1995), the upper and lower poverty lines are defined as one-half and two-thirds of national mean per capita expenditure respectively.\(^7\) The upper poverty line is 132,230 cedis per person per annum, and the lower line is 107,188 cedis. In this chapter, the lower poverty line is used as the cutoff point, because maximum targeting is easily achieved at the lower and upper end of the distribution where the within-group variance and the probability of household misclassification are lower. The lower poverty line is also used because total household expenditure aggregated from light monitoring surveys shows a large difference between urban and rural areas; the rural expenditure aggregate is substantially lower, and using an upper poverty line would have exacerbated the scope of rural poverty. Similarly, a relative poverty line is defined as fraction of the hypothesized PS mean per capita expenditure for comparison in a cross-section analysis where we look at variations in the poverty rates across regions, in the two designs and for the same reference period. The choice is partly dictated by the fact that poverty profile constructed from LMS use relative poverty lines defined as fraction of total per capita expenditure aggregated from few items (see World Bank 1997 and 1998).

In order to assess the performance of LMS when used as targeting instruments, welfare indicators and poverty indices are estimated from the two distributions.\(^8\) The results are provided in table 5.2, where the Headcount, poverty gap, and severity indices are estimated from the hypothesized PS and the full GLSS 3. The performance of the PS as an instrument for targeting is also assessed by the size of type I and type II error probability, as well as the rate of mistargeting.
Formally defined as $\varepsilon_i = (P(y_i \in P | y_i \in \bar{P}))$, type I error probability is also termed as the error of inclusion because it gives the probability of classifying households or individuals as poor, while they are actually non-poor. On the other hand, type II error probability, formally defined as $\varepsilon_{ii} = (P(y_i \in P | y_i \in P))$, is generally termed as the error of exclusion because it gives the probability of classifying individuals as non-poor while they are actually poor. The rate of mistargeting depends on the size of these two errors. Perfect targeting is achieved when the rate of mistargeting is equal to 100 percent, implying that the number of individuals classified as poor under the hypothesized PS design are also ranked as poor in the GLSS 3 or LSMS design. This successful rate of targeting occurs when the errors of inclusion and exclusion are both close to zero. Let $\zeta_{RM}(\varepsilon_i, \varepsilon_{ii})$ be the rate of mistargeting expressed as function of the error of inclusion ($\varepsilon_i$) and the error of exclusion ($\varepsilon_{ii}$). This rate is a number between 0 and $n$, where $n < \infty \zeta_{RM}(\varepsilon_i, \varepsilon_{ii}) > 1$ when mistargeting results mostly from a large error of inclusion. However, when the error of exclusion is much larger than the error of inclusion, the rate of mistargeting is confined between 0 and 1, that is, $\zeta_{RM}(\varepsilon_i, \varepsilon_{ii}) < 1$.

When household per capita expenditure aggregated from the hypothesized PS is used as the basis for constructing poverty maps, Rural Coastal and Savannah remain the poorest regions of Ghana. However, variations in the scope of differences across regions are important. While the magnitude of differences across regions is slim as measured by GLSS 3—a 4-percentage point difference exists between urban and rural areas—the scope of urban-rural difference is more significant in the hypothesized PS design (55 percent). Similarly, while over 68 percent of the population residing in the Savannah region is classified as extreme poor, the poverty incidence in Rural Forest is less than 56 percent, and these proportions are much smaller in urban areas (8 percent) and Accra (6 percent). When the poverty map is constructed from GLSS 3, the Headcount in urban areas is much higher, in part because accounting for consumption of own produce in rural areas during the GLSS 3 implementation reduces the urban/rural discrepancy and increases the overall national mean per capita expenditure, and therefore the extreme poverty line. Therefore, LMS surveys underestimate the scope of urban poverty and reduce the prospect of effective targeting for poverty alleviation. Under the full GLSS 3 design, however, targeting is more justified in urban areas where the number of intended beneficiaries is more important.

Poverty in Sub-Saharan Africa is generally much higher in rural areas where the prospects of income-generating activities are much more limited and aggregate expenditure is much lower. However, while one might expect extreme poverty to be more acute in rural than urban areas in most Sub-Saharan African countries, we rarely expect the large difference in
magnitude found in Ghana, where over 65 percent of the rural population lives under extreme poverty, compared with less than 8 percent in urban areas. The differences in scope of extreme poverty reflect the magnitude of the error of inclusion, which is relatively low in urban areas (0.04) and much higher in rural areas (0.47). Note that the size of this error is directly proportional to the rate mistargeting, and the larger the probability of error, the higher the rate of mistargeting. However, a low error of inclusion does not always imply perfect targeting, especially if the corresponding error of exclusion is much higher, as in the present scenario.

In urban areas where the error of inclusion is low and the error of exclusion is much higher (0.11), mistargeting results from a large error of exclusion—which is a consequence of undercoverage of poor households in the sample of intended beneficiaries. On the other hand, a large error of inclusion in rural areas results from oversampling of the poor population in the hypothesized PS design, which causes households normally classified as non-poor to be surveyed as intended beneficiaries for targeted interventions. Table 5.2 shows that mistargeting is relatively high under the PS design, where the population identified for targeted intervention is nearly 2.5 times larger than the true population estimate. This high rate of poor targeting is certainly inflated by the rural rate of mistargeting, which is even higher. For instance, the total number of extreme poor estimated from LMS in rural areas is over three times the actual number of intended beneficiaries. The variations in the rate of mistargeting across other rural regions are not significant; these rates have the same order of magnitude in Rural

Table 5.2 Indices of Extreme Poverty and Rate of Mistargeting across Regions: A Comparison of the Priority Surveys and Living Standards Measurement Surveys

<table>
<thead>
<tr>
<th>Regions</th>
<th>Priority Survey</th>
<th>LSMS Survey</th>
<th>PS-LSMS comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P0</td>
<td>P1</td>
<td>P2</td>
</tr>
<tr>
<td>Accra</td>
<td>0.0678</td>
<td>0.0274</td>
<td>0.0158</td>
</tr>
<tr>
<td>Other urban</td>
<td>0.0665</td>
<td>0.0325</td>
<td>0.0180</td>
</tr>
<tr>
<td>Rural forest</td>
<td>0.5543</td>
<td>0.3029</td>
<td>0.2060</td>
</tr>
<tr>
<td>Rural coastal</td>
<td>0.6731</td>
<td>0.3722</td>
<td>0.2493</td>
</tr>
<tr>
<td>Savannah</td>
<td>0.6810</td>
<td>0.4236</td>
<td>0.3082</td>
</tr>
<tr>
<td>All urban</td>
<td>0.0819</td>
<td>0.0313</td>
<td>0.0175</td>
</tr>
<tr>
<td>All rural</td>
<td>0.6506</td>
<td>0.3753</td>
<td>0.2604</td>
</tr>
<tr>
<td>National</td>
<td>0.4621</td>
<td>0.2612</td>
<td>0.1799</td>
</tr>
</tbody>
</table>

Source: Author's calculations.
The Case of Ghana

Forest, Rural Coastal, and Savannah.

The amount of leakage is directly proportional to the rate of mistargeting and will be lower in urban areas where differential rates are smaller. While the total number of the extreme poor population mistargeted in the LMS design is about half the actual targeted population in urban areas, the size of the population that are wrongly classified is over three times the number of primary beneficiaries in rural areas. In terms of resource allocation, the dollar amount of leakage that results from poor targeting associated with the LMS stratification is over three times the monetary value actually required to alleviate extreme poverty in rural Ghana.

The estimated amount required to eradicate extreme poverty (\(n_z \hat{p}_j\)) is proportional to the poverty gap, and the larger the poverty gap, the larger the amount. Hypothetically, the poverty gap estimated from the PS is about six times higher than the full GLSS estimate, at the national level. As a result, the amount required to eradicate extreme poverty if the PS is used as the basis for poverty analysis is about six times higher, other things being equal. More precisely, to fill the gap so as to ensure that there is no extreme poverty in Ghana requires about 27,997.5 (0.2612*107188) cedis per annum and per person in the PS design, instead of 4,298.5 (0.0401*107188) cedis according to the GLSS estimate.\(^\text{10}\) The potential costs and losses for central government and local authorities are considerable, in part because poor targeting and improper identification of intended beneficiaries increases the amount of leakage and the estimated amount of resources allocated for poverty alleviation. The following section proposes a method for correcting light surveys for improved targeting.

Estimating Total Expenditure for Improved Targeting

To motivate the use of LMS instruments that have limited data on expenditure, but good data on social and access indicators, location of infrastructure, and large coverage for poverty analysis and targeting, we consider using poverty predictors—which are correlates of expenditure to impute for household consumption. In Fofack (1997), a methodology for deriving national poverty predictors was proposed, and this exercise can be viewed as a model calibration for improved targeting. By combining LMS with more general LSMS and IS surveys (which are comprehensive on income and expenditure), poverty predictors and their corresponding weights are estimated from the latter two surveys and are used to impute for household total expenditure, which then serves as the basis for poverty analysis and for constructing poverty maps in the LMS setting.

As core components of national statistical programs, LMS and LSMS are both household-level surveys, with important similarities. Similarity in the sampling frame and sampling design, as well as the geographic proximity
in the implementation of these surveys, make their combination extremely appealing for poverty and policy analysis. In an early empirical study, the poverty predictors and their corresponding weights were estimated from GLSS 3 (see Fofack 1997). In order to assess the stability over time of these predictors and their corresponding weights, they were applied to earlier surveys, GLSS 1 (1987) and GLSS 2 (1989), to predict the standards of living. The expected average discrepancy based on the error of prediction was relatively small, as a result of the small absolute deviation between sampled household expenditure and predicted values. Successful rates of household classification across expenditure quintiles were achieved when the predicted values were compared with the actual welfare measure reported. Rates as high as 95 percent were attained in the extreme quintiles, and 90 percent in the intermediate ones, when based on GLSS 2.

When applied to GLSS 1 (1987), the stability of these regressors and coefficients was preserved as well: absolute deviation between predicted value and actual welfare measure reported was still relatively small. The rate of successful classification across expenditure quintiles remained high, despite the time lag between the GLSS 3 (1992) and GLSS 1 (1987). Rates as high as 92 percent were attained in the extreme quintiles, and 83 percent in the intermediate ones. The precision of welfare measure prediction is further highlighted by the fact that mistargeted households were located in neighboring quintiles, hence limiting leakage in targeting for poverty reduction.

Recently, attempts have been made to exploit the large coverage of population censuses to construct poverty maps for poverty and policy analysis, by combining the census with household surveys (see Hentschel and others 1998). While such a combination might be appealing, especially given its scope for geographical targeting, the data requirements to capture the large proportional variance observed in welfare could be enormous. Moreover, the frequency of census implementation is relatively low in Sub-Saharan Africa, which may prevent timely update of weights and welfare correlates whose precision can decline over time. While the method proposed by Hentschel and others uses a large number of regressors from the census to predict household welfare, the method used in this study draws on a different approach based on data reduction. The poverty correlates to predict welfare for poverty analysis are reduced to a set of minimum core variables that can be collected easily on a single household visit with a low level of nonsampling errors.

To impute household consumption for poverty analysis, the best correlates of welfare are first derived in the broad GLSS 3 survey using correlation analysis and regression models. The model assumes that the conditional expectation \( E(y | x_1, \ldots, x_l) \) of the response given the covariates is related to the linear predictors by the response link function \( h(x, \theta) \). Since the variance of total household expenditure across regions and within regions is large, a logarithmic transformation is applied to the response to make the
relationship between the \( y \) and the \( x \)s linear. This transformation stabilizes the error variance, reduces asymmetry in the distribution of error terms, and improves prediction. The structural form of the correcting model is specified by equation 5.4:

\[
Y = X'\beta + \epsilon
\]  

(5.4)

where \( Y \) is total household expenditure transformed to the log scale, \( \beta \) is the vector of estimated parameters relative to continuous and discrete level variables, and \( \epsilon = N(0, \sigma^2) \) is the distribution of error terms. The set of poverty predictors is mostly discrete-level variables. Most continuous variables with strong predictive capabilities are dichotomized to discriminate between poor and non-poor households. These dummy regressors were constructed and included in the model to capture the effects of qualitative independent variables.

In order to account for selection bias in the choice of the predictor variables, a conditional maximum likelihood (CML) estimation method is used to select predictors. Unlike other selection criteria,\(^{11}\) the CML method is based on the expected overall discrepancy and produces an unbiased estimation of the discrepancy, since the omission bias in the fixed model becomes additional residual variation. The best poverty predictors were the ones that contributed to a significant marginal increase in the explanatory power of the model. That is, if \( (x_p, x_2, \ldots, x_j) \) is the initial set of poverty correlates, and \( x_{i1}, x_{i2}, \ldots, x_{ik} \) for \( k \neq 1 \) are potential poverty predictors candidates, the variable \( x_{i1} \) will often be selected over \( x_{ik} \) if the conditions in equation 5.5 are true:

\[
\sum (y_i - E(\hat{y} | x_1, x_2, \ldots, x_j, x_{i1}))^2 < \sum (y_i - E(\hat{y} | x_1, x_2, \ldots, x_j, x_{ik}))^2
\]  

(5.5)

Initially, we assumed that all predictor variables were available for inclusion in the model. We then proceeded by elimination using the stepwise selection method, with a minimum level of significance. A given independent variable was removed from the model only when a marginal increase of the percentage variance of the response explained by the model as a result of its inclusion was smallest (equation 5.6):

\[
\Delta \left( R^2 \left( y \mid \sum_{j=1}^{k} \lambda_j x_j \right) - R^2 \left( y \mid \sum_{j=1}^{k-1} \lambda_j x_j \right) \right) < \epsilon
\]  

(5.6)

Applying this selection procedure to the model iteratively produces an optimal model with 10 core poverty predictors. The resulting set of poverty predictors actually has very few continuous variables and has essentially either dichotomized or discrete-level variables. This reduces errors due to long recall periods and increases the accuracy of targeting based on a pre-
diction function, because the poverty predictors and the weighted coefficients are estimated from full LSMS and IS surveys, and are imputed using information collected at the household level during the implementation of light surveys. Therefore, the poverty indices are no longer just a function of the aggregated household total expenditure, but also depend on the estimated regression coefficients, as shown in equation 5.7:

\[ P_k = f(\hat{y}, z), \text{ for } k = 0, 1, 2, \] \[ \text{where } \hat{y} = \Phi \left( \sum_{i=1}^{n} \beta_i x_i \right) \] (5.7)

where \( z \) is the poverty line. Using this methodology, the poverty predictors are derived at the national and regional level and used in conjunction with the corresponding weights to impute total expenditure. The predicted expenditure is then used as a basis for constructing poverty maps, and for classifying regions for poverty analysis and targeting. The poverty predictors were able to explain over 65 percent of proportional variance observed in the actual welfare measure reported. The proportional variance explained by the model was high at the national level, but also at regional level when the models were calibrated to derive poverty predictors for each agro-climatic region. Table 5.3 provides a complete listing of the derived poverty predictors. These predictors are derived at the national and regional level to account for regional differences in the pattern of consumption.

Results and Implications for Geographical Targeting

To assess the accuracy of poverty maps constructed from improved LMS, the incidence of poverty and other poverty indicators are computed for different agro-climatic regions using the predicted expenditure constructed from the model, estimated as the weighted sum of the poverty predictors. These estimates are compared with the poverty indicators derived from actual GLSS 3 data. Table 5.4 reports these values and the corresponding error of inclusion (type I error probability) and error of exclusion (type II error probability).

The differences in the poverty estimates decrease substantially in both urban and rural areas when the poverty predictors are used to model household expenditure. The error of inclusion is now confined between \( 0 < P(y_1 \in P | y_i \in P) \leq 13 \), from a rate as high as 0.48 in the hypothesized Priority Survey setting. It is worth pointing out that the significant decrease in the error of inclusion, which translates into improved poverty maps, is not at all compensated for by increased errors of exclusion; this error remains low across all agro-climatic regions.

The poverty indicators calculated on the basis of full GLSS data and the LMS with predicted expenditure are quite close. At the national level, the absolute relative error is less than 0.081 (ARE < 0.08), in part because the
<table>
<thead>
<tr>
<th>National level</th>
<th>Urban areas</th>
<th>Rural areas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expenditure on soap</td>
<td>Expenditure on soap</td>
<td>Expenditure on soap</td>
</tr>
<tr>
<td>Number of spouses</td>
<td>Number of spouses</td>
<td>Number of spouses</td>
</tr>
<tr>
<td>Assets score</td>
<td>Assets score</td>
<td>Assets score</td>
</tr>
<tr>
<td>% school age kids enrolled</td>
<td>% school age kids enrolled</td>
<td>% school age kids enrolled</td>
</tr>
<tr>
<td>Expenditure on meat</td>
<td>Expenditure on meat</td>
<td>Expenditure on meat</td>
</tr>
<tr>
<td>Land ownership</td>
<td>Land ownership</td>
<td>Ownership of poultry</td>
</tr>
<tr>
<td>Consumption of bread</td>
<td>% household members employed</td>
<td>Ownership of goats and sheep</td>
</tr>
<tr>
<td>Ownership of poultry</td>
<td>Use of tooth paste</td>
<td>Number of members per room</td>
</tr>
<tr>
<td>Export crops</td>
<td>% children enrolled in public school</td>
<td>Ownership of farm</td>
</tr>
<tr>
<td>Number of member per room</td>
<td>% household member literate</td>
<td>Ownership of cattle</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Accra region</th>
<th>Other urban</th>
<th>Rural forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets score</td>
<td>Expenditure on soap</td>
<td>Expenditure on soap</td>
</tr>
<tr>
<td>Expenditure on meat</td>
<td>Number hh member employed</td>
<td>Consumption of bread</td>
</tr>
<tr>
<td>% household members employed</td>
<td>Expenditure on meat</td>
<td>Use of tooth paste</td>
</tr>
<tr>
<td>Expenditure on rice</td>
<td>Assets score</td>
<td>Use of tooth paste</td>
</tr>
<tr>
<td>Number of hh members completed secondary</td>
<td>% school age children</td>
<td>Number of spouses</td>
</tr>
<tr>
<td>Expenditure on soap</td>
<td>Expenditure on bread</td>
<td>Expenditure on meat</td>
</tr>
<tr>
<td>% of school age children</td>
<td>% hh member completed secondary</td>
<td>% hh member completed secondary</td>
</tr>
<tr>
<td>Number of under-five</td>
<td>Use of tooth paste</td>
<td>Expenditure on rice</td>
</tr>
<tr>
<td>Use of paper toilet</td>
<td>Ownership of land</td>
<td>Number of members per room</td>
</tr>
<tr>
<td>% children enrolled in public school</td>
<td>Use of paper toilet</td>
<td>Use of paper toilet</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Rural coastal</th>
<th>Savannah</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Expenditure on soap</td>
<td>Expenditure on soap</td>
<td></td>
</tr>
<tr>
<td>Assets score</td>
<td>Number of spouses</td>
<td></td>
</tr>
<tr>
<td>% school age children</td>
<td>Consumption of bread</td>
<td></td>
</tr>
<tr>
<td>Number of spouses</td>
<td>Ownership of sheep and goats</td>
<td></td>
</tr>
<tr>
<td>% children enrolled in public school</td>
<td>Use of tooth paste</td>
<td></td>
</tr>
<tr>
<td>Consumption of bread</td>
<td>Expenditure on meat</td>
<td></td>
</tr>
<tr>
<td>Use of paper toilet</td>
<td>Assets score</td>
<td></td>
</tr>
<tr>
<td>Ownership of poultry</td>
<td>Use of paper toilet</td>
<td></td>
</tr>
<tr>
<td>Number of under-five</td>
<td>Gender of head</td>
<td></td>
</tr>
</tbody>
</table>

Source: Author’s calculations.
Table 5.4 Indices of Extreme Poverty and Rate of Mistargeting across Regions: A Comparison of LSMS and Imputed Expenditures

<table>
<thead>
<tr>
<th>Regions</th>
<th>Poverty Predictors (PP)*</th>
<th>LSMS type survey</th>
<th>PP-LSMS comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PO</td>
<td>P1</td>
<td>P2</td>
</tr>
<tr>
<td></td>
<td>error</td>
<td>probability</td>
<td>error</td>
</tr>
<tr>
<td>Accra</td>
<td>0.0878</td>
<td>0.0163</td>
<td>0.0040</td>
</tr>
<tr>
<td>Other urban</td>
<td>0.1344</td>
<td>0.0274</td>
<td>0.0076</td>
</tr>
<tr>
<td>Rural forest</td>
<td>0.0988</td>
<td>0.0159</td>
<td>0.0039</td>
</tr>
<tr>
<td>Rural coastal</td>
<td>0.1868</td>
<td>0.0357</td>
<td>0.0103</td>
</tr>
<tr>
<td>Savannah</td>
<td>0.2787</td>
<td>0.0461</td>
<td>0.0116</td>
</tr>
<tr>
<td>All urban</td>
<td>0.1229</td>
<td>0.0247</td>
<td>0.0067</td>
</tr>
<tr>
<td>All rural</td>
<td>0.1999</td>
<td>0.0351</td>
<td>0.0094</td>
</tr>
<tr>
<td>National</td>
<td>0.1743</td>
<td>0.0317</td>
<td>0.0085</td>
</tr>
</tbody>
</table>

* Poverty Predictors refer to LMS with imputed consumption.
Source: Author’s calculations.

The difference in Headcount indices estimated from reported LSMS expenditure and predicted welfare function figures is slim. The relatively small deviation between the predicted poverty rates and the actual rates estimated from the GLSS 3 survey is largely due to the sample size effects. The sample size at the subregional level is the smallest in the Accra and Rural Forest regions, where the magnitude of the difference is the largest. However, the error in prediction is inversely proportional to the sample size, and one would therefore expect this error to decrease substantially in the actual LMS design, where the large sample size allows a much higher representation at the regional and subregional levels. Part of the prediction error could also be attributed to random noise affecting values of expenditure reported. These prediction errors are associated with the design, and could be reduced if sampling and nonsampling errors were controlled during the survey implementation.

This section assesses the implications of large reductions of both errors of inclusion and exclusion on the poverty map. Figure 5.2 provides the spatial distribution of poverty measured using the Headcount index, across agro-climatic regions under the three types of surveys: LSMS, LMS with imputed consumption, and the Priority Survey. While the predicted poverty indices are quite close to those estimated from GLSS 3, a large discrepancy exists between these rates and PS-based estimates.

The differences between Headcount indices are maintained when the predicted expenditure is used for poverty analysis. The bias towards higher
rural poverty is preserved in the regional ranking, and ranking of five agro-
climatic regions is consistent across the two ranking criteria: LSMS-based
data and LMS with predicted expenditure. Thus, although poverty is gen-
erally widespread in rural areas, there are some variations across rural
regions reflected by the difference in their poverty indices. In terms of
extreme poverty, the Savannah remains the poorest region, followed by Rural
Coastal and Forest regions, while Accra is the least poor region in Ghana.

The performance of the proposed method is also assessed by the size of
errors of inclusion and exclusion, as well as the rate of mistargeting. Figures
5.3 and 5.4 provide estimates of errors of inclusion and exclusion relative to
the PS and the LMS with predicted expenditure for comparison. Note that
while the error of inclusion is generally much higher in the PS setting,
when estimated across agro-climatic regions, the error of exclusion, in con-
trast, is often much lower. However, the magnitude of difference between
the error of exclusion estimated from the PS and the LMS with predicted
expenditure is small, in part because mistargeting is largely due to the high
error of inclusion.

Figure 5.2 Spatial Distribution of Poverty across Agro-Climatic Regions:
Comparison of Priority Survey, LMS with Imputed Consumption
and LSMS Surveys

Headcount index

Source: Author's calculations.
The rate of mistargeting, which reflects the gap between the true population of intended beneficiaries and the population estimate based on LMS with predicted expenditure reduces substantially, as shown in table 5.3. Except the Rural Forest region, where the rate of misclassification is slightly different from unity (perfect targeting), targeting is almost perfect in all other regions. In particular, perfect targeting is achieved in all Rural and Rural Coastal areas when the predicted expenditure variable is used as the basis for household ranking and constructing poverty maps. Compared with the LMS ranking, the gains in accuracy achieved in the spatial distribution of poverty are significant, especially if one considers the fact that mistargeting under the hypothesized PS design increases the population of intended beneficiaries by a factor of three. Even in the Rural Forest region, where the error of inclusion is relatively high (0.12) and the rate of misclassification is slightly different from unity, the gap is less than 40 percent. Moreover, the rate of mistargeting is less than one, implying that poor targeting is largely due to the high error of exclusion (undercoverage of the population of intended beneficiaries), and does not necessarily translate into increased resources for poverty alleviation.

This rate of mistargeting reflects the size of both errors of inclusion and exclusion and is expressed as the ratio of estimated population of beneficiaries
to the exact population of beneficiaries in each region. As indicated earlier, these rates vary between 0 and $n < \infty$, and $0 < \xi_{RM}(\epsilon_i, \epsilon_{ii}) < 1$ reflects the undercoverage resulting from a large error of exclusion, whereas $\xi_{RM}(\epsilon_i, \epsilon_{ii}) > 1$ reflects a large error of inclusion of unintended beneficiaries in the target population. Note that the rates of mistargeting $\xi_{RM}(\epsilon_i, \epsilon_{ii})$ are relatively high: especially in rural areas, $\xi_{RM}(\epsilon_i, \epsilon_{ii}) > 1$ when the hypothesized PS is used to construct the poverty map. These high rates are largely attributed to a large error of inclusion and could increase leakage and the cost of poverty reduction programs. However, significant improvement is achieved when LMS with predicted expenditure is the basis for targeting.

The objectives of the method outlined are twofold: first, to improve accuracy of poverty maps constructed from LMS, and second, to draw on the large samples provided by the design of these surveys, as well as the nature of poverty predictors, to achieve geographical targeting at levels below administrative regions. In the counterfactual experiment presented in this chapter, the hypothesized PS is constructed from the more comprehensive GLSS 3 survey, and the sample size corresponding to the hypothesized PS is dictated by the GLSS 3 design—just as the level of disaggregation is determined by the actual GLSS 3 sample size.
The geographic profile of poverty provides living-standard indicators at the level of agro-climatic regions. However, it has been demonstrated that greater gains in efficiency and significant reduction of leakage in transfers for poverty alleviation can be achieved from fine-tuning targeting to smaller geographic units (see Baker and Grosh 1994). This is because finer disaggregation creates homogeneous groups and reduces leakage in transfers to the poorest population. The actual PS design recommends a large sample size for targeting smaller administrative units (see Grootaert and Marchant 1992). Predicting household expenditure using poverty predictors should strengthen PS analytical capabilities and enable researchers to exploit its large coverage to achieve geographical targeting, with minimum leakage, at a level of disaggregation well below agro-climatic regions.

The causes and determinants of poverty, as well as sources of large disparities across agro-climatic regions are variable. (The Savannah and Rural Coastal regions are the poorest.) While at the aggregate level, differences in potential for income-generating activities and wage inequality might constitute important factors, at the regional and district level, human capital, access indicators, and location of infrastructure might be more critical. LMS have good data on access indicators—location of schools, health centers, and water supply—and its relatively large sample size may provide opportunities for georeferencing information at subregional levels, thus improving the potential for analysis beyond fixed geographical boundaries. Moreover, overlaying poverty maps with improved spatial distribution on maps of local infrastructure (schools, health clinics, hospitals, water supplies, and roads), and presenting both maps at the same level of disaggregation, may provide a better understanding of poverty dynamics. More light may be shed on the constraints to growth and poverty reduction, and prioritizing, impact assessment, and policymaking may be improved.

Glewwe (1992), Kanbur and others (1994), and Bigman and Fofack (2000) provide a survey of targeting methods with applications to developing countries. The methods of targeting that provide criteria of eligibility for poverty alleviation programs fall into the following categories: targeting by household income, targeting by other indicators, targeting by commodities, self-targeting, and geographical targeting. While successful implementation of geographical targeting requires large data sets to achieve high levels of disaggregation and reduce induced leakage, the needs and requirements for targeting by income, commodities, and indicators are somehow different.

A successful implementation of targeting by indicators is based on the ability to easily identify a few key indicator variables that are highly correlated with household income and expenditure. Using this scheme in Côte d’Ivoire, Glewwe (1992) found that the correlates of poverty identified were essentially household amenity variables; Ravallion (1989) showed that substantial gains in targeting can be achieved if land ownership is used as the
criterion for discriminating poor from non-poor. The poverty predictors are strong correlates of welfare varying across regions, and poverty alleviation programs as well as targeting schemes can suitably be designed using these indicators. Since household amenity variables are strong correlates of poverty, indirect measures to alleviate poverty can be implemented by designing programs that use these variables to maximize transfers to the most needy.

The poverty predictor’s variables include food and non-food consumption items, and can well serve as a basis for commodities-based targeting. This targeted scheme draws on the differences observed in the consumption basket of the poor and non-poor. Its objective is to reduce the cost of those commodities that are heavily consumed by the poor through targeted subsidies. Although poverty predictors are not derived along the poverty dimension, but rather by agro-climatic regions, the methodology presented is flexible and can be used in multiple steps—first by predicting household expenditure using the poverty predictors, and then using the predicted variable to differentiate between poor and non-poor. A cross-sectional analysis which focuses on the variation in the consumption pattern of the poor by agro-climatic regions could be a starting point to investigate the causal link between variation in the depth of poverty and the nature of poverty correlates. Future research will involve exploring the association between these correlates and poverty dimension at the regional and district level, and investigating how a better understanding of that association could be used to effectively channel scarce resources to the most needy.

Concluding Remarks

Many developing countries are confronted with widespread poverty and limited resources for poverty alleviation. In most of these countries, however, broad-based poverty reduction is often an overarching economic objective and can be achieved only if the limited resources are allocated to the beneficiaries with minimum leakage. This requires that the country’s economic and poverty profiles elaborated from survey data be consistent with the spatial distribution of poverty. Effective targeting of poverty reduction also requires that the profile carefully differentiate between the poorest and the least poor regions at a fine level of disaggregation.

In the past, financial costs and logistics have led some of these countries to use LMS, which have a large sample size and are much cheaper than comprehensive surveys, as a basis for constructing disaggregated poverty maps to design antipoverty programs. The present study shows that the cost of mistargeting associated with the use of light monitoring surveys is significant for targeting purposes, and can in certain circumstances outweigh the saving made by not implementing full LSMS and IS surveys. In fact, aggre-
gated total expenditure, which is the basis for differentiating between poor and non-poor, is underestimated in the PS design. Since underestimation of total household consumption is not uniform across regions, welfare indicators and poverty maps derived from LMS may not always be consistent with the actual spatial distribution of poverty. There are variations in the dispersal rates, and ranking is not preserved across agro-climatic regions.

The present study shows that by combining more detailed surveys, which have more comprehensive income and expenditure data, with LMS, which have relatively large samples, improved poverty maps disaggregated at a level below agro-climatic regions can be constructed. This chapter shows that a substantial reduction in the rate of mistargeting, and improved poverty maps resulting from a much higher reduction of the errors of inclusion and exclusion, can be achieved by modeling LMS-based total expenditure using poverty predictors which are carefully derived from more comprehensive surveys. These poverty predictors are household-level variables available in both the much broader LSMS and IS surveys and LMS, and can be collected during the implementation of the latter in a single household visit with relatively low error in reporting.

Over the past few years, the request for poverty maps disaggregated down to levels as low as districts has been growing in developing countries in general, and in Sub-Saharan African countries in particular. These demands have been prompted by the need to have a more accurate distribution of poverty over space, but even more so by decentralization policies which are increasingly used in these countries to channel resources more efficiently to the communities. As the demand for more disaggregated information continues to grow under increasing budgetary and resource constraints, methods that optimize the use of LMS instruments which are less expensive, but have potential for geographical targeting, will be increasingly in demand. The method proposed in this chapter recommends using expenditure proxies to improve poverty mapping and geographical targeting, and is one useful way of getting more values from the LMS-limited data sets.

The accuracy of household welfare predicted from the targeting model depends on the base point of the prediction, the stability of the poverty predictors, and their corresponding weights. While modeling consumption significantly reduces the errors of inclusion and exclusion, the level of targeting attained in the various agro-climatic regions is less than perfect due to unavoidable prediction errors. These errors in prediction can be attributed in part to noise affecting actual expenditure reported and result in part from sampling and nonsampling errors. Reducing this noise will greatly improve the accuracy of prediction and the poverty maps. The stability of the predictors over time is another important question. Stability was assessed using surveys conducted under the same sampling frame, and it would be worthwhile investigating how this stability is affected by variation of the sam-
pling frame, as well as its possible implications on poverty mapping. Finally, while disaggregated poverty maps and overlaying of these maps may shed some light on the constraints to poverty reduction and the determinants of poverty, improved efficiency in transfers and allocation of resources could be achieved if geographical targeting is combined with some other form of targeting—for instance, targeting by commodities or indicators. The poverty predictors are correlates of expenditure, and could serve as a vector of transfers if we have a better understanding of the dynamic between these correlates and poverty. Future research will focus on investigating the association between these proxies and poverty.

Notes

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1. Poverty maps show spatial distribution or geographical profiles of poverty and are used by policymakers as a basis for allocating resources for poverty reduction.

2. For more details on the design and implementation of Integrated Surveys and Living Standards Measurement Surveys, see Demery and others (1992), and Grosh and Glewwe (1998).

3. A multistage stratified random sampling was used: initially, 407 clusters were enumerated and households were selected with probability proportional to size. There were 15 households drawn in each urban cluster, and 10 households in each rural cluster.

4. During the GLSS 3 implementation, the data was collected on about 107 food items, and the scope of non-food items sampled was relatively important as well.

5. A team from the Department of Economics Research Center at the University of Warwick developed a methodology for estimating imputed values for outliers and missing values used in the context of GLSS 1 and GLSS 2 survey. In the last survey, a team from the same university worked with the Ghana Statistical Services to refine the methodology and adapt it to the GLSS 3.

6. Components of food subaggregates include corn, rice, cassava, plantains, beans, groundnuts, palm oil, sugar, salt, and meat.

7. The same definitions were used in the 1987–88 poverty profile, and the 1988 base values were adjusted for inflation change over time and expressed in 1992 constant price for the latter profile. It is worth pointing out that the lower poverty line is sensibly equal to the same fraction of national mean per capita expenditure estimated from the full GLSS 3.

8. The welfare indices are selected from the $P_a$ class of poverty indices (Foster, Greer, and Thorbecke 1984), which measure different dimensions of poverty depending on the value of $a$. For $a = 0$, the $P_a$ indices represent the Headcount index; when $a = 1$, it measures the poverty gap index. The indices provide estimates of severity of poverty when $a > 1$. 
9. The symbol $P$ represents the set of poor households or individuals ($y$) and $\tilde{P}$ represents the set of non-poor households or individuals.

10. This is a hypothetical scenario for illustrative purpose because direct income transfers are not the cornerstones of anti-poverty policy in Sub-Saharan African countries, where the cost of such measures would be enormous and further deteriorate fiscal deficits.

11. Other criteria used to select subset of predictors include the $S_p$ and the Mallow $C_p$ criteria. For more detail on the rationale and criteria for model selection, see Linhart and Zucchini (1986).

12. LMS conducted in Sub-Saharan Africa over the past three years have collected data on a relatively large sample: the Kenya Welfare Monitoring Survey (1994) was based on a sample of 12,000 households, and the Ghana Core Welfare Indicators Survey (1997) was based on a sample of 15,000 households.

References


Spatial Indicators of Access and Fairness for the Location of Public Facilities

David Bigman and Uwe Deichmann

The ease, speed, and comfort with which the public can access facilities such as hospitals and schools are among the most important variables determining the benefits that individuals can obtain from the services at these facilities. The design of the sites of the public facilities that provide these services must therefore take into account not only the direct monetary costs of accessing the facilities, but also variables that indicate the ease, speed, and comfort of access. The goals that determine the location configuration of public facilities are therefore fundamentally different from the ones set up for private facilities. They include goals such as the provision of a minimum package of services to all households within a certain distance from their place of residence, or equal access to health services by all households. These goals must then be translated into decisions on the sites of the public facilities and on the services that each facility will provide by taking into account the access costs for all households and the ease, speed, and comfort of access.

Quantitative measures of accessibility can have a wide variety of uses in descriptive, explanatory, and normative studies:

- As a means for base-line characterization. In combination with detailed, geographically referenced census data, accessibility indicators can be used to compute the proportion of any subgroup of the population living beyond an acceptable threshold from a service center, thereby identifying imbalances in service provision between regions.
• As explanatory variables, for example, to investigate the reasons for spatial differences of health indicators.
• For determining the size of the population that would benefit from additional health facilities or from improvements in access roads.

Studies on public facility location and accessibility have been conducted in the disciplines of geography, economics, and regional sciences. Early studies date back to the works by Stewart and Warnitz (1958); see also Pooler (1995). In the context of public services, there has recently been a renewed interest in questions of equity and fairness as criteria for determining the location of public facilities. This interest is due, in large measure, to the ease with which a wide variety of the rather complex accessibility indicators can be computed when all relevant information is organized as a geographical information system. A second line of research focuses on the wider issue of using accessibility measures in applying spatial equity as a criterion for the provision of public services (Truelove 1993, Marsh and Shilling 1994). Accessibility indicators in this context provide criteria for comparing the quality of the services provided in different geographic areas or for different social groups. For this analysis, geographic indicators of distance and access time must be complemented with indicators that characterize the need for the public service by the various social subgroups. Accessibility is then evaluated within the framework of the analysis of the demand for these services. Examples include the number of school-age children that attend schools in an educational sector study, or the number of women of childbearing age that come to health clinics in a family planning application. The analysis of spatial equity within the framework of these studies will then focus on the degree of inequality in access, or on the maximum distance between the point of demand and the point of provision that can be accepted within the society's norms.

Studies of spatial equity in public facility locations have generally concentrated on the comparison of accessibility indicators between population groups using common measures of inequality such as the mean absolute deviation (MAD), the standard deviation, or the Gini coefficient. This chapter suggests an alternative set of summary measures as criteria of social fairness in accessibility that have the form of measures of poverty. The next section ("Approaches to the Measurement of Accessibility") provides a brief overview of common approaches to the analysis of service provision and a review of existing accessibility measures. The third section ("Criteria of Social Fairness in the Location of Public Facilities") discusses the shortcomings of these measures in the context of spatial equity analysis. The fourth section ("Accessibility Indicators Based on Poverty Measures") presents an alternative set of measures and discusses their interpretation in the context of welfare analysis. Finally, we present an illustrative application of these
measures in an analysis of family planning service centers in Madagascar in the fifth section ("An Illustration"). This chapter concentrates largely on the geographic aspects of public service provision and is thus most concerned with the effects of the spatial distribution of public services, the distance from the points of demand to the public facility, and the quality of the access road. Equally important in this evaluation are nonphysical aspects of service provision such as access to information about service availability, personal preferences for different types of services, and the economic means of the users of these services. We will briefly discuss these issues in the conclusions.

Approaches to the Measurement of Accessibility

The starting point in the spatial analysis of public service provision is to estimate demand for the services in the facilities by determining the service area for each facility, namely the geographical area from which the demand for these services will gravitate to the facility. Once that area has been determined, the potential demand for the services in the facility can be estimated. Census or survey data on the size and the socioeconomic characteristics of the population residing in the service area can be used to determine the required capacity of the facility and the type of services that it will provide. This approach is closely related to the design of market areas in economic analysis.

The simplest way to determine the service area for a given facility is to define a circular region with the facility located at the center and the radius chosen to reflect a target travel distance (or time) for the population served. National health plans often state planning goals in terms of the target distance such that all persons in the country should have access to medical or educational facilities that are located within the target distance from their place of residence. Health sector studies in Niger (Wane and others 1995) and Kenya (DSA 1997), for example, chose the target distance to be 5 kilometers. Circular service areas of a given radius obviously imply that travel in all directions takes a similar effort or the same time. In areas where terrain or dense vegetation make travel more difficult in some directions this is not a reasonable assumption, since the time required to access the facility from different points in that area may vary considerably.

If the population is sparsely spread across large areas, achieving similar access as defined by circular service areas will either require a large number of facilities or it will leave large segments of the population uncovered. In this case, an alternative approach is to partition the regional territory into an exhaustive set of nonoverlapping service areas. This can be done by means of so-called Thiessen polygons, which assign each point in a study area to the closest facility based on straight-line proximity. This purely geometric
approach has the same drawbacks as the circular areas, however, in that it assumes equal travel time in all directions. Moreover, in sparsely populated areas, services may be provided in different ways and by different means, such as mobile health clinics.

A more accurate description of the service areas can be achieved by incorporating information on the transport routes, the terrain, and so forth. This information is used, for example in a GIS analysis, to determine for each demand point the travel time to the nearest facility. Clearly, travel time to a facility that is determined by the existing road network and the quality of the access roads can be significantly different from the straight-line distance to the facility, and assigning each demand point to the nearest center so as to minimize the travel time will yield a set of irregularly shaped service areas which more accurately reflect the conditions on the ground. Figure 6.1 illustrates the large differences in the shapes of service areas for hospitals in eastern Nepal when the analysis is based on a straight-line distance only, and when the analysis incorporates information on transportation infrastructure and natural barriers (see United Nations 1997).

An alternative approach in the analysis of public service provision concentrates on the individuals or the households requiring the services, and the exact places in which they reside, rather than on the entire geographical area that surrounds the facility. This analysis typically applies the data provided by a census along with data from a variety of surveys at the household or village level that often include questions about access to services and the means of transportation. The community profile section of the Demographic and Health Surveys (DHS), for instance, contains questions about distance to the nearest health and family planning facilities as well as questions on the mode of transportation. This information can either be measured on road maps based on the actual location of the facilities and the villages or it can be based on the questionnaire responses. The latter source, however, often creates problems of consistency and reliability that may limit comparability across a larger study area and may require, in addition, independent estimates of travel time using consistent sources.

The most consistent independent source of data are digital geographic databases of transport networks and the location of service centers. These can be used to measure the shortest distance from any demand point in the study area to the closest facility. Formally, the shortest distance measure can be denoted as shown in equation 6.1 (see, for instance, Anselin 1995, Talen and Anselin 1998):

\[
E_i = \min_j (d_{ij})
\]

(6.1)

where \(E_i\) is the shortest-distance index for location \(i\), and \(d_{ij}\) is the distance from the point of origin \(i\) to the location of facility \(j\). This indicator is derived
Figure 6.1 Service Area Delineation Source: United Nations (1997)

Source: Authors' calculations.
using standard shortest path algorithms which are implemented in many commercial mapping packages. Distance may not be the most appropriate measure, however, where the quality of the transport network is highly variable or where the cost of using public transport must be taken into account. A measure of travel cost or travel time can provide a more realistic measure. For these reasons, the more generic terms “impedance” or “friction” are sometimes used in the geographical literature rather than the term “distance.”

The shortest-distance index has two drawbacks when used to determine the demand for and location of public facilities: First, this indicator considers only the spatial relationship between a given location and the service center, but not the services provided at that center. In most cases there are large differences between the services that each facility provides, and the more advanced or expensive services are typically provided only in a small number of central facilities. In that case, separate indicators should be computed for each type of service. Second, the shortest-distance index has an underlying assumption that people will use the closest facility. In general, this is indeed the decision of most people who tend to use the closest facility if the required service is provided there (Mayhew and Leonard 1982). For example, a study by the Medical Research Council in South Africa on the use of public health facilities in a region of northern Natal province, which is characterized by a poor population and sparse infrastructure, found that more than 96 percent of the people use the nearest clinic (LeSuer and others 1997). In some cases, however, people may opt to go to a facility located farther away if the quality of the service in the more distant facility is deemed better. This may specifically apply in more urbanized areas where the density of service centers is higher (Amer and Thorborg 1996). Low-income households are more likely to use the closest facility, but quality considerations are likely to become more significant the higher the person’s income. Additional considerations for the selection of the service center include government versus privately run services, and whether there are any costs for the services in the public facility (see, for example, Amer and Thorborg 1996).

When there are two facilities or more in an area, two alternative accessibility measures can be used: One is the average distance (or travel time, or travel costs), and the other is the covering index. The first is simply the average distance from a given demand point to all facilities in the area, as shown in equation 6.2:

$$T_i = \frac{\sum_{j=1}^{k} d_{ij}}{k} \quad (6.2)$$

where $T_i$ is the average distance (or travel time or travel costs) index, $d_{ij}$ is the distance between demand point $i$ and the location of facility $j$, and $k$ is
the number of facilities. This index can also be calculated only for the \( k \) nearest facilities, that is, the facilities that are located within a predetermined distance from the demand point. In this case the indicator will reflect the local density of facilities. The covering index, in contrast, is simply the number of facilities that are located within a predetermined threshold distance from the demand points. If the different facilities have different sizes or capacities, this index can also be calculated as the sum of a size attribute of all facilities that are located within a specified threshold distance or travel time. Formally, as shown in equation 6.3,

\[
C_i = \sum_j \delta_{ij} S_j
\]  

(6.3)

where \( C_i \) is the covering index, \( \delta_{ij} \) indicates whether or not a destination is within the threshold distance \( \delta \) (\( \delta_{ij} = 1 \) for \( d_{ij} \leq \delta \) and \( \delta_{ij} = 0 \) otherwise), and \( S_j \) is the size attribute for each facility \( j \). The size attribute can indicate the number of hospital beds, nurses, classroom spaces, teachers, or employment opportunities. In contrast to the shortest and average travel time indicators, which consider only the geographical distance between the demand point and the location of the facility, the covering index can also incorporate information on the size of the demand points and the quality of the services in the facility as expressed by its size attributes.

The information on size can also be incorporated into the measure of accessibility by assuming that accessibility decreases in proportion to the distance or travel time to the facility, but increases with the size of the facility. The well-known family of gravity models, which has found widespread application in fields such as transportation and migration analysis, is the best example of incorporating this information. In its original form, the gravity model states that interaction between, say, two cities, is proportional to the size of their populations and inversely proportional to some measure of distance between them (equation 6.4):

\[
I_{ij}^s = k \frac{P_i P_j}{d_{ij}^b}
\]  

(6.4)

where \( I_{ij} \) is the magnitude of interaction between cities \( i \) and \( j \), \( k \) is a constant to be estimated, \( P_i \) and \( P_j \) are the population totals for the cities, \( d_{ij} \) is the distance between the two cities, and \( b \) is the distance exponent which, in the original formulation, was set equal to 2. The model parameters can be estimated using observed interaction data (see Fotheringham and O’Kelly 1989). The gravity model gives rise to a large family of spatial interaction models (Wilson 1971) that use different pieces of information to estimate the interaction between two points—for example, information on all flows, on outflows only, or on inflows only. These models are frequently used in
health services analysis where data on the patients’ place of residence are available (Taket 1989, Thomas 1992). Incidentally, gravity models have also received renewed attention in development economics in the context of the “new economic geography” (see, for example, Krugman 1995).

Although the formulation of the gravity models is intuitively appealing, it is necessarily ad hoc since it is not derived from standard consumer theory. For a more comprehensive formulation of the measure of accessibility, the starting point must be the basic theory of consumer behavior and the most general specification of the utility function. In consumer theory, that function is given by a Von Neuman—Morgenstern (VNM) function in which consumers’ utility is a monotonic, strictly increasing, and strictly concave function of income. The implicit assumption in the standard geographical analysis is that utility is a function of two variables: the distance between the consumer’s place of residence (the demand point) and the facility (along the road network), and the size of the facility, where the size can be a composite variable representing the variety and quality of services provided in that facility. These two variables are the basic building blocks in the gravity model. The utility function can thus be written as equation 6.5:

\[ U_i = U(d_{ik}; M_k) \]  

(6.5)

where \( d_{ik} \) is the distance from the place of residence of household \( i \) to the public facility \( k \) and \( M_k \) is the “size” of that facility, which stands as a proxy for the variety of services provided. With \( K \) public facilities, \( d_{ik} \) and \( M_k \) are both \( K \)-dimensional vectors. To represent the inverse relations between the distance to the facility and the level of utility, the utility function can be written as equation 6.6:

\[ U_i = U(1/d_{ik}); M_k \]  

(6.6)

That utility function is assumed to be monotonically increasing in the two variables \((1/d_{ik})\) and \( M_k \). The gravity model combines these two variables into a single variable, \( M_k/d_{ik} \), and determines a specific functional form of the utility function.

To make this formulation less general, other assumptions must be added with respect to the structure of the utility function. In the literature on risk bearing, individuals are assumed to have no “money illusion.” Changing the monetary units of a given prize from, say, dollars to cents should not change their utility from that prize. In the geographic context, the equivalent assumption is that a change in the units of measurement of the distance from kilometers to miles will not change the “disutility” from the public facility. This assumption implies that the utility function—as a function of distance—is similar to a Cauchy equation, that is, an equation that
satisfies the following equality: \( U(x \cdot y) = U(x) \cdot U(y) \). For a positive \( x \) and \( y \) and when \( U(x) \) is monotonically increasing, the only solution of that equation is:

\[
U(x) = U(1) \cdot x^\delta \text{ for } \delta > 0
\]

and

\[
U(x) = \log_x(x) \text{ for } \delta = 0.
\]

The utility function \( U_i \) can thus be written as equation 6.7:

\[
U_i = U(M_k) / (d_{ir})^\beta \text{ for } \beta > 0.
\] (6.7)

This presentation of the utility function emphasizes that the underlying assumption in the gravity model is that the utility from the size of the public facility is simply proportional to the size. It implies therefore that the marginal utility from the size of the facility remains constant. In utility theory it is generally assumed, however, that the marginal utility from each factor is declining, and this assumption may also be reasonable with respect to the size of the public facility. If we assume, in addition, that individuals have no “illusion” with respect to the units of measurement of the size of the public facility, then the utility function will have the following form:

\[
U_i = (M_k)^\epsilon / (d_{ir})^\beta \text{ : where } \beta > 0 \text{ and } 0 < \epsilon < 1.
\] (6.8)

Under these constraints on the parameters \( \beta \) and \( \epsilon \), the utility function will be a monotonic strictly increasing and strictly concave function of the two variables. In the case of a single facility of a given size the utility function for a single demand point \( i \) can be simplified and written as equation 6.9:

\[
U_i = M^\epsilon / (d_i)^\beta \text{ for } \beta > 0 \text{ and } 0 < \epsilon < 1.
\] (6.9)

The constraint, \( \epsilon < 1 \), implies that the marginal utility from the size of the facility (or the quality of its services) is positive but decreasing. We can now compare this representation of a consumer’s utility from his spatial interactions, which has been derived from a general utility function, with the representation in the gravity model: First, the gravity model assumes that the marginal utility from size is constant. Second, the gravity model implicitly assumes a specific value of the elasticity parameter \( \beta \), which determines the percentage decline in utility with an increase in the distance by one percent. The assumption of the gravity model for the value of this elasticity, \( \beta = 1 \), may unduly restrict the analysis to a specific type of consumers.
Gravity models can be generalized to yield so-called potential models. Rather than narrowing the computation to a specific demand point \( i \) and a specific destination \( j \), the general measure of interaction can be extended to all possible or relevant destinations of a given demand point. The measure would then be the sum of the size attributes at all these destinations divided by a weighted sum of the distances to these destinations (Weibull 1976). Arentze and others (1994), and Geertman and Ritsema van Eck (1995) present recent applications. In the original formulation the measure of accessibility in the potential model is given by equation 6.10:

\[
I_i^e = \sum_j \frac{S_j}{d_{ij}^\beta}
\]

(6.10)

where \( I_i^e \) is the "classic" accessibility indicator, \( S_j \) is a size indicator at destination \( j \), \( d_{ij} \) is the distance between origin \( i \) and destination \( j \), and \( \beta \) is a distance exponent—which, along the lines of the earlier analysis of the consumer's decisions over space, represents the increasing marginal disutility from distance. The elasticity parameter can be estimated from actual data on consumers' interaction patterns. Several alternative models have been suggested, however, to characterize the interactions of consumers in space and the decline in their utility with the rise in distance (sometimes referred to as the "distance decay function"). One of the most popular is a negative exponential model:

\[
I_i^{ne} = \sum_j S_j \cdot e^{-d_{ij}/2a^2}
\]

(6.11)

where \( I_i^{ne} \) is the potential accessibility indicator based on the negative exponential distance decay function, most other parameters are defined as before, and the parameter \( a \) is the distance to the point of inflection of the negative exponential function. The main difference between this formulation and the one derived earlier from the consumer's utility function is that in the present formulation the elasticity itself is no longer constant but is rising with the rise in the distance.

The choice among the alternative formulations of the gravity model must be based on empirical evidence. In empirical studies these models were shown to describe migration flows, trade, and consumers' travel choices very well. There is often a practical problem, however, in obtaining sufficient data in order to estimate the model's parameters. All too often, therefore, the parameters of the distance decay function are "borrowed" from other studies or set at some "reasonable" value. Moreover, the gravity model itself—in practically all its formulations—is ad hoc and the parameters are arbitrarily restricted to specific values rather than estimated.
Criteria of Social Fairness in the Location of Public Facilities

Early geographical studies that developed models for determining the “optimal” location of public facilities departed from the models that have been developed to determine the location of private facilities—which such as the $p$-median problem which seeks to minimize the overall transport costs—by emphasizing the significance of the distribution of travel time or distance of the potential users. The $p$-center problem, for example, seeks to minimize the maximum distance from any demand node to its nearest facility. In economic analysis of income inequality, the equivalent formulation is the Rawlsian Max-Min principle in which the objective is to maximize the income of the poorest individual. (In the geographical context the criterion of the $p$-center problem thus represents a Min-Max principle.) When all instruments of redistribution are available without restrictions, the solution to that problem is equal income to all. In the context of the $p$-center problem, however, there are strict limitations on the policy instruments, since the demand points cannot be moved and the $p$ public facilities can be placed only in the predetermined $q$ locations which are available for that purpose.

There are other potential problems with the objective of the $p$-center problem. First, it gives very large weight to the needs of very remote households (or communities) regardless of their weight in the population. Second, it seeks to minimize the maximum distance regardless of what that distance is. The maximum distance may still be very manageable and there may thus be no justification for changing the location of public facilities to reduce this distance still further. Third, it seeks to minimize the maximum distance regardless of cost. As we shall see later, the Max-Min criterion for determining the location of public facility represents a very unique form of the underlying social evaluation function.

Closely related to this approach is the covering problem (Church and ReVelle 1976, ReVelle 1987). The set covering location problem (SCLP) determines the minimum number and location of facilities that are necessary to ensure that the entire population is covered within a certain distance. In cases where the available resources limit the number of new facilities that can be added to the system, the problem can be stated as a maximum covering location problem (MCLP) which seeks to find the optimal location of a specified number of facilities that will maximize the size of the population that can be served within a certain “acceptable” distance. The solution to this problem may benefit, however, first and foremost those individuals or communities that reside very close to the acceptable distance from a facility (just outside the covering range) while leaving uncovered those who reside farther away. An alternative strategy may be one that seeks to ensure first the coverage of those who reside furthest from a facility. This alternative highlights a fundamental problem with these optimization approaches:
Although the objectives that they establish are appealing, they are based on ad hoc criteria of social fairness.

Later geographical studies that evaluated the location configuration of public facilities from the point of view of social fairness have also focused on distributional equity as the main criterion of fairness (Taket 1989, Mandell 1991, Erkut 1993, Hay 1995, Talen and Anselin 1998; see Marsh and Shilling 1994 for a review of the relevant geographic literature). There are, however, differences between the use of equity as a criterion of fairness and social justice in economics and its use in geographical studies. In economic analysis, equity is measured in terms of money income and the policymakers have the instruments of taxes, subsidies, and income transfers at their disposal to change the existing income distribution and thereby achieve greater equity. The guiding principle in this process—and one of the axioms that the measure of inequality is required to satisfy—is the "principle of transfers," which states that a (regressive) transfer of income from one person to a more affluent person would increase income inequality and thereby worsen the overall welfare, however measured. In the context of geographical studies, this principle of (regressive) transfers can be stated as follows. Let $S_1 = (d_1, \ldots, d_i, \ldots, d_n)$ be the distribution of the distances of $n$ individuals from the public facility, where $d_1 \geq \ldots \geq d_i \geq \ldots \geq d_n$. A distribution $S_2$, which represents a relocation of the public facilities that shortens the distance to individual $j$ while increasing the distance to individual $i$, without changing the distance to any of the others—that is, $S_2 = (d_1, \ldots, d_i + e, d_i - e, \ldots, d_n)$—will be less equitable than $S_1$.

In the context of spatial analysis, the policy instruments available for achieving greater equality in access to public facilities are far more limited than the policy instruments available for achieving greater income equality. First, these instruments are limited to the relocation of existing public facilities or the addition of new facilities whereas a relocation of the demand points is, in most cases, not feasible. Second, in many cases the location of new public facilities is limited to specific areas only—for example, areas where enough space is available. Third, the decision is often restricted to the location of one or few additional facilities due to budget constraints, and the location of existing facilities must be taken as given. These restrictions make the goal of achieving or even enhancing equality much more complex and expensive.

Several accessibility indicators that reflect equity considerations have been used in the geographic literature. They include the mean absolute deviation (MAD), the standard deviation, the Rawlsian maximum deviation (Erkut, 1993), and a host of inequality measures that have been developed for the analysis of income inequality, ranging from the Gini, to Theil’s and Atkinson’s measures. Each of these measures gives different weight to the individuals that are served by public facilities, depending on their distance.
from the facility. Berman and Kaplan (1990) used the MAD measure, given by equation 6.12, as the performance measure for equity considerations:

$$
\sum_i \sum_j |d_{ij} - \bar{d}|
$$

(6.12)

In this measure, the weight of each individual is equal to the distance from the place of residence to the facility. The Min-Max measure is given in equation 6.13:

$$
MIN \left( \max_{ij} |d_{ij} - \bar{d}| \right)
$$

(6.13)

and it gives all the weight to the single individual who is furthest from the facility while the weight of all other individuals is zero.

In these measures, the "reference" point is the average distance to the facility, and the indicators measure the deviation from the ideal solution \((\bar{d}, \ldots, \bar{d})\) in which all individuals are located at an equal distance from the facility. The theory of welfare economics suggests, however, a different reference point for that evaluation which, in the present context, can be termed the "equally distributed equivalent" (EDE) distance. The EDE distance is defined as follows: If all households were equally distant from the facility at the EDE distance, the level of social welfare would have been the same as that with the actual distances of these households. Symbolically, the EDE distance \(d_E\) is defined as the distance for which:

$$
W(d_1, \ldots, d_n) = W(d_E, d_E, \ldots, d_E)
$$

(6.14)

where \(W\) is the social welfare function and \(n\) is the number of households (or consumers, or demand points) in this society. With an additive social welfare function and concave individual utility function with respect to distance, this definition implies:

$$
\sum_j U(M, d_E) = n \cdot \frac{M^e}{d_E^\beta} = \sum_j U_j(M, d_j) = \sum_j \frac{M^e}{d_j^\beta}
$$

(6.15)

From this equality we can solve:

$$
d_E = \left\{ \frac{1}{n} \sum_j (d_j)^\beta \right\}^{1/\beta}
$$

(6.16)

The reference point would then be the solution \((d_E, \ldots, d_E)\), and a reduction in the EDE distance to the facility represents a rise in social welfare. The concavity of the individual utility function implies that \(d_E < \bar{d}\), indicating that the weights given to individuals are rising with the rise in their distance to
the facility. The parameter $\beta$ represents the sensitivity of the social evaluation function to the individual distances from the facility. From this specification of the EDE distance we can conclude that, other things being equal, a reduction in the distance to the facility for any individual will lead to a reduction in the distance $d_i$ and a rise in social welfare, and that reduction is proportional to the distance of the individual from the facility. The rise in social welfare will therefore be larger the larger the distance of the individual from the facility.

Accessibility Indicators Based on Poverty Measures

An alternative approach to the evaluation of the location configuration of public facilities is closely related to the approaches in the economic literature on the measurement of poverty. In what follows, we review the possible application of the axiomatic approach to poverty measurement in order to develop criteria for evaluating access to public facilities. We then proceed to present the spatial analogs of some of the common poverty measures, and discuss their use as performance criteria in location analysis.

In the economic analysis of poverty, the starting point is the definition of the poverty line, defined as the minimum income or consumption level which is necessary to provide certain essential needs. In spatial analysis, the equivalent of the poverty line would be the maximum distance to the public facility, beyond which the services provided would not be adequate. For health clinics or hospitals, this would be the maximum response time in which patients with certain illnesses must be reached or brought to the hospital without risking their life. For schools, this would be the maximum distance from the child's place of residence to the school; beyond this distance the child is likely to drop out of school. Similar criteria can be established for other public services and other public facilities. To illustrate these criteria, we consider the specific case of public health clinics, and the poverty line will be defined as the safety threshold, or the maximum response time that can be permitted in order to secure an adequate treatment. Once the maximum response time has been determined, the next step is to measure the effectiveness of the system, namely its capacity to meet all demands within this response time. In an analogy to poverty measures, the performance criterion would be the ineffectiveness (rather than the effectiveness) of the system, and the principal difference between this measure and the one considered earlier is that the measure of the ineffectiveness focuses only on those households that cannot be served within the maximum response time.

The most common measure of income poverty in the economic literature is the Headcount index, which measures the proportion of the population with income per-person (or per "standard adult") that is lower than the poverty line income. In location analysis, this would be the percentage of
the population that the public facilities fail to serve within the maximum response time. The main deficiency of the Headcount index is that it is not sensitive to the actual distance to the facility of those that reside outside the maximum response time. A household that resides just outside the area covered within the maximum response time—that is, just beyond the safety threshold—has the same weight in this measure as a household that resides farther away. A location of a new facility aimed at reducing the Headcount measure would thus tend to cover individuals just outside the area covered within the maximum response time rather than those that reside farther away. This measure thus does not reflect the extent to which the system of public facilities fails to meet the necessary levels of safety. The Headcount measure of ineffectiveness remains unchanged with a rise in the distance to the facility of any of the households that reside outside the safety threshold.6

Another common measure of poverty is the Poverty Gap. In location analysis, the "gap" refers to the difference between the actual travel time or distance to the public facility and the maximum acceptable response time, and it is measured only for those households that reside outside the safety threshold. The mathematical specification of this measure is given in equation 6.17:

\[ P(d, z) = \frac{1}{n} \cdot \sum_{i=0}^{n} (g_i / z) \]  

(6.17)

where \( d_i \) is the actual distance from the household's place of residence to the facility; \( z \) is the safety threshold (the maximum response time), \( g_i = (d_i - z) \) is the difference (the distance above the safety threshold) of the \( i \)th household, and \( n \) is the total number of households in the community. \( P(d, z) \) is the measure of ineffectiveness when \( d = (d_1, ..., d_n) \) is the vector of the actual distances to the facility of the households that reside outside the safety threshold, and \( z \) is the safety threshold. This measure can be written as equation 6.18:

\[ P(d, z) = H \cdot (1 / q) \cdot \sum_{i=0}^{n} (g_i / z) = H \cdot G \]  

(6.18)

where \( H = (q / n) \) is the Headcount measure, \( q \) is the number of households that reside outside the safety threshold, and \( G \) is the average time/distance to the facility above the maximum response time/distance. Figure 6.2 shows the parameters of these measures in a spatial analysis.

The disadvantage of this measure is that it fails to reflect the rising marginal disutility with the rise in the distance to the facility. On these grounds, Foster, Greer, and Thorbeke (1984) (see also Sen 1974, Foster and Shorrocks 1991, Ravallion 1994 and 1996) suggested a class of poverty measures that have the following general structure:

\[ P_\alpha(d; z) = \frac{1}{n} \cdot \sum_{i=0}^{n} (g_i / z)^\alpha : \text{ where } \alpha \geq 0. \]  

(6.19)
For $\alpha = 0$, $P_0(d; z) = H$ is simply the Headcount measure; for $\alpha = 1$, $P_1(d; z)$ is the Poverty Gap. For $\alpha = 2$, the measure can be written as follows:

$$P_2(d; z) = H \cdot \left[ G^2 + (1 - G^2)C_p^2 \right]$$ (6.20)

where $C_p^2$ is the coefficient of variation of the distances to the facility of the households that reside outside the safety threshold, given by equation 6.21:

$$C_p^2 = (1 / q) \cdot \frac{\sum (d_i - d_p)^2}{d_p^4}$$ (6.21)

and $d_p = (1 / q) \sum d_i$ is the average distance to the facility of these households. The advantage of the latter index is that it is more sensitive to the safety needs of the households that reside farther away from the facility and reflects the rising disutility of these households from the location configuration of the public facilities.

An Illustration

This section provides an illustration of the use of these indicators of social fairness. Figure 6.3 shows the shortest distance indicator for a set of family planning service centers in two Faritany (province or first subnational level) of Madagascar. Travel times were computed using a road network database produced by the USAID-sponsored ANGAP (National Association for the Management of Protected Areas) project. Travel speed in off-road areas is assumed to be equivalent to an average walking speed of 5 kilometers per hour. Road quality information was converted into average travel speeds, which we used to compute travel times measured in minutes for each road segment in the transportation network. A standard shortest-path algorithm, as implemented in many GIS packages, was used to determine the distance from every 1-kilometer cell in a regular raster grid draped over the two provinces to the closest facility.
Figure 6.3 Shortest Distance Indicator for Two Provinces in Madagascar

The underlying assumption is that a person living at a given location in the study area will travel directly to the nearest road access point and continue travel to the closest facility using, for instance, a bus or collective taxi. The travel speed estimates chosen for this analysis thus assume that every person has access to public transportation. In practice that may not be the case, and it may even be unlikely in many developing countries. One could therefore carry out a second analysis with lower travel speed estimates to complement these best-case estimates with a worst-case scenario.

Information on the location of family planning service centers was collected using global positioning systems (GPS) by the APROPOP/PF family planning/reproductive health (FP/RH) program in an ongoing project that
is also supported by USAID. In the future, this project intends to also compile information on the types of services available and the capacity of each facility. Since not all services are provided at each facility, an accessibility analysis can then be conducted for each type of service using only those facilities at which the service is available.

By itself, the shortest distance indicator provides only limited information about the quality of the service delivery system. In order to get a full picture, we need to compare the information on travel times with effective or estimated demand. Data on effective demand requires a comprehensive monitoring program at the service centers which records the number of patients, their characteristics, needs, and, ideally, their place of residence. Such data could also be collected in a patient survey or a more general household survey such as a DHS. However, this information is not always readily available in developing countries, and comprehensive surveys tend to be expensive. Prospective demand therefore usually needs to be estimated. The most complete information available is the national population and household census, which provides a complete enumeration of the population and its main demographic characteristics, and is compiled by aggregating the information collected for small enumeration areas up to the district, province, and national level. While in the past small area statistics have often been difficult to obtain, the growing demand for such data and access to new technology has enabled many countries to compile data at a level of geographic detail that is useful for spatial analysis and targeting of policy interventions.

A spatially referenced database of population data by Firaisana (commune or third subnational level) from the 1993 census of Madagascar was produced by the Direction de la Démographie et Statistiques Sociales (DDSS) in Antananarivo in collaboration with the U.N. Population Fund-supported Software Development (POPMAP) Project of the United Nations Statistics Division. For the two provinces studied, there are 587 communes with an average population size of 10,529. The population within each commune is assumed to be distributed homogeneously. This may not always be the case in areas where terrain leads to a fragmented habitation pattern, but in light of the small administrative units, constant densities are a reasonable approximation for this illustrative application. Due to the nature of the service centers in this study, we chose the number of women in reproductive age (15–49) as the reference group rather than total population. Each commune has on average 2,483 women in reproductive age. In a purely family planning-oriented study this will, of course, not provide actual demand at the service centers. Ideally one would estimate the number of women in this age group who do not want additional children, using information, for example, from a DHS. However, population programs are increasingly oriented towards providing more comprehensive reproductive health services, which broadens the prospective user base significantly.
Using standard GIS functions, we cross-tabulated the total number of women in childbearing age by travel time to their closest facility (figure 6.4). After specifying a maximum acceptable travel time, this information, in turn, can be used to compute FGT-like accessibility indicators (Foster, Greer, and Thorbecke 1984). In this application, the threshold travel time was set to 60 minutes, the time in which an average person can cover about five kilometers on foot and a correspondingly larger distance by public or private transport. Obviously the choice of the threshold distance is as crucial in accessibility studies as the definition of a poverty line is in poverty analysis. The ability and willingness of people to travel to a facility will vary depending on age, health, economic means, the cost and quality of service at the target facility, and other factors. People in rural areas may be willing to travel farther than persons in urban areas. Amer and Thorborg (1996), for instance, found in a study of health facility use in Dar Es Salaam that patients were willing to travel about two kilometers or approximately 30 minutes. More than 90 percent traveled on foot, and people were willing to walk somewhat farther to a private or voluntary health facility than to a government clinic.

Figure 6.4 shows that approximately 57 percent of the women in reproductive age in the two provinces of Madagascar for which service center locations are available live within 60 minutes of the nearest facility. We can now summarize this information by political, administrative units using the

![Figure 6.4: Number of Women in the Reproductive Age Group by Travel Time to the Closest Service Facility](image)

*Source: Authors' computations.*
indicators outlined above. To avoid the undue influence of a small number of very large travel times, we used a maximum (reference) travel time that covered 99.9 percent of the population and 99 percent of the total area—517 minutes—rather than the maximum estimated travel time of 705 minutes. Table 6.1 shows the Headcount, the Access Gap, and the weighted Access Gap (severity) measures for the two provinces. To complement the Headcount index, we also computed each province’s share of the total number of women in reproductive age who live beyond an acceptable distance. As can be easily verified, the indicators satisfy the additivity or subgroup consistency requirement; that is, the population-weighted average of the Access Gap and severity measures for the two provinces corresponds to the measures for the entire region.

Looking at the province-level figures, Fianarantsoa province has poorer overall accessibility by any measure. However, a more complex picture emerges when we compute the indicators at the Firondronana (district or second subnational) level. The results at this geographic level are shown graphically in figure 6.5 rather than in tabular form. The maps show the percentage of all women in the region living beyond the threshold distance, as well as the Headcount index, the Access Gap, and severity (P2) measures. Districts are shaded using a quintile classification whose ordinal ranking, while leading to class ranges of unequal size, highlights the different policy options very clearly. Assuming that the district is the level at which decisions about service delivery are made, we see that the geographic units that would be targeted—that is, those with the highest indicator scores—vary depending on which indicator is used.

- If the objective is to reach the largest absolute number of women that currently live beyond the predetermined distance, resources would be

<table>
<thead>
<tr>
<th>Province</th>
<th>Numbers of WRA 15–49</th>
<th>Numbers of WRA living beyond 60 min. travel time</th>
<th>Percent of total WRA living beyond 60 min. travel time</th>
<th>Headcount index (percent)</th>
<th>Access Gap index</th>
<th>Severity index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antananarivo</td>
<td>870</td>
<td>266</td>
<td>42.7</td>
<td>30.6</td>
<td>4.0</td>
<td>1.1</td>
</tr>
<tr>
<td>Fianarantsoa</td>
<td>588</td>
<td>358</td>
<td>57.3</td>
<td>60.9</td>
<td>9.8</td>
<td>3.0</td>
</tr>
<tr>
<td>All districts</td>
<td>1,458</td>
<td>624</td>
<td>100.0</td>
<td>42.8</td>
<td>6.3</td>
<td>1.9</td>
</tr>
</tbody>
</table>

* Using 517 minutes as a reference maximum travel time which covers 99 percent of the total area (99.9 percent of the population).

Source: Authors’ computations.
allocated to the districts that are shaded in the darkest color in map a of figure 6.5. These districts are primarily located along the northern coastal region of Fianarantsoa province and in the northwest of Antananarivo province.

- If the objective is to improve access in those districts where the largest proportion of the district’s women in reproductive age live beyond the predetermined distance, resources would be channeled to districts within the highest category in the Headcount index (map b of figure 6.5). Most of the target districts in this case are located in the south of Fianarantsoa province and in the northwest of Antananarivo province.
• Severity of the lack of access to services is best shown in maps c and d of figure 6.5. These two maps show a fairly similar pattern. In both cases, resources would be allocated to districts in the southwest of Fianarantsoa province, although one district in the northwest of Antananarivo province would also be the target of these allocations.

This example also shows how decisions about geographic targeting of resources and policy interventions can be improved by incorporating high-resolution, spatially referenced information. More precise allocation of funds reduces the chance that communities most in need will be ignored and that leakage of funds to less needy communities will occur. In the illustration in this section, we considered only a limited amount of information regarding the demand for services and the quality of the services provided at each facility. In a realistic application the analysis should also include data for various population groups, primarily about the effects of income and the quality of service. The macroeconomic conditions in the country, the national health policy, and the institutional arrangements may also be relevant (see, for example, Smith 1993).

Conclusions

This chapter suggests a new set of indicators for evaluating the social fairness of a location configuration of public facilities. These measures are the spatial analogues to measures of poverty in economic analysis, and are designed to satisfy a set of axioms that describe criteria of fairness. These indicators are easy to interpret and, similar to poverty measures, they have the property of subgroup consistency. The clear interpretation and the ease of computation of these measures make them suitable for a wide range of applications. The results can be represented in graphical form, thus clarifying the interpretation still further, and the analysis of alternative policy options in terms of their effects on these measures is straightforward. An important use of indicators of social fairness is to establish priorities in determining the location of additional public facilities; the indicators that have the form of poverty measures focus on the needs of the population that is not covered by the existing facilities within the acceptable standards of distance or travel time. An illustration of the application of these indicators measures the effectiveness of family planning centers in Madagascar and shows that the choice of an indicator can greatly influence the priorities between districts for the location of new centers. These different priorities reflect, in turn, different underlying approaches to the concept of fairness in spatial analysis: Whereas the Headcount indicator focuses on the number of persons who currently do not have access to the facilities within the acceptable standard, the Access Gap focuses on the persons who are the most distant from the
facility. The Headcount index thus gives priority to the more dense, semi-
urban areas, whereas the Access Gap index gives priority to the more
remote rural areas.

The conceptual and computational simplicity of these indicators—par-
ticularly in comparison to many of the indicators that have been derived
from location/allocation models in operations research—make them suit-
able for immediate application. These applications may require, however,
additional data on the population and on the services provided by the facil-
ities. These data are available in most developing countries and their presen-
tation as a GIS database can greatly facilitate the analysis. The incorpora-
tion of additional data may also allow proper adjustments in the structure
of the indicators themselves in order to introduce additional criteria of fair-
ness and effectiveness. Thus, for example, indicators of access to family
planning service centers may focus on the access of poor women or women
in a specific age group rather than the access of all women. A proper adjust-
ment of the indicators may also establish different accessibility criteria for
the different services provided by these centers. These adjustments are
straightforward, and they make these indicators particularly suitable to
incorporate a wider variety of criteria in addition to distance.

Notes

A previous version of this chapter was presented at the workshop on “Geographical
Targeting for Poverty Reduction and Rural Development,” conducted at the World
Bank on November 11, 1997.

We were fortunate to have access to a number of data sets for the Madagascar
sample application, which were produced by the Direction de la Démographie et
Statistiques Sociales (DDSS), and the APPROPO/USAID and ANGAP/USAID
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World Bank.

David Bigman is at the International Service for National Agricultural Research
(ISNAR). He was at the Africa Region of the World Bank when this chapter was writ-
ten. Uwe Deichmann is with the Development Research Group of the World Bank.

1. It should be noted, though, that published maps and digital data sets of trans-
portation networks are often incomplete and may include roads that have become
unusable or that have been planned but were never completed.

2. The reason for specifying the Transfer Axiom for regressive rather than progres-
sive transfers is that, with a progressive relocation of the facility the two individuals
may just “trade places” in the distribution as an effect of the relocation so that \( d_i \geq d_f \)
before the relocation, but \( d_i - \varepsilon < d_f + \varepsilon \) after the relocation.
3. These needs can be specified, for example, in terms of the food expenditures needed to provide the minimum necessary caloric intake.

4. In risk analysis, the comparable concept is the safety first criterion. This criterion is concerned only with the risk of failing to achieve a certain minimum target or secure prespecified safety margins. The risk can then be expressed as a probability statement: \( P(x \leq z) \leq \beta \) where \( x \) is the random variable of, say, profits; \( z \) is the minimum profit target, often referred to as the "disaster level" or the "safety threshold;" \( P() \) is a probability statement; and \( \beta \) is an acceptable limit on the probability of failing to reach that target.

5. To take account of the difference in consumption between children and adults, the consumption of children younger that 13 years old is calculated as a fraction of the consumption of adults.

6. It should be noted that when the MCLP is stated in its inverse form of minimizing the proportion of the population that resides outside the threshold, it has the same objective.

References


Part Three

Applications of a Geographical Information System (GIS) for Geographical Targeting
Evaluation of Food Security in the Sahel: An Analysis Using the Demographic and Health Survey (DHS) Data with a Geographical Information System

Mark McGuire

The process of preparing a plan for the spatial distribution of health or education programs, selecting sites for economic development activities, or designing the road infrastructure, requires a wide variety of detailed data on the climate and geography of the target area, and on the socioeconomic characteristics of the population that lives in this area. In West Africa, a considerable amount of data has been collected over the last decade on geographic regions and economic sectors by different organizations, government ministries, and international organizations. However, these data collection efforts often are not followed by comparable analytical efforts, and even when analytical efforts have been made, they were not integrated into regional program planning. The objective of this work is to shift the focus from collecting new data to utilizing existing databases, to better respond to the needs of decisionmakers in the area of food security, vulnerability assessments, and regional planning. In these times of cutbacks and downsizing, the demand for information has not subsided and organizations and institutions are compelled to find ways to make more efficient use of existing resources and databases.

In recent years, there has been a concerted effort of USAID to extend spatial analysis in Sub-Saharan Africa, with the objective of improving the understanding of vulnerability to food insecurity. Another objective is to strengthen the linkage between the spatial data that has become available
and analysis of these data to improve decisionmaking in this critical area. This chapter will describe the databases collected under several USAID projects in Sub-Saharan Africa, review the basic vulnerability assessment model used by the Famine Early Warning System (FEWS), and evaluate the relations between the mapping of vulnerability to the food insecurity determined by these data, and poverty mapping.

The USAID study made use of the linkage established in previous work among the databases in West Africa under a project entitled “West Africa Spatial Analysis Prototype” (WASAP). This project had three main objectives:

1. Geocoding the Demographic and Health Survey (DHS) clusters from West and Central Africa,
2. Developing socioeconomic indicators from DHS data, and
3. Developing a georeferenced regional database, including socioeconomic and biophysical information.

The DHS program was created to provide an internationally comparable set of data to describe health and demographic characteristics of populations in developing countries. There are many publications describing the sampling characteristics of the DHS, individual country reports, and various comparative studies and analytical reports (see MACRO, Intl. 1997a, 1997b, 1996, 1994). The following is a brief description of the DHS database:

The DHS is a national sample survey designed to provide information on fertility, family planning, and health. The DHS involves interviewing a randomly selected group of women who are between 15 and 49 years of age. These women are asked about their background, the children they have given birth to, their knowledge and use of family planning methods, the health of their children, and other information that is important to understand their behavior.

Typically, the DHS sample is selected in two stages. Initially, a predetermined number of enumeration areas (EA) are chosen, usually stratified based on geographic region, or urban or rural residence, with equal probability. A complete household listing and mapping activity is next conducted in all chosen EAs. The second sampling stage is based on this listing of households. Households are selected from these lists for inclusion in the survey with probability proportional to the size of the EA. All women age 15 to 49 years in selected households are eligible for interview.

The DHS data in the WASAP database are aggregated to the cluster level, and various demographic and health indicators can then be calculated for each cluster. Each cluster contains approximately 30 households and the cluster-level indicators can then be aggregated to higher levels (for example, subregions within a country or user-specified geographic areas). The DHS indicators used in the WASAP database are grouped according to the following characteristics:
• Individual and household background characteristics
• Women’s fertility and fertility preferences
• Family planning practices of currently married women
• Access to prenatal and delivery care
• Status of maternal and child nutrition
• Access to childhood immunization
• Prevalence of childhood morbidity and treatment
• Knowledge of and attitude towards HIV/AIDS
• Availability of services at the cluster level.

The DHS data are included as part of the WASAP database, as are other variables and geographic characterizations (for example, economic diversity, agro-ecological zones, and accessibility). Figure 7.1 illustrates the distribution of the DHS clusters in the WASAP database with an example of a geographic characterization used in this study, that is, aridity zones (which will be discussed in more detail in the fourth section of this chapter, “Results and Discussion”). The data are stored in a georeferenced format and are readily accessible for analysis in a geographic information system (GIS). Among other results, the WASAP project demonstrated the benefits of georeferencing data to:

1. Examine the spatial distribution in the DHS data
2. Integrate different surveys for the same geographic area
3. Allow changing between geographic units of analysis
4. Integrate socioeconomic data with biophysical data.

Overview of the FEWS Project and Vulnerability Assessments

Since 1985, the USAID-funded FEWS Project has been collecting and analyzing secondary data related to food security in several Sub-Saharan African countries. A GIS has been an important tool for the storage, analysis, and presentation of FEWS products and information. The primary medium for disseminating this information is through monthly bulletins and via the Internet.

In addition to the monthly FEWS bulletins, the project has also been conducting periodic Vulnerability Assessments (VA) that summarize the food security situation in a given country. Vulnerability is defined in the FEWS context as “relative susceptibility of households to various levels of food insecurity”—that is, food shortages that would have an impact on the health or physiological development of individuals. The VA analysis examines factors that affect food availability (for example, crop production, rainfall, pasture conditions, and imports and exports) as well as factors that affect access to food (such as prices, household income, and proximity to markets).
VAs are usually done country-by-country, but in 1994, FEWS conducted a Regional Vulnerability Assessment (RVA) as an attempt to describe the food security situation across multiple countries in the Sahel (Mali, Burkina Faso, Niger, and Chad). The RVA addressed such issues as how to select and analyze food security indicators that would be comparable across different countries, how to determine the most appropriate geographic unit of analysis, and how to deal with missing or incomplete data for certain countries (Wright and others 1994). The model differentiates vulnerability into the temporal dimensions of baseline and current vulnerability, defined as follows:

- **Baseline** (or chronic) vulnerability to food insecurity is the result of poverty, riskiness of income sources, and limited access to alternative income sources. Baseline vulnerability indicators attempt to capture relative wealth and stability of income as a description of the general economic environment.
- **Current** (or transitory) vulnerability is the result of major changes in income or production for own consumption in the past three years, such as recent changes in growing conditions, crop production, general functioning of the cereal markets, and civil insecurity situations.

Factors that lead to chronic vulnerability can be further subdivided into those factors that affect the resource base (for example, length of growing season, variability of the growing season, variability in rainfall, and physical access to infrastructure, such as markets, schools, and health clinics), and those factors that affect the income base within the household (for example, as given by per capita production of cereals, livestock, and cash crops). Ideally, household surveys should be used to get a more complete picture of the income structure, but secondary, aggregated data were used as proxies for income in the RVA. However, when taken together as a whole, the chronic factors give an indication of the relative long-term vulnerability to food insecurity of a population in a given area or, conversely, the apparent resiliency of the population to deal with economic or climatic shocks that may disrupt the food security situation. The RVA was one of the first attempts by the FEWS project to compare vulnerability across multiple countries. Since this study was completed in 1994, there have been a number of developments in VA methodology, both within the project and outside, but not much in the way of regional analysis or cross-country comparisons.

This brief overview of the FEWS and WASAP projects illustrates the utility of linking socioeconomic data with biophysical data using a GIS. The WASAP project was a significant step forward in that, in addition to demonstrating the utility of a georeferenced database to study cross-sectoral issues, the project also made these data more available and accessible to sector specialists interested in their operational use. The FEWS project has also made important contributions in studying and analyzing cross-sectoral issues, by combining socioeconomic and biophysical factors from a food security per-
spective. Other initiatives to make existing socioeconomic data more widely available, accessible, and integrated across sectors are now underway.

One example of a project that combines socioeconomic data with biophysical data is the poverty mapping being conducted by the World Bank and others. The purpose of poverty mapping is to identify populations that would be most affected by major economic disruptions, and to help guide policies and programs to alleviate poverty. Poverty mapping and vulnerability assessments have similar objectives. The next section discusses the assumptions underlying vulnerability and poverty mapping with the DHS variables.

Vulnerability and Poverty in the DHS Data

Henninger (1997) indicated that the baseline (chronic) data and indicators used in the FEWS vulnerability assessments could be adapted to meet the needs of a poverty analysis, and the results of poverty mapping could be incorporated in vulnerability and food security assessments. The various approaches presented at the World Bank-sponsored Geographical Targeting Workshop for poverty alleviation illustrated the overlap of data and indicators used in the different approaches for vulnerability assessment and poverty mapping (such as household income, consumption, expenditures, census data, health and nutrition, education, environmental, and accessibility). The largest difference is the scale and geographic coverage of the data and the level of effort required to get the desired results.

The various reviews of poverty mapping and assessment of vulnerability to food insecurity point out the difference between poverty and vulnerability, and note that poverty is not the same as vulnerability (Glewwe and Hall 1995). There are, however, similarities between the basic goals of poverty mapping and the assessment of vulnerability to food insecurity.

Vulnerability assessments attempt to identify where the poorest people are, but they focus on those people who live in "risky" environments and would be most affected by a disruption to their livelihoods such as prolonged drought, major crop failure, devastating livestock disease, or major macroeconomic shocks. The poorest tend to have not only low incomes, but also low and unstable resource base. Poverty mapping attempts to identify where the poor people, particularly the chronic poor, reside, taking into account their low income or low consumption, but not their low resource base. By focusing on the income components, poverty mapping may ignore the effects of biophysical factors such as the rainfall regime and soil type. Vulnerability mapping identifies more biophysical factors, but most methods now assume that some measure of income is a critical component to characterizing susceptibility to food insecurity.

In our basic regional model of vulnerability, we assume that poor people tend to be more food insecure and that the major determinants of food
security are income related. The data on the income-related components are, however, the most difficult and costly to gather. Direct or proxy indicators can therefore improve the mapping of poverty and vulnerability.

In general, the poorest people, as well as the people most vulnerable to food insecurity, tend to have similar demographic, socioeconomic, and health characteristics, such as low levels of education, high fertility rates and more children, limited access to health facilities and schools, and poor health and nutritional status. The data on these characteristics are included in the DHS data. DHS data would allow the inclusion of these demographic and health factors in the basic model of vulnerability to food insecurity and to develop proxies for income-related measures. For example, access of women to prenatal care (a DHS variable) is partly a function of income, of the proximity of the health facility, and mother’s level of education (also DHS variables).

Study Site Description

We first created several analysis scenarios, following the aggregation of certain DHS variables by various geographic characterizations, such as aridity zones or vulnerability classes. For this analysis we used the geographic information in the WASAP database, which included 14 West and Central African countries.

Subsequently, we focused on those countries that overlap between FEWS vulnerability assessments and the DHS variables, such as Mali, Niger, Burkina Faso, and Senegal. These selected countries are the study area to test various hypotheses between DHS variables and vulnerability characterizations. The resulting subset database comprised 1,023 DHS clusters as summarized in Table 7.1.

Table 7.1 Study Site Summary of DHS Database.

<table>
<thead>
<tr>
<th>Country</th>
<th>Administrative level</th>
<th>Number of clusters</th>
<th>Urban (%)</th>
<th>Rural (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Senegal</td>
<td>30 departments</td>
<td>258</td>
<td>132 (51)</td>
<td>126 (49)</td>
</tr>
<tr>
<td>Mali</td>
<td>47 cercles, including Bamako</td>
<td>300</td>
<td>118 (39)</td>
<td>182 (61)</td>
</tr>
<tr>
<td>Burkina Faso</td>
<td>30 Provinces</td>
<td>230</td>
<td>110 (48)</td>
<td>120 (52)</td>
</tr>
<tr>
<td>Niger</td>
<td>36 arrondissements, including Niamey</td>
<td>235</td>
<td>105 (45)</td>
<td>130 (55)</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>143</td>
<td>1023</td>
<td>558 (55)</td>
</tr>
</tbody>
</table>

Note: Numbers in parentheses are percent of total.
Results and Discussion

The results of the analysis of DHS data, in relation to selected indicators of food security, are presented along the following three axes: (1) aggregating DHS statistics by broad geographic zones, (2) using multivariate analysis of DHS data at the cluster level, and (3) developing summary indicators by subnational administrative units.

Aggregated DHS Statistics by Geographic Zone

One way to represent and analyze the DHS indicators is to develop aggregated statistics for a given variable relative to some geographic characterization or geographic construct. A geographic construct could be national or subregional boundaries, or other geographic areas of interest, such as agro-ecological zones, FEWS vulnerability classes, or economic diversity zones. These geographic constructs can be thought of as ways to classify and organize data that are more explicit to a given sector than simple administrative units (such as the department, province, or arrondissement).

As part of the WASAP project, the relationship between selected DHS variables and various geographic constructs was examined (World Resources Institute (WRI) 1996a, 1996b, 1996c). One of the case studies examined the relationship between child nutritional status and the aridity of the child’s place of residence. The anthropometric indicators of child nutrition included stunting (low height-for-age), wasting (low weight-for-height), and underweight (low weight-for-age). Aridity zones were taken from the International Center for Research in Agroforestry (ICRAF) in Nairobi, Kenya. The aridity index (AI) was used as given by the World Atlas of Desertification, in which AI is defined as the ratio of precipitation to potential evapotranspiration (table 7.2). The distribution of the DHS clusters in the WASAP database and the ICRAF aridity zones are shown in figure 7.1.

Results (figure 7.2) show a gradual decline in malnutrition indicators in the transition from the arid zones in the north to the more fertile and humid zones along the coast. The only exception is the percentage of children stunted, which is highest in the semi-arid zone. Further analysis shows a significantly higher incidence of malnutrition in rural areas compared with urban areas, with the highest proportion of stunted children in the dry subhumid zone of the urban clusters.

The United Nations Environment Programme (UNEP) poverty-mapping project also examined malnutrition in the various aridity zones, as well as in land degradation zones, focusing primarily on the rural clusters (UNEP 1997). The UNEP study also used the DHS variables to approximate a Human Development Index (HDI), using child mortality, adult female literacy, primary school enrollment, and percentage of children stunted as surrogates
Table 7.2 Aridity Zones and Population Characteristics of the WASAP Database

<table>
<thead>
<tr>
<th>Aridity zone code</th>
<th>Aridity zone</th>
<th>Aridity index (AI) range</th>
<th>Estimated population 1994 (millions)</th>
<th>Person/km²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Hyper arid</td>
<td>&lt; .05</td>
<td>.4</td>
<td>.35</td>
</tr>
<tr>
<td>2</td>
<td>Arid</td>
<td>.005–.20</td>
<td>.8</td>
<td>9.57</td>
</tr>
<tr>
<td>3</td>
<td>Semi-arid</td>
<td>20–.5</td>
<td>51.2</td>
<td>50.5</td>
</tr>
<tr>
<td>4</td>
<td>Dry sub-humid</td>
<td>.5–.65</td>
<td>15.4</td>
<td>41.3</td>
</tr>
<tr>
<td>5</td>
<td>Moist sub-humid</td>
<td>65–1.0</td>
<td>30.7</td>
<td>35.6</td>
</tr>
<tr>
<td>6</td>
<td>Humid</td>
<td>&gt; 1</td>
<td>47.1</td>
<td>65.1</td>
</tr>
</tbody>
</table>

Source: Adapted from World Resources Institute (1996).

For poverty levels. The human development variables used in the UNEP study are summarized by aridity zones in Table 7.3. These results show a clear north-south relationship for three of the four indicators: child mortali-

Figure 7.1 DHS Cluster Locations and ICRAF Aridity Zones

Source: WRI, Macro Int'l, BUCEN, ICRAF; June 1997.
Figure 7.2 Child Malnutrition by Aridity Zone

Source: Adapted from WRI, 1996a.

ty, adult literacy, and school enrollment, but were less clear for the stunted children index—although there is a slight peak in the semi-arid zone (similar to the WRI results).

The examples given above illustrate how information by different geographic zones can be used to study socioeconomic variables in the context of vulnerability to food insecurity. The data raise several questions however.

For example, why do the malnutrition data indicate a slight, but statistically significant peak in the semi-arid zone? Health data are not typically analyzed relative to environmental data and it is difficult to draw absolute conclusions. However, the analysis does provide a new way of looking at

Table 7.3 Proxy Variables Used by UNEP to Develop a Human Development Index (HDI) from the WASAP Database.

<table>
<thead>
<tr>
<th>Aridity zone</th>
<th>Child mortality</th>
<th>Adult literacy</th>
<th>School enrollment</th>
<th>Stunted growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arid</td>
<td>31.7</td>
<td>4.1</td>
<td>13.1</td>
<td>36.9</td>
</tr>
<tr>
<td>Semi-arid</td>
<td>26.7</td>
<td>6.3</td>
<td>15.8</td>
<td>37.8</td>
</tr>
<tr>
<td>Dry subhumid</td>
<td>21.7</td>
<td>10.0</td>
<td>25.1</td>
<td>34.9</td>
</tr>
<tr>
<td>Moist subhumid</td>
<td>17.3</td>
<td>21.5</td>
<td>36.9</td>
<td>33.8</td>
</tr>
<tr>
<td>Humid</td>
<td>17.9</td>
<td>42.3</td>
<td>61.0</td>
<td>32.0</td>
</tr>
</tbody>
</table>

Note: Units are the average value (in percent) of the DHS variables by aridity zone.
Source: From UNEP (1997).
the question, and among the plausible explanations are the following. (1) The inherent variability in the DHS data is greater in the semi-arid zone than the arid zone. (2) The diet of the principally nomadic groups in the arid zone (that is, groups with more dairy products in their diet) is different from that of the populations in the semi-arid zone, where rain-fed agricultural systems are the most variable.

These examples illustrate how socioeconomic data (derived from the DHS database) can be analyzed with respect to biophysical data instead of simply aggregated by administrative units. The examples also illustrate the utility of having a georeferenced database, which, in addition to the new analytical capabilities, allows the results to be readily displayed in maps. These examples suggest that there are trends in certain DHS variables when aggregated across different kinds of biophysical geographic zones. To further examine the DHS data and determine which variables would contribute the most to the spatial characterization of vulnerability, we used multivariate analysis techniques, which are discussed in the next section.

Using Multivariate Analysis

To further explore the possibility of using the DHS cluster-level data to make inferences about the relationship between variables and the variability between clusters, we resorted to multivariate analysis techniques (such as principal components analysis, or PCA). The sample unit for the multivariate analysis was the cluster itself, as compared with the broad summary statistics by geographic strata described above. Our assumption was that indicators are valid estimates at the cluster level since each cluster actually comprises approximately 20 to 30 samples at the household level.

The first step was to select a subset of variables from the extensive DHS database, focusing on those variables we expected to be most appropriate in the basic model for describing vulnerability to food insecurity. The initial subset of variables included child mortality, child nutrition (wasting, stunting, underweight), education, and various household characteristics. We also selected a corresponding subset from the FEWS biophysical variables as presented in the baseline vulnerability assessment methodology. The FEWS income base indicator was not used in this analysis because it represented only agricultural income, and one of the underlying goals for exploring the DHS database was to find proxy variables that could be used to fill in the gaps in the income-related components.

The next step was to develop descriptive statistics for the DHS subset using the 1,023 clusters in the study site (as given in table 7.1). From the initial subset, only those variables that had a "quasi-normal" frequency distribution as given by the descriptive statistics and skewness measures were retained for further analysis. The descriptive statistics were developed for each selected DHS indicator using the SPSS statistical package and then
mapped in ARCVIEW to examine the geographic coverage of the indicator. We also examined the correlation matrices and removed those variables that were not highly correlated. The final subset was then analyzed using PCA.

The results of the PCA indicate that the first four principal components explain over 81 percent of the variability among the clusters (table 7.4). The loadings of the first four components were interpreted as follows:

- PC1 —> Education/literacy/household income status
- PC2 —> Biophysical or resource base status
- PC3 —> Demographic and fertility status
- PC4 —> Children's nutritional status

Although the results of the PCA and the interpretation of the components do not provide a causative model for vulnerability, the results are not inconsistent with what has been indicated in previous studies: the relative importance of education and income in explaining the variability between the clusters, especially as it relates to poverty or vulnerability status. These findings lend support to the assumption that the cluster-level data can be used to characterize the relationship between education, fertility, access, and biophysical parameters as determinants of vulnerability to food insecurity.

**DHS Indicators Summarized by Subnational Administrative Units**

The final presentation of the results was designed to be more useful to policymakers and regional planners. Examining the DHS variables aggregated by geographic zones or as clusters may lead to better understanding of vulnerability and child mortality and malnutrition, but these techniques are too broad (or too detailed) to use in planning regional programs and interventions. To address this concern, we summarized the results of the DHS analysis at the second administrative level, which corresponds to departments (Senegal), cercles (Mali), provinces (Burkina Faso), or arrondissements (Niger), as given in table 7.1. However, often the data do not provide exhaustive coverage at these levels. Usually, data are available at higher administrative levels (level 1), but they do not contain sufficient detail at lower levels. For this reason, we extended the use of the DHS data slightly beyond its original design in order to provide reasonable estimates at the second administrative level, since the DHS sampling design is generally consistent across these countries and contains the same variables.

In order to represent the results at subnational level, we used several basic data manipulation techniques: spatial filtering, to increase the coverage of the DHS data, and rescaling and ranking, to develop indexes that could be compared across the four countries. Only the variables that were selected in the final stage to characterize vulnerability across this region were filtered, rescaled, and ranked. A brief description of the spatial filtering technique will be presented along with examples of the final indexes.8
Table 7.4 DHS Cluster-Level Principal Component Analysis

<table>
<thead>
<tr>
<th></th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total variance</strong></td>
<td>3.921</td>
<td>2.387</td>
<td>1.733</td>
<td>1.713</td>
</tr>
<tr>
<td><strong>explained (rotated values for PCA)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Eigenvalues</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Percent of variance</strong></td>
<td>32.7</td>
<td>20.0</td>
<td>14.4</td>
<td>14.3</td>
</tr>
<tr>
<td><strong>Cumulative percent</strong></td>
<td>32.7</td>
<td>52.7</td>
<td>67.1</td>
<td>81.4</td>
</tr>
<tr>
<td><strong>Average cumulative rainfall</strong></td>
<td>0</td>
<td>.922</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Average length of growing season</strong></td>
<td>0</td>
<td>.939</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Variability of growing season</strong></td>
<td>0</td>
<td>−.808</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Percent of HH with no education</strong></td>
<td>.881</td>
<td>0</td>
<td>.322</td>
<td>.177</td>
</tr>
<tr>
<td><strong>Percent of women who can read</strong></td>
<td>−.838</td>
<td>0</td>
<td>−.376</td>
<td>−.164</td>
</tr>
<tr>
<td><strong>Percent of HH attending primary school</strong></td>
<td>−.859</td>
<td>0</td>
<td>−.225</td>
<td>−.138</td>
</tr>
<tr>
<td><strong>Percent of HH with natural flooring</strong></td>
<td>.839</td>
<td>0</td>
<td>.205</td>
<td>.261</td>
</tr>
<tr>
<td><strong>General fertility rate</strong></td>
<td>.304</td>
<td>0</td>
<td>.802</td>
<td>.164</td>
</tr>
<tr>
<td><strong>Percent of HH below age 15</strong></td>
<td>.248</td>
<td>0</td>
<td>.843</td>
<td>.104</td>
</tr>
<tr>
<td><strong>Percent of women receiving prenatal care</strong></td>
<td>−.812</td>
<td>0</td>
<td>0</td>
<td>−.258</td>
</tr>
<tr>
<td><strong>Percent of children stunted</strong></td>
<td>.264</td>
<td>0</td>
<td>.142</td>
<td>.866</td>
</tr>
<tr>
<td><strong>Percent of children underweight</strong></td>
<td>.319</td>
<td>0</td>
<td>.139</td>
<td>.844</td>
</tr>
</tbody>
</table>

Note: Units are factor loadings for the first four principal components.
HH = household, percent = proportion. See Appendix for detailed description of variables.

Spatial Filtering Technique

Originally, the DHS surveys were designed to provide statistically reliable estimates at the national level, or at the level of subnational units (1st administrative level) such as regions in Mali and departments in Niger. In many cases, at the second administrative level, there are not enough DHS clusters within the administrative unit to calculate a reliable estimate. However, we wanted to test the feasibility of extending the DHS data slightly by applying a spatial filter that would include neighboring clusters to increase the sample size and reduce the standard error of the estimate. The spatial filtering technique used in this study is similar to techniques used in image processing and for generating surfaces from points (such as rainfall surface images from point rainfall data). Filtering helps to smooth (or mask) some of the variability and can be used to fill in gaps in the data coverage, increase the sample size, and reduce the standard errors of the estimates. The basic assumption required to employ this type of filtering is that the neighboring points (that is, nearest neighbor clusters) sufficiently represent the administrative unit in question.

Two different administrative units were selected to illustrate this point—Soum, Burkina Faso, and Bakel, Senegal (figure 7.3). One of the DHS indicators, the proportion of children underweight, was calculated under several scenarios, as shown in table 7.5. For example, using only the origi-
nal three clusters that fall within the Soum province, the value for proportion underweight was calculated and its value was 42.3. This was only based on 36 cases (weighted) and therefore has a large standard error (SE) of 8.76, and a relative error (RE) of 20.7 percent (RE = SE divided by indicator value). If we assume that the “nearest neighbors” are representative of this province, and select the four nearest clusters, we can increase the sample size to 7 clusters, which comprises 120 cases and reduces the SE to 1.60 and the RE to 3.8 percent. Adding the next two nearest clusters did not change the results significantly.

There are several limitations to this type of filter, especially in the context of DHS data. The nearest neighbors are not always the most appropriate to include in the extended sample. Sometimes the nearest cluster to a predominantly rural administrative unit may be urban. To prevent the bias, we avoided mixing urban and rural clusters across administrative units. Also, we did not take samples across international borders since there are implications regarding the impact of government policies on health, education, and the resultant DHS indicators. Finally, in some cases, the geographic context needs to be taken into account to select the most appropriate clusters. In the case of Bakel, the clusters along the river in Matam department, although further away, are likely to be more similar to Bakel than the nearest clusters in the “far away” Tambacounda department. This contextual filter was not used often and was fairly easy to implement with a basic understanding of Sahelian economic and cultural geography, but would be more difficult to implement as an automated program.

The spatial filtering routine used in this study is experimental, but it appears that the process works and yields reasonable results, allowing some of the DHS variables to be used at a more detailed level. This is an important consideration from a regional planning perspective, and some type of filtering or summarizing routine would be necessary to retain subnational detail for regional analysis, especially when combining data from different surveys or data sources. In this filtering example, if a relative indicator to

<table>
<thead>
<tr>
<th>Administrative unit name and number of clusters</th>
<th>DHS indicator value in percent, e.g. proportion underweight</th>
<th>Number of cases in sample</th>
<th>Standard error (SE) indexes</th>
<th>Relative error = SE/indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soum 3</td>
<td>42.3</td>
<td>36</td>
<td>8.76</td>
<td>20.7</td>
</tr>
<tr>
<td>Soum 7</td>
<td>41.1</td>
<td>120</td>
<td>1.60</td>
<td>3.8</td>
</tr>
<tr>
<td>Soum 9</td>
<td>41.5</td>
<td>182</td>
<td>1.45</td>
<td>3.5</td>
</tr>
<tr>
<td>Bakel 2</td>
<td>28.3</td>
<td>46</td>
<td>7.36</td>
<td>26</td>
</tr>
<tr>
<td>Bakel 6</td>
<td>32.6</td>
<td>95</td>
<td>3.19</td>
<td>9</td>
</tr>
</tbody>
</table>

Figure 7.3 Examples to Illustrate Spatial Filtering of DHS Clusters

a. Soum province, Burkina Faso

b. Bakel department, Senegal
rank the different administrative units across the region is sufficient, then we will be confident in assigning a value of 41.5 for Soum and a value of around 32 for Bakel for the proportion underweight. However, the values of the filtered variables should be compared with more site-specific information at the national level (if it exists) and used appropriately.

The final step in the presentation at the subnational level uses an approach similar to that of the UN to develop the Human Development Index (HDI) and others. Each of the final variables given in table 7.4 were scaled from 0 to 1 and then in most cases, using the results from the multivariate analysis, were grouped into meaningful composite indexes. We scaled the data so that 0 was “bad” and 1 was “good” from a food security perspective, across the four countries. The final indexes were grouped into the following categories:

- **Biophysical** = combining length, variability, and average cumulative rainfall
- **Education** = combining percent attending primary school with inverse of percent with no education
- **Demographic** = combining fertility with percent of household members less than 15 years old
- **Nutrition** = inverse of combining stunting and underweight
- **Access** = percent of women receiving prenatal care, used as proxy for access, in general
- **Flooring** = inverse of percent of household with natural flooring, used as income proxy.

Once all the selected indicators were aggregated, filtered, and rescaled at the 2nd administrative level, they could be studied individually or in various combinations or used to develop a composite index. Figure 7.4 shows a summary map of the biophysical index that was derived by rescaling the three image-based indicators: length, variability and average cumulative rainfall. This relative biophysical index corresponds to the well-known agro-ecological bands across the Sahel, but with slightly more detail than the broad bands used in the map of aridity zones, and each administrative unit now has a single value that can be compared to other types of data (for instance, the DHS variables).

Figure 7.5 illustrates the results for the final composite vulnerability index. The final composite index was a simple average of the six composite indexes described above. In a relative and chronic sense, and ranked across the four countries, the worst situation from a vulnerability to food insecurity perspective is in most of Niger, northern Burkina Faso, and in Mali along the border with Mauritania and Burkina Faso. The food security situation is better in coastal and northern Senegal and around the urban centers of Bamako, Ouagadougou and Bobo-Dioulasso, Burkina Faso. Again, these are not surprising results and confirm what would probably be surmised if the
Figure 7.4 Composite Biophysical Index


Figure 7.5 Final Composite Vulnerability Index

individual DHS country reports were summarized for the different countries and combined with biophysical data. The difference here is that all of the data for the entire region (in this case, the four countries) is in the same database, and can more easily be analyzed and studied to draw inferences on regional perspectives. In general, those areas with a higher resource base, more education, fewer and healthier children, with good access, and not with natural flooring, are less vulnerable.

Two examples are offered to illustrate how the final composite indexes may be used from a regional planning perspective: graphically (in two-dimensional plots) and geographically (by querying the database to display only those regions that contain certain characteristics). First, one can examine the final tables to look for the most significant factors in any given region, or, to identify the anomalies and then determine why they are different. However, it is difficult to scan the entire summary table and interpret the regional significance. This technique would work to evaluate certain subnational areas or to verify the indicator values for a given region.

Another way to utilize the final results is by plotting the composite indicators, two at a time (figure 7.6, showing access and malnutrition). The trend

**Figure 7.6 Access and Nutrition Index Derived from DHS Data**

Nutritional index

in the scatterplot is consistent with our assumptions: increased access to prenatal care is positively correlated with improved child nutritional status. From a food security perspective, we can use this relationship to show those areas with better (or worse) access and better (or worse) nutritional status, assuming that these areas would be less (or more) vulnerable to food insecurity. However, from a regional planning perspective, it may be more interesting to examine the anomalies and develop various what-if scenarios: For example, what if we wanted to isolate the worst cases (lower left quadrant in figure 7.6), or, what if we are most interested in those cases that have relatively good nutritional status but poor access (upper left quadrant in figure 7.6)? Conversely, for cost recovery programs, a regional planner may want to isolate those cases that already have good access and good nutritional status (upper right quadrant in figure 7.6).

To help visualize the results of this analysis the database can be queried using a GIS to isolate areas with certain characteristics, and display these on the map. Example queries (or what-if scenarios) are illustrated in figure 7.7, which shows the same two indicators discussed above—access and nutrition—but displayed geographically. The queries are essentially isolating three of the four major quadrants that are graphically displayed in figure 7.6. Using an arbitrary index value of 0.50 to delineate the quadrants into "good" and "bad," the maps show the following scenarios:

- Query 1 = areas with poor access and poor nutrition
- Query 2 = areas with good access and good nutrition
- Query 3 = areas with poor access and good nutrition.

Note that in figure 7.6 there are no cases in the lower right quadrant, which would be interpreted as good access to prenatal care and poor nutritional status. The results from this type of analysis can then be used to plan regional programs and intervention activities, depending on the question being asked and the relevant quadrant. Of course, these results should be verified with supporting information and detailed local knowledge from within the different countries, but they do provide a useful tool to help visualize where these different what-if scenarios exist across a broad geographic region.

Conclusions and Implications

This study had two primary goals—to improve understanding of vulnerability to food insecurity and to strengthen the linkages between information provided and analysis done by a wide variety of projects in West Africa. We did gain new insights into vulnerability issues and worked closely with other projects using existing data to strengthen the linkages between several West African activities. This final section will address some of the lessons learned from this study and implications for database development,
Figure 7.7 Example Queries with Final Indices

Query 1 =
Access < 0.50 and
Nutrition < 0.50

Query 2 =
Access > 0.50
Nutrition > 0.50

Query 3 =
Access < 0.50 and
Nutrition > 0.50

vulnerability assessments, and development planning from a regional perspective.

This study did encounter the persistent questions of what scale to use, what geographic regions to include, and what geographic units should be used in the analysis. Clearly, a compromise between the level of detail that can be obtained from detailed surveys and how that information is retained when aggregated to subnational levels is unavoidable.

With databases as extensive as the ones used in this study, there is usually no single answer to these questions. The very nature of having a complex database that is acquired from different sources with different objectives, and integrated across sectors and geographic regions, implies that there will be technical questions to address. In this study, we used a combination of analysis units and geographic regions, depending on the type of analysis. One of the advantages of using a GIS is that all the database components are already linked geographically by virtue of being in geographic format, and it is much easier to change between units of analysis.

However, some types of data lose their meaning and significance if the units of analysis are pushed too far. The DHS data is easily summarized at the country or subregional level, or by broad geographic constructs, but the next level of detail is problematic. The spatial filtering technique that was utilized in this study may offer one method to get around this, but this technique is experimental and still needs to be verified and automated. Even though this technique appeared to work in a regional setting, it is likely to mask important details in some areas. Again, this is the trade-off between retaining detail and striving for consistency across the region to enable regional analysis and cross-country comparisons to be made. The advantage of using a database such as the DHS is that it has already received international recognition and has been the basis of study and analysis by many researchers and scholars. The survey designs are consistent and compatible, which allows for cross-country comparison. This is not always apparent when attempting to combine surveys or results from different projects that have used different procedures and techniques.

From a food security perspective it is clear that many of the DHS variables are related to certain aspects of our basic model of vulnerability, at least for the chronic, long-term component. The final vulnerability map (figure 7.5), which was based on a combination of biophysical and socioeconomic variables, gives a reasonable characterization of those areas that are chronically vulnerable to food insecurity. It appears that the DHS data helped to fill in a major gap in our information base, that is, how to obtain proxy measurements for household income that we know are critical to describing vulnerability. The approach of ranking the 2nd level administrative units provides one method for retaining as much level of detail as possible, but summarized across the region.
This analysis also helped to clarify and question some of our basic assumptions and definitions of vulnerability; for example, the apparent anomalies encountered with the malnutrition data in the remote and arid zones may lead to redefining how these zones are characterized from a vulnerability perspective. Most vulnerability assessments have focused on the rural poor and mostly agricultural populations and have not properly assessed the pastoral and agro-pastoral communities. It is more difficult to assess the situation in pastoral and nomadic communities, but there is evidence that our basic assumptions about vulnerability do not necessarily apply in this situation and may need to be adjusted.

There should also be more follow-up on the similarities and differences between vulnerability assessment methodologies and poverty mapping. The major difference may simply be a matter of the scale and level of detail that is required to obtain the desired results. Poverty mapping is often part of a process designed to understand and attack the root causes of poverty; hence, it requires a more rigorous survey design and is less likely to be satisfied with the use of proxy values. Vulnerability assessments have historically used proxy indicators, which may have been sufficient from an early warning perspective, but more and more, there is a desire to add more details as to the nature and cause of the vulnerability to assist in preparing more efficient responses to a food security situation.

The examples presented in this report were primarily from the health and food security sectors, and were geared towards supporting regional planning for USAID in West Africa. Since this current study was initiated there have been major changes in USAID’s regional structure and the findings from this study will need to be integrated into USAID’s Regional Strategic Plan for West Africa. This will include linking with other USAID-funded regional programs and sharing the findings of this study with other international and regional institutions. The technical expertise is available within the region and other institutions are looking at similar issues regarding the integration of biophysical and socioeconomic data to help assess and monitor poverty, food security, health, and education issues.

There will most likely be a growing interest for others to use the WASAP and DHS database, not only for regional analysis and planning, but also as a training tool in creating such a database and using a GIS. Some of the results presented in this study could serve as a starting point to work with a regional planning team or strategic objective team to select the areas with the highest (or lowest) relative malnutrition levels. By using map queries, new scenarios could be developed to isolate areas that meet other criteria and identify their development planning needs.

The database queries could be done without a GIS, but it is much easier and the results can be directly displayed in map format to allow for a more powerful presentation of results. One simple example would be to design
queries that summarize selected DHS variables for only rural clusters for certain countries, or within selected subregions. This would be a useful output and presentation tool for strategic planning of health and education programs.

Finally, this project utilized the extensive efforts that had already been made by others—in this case, the WASAP collaborative effort between MACRO, Intl., WRI, and BUCEN. One of the primary goals of this study was to illustrate how an existing database could be analyzed and exploited more efficiently. More efforts are required to look at the connections between vulnerability mapping and poverty mapping—to emphasize where they differ and where they converge and to develop synergy between the two approaches.
# Appendix

## Description of Variables Used in PCA Subset

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Average cumulative rainfall from Meteosat rainfall estimates</td>
</tr>
<tr>
<td>2</td>
<td>Average length of season, from NOAA-NDVI historic average, 1982–1994</td>
</tr>
<tr>
<td>3</td>
<td>Average variability of cumulative NDVI (coefficient of variation), from NOAA-NDVI historic average, 1982–1994</td>
</tr>
<tr>
<td>4</td>
<td>Proportions of HH members 15 years of age or older with no years of education</td>
</tr>
<tr>
<td>5</td>
<td>Proportion of HHs with natural flooring, i.e., sand, earth, etc.</td>
</tr>
<tr>
<td>6</td>
<td>General fertility rate for the three year period preceding the survey</td>
</tr>
<tr>
<td>7</td>
<td>Proportion of HH members below age 15</td>
</tr>
<tr>
<td>8</td>
<td>Proportion of women aged 15–49 years that can read easily or with difficulty</td>
</tr>
<tr>
<td>9</td>
<td>Proportion of births in the last three years for which women received prenatal care from a doctor, nurse, midwife, or trained auxiliary midwife</td>
</tr>
<tr>
<td>10</td>
<td>Proportion of all children at the age of primary education currently attending school</td>
</tr>
<tr>
<td>11</td>
<td>Proportion of all children at the age of secondary education currently attending school</td>
</tr>
<tr>
<td>12</td>
<td>Proportion of children 3–35 months that are stunted; where height-for-age z-score falls below –2 standard deviations of the median height-for-age</td>
</tr>
<tr>
<td>13</td>
<td>Proportion of children 3–35 months that are underweight; where weight-for-age z-score falls below –2 standard deviations of the median weight-for-age</td>
</tr>
<tr>
<td>14</td>
<td>Proportion of women aged 15–49 who are currently employed</td>
</tr>
</tbody>
</table>

*Note: See MACRO, Intl., 1997b for more detailed description of all DHS variables.*

**HH = households**

**Source:** All are from DHS database, except the first three, which are image-based indicators from the FEWS project.
Notes

The author is under contract with Associates in Rural Development, Inc.

1. This chapter summarizes work in progress under a contract between USAID’s Regional Economic Development Services Office for West and Central Africa (REDSO/WCA) in Abidjan, and Associates in Rural Development (ARD), Inc., in association with the FEWS Project.

2. The WASAP data are stored in ARCVIEW® format. All the necessary parameters required to aggregate the cluster-level data to higher levels, such as subnational administrative units, are provided in the WASAP database, including the numerator and denominator values used to compute the indicator and sampling weights for each cluster. Programs to calculate aggregated, weighted indicators at a user-specified level are also included in the database (for instance, ARCVIEW script files written by Trevor Croft at MACRO, International). A more complete description of the WASAP and DHS databases can be found in reports by MACRO, Intl. and WRI (see MACRO, Intl. 1997a, 1997b, and WRI 1996c or the DHS website at http://www2.macroint.com/dhs).


4. See Vulnerability Assessments at the FEWS website (www.info.usaid.gov/fews/fews.html) and various FEWS publications—for example, FEWS/Malawi (1996). For reviews of vulnerability assessment techniques see Henninger, 1997; WFP (1996); Deichmann (1997); UNDP Poverty Guidebooks (1997); Ramachandran and Eastman (1996); Riely (1995); and Downing (1991).

6. For example, see footnote 3 and the World Bank Living Standards Measurement Study (LSMS) publications Nos. 88, 117, and 129.

7. See World Bank (1997).

8. See McGuire (1998) for more details on the idea of the spatial filtering of DHS clusters.

9. See also Pison and others (1995). This report examined recent changes in the demographic situation of Senegal, particularly those related to fertility and mortality rates.

References


Using a GIS to Target River Blindness Control Activities in Guatemala

Frank O. Richards

Human onchocerciasis is a parasitic infection that can result in severe skin disease, visual impairment, and blindness. The condition is caused by a parasitic worm (*Onchocerca volvulus*), and transmitted by the bite of a vector black fly of the species *Simulium*. Because black flies breed in rapidly flowing rivers and streams, onchocerciasis is often called “river blindness.” The adult parasites (males and females) live and mate in human tissues, often just under the skin where they may become encased in a fibrous tissue reaction that manifests clinically as subcutaneous nodules. The adult females produce embryos (microfilaria) that leave the nodule and swarm underneath the skin. To survive, they must be ingested by black flies, develop in the fly to infectious stages, and then be inoculated back into humans, where they reach adulthood and so continue their life cycle. The microfilaria irritate tissues, and, when they enter the eye, cause loss of vision and sometimes blindness (WHO 1987, 1995).

An estimated 18 million persons are infected with *Onchocerca volvulus* in Africa and Latin America. The infection is focal in nature, stable (that is, not prone to explosive epidemics), and occurs in its worst forms in remote, rural regions, where more than 90 percent of persons can be infected. Most of the skin and eye involvement occurs in villages, where more than 40 percent of adults have nodules (hyperendemic onchocerciasis); communities with 20 to 40 percent nodule prevalence (mesoendemic onchocerciasis) are also at risk for severe manifestations of the infection (WHO 1987, 1995).
Until recently, the only two methods for controlling onchocerciasis were by surgical removal of the nodules containing the adult worms (nodulectomy) or by reduction of vector black fly populations through application of insecticides. In Guatemala and Mexico, the ministries of health have had long-standing programs in which communities in disease-endemic areas are visited once or twice per year by special medical teams that surgically remove the nodules. In West Africa, a large vector control program (the Onchocerciasis Control Program) has been operational since 1975, and uses fixed-wing aircraft and helicopters to apply insecticides to large rivers (WHO 1987, 1995). However, a new tool to control this affliction was introduced in 1987 when ivermectin (Mectizan® from Merck & Co.) was licensed for human use (Mectizan® Expert Committee 1990, Hopkins and Richards 1997, Taylor and Greene 1989). Ivermectin is a safe microfilaricidal drug that prevents skin and eye disease from onchocerciasis when provided to infected persons as a single oral dose annually or semiannually. It is safe enough to allow large-scale (mass) administration to eligible populations (persons greater than five years of age, nonpregnant women, or women not breastfeeding very young infants). The World Health Organization encourages mass treatment in communities with severe (meso- or hyperendemic) onchocerciasis. In 1987, Merck generously donated ivermectin free of charge for public health efforts against river blindness, and so it has become the cornerstone of a global control initiative. Community-based ivermectin delivery treatment programs have safely provided millions of treatments in Africa and in all six disease-endemic countries of Latin America over the last ten years (Hopkins and Richards 1997, Taylor and Greene 1989).

Targeting Communities to Be Treated with Ivermectin

One must identify quickly, economically, and accurately those hyperendemic and mesoendemic communities where ivermectin distribution would have its greatest benefit. A first step taken by all ivermectin distribution programs is to establish a “target” area (Taylor and others 1992, Ngoumou and Walsh 1993). As treatment is ultimately delivered at the community level, targeted areas (states, districts, provinces, and so forth) must be refined to the targeted communities, where the final implementation of the program occurs. Based on the targeting exercise, the program commits itself to treat the entire eligible population with ivermectin, for an indefinite period of time. It is important, therefore, that these targeted areas be carefully selected, based on available epidemiological information, knowledge of environmental factors that support dense black fly populations, and rapid field assessment surveys (Taylor and others 1992, Ngoumou and Walsh 1993, Mace and others 1997, Richards 1993).
The Use of GIS for Targeting

Guatemala is a country of about 9 million inhabitants located in Central America. Mexico borders it to the north, Belize to the east, the Pacific Ocean to the west, and Honduras and El Salvador to the south. Guatemala has four recognized onchocerciasis endemic areas and an estimated 400,000 persons at risk of infection with onchocerciasis (Richards 1993, Brandling-Bennett and others 1981, Tada and others 1979, WHO 1996, 1997, Yamagata and others 1986).

The most important endemic area in Guatemala (with the greatest numbers of infected persons and the most communities with meso- or hyperendemic disease) is known as the Central Endemic Zone (CEZ) (Yamagata and others 1986). This area is in a mountainous region on the slopes of the Pacific piedmont, near the central highlands, just south of the large volcanic Lake Atitlán. The CEZ has an estimated area of about 900 square kilometers, and spans four departments (states). The population consists primarily of poor, indigenous people of Mayan descent who mostly live and work on small (populations 75–1,500), privately owned coffee farms called fincas. These farms are scattered through the mountains, and generally lie at elevations between 500–1,500 meters that favor both coffee cultivation and breeding of the vector black flies (Richards 1993, Ramirez 1986, Shelly 1988). The Guatemalan Ministry of Health (MOH) has provided nodulectomy services to the populations in the CEZ for decades, and has extensive files on nodule rates in communities in the area (Yamagata and others 1986).

The Guatemalan Ministry of Health adopted in 1989 the strategy of community therapy with ivermectin for onchocerciasis control. Along with this decision, it was resolved to carry out a comprehensive review of available epidemiological data and revise the maps of the endemic areas to establish a list and the locations of targeted communities. Despite the existence of an extensive MOH archive on onchocerciasis from the years of nodulectomy activities, it was also recognized that these data were incomplete, and that there were many fincas in the CEZ for which there were no data. How many was unknown. There were other questions: Would all villages of unknown endemicty falling in the elevation range of 500–1,500 meters have to be visited and evaluated for inclusion in the ivermectin program? Could villages with no data at any elevation be first stratified based on other environmental factors into those at greater and lesser risk?

To address these questions, the MOH launched a pilot project in partnership with the Centers for Disease Control and Prevention and the Universidad del Valle de Guatemala to apply new geographic technologies in parallel with the process of epidemiological data review and map revision. The primary goal of the project was to develop a GIS for targeting both
communities known to have onchocerciasis, as well as those communities suspected of having significant (meso- or hyperendemic range) prevalences. The results of some of this work have been reported (Richards 1993). The project also sought to strengthen the overall health infrastructure and surveillance system by creating maps that could be used for many other disease-control efforts.

Geographical information systems (GIS), which combine rectangular database and spatial digital mapping functions, have an enormous potential for assisting in targeting activities. Powerful and relatively inexpensive GIS software is available for microcomputers, most notably MapInfo (MapInfo Corporation), Atlas*GIS (Strategic Mapping/Environmental Systems Institute Research) and ARCINFO ARCVIEW Environmental Systems Institute Research (ESRI). Most recently GISs have become tools used in planning operational phases of tropical disease research and control. The global positioning system (GPS), the digitizing tablet, and remotely sensed data (satellite images and aerial photography) are other new and important tools used to create multiple and rich data layers in the GIS. GIS maps can fill a common void in developing countries where large scale (1:250,000 or greater) maps are restricted, outdated, or nonexistent.

When the project was initiated in 1989, GIS consultation, specialized equipment (scanners and plotters), and digital or remotely sensed data were very expensive, so only a middle range vector-based geographic information system (Atlas*GIS® for DOS, and later, Windows® Atlas*GIS) and a small digitizing table (SummaSketch®, Summagraphics Inc.) were used. The four data components in the system design were (1) the community inventory, (2) the digital map, (3) the MOH epidemiology data set, and (4) the vector flight-range area. The community inventory and the MOH data sets were rectangular (tabular), georeferenced FoxPro® (Dbase®) data sets. The digitized map and data sets for the vector flight-range area were GIS-generated (vector-based) geographic files. In the process of executing this project, we also evaluated and used a GPS, evaluated two commercially available data sets, and produced large hard copy paper maps for field use.

Methodology

Permission was granted from Guatemalan military authorities to purchase the complete set of restricted 1:50,000 maps (dated 1974–1981) prepared by the Guatemalan Instituto Geographico, in collaboration with the U.S. Defense Mapping Agency. These maps became the principal source of information for the GIS. We selected those map sheets that overlayed the four Guatemalan disease-endemic areas and then identified all communities on those maps (Yamagata and others 1986), along with their latitude, longitude (read with a special transparency designed for this purpose), and elevation.
A FoxPro® file was created in which each community was entered as a unique record. Over 3,000 communities were identified on the maps and entered into the database (Richards 1993), which was called the community inventory. Community names in the database were frequently repeated, and some names appeared over ten times (table 8.1). Indeed, there were 28 communities named “La Esperanza.” To avoid confusion, it was critical for geocoding purposes that each community is assigned a unique identification number. This identification number was used to link (using the relational database function) the community inventory with the MOH epidemiology database (see below). In all data entry activities we followed routine data quality assurance activities: we printed hard copies of the computer files and compared them with the data extraction forms, and we routinely backed up the hard disk.

The Digital Map

The “digital map” was an Atlas*GIS geographic file created from the same 1:50,000 maps used to create the community inventory. The basic feature data were derived from selecting important lines and regions to provide the substance of the disease-endemic area over which the points of community

<table>
<thead>
<tr>
<th>Community name</th>
<th>Number of communities with shared name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buena Vista</td>
<td>13</td>
</tr>
<tr>
<td>Buenos Aires</td>
<td>10</td>
</tr>
<tr>
<td>El Carmen</td>
<td>10</td>
</tr>
<tr>
<td>El Milagro</td>
<td>13</td>
</tr>
<tr>
<td>El Paraiso</td>
<td>10</td>
</tr>
<tr>
<td>El Porvenir</td>
<td>13</td>
</tr>
<tr>
<td>El Progreso</td>
<td>7</td>
</tr>
<tr>
<td>El Recuerdo</td>
<td>14</td>
</tr>
<tr>
<td>El Rosario</td>
<td>13</td>
</tr>
<tr>
<td>El Socorro</td>
<td>10</td>
</tr>
<tr>
<td>La Esperanza</td>
<td>28</td>
</tr>
<tr>
<td>La Providencia</td>
<td>17</td>
</tr>
<tr>
<td>La Reforma</td>
<td>7</td>
</tr>
<tr>
<td>La Trinidad</td>
<td>9</td>
</tr>
<tr>
<td>La Union</td>
<td>11</td>
</tr>
<tr>
<td>Las Delicias</td>
<td>14</td>
</tr>
</tbody>
</table>

Source: Data from Guatemalan Instituto Geographico, in collaboration with the U.S. Defense Mapping Agency.
inventory were plotted. Using a small (SummaSketch®) digitizing table, important features (roads, lakes and rivers, and 500 and 1,500 meter elevation contour lines) were created in their exact (at 1:50,000 scale) latitude-longitude positions (Richards 1993).

Unfortunately, the 1:50,000 maps did not show political or administrative boundaries of the departments or counties, which were critical elements for linking MOH data to the community inventory (see below). To obtain the political boundaries, we digitized the county and department boundaries from maps of a considerably smaller (1:1,000,000) scale (see map 8.1). Plotting the community inventory on the digital map allowed us to determine the county and department of each community. Differences in scale, however, resulted in a sacrifice of accuracy of administrative positions for communities located near the administrative borders.

*The Epidemiology Data Set*

A comprehensive retrospective review of MOH data for 11 years (1980–1990) was carried out from March to October 1992. A special office was assigned for the completion of this task at the MOH’s Department of Onchocerciasis. All files produced during field visits to disease-endemic communities by nodulectomy teams were gathered and reviewed. Date of visit, community name, county, department, population size, number of persons examined, and nodule rates were coded on data extraction forms and then keyed into a FoxPro® file (the MOH epidemiology data set). A data entry software program was developed that first searched the community inventory data set to identify the name, county, and department of the entry community, and then, with a match, extract and write the appropriate ID to the newly generated MOH epidemiology file record entry. Since community inventory identification numbers were associated with latitude, longitude, and elevation, all such matches automatically georeferenced the MOH epidemiology data set. Those MOH records that did not match a record in the community inventory were assigned a new ID number by the program, and that community was automatically entered into the community inventory and labeled as “position unknown” (thus flagged for later GPS reading in the field).

The MOH epidemiology data set was analyzed by calculating community endemicity, based on the simple mean nodule rate (the ratio of persons with nodules to total persons examined) for all entries for a given ID number over the 11-year period. Nonendemic communities were defined as having a nodule prevalence of zero, hypoendemic communities a prevalence of 1–20 percent, mesoendemic 20–40 percent, and hyperendemic ≥40 percent.

The project purchased the least expensive global positioning system then available on the market, the Sony IPS-360, a handheld, nondifferential, four-channel GPS system. GPS units, by reading signals from navigational satel-
lates on 12-hour elliptical orbits at 20,000 kilometers altitude, can calculate a latitude-longitude position and an elevation accurate to within 30–100 meters. (Calculations based on civilian frequencies are influenced by "selective availability," which is a random error placed in the satellite’s time signal to reduce accuracy). The unit was set on a coordinate area for Central America (North America 1927) at the highest allowable precision setting (accepting only a dilution of precision < 6). The GPS then was tested at the Universidad del Valle de Guatemala against the (working) scale of 1:50,000 maps. Thirty-three GPS readings were taken at the same open site (the NE corner of the football field on the campus). Data were obtained on 16 different days, at different times over a 36-day period. Latitude-longitude (to the nearest 10th of a second), elevation in meters, and the unique ID numbers of the four satellites used to calculate the position were recorded. GPS readings were compared with a position read from the appropriate 1:50,000 map. The map is of large enough scale to show the corner of the football field where GPS readings were taken—longitude 90° 29' 35" W, latitude 14° 36' 19" N, elevation 1,490 meters above sea level.

After testing showed acceptable latitude and longitude readings at scale (see results), field reconnaissance was conducted together with MOH field staff to verify presence and locations of all meso- and hyperendemic communities in the MOH epidemiology data set that could not be identified on the maps.

GIS Analysis

GIS analysis of the data sets was based on the knowledge that the maximum flight range of the black fly vector of onchocerciasis (Simulium ochraceum) in the CEZ is 5 kilometers (Collins and others 1992). Using the GIS buffer function, we undertook two buffering exercises to create circular 5-kilometer vector flight ranges, (1) around hyperendemic and (2) around both hyper- and mesoendemic communities. By merging these buffers, we defined putative disease-endemic areas that captured or excluded other communities in the vicinity. We compared these two target areas for their ability to capture known and suspected communities in need of treatment. Suspected communities were defined based on their being positioned at an elevation between 500–1,500 meters elevation. The best strategy was used to generate a listing of targeted communities recommended for either ivermectin distribution or additional epidemiological assessment.

Evaluating the Data for Targeting

Two available digital sources of georeferenced community settlement data were compared with the databases we created. The first source was the Digital Chart of the World (DCW). The DCW, which can be found both in
the public domain as well as in costly value-added formats adapted to different commercial software products, is primarily based on the U.S. Defense Mapping Agency Operational Navigational Chart series, the largest scale unclassified series available with complete global coverage. It contains layers that include international boundaries, settlements, roads, and elevation contours, along with 100,000 place-name entries. The second source of information was 1:500,000-scale data used to prepare the 1984 Gazetteer for Guatemala. These data (obtained from the U.S. Defense Mapping Agency) consisted entirely of points (not regions or lines) of latitude and longitude (rounded to the nearest minute), names of the position, and position type (for example, human settlements, rivers, mountain peaks, parks, and so forth).

To make the GIS project interesting and relevant to the MOH field workers, we produced hard copy, color thematic maps (the size of common tourist road maps) from which community names and their identification numbers could be read. Their production required considerable time given the need to adjust hundreds of labels to allow a legible printout. These maps were provided to field workers (who had previously relied upon hand drawn maps), and we noted if they found them useful in their operational activities.

Results

Figure 8.1 shows the CEZ community inventory (716 communities) plotted on the digital map for the Central Endemic Zone, along with the positions of supplemental GPS readings. The MOH epidemiology data set had 1,793 records, representing the visits to 517 communities in all four disease-endemic zones of Guatemala. Overall, there were 152 (29 percent) nonendemic communities, 196 (38 percent) hypoendemic, 111 (21 percent) mesoendemic, and 58 (11 percent) hyperendemic. The CEZ was clearly the most important onchocerciasis endemic area in Guatemala. Of the 365 endemic communities identified in the MOH data set, 308 (84 percent) where in the CEZ; more important, 55 (95 percent) of 58 hyperendemic communities and 89 (80 percent) of 111 mesoendemic communities were found there. Figure 8.2 shows the positions of the meso- and hyperendemic communities identified in the CEZ.

The MOH data analysis for the CEZ showed that 52 (17 percent) of communities visited were nonendemic, 112 (36 percent) were hypoendemic, 89 (29 percent) mesoendemic, and 55 (18 percent) hyperendemic. However, there were an additional 408 villages (57 percent of the total of 716 communities) in the CEZ community inventory without MOH data. These required targeting classification.

Thirty-eight (7 percent) of the communities on file with the MOH could not be matched in the community inventory. Field reconnaissance was
Figure 8.1 Central Endemic Zone for Ochocerciasis, Guatemala

Supplemental GPS readings (N=38)

LEGEND

The 1:50,000 digital map and community inventory

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needed to verify the presence of the missing communities (particularly the meso- and hyperendemic communities in the MOH data set), and to obtain a latitude and longitude reading to plot their location in the GIS.

We evaluated the GPS unit before field reconnaissance. During the testing period, the GPS unit fixed on signals from 13 different satellites. The most frequent readings were taken from satellites 29 (17 observations), 1 and 14 (each with 13 observations), 15, 18, 25, 28 (each with 12 observations). Figure 8.3 shows a spatial analysis (each tick = 100 meters) of the horizontal plain of the football field. The star in the figure indicates the position (90° 29' 35 W, 14° 36' 19” N) read from the map. The central position of the GPS readings (“central GPS position”) was calculated to be 90° 29' 33.9” W, 14° 36' 21.6” N, which was 85 meters SSW from the map position. Figure 8.4 shows a plot of horizontal and vertical distances from the map position. The mean GPS elevation was 1,525 meters, or 35 meters above that of the

Figure 8.3 Spatial Analysis of the Horizontal Plain

![Spatial Analysis of the Horizontal Plain](image)

Source: Author's calculations.
map (range −96 to +204) and 48 meters above the field's actual elevation. Statistically, the mean GPS elevation was different from that of the map (1,490 meters, z = 2.39, p < 0.05). Similar to the findings on the horizontal plane, 79 percent (26) of elevation observations fell within 100 meters of the map position. In univariate analysis, the outlying GPS readings did not correlate with time of day, day of reading, or satellite fix.

All spot GPS readings were within a 300-meter sphere of the map position; the average horizontal and vertical GPS positions clustered 85 meters and 35 meters respectively from the map position. Nearly 20 percent of positions were beyond the stated accuracy range (30–100 meters) of the unit. On the horizontal plane, this GPS error was not a major concern at the operational scale requirements. However, a similar variance in GPS elevation readings could potentially result in misclassification of unacceptable numbers of communities. It was concluded that GPS readings of latitude and longitude, but not elevation, were acceptable in the targeting application.
Contour lines in the GIS derived from the 1:50,000 maps continued to serve as the guidelines for elevation of GPS points. Field surveys led by MOH field staff were successful in identifying all meso- and hyperendemic village positions in the CEZ.

Four hundred and eight (57 percent) of the 716 communities in the CEZ community inventory were without MOH data, and therefore required targeting classification. Of the 408 communities without data, 140 (34 percent) were found in an elevation of high risk (500–1500 meters), and so were classified as “suspect.” The remaining 268 above or below that elevation were called “nonsuspect” (table 8.2). We defined a disease-endemic area for the treatment program to determine which of those 408 communities were to be targeted. In the first strategy, the series of 5-kilometer vector-flight ranges were drawn around the 55 hyperendemic communities (figure 8.5). Figure 8.6 shows the disease-endemic area that was created (GIS determined plane dimensions 143 kilometers perimeter, 837 square kilometers area, maximum east-west extent 48 kilometers, maximum north-south extent 30 kilometers). There were a total of 356 (50 percent of the CEZ community inventory) villages within the newly defined disease-endemic area (table 8.2). Of these, (1) 55 (15 percent) were hyperendemic communities used to create the flight range buffers, (2) 165 (46 percent) were communities for which there existed MOH data indicating less severe onchocerciasis, (3) 24 (7 percent) had already been determined to be nonendemic by the MOH survey, and (4) 111 (31 percent) were communities for which no MOH data were available.

We observed however, (figure 8.6) that seven of the mesoendemic villages, as well as 59 percent of suspect villages, fell outside of the hyperendemic zone, observations suggesting that this buffer area was not sufficient to

<table>
<thead>
<tr>
<th>Table 8.2 GIS Buffering Exercise Communities to Be Assessed or Treated</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total</strong></td>
</tr>
<tr>
<td><strong>In CI</strong></td>
</tr>
<tr>
<td>(percent total)</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>Hyperendemic</td>
</tr>
<tr>
<td>Mesoendemic</td>
</tr>
<tr>
<td>Hypoendemic</td>
</tr>
<tr>
<td>Not endemic</td>
</tr>
<tr>
<td>Suspect</td>
</tr>
<tr>
<td>Not suspect</td>
</tr>
<tr>
<td><strong>Total</strong></td>
</tr>
</tbody>
</table>

Note: *CI = Community Inventory of the Central Endemic Zone of Guatemala
Source: Guatemalan Instituto Geographico, in collaboration with the U.S. Defense Mapping Agency.
capture all communities in need of treatment. Therefore, a second GIS-targeting strategy (figure 8.7) was run to buffer around both the 55 hyperendemic communities and the 89 mesoendemic villages. This second disease-endemic area had GIS-calculated plane dimensions of 162 kilometers perimeter, 1,109 square kilometers area, maximum east-west extent 58 kilometers, and maximum north-south extent 32 kilometers. Within the newly defined disease-endemic area, there was a total of 482 villages (67 percent of the CEZ community inventory—table 8.2), of which (1) 144 (29 percent) were the meso- or hyperendemic communities used for buffering, (2) 108 (22 percent) were communities for which there existed MOH data indicating less severe onchocerciasis, (3) 40 (8 percent) had already been determined to be nonendemic by MOH survey, and (4) 190 (39 percent) were communities for which no MOH data were available. Eighty percent of suspected villages in the Community Inventory (CI) were captured. This last exercise provided the final analysis of the target for either ivermectin distribution, or additional (fringe area) rapid assessment: 190 (47 percent) of the 408 communities without data should be evaluated or treated in the program.

**Alternative Data Products**

Figure 8.8 shows the comparison of community inventories in the onchocerciasis target area derived from the three different data sources. Despite having over 100,000 place name entries, only three human settlement points, all unnamed, were found inside the target area defined in figure 8.7. In contrast, the 1984 gazetteer data showed 204 communities inside the defined target area, and so was a much better source of information than the DCW. However, note that of the 256 disease-endemic communities found in the CEZ, only 125 (49 percent) could be matched in the gazetteer data set (versus 93 percent in the 1:50,000 community inventory before being supplemented with GPS readings). The success in matching MOH epidemiology data to that in the gazetteer is presented in table 8.3. Only 51 percent of meso- or hyperendemic communities in the MOH data set would have been matched if the gazetteer data had been used.

A comparison of distances was made between the 197 communities that were found in both the gazetteer and the 1:50,000 community inventory (figure 8.9). Three community pairs were excluded from the analysis since their relative positions were extreme outliers (separated by greater than 3 kilometers). The mean distance of separation among the 194 community pairs was 800 meters, suggesting that the error between the two data sets which was approximately ten times the difference of GPS and 1:50,000 map readings (85 meters).

Despite the considerable time required for their production, we found that the hard copy “tourist road maps” were received by the field workers
with enthusiasm. They provided corrections (new communities, changes in position, and so on) by placing notes directly on the maps while in the field. The maps that were later returned to the GIS unit at the Universidad del Valle were tattered and torn—evidence of their usefulness; the notes on the maps were used to update the GIS so that new and improved maps could be generated. The feedback loop mechanism that characterizes an accurate

Table 8.3 Endemic Communities Identified in the Gazetteer Database

<table>
<thead>
<tr>
<th>Endemic class</th>
<th>Total endemic communities</th>
<th>No in gazetteer (percent total)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hyperendemic</td>
<td>55</td>
<td>28 (50%)</td>
</tr>
<tr>
<td>Mesoendemic</td>
<td>89</td>
<td>45 (51%)</td>
</tr>
<tr>
<td>Hypoendemic</td>
<td>112</td>
<td>52 (46%)</td>
</tr>
<tr>
<td>Total</td>
<td>256</td>
<td>125 (49%)</td>
</tr>
</tbody>
</table>

Source: Author's calculations.
surveillance system is based on the premise that those who produce data need it returned to them later as a useful analytic product.

Discussion

We describe the use of a GIS to target a public health intervention in a developing country. Georeferenced databases, not software, were the keys to this exercise. Three databases were created: (1) a digital map (that is, a spatial geographic database created by digitizing maps of different scales); (2) a georeferenced community inventory database (created by entering latitude and longitude data from maps and GPS units); and (3) an MOH epidemiologic database (relationally linked by unique ID numbers to the community
inventory). The result of the analysis was a set of targeted communities generated through the use of a unique GIS function called buffering. Communities falling inside the buffer area were targeted for an intervention (treatment or further assessment); those outside were not. Accordingly, this spatial process generated new data to stratify communities that otherwise were without epidemiological information, and program management found new guidance in decisionmaking related to field activities of a control program.

Obtaining a relatively complete listing and position of the smallest and most marginal of rural villages inside and around the known disease-endemic areas was challenging (Estes 1994, Hastings and Clark 1991). Large-scale (≥1:200,000) maps are usually not readily available in developing countries, and if found they are frequently out of date, incomplete (that is, missing adjoining sheets), or restricted by security forces. In 1987, paper maps at scales of 1:100,000 were available for only 59 percent of the earth’s surface, with the developing world being that part of the globe least well mapped. Even in the United States, where coverage at 1:100,000 is 100 percent, only 14 percent of these maps were printed within the last 10 years, and 9 percent of what is available was produced 40 years ago (Estes 1994). However, finding maps of scale 1:500,000 to 1:1,000,000 is not difficult, and indeed may be obtained in a digital format (for example, from the gazetteer and DCW).

In contrast to rapid “address-matching” and “zip-coding” programs that are commonly included with GIS software for marketing and business applications, georeferencing of existing MOH field records was time-consuming and labor-intensive. Difficulties encountered included the repetition of community names, use of different scales, lack of maps with county and state boundaries, and data inconsistencies. Frequent plotting exercises, meetings with MOH field workers, and field reconnaissance opportunities were needed to review the results, ask questions, identify missing communities, and estimate positions. It is important to recognize that this tedious process was necessary despite the fact that we enjoyed the advantage of working at a relatively large (1:50,000) scale. Onchocerciasis-mapping efforts in Africa are usually not so fortunate (Ngouomou and Walsh 1993, Mace and others 1997, DeSole 1991).

Throughout the targeting exercise we had to keep in mind that we were not cartographers. The failure to produce a perfect map was not an excuse to slow the project; nor did we find that slight imperfections jeopardized the general usefulness of the final GIS for decisionmaking. Health officials, and their GIS consultants, must recognize that detail and scale may (and should) be sacrificed for the sake of time, money, and a higher purpose. Similarly, the paper maps we created would not have met a cartographer’s standards, since they contained data from different scales, and were only specifically
detailed to assist managers and field teams in accomplishing their programmatic objectives.

Although the community inventory could have been developed as an internal point layer from within Atlas*GIS (AGIS), we chose to make the community inventory database an independent point file that could stand alone, separate from the software itself. Rather than restricting ourselves to an internal position code generated within Atlas*GIS, we wanted our data in an industry-standard code (FoxPro®), and georeferenced with universal position coordinates (latitude and longitude). This strategy allowed easy transfer of the community inventory into other GIS formats (if a more sophisticated spatial analysis were required), and provided data safety in what was then a highly volatile software market (that is, rapid entry and exit of companies, formats, and data protocols). Using latitude and longitude coordinates also allowed easy addition of GPS data.

About 8 percent of the communities listed in the MOH database could not be found on the large-scale maps, so field readings on-site with a GPS became indispensable for completing the GIS. Horizontal position readings taken with the hand-held units could easily be introduced into a database of 1:50,000 scale. Elevation readings with a GPS, however, were not sufficiently accurate for our needs.

In contrast to GPS, readily available digital data (gazetteer and DCW) were not useful, as neither were sufficiently accurate to meet the demands of our MOH matching exercise. If we had used these readily available data sets we would have saved the time and costs of entering community data from large-scale formats (1:50,000 maps in this case) at the expense of completeness and accuracy when matching to MOH data files during the georeferencing phase of the project. The costs incurred building a digital map and community inventory from nondigital sources is decreasing now that maps can be converted to digital files using new scanning hardware. In any event, these costs should only be borne once, as other projects using a GIS should be able to benefit from the investment. Sharing of GIS data between units and institutions is important, but better yet is data trading of one data set or layer for another developed by other projects or sectors (such as agriculture or hydrology). GIS networking should be encouraged, since data trades can be a win-win situation for all involved (Hastings and Clark 1991).

GIS projects must make an effort to generate products helpful to the computer-illiterate field worker. Unless the GIS application is of use to the field workers actually involved in operations, the field workers will not provide observations to assist in the GIS development, and as a result the accuracy and validity of the GIS suffer. We found that production of GIS-generated paper field maps improved collaboration with the field teams, linked the office-based GIS unit to the actual field situation, and provided a route for the feedback needed to keep the GIS current. Printing large color maps
is now becoming more feasible in developing countries as the prices of large-format plotters drop.

For the present, GIS applications in the developing world have to be built, not bought. Training programs that teach new geographic positioning technology must devote time to developing "building" skills such as map digitizing, the importation of data from diverse sources, data sharing, and the use of GPS. Course curricula should provide exercises based on these real-life experiences, appreciation of scale, and anticipation of the problems of retrospective data review and georeferencing described here. If GISs are to be used in decisionmaking, the users must become efficient at combining and manipulating information from different sources and scales to get a timely result.

In conclusion, geographical information systems and georeferenced databases will play an increasingly important role in disease targeting activities in the future. The work and cost of building a GIS should decrease with increasing availability and cataloging of detailed (large-scale) digital data sets. We cannot envision, however, a way to avoid the major task of georeferencing existing epidemiologic data, which was the key element in this targeting exercise.

Notes

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Testing the GPS Unit

1. Thirty-three GPS readings were taken at the same open site (the NE corner of the football field on the campus of the Universidad del Valle de Guatemala, or UVG). GPS readings were compared with a position read from the appropriate 1:50,000 map. Figure 8.1 shows a spatial analysis (each tick = 100 meters) of the horizontal plain of the UVG football field. The star in the figure indicates the position read from the map. The central position of the GPS readings was 85 meters SSW from the map position. Figure 8.2 shows a plot of horizontal and vertical distances from the map position. Similar to the findings on the horizontal plane, 79 percent (26) of elevation observations fell within 100 meters of the map position.

References


A Geographical Information System Applied to a Malaria Field Study

Allen W. Hightower, Maurice Ombok, Richard Otieno, Richard Odhiambo, and William A. Hawley

How many people live within five kilometers of the proposed clinic location? Where are the houses in the village that were included in a survey of the use and acceptance of insecticide-impregnated bednets? What spatial features, such as proximity to seasonal streams, are associated with the prevalence of households that have elevated malaria transmission pressure, even during the dry season? During the dry season, are there focal areas of elevated mosquito abundance that can be targeted for an effective control program? These questions demonstrate just a few of the reasons that the analysis of spatial relationships has long been an integral part of public health planning, day-to-day operations, and research activities. Although affordable geographical information system software has simplified this effort, an accurate base map is required for any GIS analysis. Lack of such maps is a substantial obstacle for researchers wishing to perform geographic analysis in tropical disease research since studies are often conducted in areas where existing maps are inaccurate, insufficiently detailed, or outdated. Various methods, each applicable to particular circumstances, can be used for base map production. Performance of a geographic survey requires special skills beyond the reach of those not professionally trained in these methods. Sketch maps are normally created only for operational purposes. They are inaccurate and lack a coordinate system needed for spatial analysis. Satellite images and remotely sensed data are useful when finely detailed spatial analysis is not required (Beck and others 1994, Clarke and
others 1991, Malone and others 1994, Malhotra and Srivastava 1996). Aerial photography is expensive if archived aerial photographs are not available to the researcher (Gunawardena and others 1996). Furthermore, security concerns can make access difficult. Use of the global positioning systems can provide an accurate, detailed map of any tropical site. As explained in more detail later, a GPS unit is a hand-held electronic tool that uses signals from satellites to compute the longitude, latitude, and altitude of a location. Without differential correction, GPS provides adequate, but not extraordinarily accurate maps (Snow and others 1993, Richards 1993). A simple modification of a GPS, known as differential GPS (DGPS), can be used to produce a highly accurate base map in a tropical area. In this chapter we detail the use of differential GPS to map an area in western Kenya where two large-scale studies are being conducted, perform some simple spatial analyses by linking study data from these and other projects to these maps, and discuss the other applications of this system. The GPS and GIS mapping technology presented here will also be contrasted with that presented earlier to demonstrate how this technology has improved rapidly from the standpoint of user friendliness over the past few years (Hightower and others 1998).

Two collaborative studies between the Kenya Medical Research Institute (KEMRI) and the Centers for Disease Control (CDC) of the development of natural immunity to malaria and the use of insecticide-impregnated bednets in reducing childhood mortality in western Kenya provided the framework for this effort. The longitudinal study of the development of immunity to malaria in young children was carried out in a 70-square-kilometer area in Siaya district in western Kenya, approximately 50 kilometers southwest of Kisumu (Shi and others 1996). Clinical, hematologic, parasitologic, immunologic, entomologic, and demographic data were regularly collected for each participating family in 15 villages. The demographic data consisted primarily of census data collected at the beginning of each project and updated regularly. The entomologic data consisted of weekly trap collections for each study household. Clinical data were collected biweekly. Blood samples were obtained monthly or whenever any fever was reported. Blood samples were used to measure parasitemia, hemoglobin levels, and on certain subsamples, immunologic parameters. Since all of these data were collected with household identifiers, opportunities for examining spatial hypotheses exist in many disciplines if a map of study households, health care centers, mosquito larval habitat, bodies of water (such as rivers and lakes), roads, and other features of interest could be produced in a computer-readable format and linked to the various study databases through a GIS and other statistical software. Existing maps and aerial photography were either unavailable, inaccurate, or too outdated to be useful for mapping
households and many of the other features of interest (Survey of Kenya 1970).

The second project, which includes the 15 villages in the natural immunity project and over 60 more in adjacent areas, evaluates the effect of insecticide-impregnated bednets on childhood mortality. This is a simple and inexpensive intervention. Bednets are soaked in an odorless insecticide and draped over beds to keep mosquitoes out. The insecticide prevents the mosquitoes from entering the net, even if there are small holes in the net. Because malaria-transmitting mosquitoes feed only at night, sleeping under the nets should effectively reduce illness and mortality due to this disease. All of the villages in this project have now received bednets. Since the Immunity study villages were also included in this chapter’s study, we had detailed longitudinal data on a subset that allowed us to evaluate the effects of using impregnated bednets on the development of a child’s immune system, as well as their impact on mosquito populations in the study area.

Methods

The Global Positioning System

Twenty-four satellites (21 for navigational purposes, 3 active reserves) orbiting at an altitude of approximately 10,900 miles (20,200 kilometers) form the global positioning satellite network (French 1996). GPS satellites continuously broadcast the time and their orbital path to provide the information used by a terrestrial GPS unit. Data received from four satellites allow the GPS unit to calculate latitude, longitude, and altitude, while data from three other satellites allow calculation of latitude and longitude only. The exact methodology for how position fixes are computed is described in detail elsewhere (French 1996, Herring 1996).

GPS Errors

The computations of a GPS position fix are subject to error from several uncontrolled factors—among others, atmospheric conditions (French 1996, Herring 1996, Magellan Systems Corporation 1995). The largest error component, selective availability (SA), is the intentional error component added for security purposes at each satellite. Because SA error varies with time and from one satellite to the next, when a GPS unit changes the group of satellites it is using to compute a position fix, the different SA error term results in a sudden change in the computed location. As long as the same set of satellites is in use by the GPS unit, errors are highly correlated with respect to time. This prevents short-term averaging of GPS readings to circumvent
the deleterious effects of SA. A single reading on a standard GPS unit has an
error of 100 meters horizontal, and 156 meters vertical (French 1996, Herrig
1996). Approximately 55 meters of the horizontal error is due to SA
(Magellan Systems Corporation 1995).

Differential GPS

Errors of 100 meters for horizontal measurements (latitude and longitude)
and 150 meters for vertical accuracy are far too large to make simple GPS
use practical for mapping the locations of objects that are relatively close
together, such as households within villages. Such large errors will result in
gross distortion of the true spatial relationships between the measured
points, and make a map produced with simple GPS readings very confus-
ing to use for operational purposes.

Differential GPS circumvents the effects of SA and environmental errors
to produce a highly accurate position fix. Several different approaches to
gPS exist, but each employs the principle of having two GPS units simulta-
aneously taking readings from the same set of satellites. One GPS unit is
located at a fixed control site, preferably a known location, and the others
become the roving field units. As a result, the position fixes for both GPS
units are subject to the same SA and clock error terms. If the units are rela-
tively near to each other (under 50 kilometers), the precisely timed GPS sig-
nals travel through similar ionospheric and tropospheric conditions
(Magellan Systems Corporation 1995). For both units, each position fix is
stored to a computer file, along with the exact time of the reading and the
set of satellites used to compute the location. The matching files for the two
GPS units are then downloaded to a computer. Software is used to pair or
synchronize readings that were taken at exactly the same time. There are
several techniques for doing this, but for each, the location of the remote
GPS unit is computed by adding the distance between the two GPS units to
the known location of the control GPS unit. In our application, this involved
simultaneous creation of computer files on control and remote GPS units,
followed by copying these files to a computer and running software to fig-
ure calibrated positions.

We established a GPS base station to serve as a control point near at the
computer center in our field station near Kisumu, Kenya. A collapsible 8-
meter antenna was constructed to lift the receiver above any obstacles that
might block satellite signals. A cable connected the antenna to the GPS unit,
which in turn, was connected to the computer. The exact location of the con-
trol GPS unit was unknown, so thousands of readings were taken over sev-
eral days and averaged to provide an estimate of the true location. Because
this position was used as a correction factor for all remote sessions, any
error associated with estimating the control location was consistent across all remote points—having the effect of moving the entire map in one direction or another.

Equipment and Personnel

We used four Magellan Pro Mark Xcp GPS units (Magellan Systems Corporation 1995). (Use of trade names is for identification only and does not imply endorsement by the Public Health Service or by the U.S. Department of Health and Human Services.) These units use the latest “all-in-view” technology described below. The units record data from all available GPS satellites, unlike previous generations which required manual selection of satellites based on a software analysis of satellite orbits (Hightower and others 1998). One unit is used for the permanent GPS base station, and the other three are field units. Tripod antenna extensions (2.5 meters) for each field GPS unit, battery powered hand held radios, replacement batteries for the GPS units, and a list of compounds to be mapped round out the equipment list for the field teams. Total equipment and software costs were approximately US$25,000 for the GPS equipment and GIS software. (Note that all dollar amounts in this paper are U.S.) One person is needed to operate each of the three field GPS units. A local village health worker who knows where to find the points (compounds, stores, and so forth) to be mapped meets each field GPS team member. A computer specialist, working part-time on this project, was responsible for GPS to PC data communications at the field station, using the Microsoft Windows® 95–based post-processing software to compute the calibrated positions, to enter data on a Pentium® computer.

About one hour of computer work was necessary to process six hours of GPS data—generally between 6 and 8 megabytes of data representing roughly 100 positions. Approximately six person-months of effort were required for the fieldwork, post processing, and data entry for this relatively large-scale mapping project. Total costs of labor and supplies to map the bednet project area have not exceeded $10,000. However, these costs are highly dependent upon where the work is being done, and will vary with different mapping projects.

GIS Analysis

Atlas GIS (Environmental Systems Research Institute, Inc. 1991), ArcView 3.0 (Environmental Systems Research Institute, Inc. 1996a), and SAS (SAS Institute 1989) were used for all spatial analyses. Location information was linked to parasitology and entomology databases through common
identifiers. In the Immunity project, there was entomologic, immunologic, epidemiologic, meteorologic, demographic, and parasitologic information that could be linked to each household.

Automated or batch computing of distances between one group of points to another is a feature that is not available in the popular entry-level GIS programs unless supplemental programming tools or extension modules are purchased. A SAS program was developed that computes all possible distances from one group of points to another, chooses the smallest distance from each point in the first group to any point in the second group, and then creates an output database with household identifiers and the desired distances. The distance computations account for the curvature of the earth by computing arc length instead of linear distance (USGS paper 1395). This distance is then used as a basis for computing spatial statistics (that is, the parasitemia rate for households 0–200 meters, 201–400 meters, and so on from the nearest mosquito breeding site) or can be used in further statistical modeling. This process is called buffer creation and is available in virtually all entry-level GIS packages without supplementary programming.

GIS software is necessary for displaying data on maps and customized map production. GIS maps consist of layers. A map layer is defined by the user's convenience, but normally consists of a group of related features. For example, compounds, roads, streams, medicine stores, and schools are stored in separate map layers in this system. We can turn layers on or off as desired, highlight compounds to be visited for survey purposes, or restrict the map to a subset of villages to produce customized maps. Data can be associated with any map layer. Buffer zones can be created (for example, to highlight all households with 500 meters of the lakeshore). A map that displays data, such as the number of mosquitoes trapped in a household during a specific time period, is called a thematic map. Data of this type can be presented with a dot at the compound's location, with the size of the dot being proportional to the magnitude of the variable mapped. A map of the United States with the states having color or shading that is related to the incidence of a particular disease is another example of a thematic map. In our application, virtually all of the databases are related to households, or individuals within the households. For several years, Atlas GIS, an entry-level GIS product, met all of our customized mapping and thematic mapping needs.

However, modules that greatly expand the spatial analysis capabilities of entry-level GIS software can be purchased and used, if statistical programming expertise is not available. ArcView has many of the same features as Atlas GIS, but it is more expandable from the standpoint of offering several specialized analysis modules. While not inexpensive, these modules
offer greatly enhanced analytic capabilities in specialized areas. The ArcView Spatial Analyst module (Environmental Systems Research Institute, Inc. 1996b) was used for the surface interpolations. Surface interpolation takes the concept of the thematic map a step further by expanding the analysis from the compound locations to the entire area containing the compounds. Given the map of compound-level mosquito abundance, it finds the best-fitting surface that smooths the observed data points. Such a surface shows the contours of mosquito abundance or malaria risk for the study area and could be used to identify areas of high, medium, and low mosquito abundance or malaria risk. High-risk abundance areas would then be logical targets for focal control efforts, if these areas could be demonstrated to be reasonably consistent across time. They would also allow the estimation of the vector abundance for any proposed building site in the study area. Spline functions, kriging, and inverse distance weighting are a few of the methodologies for estimating these surfaces (Cressie 1993). For this chapter, inverse distance weighting was used to interpolate surfaces. The map of the study area is divided into a grid, and the observed data for the dozen nearest compounds to the centroid of the grid cell are then averaged with weights inversely proportional to the distance from each compound. This process is repeated for each cell of the grid to obtain the smoothed surface for the variable of interest. The estimates can then be categorized to form contour lines, if desired. This is a general methodology that allows many of the fitting parameters to be varied as desired, such as the number of nearest neighbors used, the criteria for determining nearest neighbors, or the functional form of the inverse proportionality (linear, quadratic, or other polynomial).

Quality Assessment

Maps of each of the 15 villages were produced and distributed to village monitors, who assessed their accuracy and completeness. Special opportunities often arose for external validation. Many households were near roads, so they were checked to verify that the map showed them on the proper side of the road and at the correct approximate distance. Households or compounds that were clustered were also checked for proper distances and relative geometric relationships. Features of interest that had not been mapped were noted for later inclusion.

The performance of the GPS units and the post-processing software, as well as correct usage by the operators, was checked by placing the two units next to each other, designating one as the control unit, collecting positional information for 20 sessions of 5 minutes each, and computing the calibrated location of the remote unit. The mean and standard deviations of the
calibrated longitudes, latitudes, and altitudes of the remote units were then computed.

Demonstration Data

Entomology and parasitemia data from the Immunity study for the months of June and September 1995 are presented to represent rainy and dry seasons, respectively. Parasitemic compounds were defined as having at least one child under five with any malaria parasitemia during the month in question. We had parasitologic and sufficient entomologic data (three or more visits during the month) for 394 households in June and 416 households in September. Potential larval habitats were defined as the lakeshore, streams and rivers, and pits dug to collect water for cattle. Multiple linear regression, correlation coefficients, and $r$-square statistics for each month were used to examine the relationship between distance from major mosquito breeding sites and average numbers of trapped mosquitoes by species for each month.

Results

The Bednet project (figure 9.1) covered an area of 192 square kilometers over a rectangular area roughly 12 kilometers long and 7 kilometers wide, encompassing 75 villages. Geographic features included 7,209 compounds, 65 schools, 1 nursery, 1 polytechnic school, 110 churches, 9 health care facilities, 1 rural AIDS counseling center, 70 major mosquito breeding sites, 10 borehole wells, 7 shopping areas, major roads, streams, and the shore of Lake Victoria. In terms of distances, 42.0 kilometers of roads, 54.3 kilometers of streams, and 15.0 kilometers of lakeshore were mapped. The Immunity project area (figure 9.2) contains 15 villages in the southeastern section of the Bednet project.

Of the twenty sessions taken with the two GPS units stationed next to each other, one (5 percent) had insufficient overlapping data to estimate a calibrated position. This is normally caused by the loss of a satellite signal during a session. Of the 19 remaining sessions, the longitudes had a standard deviation of 4.01 meters, the latitudes had a standard deviation of 5.34 meters, and the altitudes had a standard deviation of 4.78 meters. The two-dimensional standard deviation of these sessions was 3.11 meters and the standard error of the mean was 0.714 meters.

Table 9.1 relates parasitemia prevalence and entomologic measures to the distance from the household to the nearest major larval habitat. For the month of June 1995 (a rainy month), the average household prevalence of parasitemia in children less than 5 years old steadily decreased with
### Table 9.1 Parasitemia Prevalence and Entomologic Measures by Household and Distance to the Nearest Mosquito Larval Habitat, June and September 1995

<table>
<thead>
<tr>
<th>Distance to nearest larval habitat</th>
<th>Parasitemia rate (percent) in children &lt; 5 years</th>
<th>Anopheles gambiae: average number trapped per collection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Month</td>
<td>Month</td>
</tr>
<tr>
<td>0–200 meters</td>
<td>June 75.8+39.1 n=75</td>
<td>June 1.76+2.53 n=69</td>
</tr>
<tr>
<td></td>
<td>September 58.5+47.8 n=71</td>
<td>September 0.09+0.19</td>
</tr>
<tr>
<td>201–400 meters</td>
<td>June 71.1+42.7 n=214</td>
<td>June 1.49+1.71 n=176</td>
</tr>
<tr>
<td></td>
<td>September 69.4+43.4 n=206</td>
<td>September 0.05+0.18</td>
</tr>
<tr>
<td>401–600 meters</td>
<td>June 70.2+43.1 n=117</td>
<td>June 1.90+2.31 n=113</td>
</tr>
<tr>
<td></td>
<td>September 64.7+45.3 n=109</td>
<td>September 0.03+0.10</td>
</tr>
<tr>
<td>&gt;600 meters</td>
<td>June 67.1+46.3 n=39</td>
<td>June 2.09+2.05 n=37</td>
</tr>
<tr>
<td></td>
<td>September 57.8+47.7 n=30</td>
<td>September 0.02+0.06</td>
</tr>
<tr>
<td>p-value*</td>
<td>0.3437</td>
<td>0.1530</td>
</tr>
<tr>
<td></td>
<td>0.5594</td>
<td>0.0039</td>
</tr>
</tbody>
</table>

Note:
- * Linear regression, two-tailed test. Percent of children in household with parasitemia or average number of mosquitoes captured per weekly trapping session versus minimum distance (in meters) from household to nearest larval habitat.
- n = number of mosquitoes captured.
- Source: Hightower, Otieno, and others 1998.

Increasing household distance (defined in 200-meter buffer categories) from larval habitat, but this difference was not statistically significant ($p = 0.3437$ linear regression). There was no relationship between distance to larval habitat and average parasitemia prevalence for the month of September, a dry month. Average numbers of trapped mosquitoes were related to the distance of the household to the nearest breeding site for *Anopheles gambiae* for the dry month, but not the wet month (September: $p = 0.0039$; June: $p = 0.1530$, linear regression).

Figure 9.3 shows the average number of trapped *Anopheles gambiae* weekly by household for the months of June and September 1995. The size of the dot for each household is proportional to the average number of mosquitoes collected during the weekly trappings for that month. Mosquito abundance drops off rapidly from June to September. Villages vary significantly in the numbers of mosquitoes trapped by household (all months, $p < 0.01$, one way analysis of variance). There is considerable variation in mosquito abundance both within and between villages.

Figure 9.4 shows the interpolated surfaces for the average number of *Anopheles gambiae* trapped weekly for the same two months of July and September 1995. Overlaid on the surfaces are the compound-specific abun-
dance measures shown in figure 9.3. Assessment of the overall trends is much easier in figure 9.4 than in figure 9.3. For example, in June, most of the study area is in the two highest categories. In September, most of the study area is in the two highest categories. Also, notice that it is much easier to see specific details in the transition in the areas of high and low transmission pressure from rainy to dry season in these maps when compared to the
Figure 9.4 Estimated Areas of High, Mid-High, Mid-Low, and Low Mosquito Abundance

June 1995

September 1995

Source: Author's calculations
maps just showing vector abundance by compound. Assessment of the potential mosquito abundance at proposed new construction sites is also much more easily done with figure 9.4 than figure 9.3.

Discussion

We have shown that it is feasible to use differential GPS to produce a highly accurate map of study households and other points of interest in a large-scale study of malaria in an area encompassing more than 75 villages over 190 square kilometers. Without differential GPS, positional errors are such that any mapping of objects within 200 meters or so of each other will yield inconsistent spatial relationships between map features, since the errors associated with use of nondifferential GPS can be on the scale of 100 meters. Use of simple GPS readings is appropriate when the objects to be mapped, such as villages, are relatively far apart (Richards 1993). In addition, we have shown that it is easy to map linear features such as roads, rivers, and lakeshores. The comprehensive maps have considerable use in the operational activities of the project and a GIS allows customized maps to be produced rapidly.

Even though DGPS was used to map our entire study area, other groups may find different existing digitized base maps a useful starting point, such as the Digital Chart of the World (Defense Mapping Agency of the United States); digitizing existing small-scale maps can also provide a basis for geographic mapping. Searching the Internet or querying GIS interest groups on the Internet is a worthwhile activity to find such maps. In our experience, these maps were quite old, and when checked, not accurate enough for our needs. It is relatively simple to combine GPS-produced maps with existing digitized maps, but one must be careful to convert both types of maps to the same map-projection system (like UTM) before combining them. This is easily done even in entry-level GIS software.

Our efforts at quality assessment raise several points. First, the results from the 20 sessions with the GPS units adjacent to each other demonstrate the greatly increased precision associated with differential GPS. A previous study not using DGPS reported a standard error of 47 meters associated with repeat measurements of 43 randomly selected households (Snow and others 1993), with an average discrepancy of 36 meters from the original measurement. In our example using DGPS, the standard error (variability of the mean of a group of 19 measurements) was 0.714 meters, or a standard deviation of 3.11 meters (reflecting the variability in the calibrated readings). Thus, DGPS greatly reduces the errors and variability in positional measurements associated with mapping. This allows mapping of features that are close together in a manner that will maintain spatial relationships with a high degree of integrity.
The expense and effort required to create this GIS was small relative to the other costs of the two field projects, with expenses being approximately $35,000. Of this amount, approximately $25,000 was for hardware and software. The GIS maps, databases, and GPS equipment and expertise continue to be used on other field activities. Those conducting smaller scale projects or one-time studies should consider renting DGPS equipment to reduce costs. DGPS equipment has made dramatic improvements in user friendliness and novices can become quite proficient in less than a week. DGPS units can be rented for approximately $150 per week, depending upon features. Rental of 4 high-end units for a month would then cost about $2,500—a substantial savings. Given the differential between purchase and rental costs, renting equipment and bringing in an expert consultant is a financially viable option in many cases.

Training field staff to perform the necessary duties for DGPS mapping presented no difficulties. Because existing staff were employed for the mapping operations on a part-time basis, the new duties were a novelty, and the opportunity to use recent aerospace technology to produce a map of the study area was exciting to all involved. Moreover, recent improvements in GPS technology have greatly simplified mapping operations. Improvements include faster GPS-to-PC communications, and the ability to obtain sub-meter accuracy with data collection sessions of less than 10 minutes. The net effect is to make the use of differential GPS a much simpler process than just two years ago. Our experience with even newer differential GPS units confirms that they continue to become even more user friendly.

A system such as DPGS has several applications outside of the mission of our operation. Since there is census and demographic information available for each compound, a GIS could be used for many types of public health planning for activities in the area. The system could be used, with the inclusion of buffers, to summarize the population characteristics within the catchment areas, or within walking distance of existing or proposed health care delivery systems such as clinics, medicine stores, nutrition programs, or vaccination campaigns. Indeed, many of the urban planning and marketing applications of GISs could have parallel uses in public health planning. Other surveys conducted in the study area could be linked to the GIS as long as they use the same compound identifiers.

The analyses presented here were intentionally simple and were intended to present only some of the potential uses of the GIS and GPS data. We have shown that GIS software need not be mastered to conduct many useful spatial analyses once locational information has been obtained. Indeed, the spatial capabilities of the most popular entry-level GIS programs are limited, and the automated computation of distances requires supplementary programming efforts or purchases (Kitron and others 1994). Fortunately, computation can be easily done in most statistical programs.
Our example used distance in 200-meter categories (or buffers) from the household to the nearest major potential larval habitat. However, many other distance variables, such as distance to the nearest health clinic or medicine store, could just as easily be computed and additionally incorporated into a statistical analysis.

However, GIS software is necessary for displaying data on maps, because it can produce customized maps, using observed data at many points (in our case, compounds), of a study area to estimate areas of high and low risk of disease or abundance of a vector. Most of these tasks can be handled by any entry-level GIS program, which will also handle most day-to-day operational mapping needs of the project. An entry-level GIS provides the tools needed for most, if not all, planning operational activities. Creation of buffer zones to see how many people live within 5 kilometers of a proposed clinic site is an example of such a task. Buffer zones can be used to assess risk factors, such as nearness to rivers during dry seasons. A GIS gives control programs the ability to monitor exactly what is happening down to the compound level. Entry-level products can be used to produce monthly maps of mosquito abundance by compound. More advanced GIS and spatial analysis topics include examining issues of time-space clustering and surface interpolation, which are more germane to the research and control aspects of a program. Surface interpolation allows the estimation of risk or prevalence contours, which allows targeting of control or treatment programs. These two tasks require the use of a mid-level GIS program with the purchase of supplemental modules or the availability of a person with statistical or GIS programming expertise.

Key to making a GIS work is the availability of personnel with expertise in GIS software to the operational and research staff of the project. This person should have a relatively well-equipped, but not necessarily expensive, Pentium-class computer with generous memory and hard drive capacity, at least a 17-inch monitor, and a reasonable color inkjet printer available with sufficient supplies for the needs of daily map production. All of this can be purchased for well under $3,000. GIS software can be purchased for as little as $800 to as much as $5,000, depending upon the sophistication of the product and the number of add-on modules. As entry-level GIS software can be easily mastered, this level of expertise should be easy to develop within an existing organization.

Our current activities include more in-depth analyses of the entomological and parasitological data (Hawley and others 1998, Hightower, Ombok, and others 1998, Hightower and others 1997, Gimnig and others 1998). Remote sensing data on vegetation zones and hydrology taken at several times during the study period will be added for analysis of the effects of ecological change on the study outcomes. Cross-sectional surveys on the prevalence of bloody diarrhea and childhood mortality have been linked to a GIS
to investigate clustering for these issues. Researchers using data from this field site now have the option of investigating the spatial aspects of virtually any topic they are pursuing.

We have shown that survey-grade GPS mapping and GIS analysis are affordable, feasible, and useful in the planning, operational, and research activities of a tropical disease research site. These tools, once the province of highly trained professionals, have become sufficiently user-friendly that even novices can successfully employ them. As a result, applications are becoming more commonplace, and GISs and GPSs are becoming part of the everyday vocabulary. Public health professionals would be well advised to consider the benefits of GISs and GPSs while they are planning new tropical disease field activities.

Notes

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Allen Hightower and William Hawley are at the Division of Parasitic Diseases, National Center for Infectious Diseases, National Centers for Disease Control and Prevention, Atlanta, Georgia. Maurice Ombok, Richard Otieno, and Richard Odhiambo are at the Kenya Medical Research Institute.

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A Geographical Information System as a Component of the Animal Health Information System in Thailand

Pramod Sharma and Angus Cameron

In most developing countries, agriculture is the major sector in the economy, and employs a large proportion of the population. For agriculturalists in these countries livestock are often one of their most important assets, second only to land. The Paris-based Office International des Épidémiologies (OIE) estimates that animal disease may result in losses of up to 20 percent of production (OIE 1993). Diseases of livestock have serious effects at many levels, especially as they are usually more severe, more widespread, and inflict more social and economic damage than in industrial countries. At the same time, the resources available to identify, assess, and control these diseases are often scarce. For this reason, it is important that any resources available are effectively targeted to achieve the most benefit.

Accurate information about the health status of a nation’s animal population is critical in the fight against animal diseases. Without measures of the frequency and economic importance of a particular disease, a government’s task of targeting disease control is almost impossible. Without comprehensive disease reporting systems and ongoing measures of recording disease incidence, the efficacy and endpoint of any control program is impossible to measure. Without an internationally acceptable system of epidemiological surveillance and animal health information management, the establishment of national freedom from disease or a disease-free zone is impossible to achieve.

Unfortunately, in many developing countries the systems in place for the collection, management, and reporting of animal health information are not
able to gather the type of information required for informed priority setting, disease control program planning, implementation, and monitoring. Nor are these data-collection systems able to meet international requirements for the substantiation of claims of freedom from disease. This is despite sometimes substantial investment in veterinary infrastructure and disease control activities, such as laboratory diagnostic facilities and vaccination programs.

This chapter reports on research that was carried out in Thailand and the Lao People’s Democratic Republic (Lao PDR). The Thai study area consisted of the three northern provinces, Lampang, Lamphun, and Chiang Mai. The area covers about 40,000 square kilometers and approximately 3,000 villages. The Lao PDR study area selected consisted of Vientiane Municipality, covering about 3,600 square kilometers and containing approximately 500 villages. In Lao PDR, there has previously been virtually no development of an animal health information system. While Thailand represents one of the most advanced of the developing nations in Southeast Asia, Lao PDR is one of the least developed, and the need for improved animal health information is obvious.

Farming systems in Thailand and Lao PDR are similar, despite differences in their levels of development. The main livestock species are cattle, buffalo, pigs, and chickens. Foot-and-mouth disease (FMD) in village cattle and buffalo was chosen as the “model” disease for the development of the techniques. This disease was chosen because it has a significant impact on the livestock industries of countries in which it is endemic and it arouses a great deal of international interest and funding (mainly because of its importance to trade).

The purpose of the research project was to improve animal health by addressing the problems of a lack of reliable population-based information, poor data management, and reporting in both countries. We proposed that a strategic approach, involving the introduction of two core elements of an animal health information system, could effectively address the problems of the systems currently used in developing countries. These core elements are (a) the collection of key animal health information using active surveillance techniques, and (b) the introduction of appropriate information technology (including a GIS), to improve the collection, management, analysis, and reporting of animal health information.

Animal Health Information System in Thailand and Lao PDR

An animal health information system is a system for the collection, storage, analysis, and reporting of information related to the health of animals. As such, virtually every country has some form of animal health information system. There are, however, a wide range of systems that reflect the interaction of the following factors and limitations: disease situations (generally
endemic diseases with high morbidity or high mortality, or both); dependence on agriculture (when the agricultural sector is a major employer); veterinary infrastructure (generally poorly developed with staff having only basic skills), physical infrastructure (where poor communications and transport systems can make it difficult to provide services and gather relevant information); financial resources (where the collection of animal health information has lower priority); and integration of technology (where dominant paper-based systems can limit efficiency).

While published materials are scarce, we can evaluate the characteristics of existing animal health information systems in terms of their ability to achieve four broad objectives: (a) to collect basic animal health information; (b) to help assess priorities and develop policies; (c) to support the implementation of disease control programs; and (d) to meet international disease-reporting obligations. This discussion is limited to an examination of the animal health information systems of Thailand and Lao PDR.

Both the Thai and Lao PDR systems are only partly able to identify which diseases are present and their geographic distribution. Information from laboratory submissions may only be used to identify which diseases are being diagnosed more often or which diseases are resulting in laboratory submissions, but it does not indicate the significance of those diseases. Both Thai and Lao PDR systems are unable to make valid incidence or prevalence estimates. The disease information upon which these estimates must be based comes from the diagnostic laboratory submissions. The proportion of actual cases of diseases that results in submissions is unknown, and the source population is unknown.

Thailand’s FMD serosurveillance system attempts to collect data from a representative sample of villages to estimate the proportion of animals with protective titres against FMD. Unlike passive data collection systems, it uses survey techniques to collect data from a sample of livestock and uses data from this sample to make inferences about the population. While the data from the serosurveillance is potentially much more representative of the population than passively acquired data, the sampling strategy employed (purposive sampling of villages, and convenience sampling of animals) results in biased data of unknown precision.

Neither system is able to collect the valid, quantitative epidemiological data that is necessary to determine the epidemiology, geographic, and temporal patterns of disease, and risk factors associated with the major problems. There is virtually no capability to manage, analyze, or report information on the spatial distribution of disease, except in crude tabular form, or through the use of inaccurate, hand-drawn maps. Neither system routinely collects information on the impact of diseases or the losses associated with them.

Village livestock population figures are collected by both countries, and these figures may be used to estimate the population at risk for incidence or
prevalence calculations. Similarly, livestock movement and vaccination data are collected. Although these data sources may be reported, there is no integration of this data with the rest of the system, and no analysis. For instance, vaccine usage data for a particular area cannot be easily linked to outbreak data from the submissions database, or to population data to help determine the likely number of susceptible animals in the area. Livestock movement data is not analyzed for movement patterns that could be linked to outbreak data to predict areas where disease is likely to spread. There is no capability for this type of spatial analysis or modeling.

The information currently collected by both systems may be used for setting priorities. However, the limitations of these reporting systems, such as the inability to make assessments of the relative economic impact of different diseases, mean that the basis on which decisions are made may not be valid. Reporting systems are based on the use of written or verbal descriptions, and tabulated data and the right information are often not available for decisionmakers.

No continuous disease monitoring is taking place in Lao PDR. Rabies and FMD monitoring is used in Thailand to support the control programs. Figures gathered might certainly assist in program evaluation, but problems with sampling mean that there is a danger that the results could be misleading. Analysis of this data is unable to properly describe variations in the geographic distribution of the diseases, which may be important to the understanding of the epidemiology and control of the disease. The laboratory submission system currently in place in both countries is appropriate for the detection of emerging diseases. However, the systems used in Thailand and Lao PDR are unable to provide convincing measures of disease occurrence nor support claims of freedom from disease.

Data-handling systems are not adequate to provide consistent and reliable figures. For example, two Thai sources differ almost fifty-fold in reporting the total number of animals having contacted FMD in 1992. Such discrepancies in internationally published data undermine the credibility of disease status claims. For international trade purposes, trading partners are now in a position to demand epidemiologically sound substantiation of claims of disease freedom or of disease prevalence levels. The systems in Thailand and Lao PDR are not able to provide proofs that would withstand epidemiological scrutiny. It appears that most of the reasons why animal health information systems fail in developing countries are outside the control of veterinary authorities. However, it is clear that two key problems within the veterinary authorities’ control severely limit the effectiveness of systems: the absence of valid measures of disease occurrence at the population level, and problems with data management.

Disease information in the systems described is collected primarily through the diagnostic laboratory submission system and represents a pas-
sive surveillance system. The livestock owner initiates submission of specimens in order to make a diagnosis and solve the disease problem. Passively acquired data has the advantage that it may be less expensive to collect than other data sources (Martin and others 1987, Willeberg 1985). All that is needed is a recording system, as the data is already being generated for diagnostic purposes. The disadvantages of passive surveillance systems are that the disease information is usually incomplete and biased, and reliable measures of disease occurrence cannot be calculated (Hueston 1993). The concerns regarding limitations of passive surveillance are well documented (see, for example, Oka and others 1992, Ogundipe and others 1989, McCallon and Beal 1982, and Hurd and others 1994).

Animal health information systems use data from a range of sources. Currently in Thailand and Laos PDR, each type of data is analyzed and reported in isolation—laboratory submission data, livestock population data, livestock movement data, surveillance data, and vaccination data. To provide value-added information to decisionmakers and disease control program administrators, these different data sources need to be integrated so that the relationships between them can be better understood. Centralized data storage systems that manage data at a fine level of detail are required.

In Thailand, although complex reporting systems exist, the presentation of data is often confusing and difficult to interpret. Information relating directly to animal health may be buried amongst administrative data, and long series of tables deter the reader from searching out the real meaning. For instance, the Livestock Development Regional Annual Reports from the Department of Livestock Development (DLD) in Bangkok are the main reporting instruments for animal disease in each of the nine regions. The 1994 report for Region 5 contains 173 pages, made up of one map, one graph, and the rest tables and text descriptions. Administrative information makes up 82 percent of the report, and disease information 18 percent. Only one percent contains any form of analysis and interpretation. A great deal of data is contained within the report, but it is in a form which makes it hard to interpret and difficult to access.

Improving the Animal Health Information System

A wide range of solutions would be needed to address the many problems that have been identified. Our research proposed that the main limitations of the information systems could be addressed using a strategic approach to implement the core elements necessary for an effective system. These core elements are improved information gathering, based on active surveillance, to quickly collect data for reliable, unbiased measurements of disease occurrence; and appropriate implementation of information technology in the form of a
geographical information system (GIS) to improve animal health information management and reporting.

In order for these core elements to be effective in the developing country context, they must meet a set of four key criteria arising from the constraints faced by Thailand and Lao PDR: (a) any solution must be able to be implemented at a reasonable cost; (b) information must be able to be gathered and processed quickly, so that it is still relevant when it is used for decision-making; (c) information must be reliable; and (d) any solution must be able to be practically applied and be appropriate for the situation in which it will be used.

Active surveillance involves the active collection of accurate and representative field data on the health of the livestock population (Martin and others 1987). To maximize the value of active surveillance, it must be based on statistically sound survey techniques (Hueston 1993). In theory a survey can be a total count of the population—a prohibitively expensive exercise. Usually the survey is based on a small proportion of animals in the population (that is, a sample). The validity of sample estimates from a survey depends on how representative the sample is of the study population.

There are many ways to select a sample from a population for a survey (Cochran 1977, Levy and Lemeshow 1991, Kish 1995). Every sampling strategy is a compromise between many competing factors, such as data accuracy, cost, ease of field operations, and complexity of analytical procedures. These considerations mean that the use of more complex sampling designs are beyond the capacity of the veterinary services of most developing countries, without the assistance of external statistical expertise for survey design and analysis. They explain in part the failure of developing countries to adopt active surveillance techniques. Clearly, problems of resources and infrastructure must be addressed in the larger national context. However, the research undertaken in our study attempted to address some of the reasons for lack of adoption of sound active surveillance techniques. The question of how active surveillance techniques could be implemented in developing countries was also considered. The use of a GIS in this context was regarded as crucial.

A GIS is a specialized computer database that handles two types of information: geographic information (the location of features, be they countries, administrative boundaries, rivers, roads, villages, or farms); and attribute data (for example, the attributes of a village may include the name, the number of each species of animals present, diseases that have occurred, the average titre of the animals to a particular pathogen, feed available and so on). What makes a GIS different from a standard database is its ability to perform spatial analysis on the information stored. The spatial relationship between features and their associated attributes can be analyzed to reveal underlying patterns.
One of the objectives of an animal health information system is to provide a better understanding of the epidemiology of disease. An important component of the epidemiology of a disease is the distribution of that disease in relation to a number of factors (such as species, age, sex, and time). One of the most important of these factors is the disease’s geographic distribution (Garner and Nunn 1991). The use of a GIS offers the ability to include the spatial distribution of disease in the analysis of all the other factors (Clarke and others 1996).

Examination of the spatial component of animal health data via a GIS also provides the ability to quickly identify data errors, since missing and out-of-range data are easily identified when the data is mapped. Disease maps are able to convey the relative levels of disease graphically, through the use of color or different symbols. They also convey the relationships between different geographic areas. The production of accurate, attractive, well-presented disease maps can be completely automated, and achieved in seconds, given a database of up-to-date information.

Many authors have recommended the specific inclusion of a GIS in an animal health information system (Morley 1988; Sharma 1994, Thursfield 1995). A GIS has been successfully applied to a number of specific problems in veterinary epidemiology, such as estimating the risk of East Coast Fever to livestock in Africa (Lessard and others 1988); the analysis of chemical residue data from abattoirs (Van der Logt and others 1994); examination of the epidemiology of tuberculosis in possums (Pfeiffer and Morris, 1994); or of Aujeszky’s disease in pigs (Marsh and others 1991; Belfrage and others 1994; McGinn and others 1994). One of the more common uses of the technology has been as an aid in the control of disease outbreaks, especially FMD (Sanson and others 1991a, 1991b, and 1994).

There are however relatively few examples of the inclusion of a GIS as an integral part of an animal health information system. These examples demonstrate the acknowledged need for an understanding of the spatial distribution of disease, but eschew the use of a fully functional GIS, probably because of the perceived expense and complexity of setting up such a system. The potential benefits for an animal health information system are clear, but the use of powerful GIS systems seems to be limited to specific research projects and a few information systems in industrial countries.

Making a GIS Part of an Animal Health Information System

In Thailand, a pilot system was established covering three provinces in the north of the country. This system is now being extended to give complete national coverage. The base geographic data used consisted of provincial, district, and subdistrict boundaries, and village point locations. The village was used as the finest level of detail. Epidemiologically, all the livestock in
a single village can be treated as a single herd, as they are in relatively close contact and share the same disease risks. The geographic data was digitized using 1:50 000 maps maintained by the Thai National Statistics Office. Other spatial data included in the system are roads, waterways, livestock market locations, and veterinary office locations. Climatic data maps (showing rain and temperature) were also incorporated into the system. In keeping with the objective of establishing an effective system, appropriate for use in developing countries at reasonable cost, all the data was maintained on two Pentium® desktop computers. These were capable of managing all the data required for a national system covering over 60,000 villages. The software used was ArcInfo and ArcView (from Environmental Systems Research Institute, Redlands, California).

Attribute data was maintained at the village level, and aggregated up to the subdistrict, district, or provincial level for various types of analysis. The various data sources were linked to the maps using standard village and subdivision codes maintained by the National Statistics Office. The main data sources were village livestock populations, collected by the Department of Livestock Development, and disease records from the regional diagnostic laboratory. Other data included (human demographics, agricultural data, and so forth) were derived from two village-level censuses, run by the National Statistics Office and Thammasat University. The Thai system was used for data management, livestock disease and population mapping, development and implementation of improved active surveillance sampling techniques, assisting with disease outbreak response management, and the tempo-spatial analysis of epidemiological data.

In Lao PDR, a GIS was specifically set up to improve the efficiency and validity of sampling strategies as part of active surveillance activities. The system included provincial and district boundaries, village locations (with, however, incomplete coverage), and it incorporated both raster-format aerial photographs and vector format–interpreted satellite images showing land-use data. Lao PDR lacks the sophisticated statistical infrastructure of Thailand, and the data used in our project was acquired from other projects in our area of interest.

Disease and Livestock Population Mapping

In Thailand a range of data sources can be used to produce disease maps. Passive disease reporting, usually in the form of reports of disease events, or through diagnostic laboratory submissions, remains a key source of disease incidence information. This is, therefore, the information that is most likely to be used for disease mapping. Disease reports or submissions are associated with their place of origin, be it a farm, village, suburb, or province. An alternative to the use of passively acquired data is active sur-
veillance. Special purpose surveys can yield estimates (usually of disease prevalence) for defined geographic areas. Besides data on the occurrence of disease, it is necessary to have information on the livestock population at risk of disease in order to calculate meaningful incidence or prevalence estimates. This information is routinely collected by many government veterinary services or may be available through agricultural census information. It is a core component of any GIS for animal health.

Disease maps can take many forms. The simplest is a point map showing the location of disease events over a period ("pin maps"). While this displays the distribution of disease, it does not take into account the distribution of the underlying population. Similarly, choropleth maps of the number of disease events in subregions may be useful for planning the veterinary needs of an area, but they do not provide any information about risk. Converting counts of disease events into rates and mapping incidence or prevalence allows a more meaningful interpretation of the disease situation. The main purpose of these maps is to identify areas of greater or lesser risk of disease than the average. Choropleth maps of the relative risk for each geographic subdivision are quickly able to show the location of problem areas. The routine production of these maps has the potential to provide a more realistic, easy to interpret picture of the disease situation to decision-makers. The generation of these maps can be completely automated.

A GIS as a Survey Tool

Traditionally, random sampling depends on the presence of a reliable sampling frame, in which every member of the population is listed and has a known probability of selection (Levy and Lemeshow 1991). Work in Lao PDR on the development of active surveillance techniques for developing countries has shown that such a sampling frame does not always exist. Sometimes no frame exists at all, the frame may be incomplete, or a frame exists, but its reliability is not known. In any case, it may be necessary to draw a random sample independently of, or in the absence of, the sampling frame.

Random geographic coordinate sampling (RGCS) offers a technique for the selection of a random sample without the need for a sampling frame. In RGCS, pairs of random numbers are generated, which are interpreted as the x and y coordinates of a geographic point. All the villages within a certain radius of the random point are identified, and one is chosen at random. The technique used in Lao PDR and Thailand is a modification of previously used geographic sampling approaches.

This technique can be carried out successfully with a hand-held GPS unit and a four-wheel drive vehicle. It can be, however, very expensive. Human population tends to cluster along valleys or roads, and large areas of a district often have no villages at all. Access to these areas may be difficult, and
random points falling in these areas will yield no villages. In cases where the spread of villages is uneven, much time and effort can be wasted in locating remote points with no villages nearby.

A serological survey using random geographic coordinate sampling was carried out in Lao PDR. A GIS was used to plan the survey, and to increase the efficiency of the fieldwork by incorporating data from remote sensing images into the system. First, a GIS was used to automate the task of selecting random points. Although no detailed digital maps of the survey area existed, a simple map of district boundaries was digitized. A program was written which generated a number of random points within the boundaries of the study area. These random points were printed out and entered into the GPS.

Random points need to be visited to determine if any villages lie within a certain radius of these points. No reliable maps for the study area showing villages existed, as they were either incomplete or out of date. The use of remote sensing data offered an opportunity to visually inspect the area around a randomly selected point to determine if a village is likely to be nearby. Two sources of data were available from projects working within the same government ministry: interpreted SPOT satellite images for the entire study area, being used by a forest inventory project; and aerial photography for a smaller part of the study area, being used by a forestry training project. The data was loaded into ArcView and displayed as a backdrop to the map of the study area. The program used to generate the random points also drew circles of the required radius around these points. It was then a simple matter to examine each point to see if there was evidence of a village within that radius.

The aerial photography data was very detailed, with individual buildings being clearly distinguishable. In the satellite photos, villages were often less easy to identify, but agricultural land (mainly rice fields) was easily distinguished from forested areas. A conservative approach was used, in which any point in or near agricultural land was visited by the survey team to confirm if a village was present. Points lying in the middle of forest areas with no sign of human habitation were excluded. The sample size for the survey was 40 villages. Of the initial random points selected, 44 were excluded using the GIS with remotely sensed data, and a further 82 points were visited to obtain the sample of 40 villages.

A GIS for Targeting Disease Outbreak Response

Thailand is currently undertaking a very large control and eradication program for foot-and-mouth disease. One control option available is the use of ring vaccination around an outbreak. When ring vaccination is used, all animals within a defined radius of the outbreak are vaccinated, to help prevent
the local spread of the disease. To be effective, ring vaccination must be carried out very quickly, to ensure that nearby animals develop protective antibodies before they are exposed to the virus. When managing the response to an outbreak, veterinary authorities require a great deal of information to be made quickly available: where is the outbreak, where are the neighboring villages, how many fall within a defined radius of the outbreak, how many animals need to be vaccinated, and so on. To collect this type of information manually can require days or weeks.

A GIS can access multiple data sources instantly, and interpret the spatial relationships between them. As part of the pilot GIS implementation in northern Thailand, a program was developed to quickly provide all the information required to manage the response to a disease outbreak. The program user first identifies in which village the outbreak has occurred, and specifies the radius of the ring vaccination buffer. The program, displaying a map of the area, including all villages, administrative boundaries and roads, then does a series of calculations and produces reports. First a circle is drawn on the display, representing the boundary of the ring vaccination buffer. Then all villages inside the buffer are identified, and their total susceptible livestock population calculated. Next, this data is broken down by district. District Veterinary Officers deliver field veterinary services in Thailand. In an outbreak, district officers are responsible for vaccinating those villages falling within their district. The number of villages and total livestock numbers for each district are calculated; and the name, telephone number, and distance from the outbreak of the relevant district officers are identified. An important part of the outbreak response is to control livestock movements in and out of the buffer by setting up roadblocks. The program calculates the number and location of roadblocks, giving their map coordinates and the type of road. In some parts of the country, access to villages is difficult, especially during the rainy season. The program identifies the villages that lie more than two kilometers from the nearest road.

The results of all these calculations are then reported. The on-screen map shows the location of the outbreak, all villages in the ring vaccination zone, the location of district veterinary offices, and the location of all roadblocks. This map can be zoomed, interactively interrogated to find the names or populations of particular villages, or printed. A report is produced listing the total number of livestock that need to be vaccinated, and the breakdown by district, roadblock location and types, and the number of remote villages. Finally, a listing of all villages requiring vaccination, with available figures on the population of all species, is displayed.

The key features of this system are as follows: It can provide almost all the relevant information needed by the veterinary authorities in charge of planning a ring vaccination response to an outbreak, quickly and simply; it is based on the integration of data from a range of preexisting sources; it was
developed quickly and at almost zero cost (once the GIS was established); and it is easy to modify and enhance as more data becomes available (such as vaccination records that may show which villages require revaccination, and which are probably already protected).

GISs and Visualization

One of the roles of epidemiology is the identification of patterns in the distribution of disease. Such patterns may lead to a better understanding of the mechanisms of disease, and offer insights into potential control options. The distribution of diseases may be examined in many ways—distributions with respect to sex, age, diet, genetic makeup, space, time, and so forth. When a pattern is detected (for example, disease is more common in animals of a certain age), control options can be developed (such as targeted vaccination for that age group). Once the data is collected, the first step is to examine it for patterns. A GIS offers, through the production of disease maps, the ability to examine the spatial distribution of disease and find meaningful patterns. An armory of statistical techniques exists for the analysis of such patterns. Similarly, graphical and analytical techniques exist for analysis of the temporal distribution of disease (time-series techniques). However, the simultaneous examination of the spatial and temporal distribution of disease is more difficult. If we observe on a map that many cases appear to occur in the same area, are they occurring simultaneously? If we look at a graph of disease incidence over time and notice a peak, are these cases occurring in the same place? Statistical techniques exist to analyze the space-time “distance” between disease events, but little data is available for the identification of these patterns in the first place.

Using a GIS in Thailand, a tool for exploratory data analysis was developed that allowed simultaneous display of the temporal and spatial distribution of a disease. The data displayed came from the diagnostic laboratory submissions database, and contained a disease diagnosis, the origin of the submission, and a submission date. This provided the three necessary components for analysis: the what, where, and when.

A program was developed with the ArcView programming language (Avenue). The user creates a map of all disease events in a certain period. The program then “animates” the map by passing through the chosen period one day at a time, displaying new disease events (for an arbitrary period chosen by the user) and then erasing them. Using this simple technique, it is easy to see the wave of progression of an epidemic, or the random scatter of a sporadic disease. The program was used to examine several diseases in the study area, and revealed new patterns, suggesting new hypotheses. For example, while two serotypes of one disease were known to occur in all parts of the study area, and follow an annual cycle, it was not known that


In recent years, Bangladesh has taken major strides in delivering financial services to the rural poor. The providers of these services have mainly been innovative group-based credit programs run by several nongovernmental organizations (NGOs). A number of studies are now available that describe how these new institutional arrangements dispensed with physical collateral and facilitated access of the poor to savings and credit services (Zeller, Sharma, and Ahmed 1996; Hossain 1988). However, scant attention has so far been given to the determinants of placement of NGO branch institutions and the client coverage of their operations across regions. Khandker, Khalily, and Khan (1995) find that commercial banks in Bangladesh favor economically better-off areas, and a study in India (Binswanger, Khandker, and Rosenzweig 1993) concluded that commercial banks were more likely to be located in places where the road infrastructure and marketing system are relatively developed. Is this also the case with the group-based credit systems of NGOs? In other words, do NGO programs target their services to the poor in relatively underdeveloped or disadvantaged regions, or do they locate their branches in the relatively better-endowed areas? What kinds of tensions arise among mission goals, performance standards, and operational restraints at the operations level? Once branches have been placed, what does client coverage look like across branches? For example, do the decisions on branch placement and client coverage follow similar patterns, or is there evidence of discontinuity? To what extent does the decision related to client coverage appear to be decentralized
(Ravallion and Wodon 1998)? Knowing whether certain types of areas are systematically favored or disfavored is of interest and importance to policymakers as well as to program managers. This knowledge can also assist in disentangling program effects from location effects and hence it is useful for an assessment of the impact of group-based credit programs (Rosenzweig, Pitt, and Gibbons 1995).

For administrative purposes, Bangladesh is divided into four divisions and 64 districts. Each district is further divided into thanas. A thana is an administrative unit that corresponds with the jurisdiction of a police station. This chapter makes use of secondary level data from 391 thanas to examine the placement of branches and group coverage of three well-known NGO credit institutions in Bangladesh: Association of Social Advancement (ASA), Bangladesh Rural Advancement Committee (BRAC), and Proshika Manobik Unnayan Kendra (PROSHIKA). In the next section (“The Institutions”), major characteristics of these NGO institutions are described (see Zeller, Sharma, and Ahmed (1996) for more detail). The third section (“Factors Affecting the Placement of Branches”) proposes a number of hypotheses on placement of branches that were tested econometrically, and the results are presented in the fourth section (“Econometric Specification”). Client coverage of NGOs branches is analyzed in the fifth section (“Client Coverage”). The last section summarizes conclusions and policy implications.

The Institutions

There are five common threads in the institutional structures of the ASA, BRAC, and PROSHIKA: First, services are strictly targeted to a well-defined set of clients: The most common criterion is the amount of land owned, and all three NGOs target landless or near-landless households. Second, credit is always provided to small groups of borrowers on the basis of joint liability and without the pledging of any physical collateral. Third, even though loans are made out to individual members, the entire group is denied further credit when outstanding arrears exist for any one of the members. Fourth, lending activities are supplemented by training activities in areas such as entrepreneurial skill development, management of microenterprises like shopkeeping and crafts production, education on social awareness, and family planning activities. Fifth, groups are required to contribute to an emergency fund that may be used when members experience household and other emergencies.

Loan recovery rates of all three institutions are impressive when compared with those of commercial banks: During the period 1992–1993, for example, they were 100 percent for ASA, 98 percent for BRAC, and 93 percent for PROSHIKA. Additional institution-specific details follow below.
Association for Social Advancement (ASA)

ASA, one of the largest indigenous NGOs in Bangladesh, was set up in 1978. It implements programs in the areas of income generation, integrated health, and education and empowerment of the poor, and its Income Generation through Credit Program (IGCP) was launched in 1989. The principal objective of the program is to increase income levels and purchasing power of poor households. ASA extends credit facilities to the female members of poor households for investment in various income-generating activities. The major income-generating activities receiving support under the IGCP program are paddy husking, cow and goat rearing, poultry farming, small trading, and handicrafts. Nearly 190,000 members received loans under the program in 1993.

Bangladesh Rural Advancement Committee (BRAC)

BRAC was set up in 1972, following the independence of the country in 1971. At its inception the primary goal of BRAC was to participate in the post-independence rehabilitation work of the war-ravaged country. It launched its campaign with a small rehabilitation project in Sylhet district in the northeast of Bangladesh. Gradually BRAC expanded its operation to other parts of the country. BRAC initiated its credit program in 1976 (BRAC 1991). The present form of the program, which was introduced in 1990, is known as the Rural Credit Project (RCP). RCP is an important component of BRAC’s larger Rural Development Project (RDP). The objectives of RDP are four-fold: (1) to generate employment opportunity for both males and females; (2) to mobilize underutilized and unutilized resources; (3) to assist in diffusing appropriate technology in rural areas; and (4) to promote better health care. The cumulative amount of loans disbursed through RCP from 1990 through 1992 stood at 1,745 million taka (approximately US$ 45 billion), and during 1992, short-term loans accounted for 94 percent of total disbursement. Loans are generally extended for a specified line of projects. In 1992, for example, rural trading and food processing accounted for nearly 73 percent of the loans. Livestock, agriculture, rural industry, and irrigation accounted for another 23 percent. As of June 1993, 70 branches of RCP were in operation with a coverage of 379,000 members.

Proshika Manobik Unnayan Kendra (PROSHIKA)

PROSHIKA was founded in 1976 with the aim of empowering the poor by enabling them to participate in mainstream economic activities. Its objectives include achieving structural poverty alleviation, improving the status
of women, and increasing people’s participation in public institutions. PROSHIKA operates group savings and revolving loan fund activities under its Employment and Income Generating (EIG) program. The revolving loan fund program was launched in 1983 and in the 1992–1993 financial year funded 10,809 projects with total fund disbursements of nearly 224 million taka.

Factors Affecting the Placement of Branches

The placement rule followed by NGOs is specified in equation 11.1, where the decision to place a branch, \( B_i \), by an NGO credit institution is specified as a function of

\[
B_i = f(P_i, E(D_i), E(C_i), R_i)
\]  

(11.1)

where \( P_i \) is a vector that describes poverty conditions in thana \( i \), \( E(D_i) \) is the expected level of demand for credit services in that thana, \( E(C_i) \) is the expected level of cost of providing services, and \( R_i \) is an index of the risk of conducting credit-related business in the thana. Each of these is discussed below.

Poverty Targeting

All three NGOs, which are among the largest in the microfinance NGO movement in Bangladesh (Credit and Development Forum 1996), claim to be guided, first and foremost, by a common mission to serve the poorest in the rural areas (ASA 1996a and 1996b, Lovell 1992, BRAC 1994). ASA, which provides credit exclusively to women, for example, aims at creating “a broader space for marginalized women of rural areas so they can participate in income generation activities to increase income” (ASA 1994). BRAC, on the other hand, aims to work “exclusively with disadvantaged sections of the community” (Chowdhury, Mahmood, and Abed 1991) and focuses on poor, landless groups, and PROSHIKA has an explicit mission to “empower the poor” (Jahangir and Zeller 1995). Given these kinds of mission statements, a reasonable hypothesis is that, conditional upon other factors, thanas with higher poverty levels will have a higher probability of a branch placement.

There are, however, two additional questions: (1) What criteria of poverty do these institutions apply with respect to individuals in targeting their operations, and (2) What criteria do these institutions apply in making the operational decisions on which areas to target their activities? The answer to the first question is relatively straightforward. All three programs have clear and strict poverty-based eligibility rules that are well enforced. BRAC lends
only to those who own less than 0.5 acres of land and additionally work as laborers for at least 100 days in a year (Lovell 1992). ASA, on the other hand, lends to women owning less than 0.5 acres of land, whose income do not exceed 1,200 taka (approximately US$31) per month, and who also sell their labor for at least 200 days a year. However, the response of NGOs to differences of poverty levels across different locations when making decisions about branch placement is a more difficult question. A reasonable assumption is that the NGOs base their decisions on various types of indicators of poverty. One testable hypothesis is that NGOs locate their branches in thanas that have larger proportions of households owning less than 0.5 acres of land, as this criterion most closely defines their target households. This need not be the only criterion, however. Two additional criteria are proposed in this study: literacy rates per thana, and thana-based levels of the “distress” index developed by the Helen Keller Institute (HKI) in Dhaka, Bangladesh. Literacy rates generally highly correlate with poverty levels, and the HKI distress index combines information on susceptibility to flooding (a frequently occurring natural disaster in Bangladesh), general wage levels, and availability of irrigation facilities—all being major factors affecting the level of well-being in Bangladesh.

Expected Level of Demand for Credit Services

The expected level of demand for credit services in an area is likely to receive important consideration for two reasons. First, it would be important for the NGOs to avoid areas where credit demand is likely to be either non-existent or lower than some minimum threshold making credit delivery prohibitively costly to administer. Second, the marginal impact of NGO services on participating households, a major concern for the NGOs, is likely to be the highest in areas with the strongest credit demand. This is because credit demand is likely to be the strongest in areas that are affected relatively less by other constraints—for instance, on labor and product markets, transportation, and information. Hence, expected demand for credit is expressed as equation 11.2:

\[ D(D_i) = g(W_i) \]  \hspace{1cm} (11.2)

where the vector \( W_i \) consists of thana-level variables that affect the level of credit demand and may include the following variables:

- Level of physical infrastructural development such as access to markets, roads, electricity, irrigation, and other services
- Agroclimatic conditions, and general income levels
- The level of urbanization and commercialization of the local economy.
Cost of Supplying Services

In general, profit-seeking institutions select locations where expected revenues are at least as high as expected total cost (fixed costs plus variable costs). However, this may not necessarily be the case of NGOs as they do not have profit maximization as their explicit objective. Also, the NGOs receive subsidies of different types to operate in specific geographical areas and also implement various types of cross-subsidization schemes between branches. For these reasons they are not likely to base their placement decision solely on potential net revenues. How expected unit-costs of operation affect placement of branches, therefore, is essentially an empirical issue.

There are at least two other cost-related issues that are likely to be important in the placement calculation. These concern general security and the availability of banking services. Credit transactions necessarily involve the handling of cash, which raises security concerns. Proximity to police stations and other law and order establishments, therefore, is likely to be important. Moreover, when NGOs do not provide their own banking services but depend on the branch of a commercial or parastatal bank to make cash disbursements and deposits, convenient proximity to commercial banks becomes important. If commercial banks are generally located in areas that are more urbanized or benefit from better infrastructure, as Binswanger, Khandkar, and Rosenzweig (1993) have shown, then NGOs may also tend to place branches in or near these locations.

A third issue relates to staffing of branches. Since branch managers are recruited from a central pool, and since salaries and other compensations do not reward appointments in more remote locations, managers are likely to prefer locations that have fairly well-developed services (such as education, market, and health). If these considerations are significant in the decision to place branches, placement will be higher in thanas that have such services.

To account for all these considerations, we let the expected total cost function be specified as shown in equation 11.3:

\[ E(C_i) = g(Z_i) \]  \hspace{1cm} (11.3)

where the vector \( Z_i \) consists of thana-level variables that affect the level of unit service delivery costs. In practice, vectors \( W_i \) in equation 11.2 and \( Z_i \) in 11.3 are likely to be very similar if not identical.

Perceived Riskiness

An important goal of NGO-administered credit programs is to maintain high repayment rates. Indeed, as noted earlier, all NGO programs report repayment rates in excess of 90 percent. Maintaining near-perfect repay-
ment rates is critical for NGOs. This is because most of the subsidies they receive from national and international donors appear to be conditional on maintaining such rates. This objective of maintaining high repayment rates may also affect the placement of branches. In particular, NGOs are likely to avoid areas where marginal returns from new microenterprises are low (poor, backward areas where complementary services either do not exist or are highly inadequate). They are also likely to avoid areas that are highly susceptible to natural disasters such as flooding and other covariant risks. We let the risk expectation function be specified as equation 11.4:

\[ E(C_i) = g(V_i). \]  

(11.4)

Elements in \( V \) include poverty indicators such as literacy rate, level and distribution of landholding, and also the HKI distress level indicator described earlier.

Econometric Specification

A linear specification of the placement equation 11.1, upon substituting for 11.2 through 11.4, would be equation 11.5:

\[ B_i = P_i \alpha + W_i \beta + Z_i \gamma + V_i \delta. \]  

(11.5)

However, as indicated in the previous section, it is, in principle, (and also because of data limitations) very difficult to identify \( P, W, Z, \) and \( V \) separately. For example, it is very difficult to find variables that affect poverty levels but not credit demand or riskiness of conducting business. A more practical formulation is therefore to regard the elements in \( P, W, Z, \) and \( V \) to be common and represented by the vector \( X_i, \) as in equation 11.6:

\[ B_i = \sum \eta_i X_i + \mu_i + \epsilon_i. \]  

(11.6)

and interpreting its coefficient \( \eta_i = (\alpha_i + \beta_i + \gamma_i + \delta_i) \) as the combined effects of the four determinants of placement. After all, infrastructure, urbanization, and other community-level endowments are likely to jointly affect levels of poverty as well as demand for credit services, the cost of credit service delivery, and the riskiness of conducting business. Similarly, susceptibility to natural disasters simultaneously affects poverty, credit demand patterns, and the riskiness and costs of doing business. Note that a priori expectations on the sign of \( \eta_i \) are difficult to place unless \( \alpha, \beta, \gamma, \) and \( \delta \) are of the same expected signs. In some cases, however, it is still possible to make some inferences by computing the estimated sign of \( \eta_i \) with expected signs of \( \alpha_i, \beta_i, \gamma_i, \delta_i. \) This is done below in the fifth section of this chapter.
A different consideration is the effect of unobservables. If placement of government infrastructural programs and levels of poverty are functions of unobservable factors (such as agro-climactic potentials of lands, or historical or political considerations), then exclusion of such factors in equation 11.6 is likely to lead to biased estimates of $\eta$s. In order to minimize bias arising out of location-specific unobservables, a district level of effect $\mu_d$ is included in equation 11.6. Since $B_j$ in 11.6 is a binary-dependent variable taking the value (0,1), the equation is estimated using the fixed-effects logit estimation that sweeps out the effects of district-level unobservables.

The vector $X$ in equation 11.6 contains the following variables (see table 11.1 for descriptive statistics):

**Poverty-related variables:**
- Landsize. The percentage of farms in the thana that are below 0.5 acres in size.

Table 11.1 Descriptive Statistics of Regression Variables—Thana Level
(n = 391)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variables:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Presence of NGO (dummy variable)</td>
<td>0.40</td>
<td>0.49</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Client density$^1$</td>
<td>17.86</td>
<td>33.01</td>
<td>0.00</td>
<td>297.59</td>
</tr>
<tr>
<td><strong>Independent variables:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electricity</td>
<td>6.96</td>
<td>8.47</td>
<td>0.00</td>
<td>54.90</td>
</tr>
<tr>
<td>Landsize</td>
<td>23.90</td>
<td>7.60</td>
<td>1.97</td>
<td>52.87</td>
</tr>
<tr>
<td>Literate</td>
<td>24.54</td>
<td>9.94</td>
<td>11.0</td>
<td>60.4</td>
</tr>
<tr>
<td>Market</td>
<td>26.22</td>
<td>13.37</td>
<td>1</td>
<td>75</td>
</tr>
<tr>
<td>Density</td>
<td>791.10</td>
<td>666.54</td>
<td>93.20</td>
<td>10,557.35</td>
</tr>
<tr>
<td>Urban</td>
<td>11.26</td>
<td>16.58</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Road</td>
<td>0.17</td>
<td>0.21</td>
<td>0.00</td>
<td>2.61</td>
</tr>
<tr>
<td>Post office</td>
<td>16.18</td>
<td>9.69</td>
<td>1</td>
<td>82</td>
</tr>
<tr>
<td>Hospital</td>
<td>12,576.33</td>
<td>11,499.45</td>
<td>0</td>
<td>99,726</td>
</tr>
<tr>
<td>Doctor</td>
<td>42,905.03</td>
<td>44,555.82</td>
<td>0</td>
<td>329,739</td>
</tr>
<tr>
<td>Distress</td>
<td>1.1</td>
<td>0.15</td>
<td>1.0</td>
<td>1.5</td>
</tr>
</tbody>
</table>

$^1$ Client density is defined as the number of NGO clients in the thana divided by the thana's total population.

• Literacy. The percentage of population literate in the thana.

Infrastructure-related variables:
• Electricity. The percentage of villages electrified in the thana.
• Market. The number of number of market centers in the thana.
• Density. The population density of the thana.
• Urban. The percentage of urban population in the thana.
• Road. The kilometer of metaled road per 1,000 persons in the thana
• Hospital. The number of population per hospital bed in the thana.
• Doctor. The number of population per doctor in the thana.
• Post office. The number of post offices in the thana.

Risk/poverty-related variables:
• Distress. The thana-level distress index (HKI) computed by the Helen Keller Institute.

All data, except for the distress level which has been directly obtained from Helen Keller International in Dhaka, are published in various issues of the statistical yearbook of Bangladesh, published by the Bangladesh Bureau of Statistics (1994). Data on the dependent variables for the different programs have been obtained from annual reports from BRAC, ASA, and Grameen Bank for 1994 (BRAC 1994; ASA 1994; Grameen Bank 1994). The data for PROSHIKA also refer to 1994, and were obtained through interviews with staff from its headquarters in Dhaka.

Econometric Results: Placement of Branches

The estimated logit equation on branch placement is presented in table 11.2. A number of interesting results are discussed below. The coefficients of Road and Post office are positive and significant at the 5 percent level. These are both infrastructural variables measuring the extent of transportation and communication facilities in the thana. The percentage of urban population in the thana (Urban) and population density (Density) are not statistically significant. Neither are the two health service indicators, Hospital and Doctor, the number of market centers in the thana (Market), or the percentage of villages that are electrified in the thana (Electricity). It appears, therefore, that placement decisions are attentive to transportation and communication facilities, but that the net effect of other infrastructural facilities measured or proxied by population concentration, urbanization, and the availability of medical and health services appears to be insignificant.

The coefficient of Literate is negative and is strongly significant. Hence placement of branches appears to respond to literacy rates, with more branches being placed in thanas with lower literacy rates. Note that if considerations of demand, costs, and riskiness favor thana with higher literacy rates—that is, if \( \beta_{\text{Literate}} + \gamma_{\text{Literate}} + \delta_{\text{Literate}} > 0 \)—then it may be concluded that
Table 11.2 Placement of NGOs: Estimated Fixed-Effects Logit Equation

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>t-Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsize</td>
<td>0.0242372</td>
<td>0.987</td>
</tr>
<tr>
<td>Literate</td>
<td>-0.102779</td>
<td>-3.631**</td>
</tr>
<tr>
<td>Electricity</td>
<td>0.0156035</td>
<td>0.842</td>
</tr>
<tr>
<td>Market</td>
<td>0.0144544</td>
<td>1.162</td>
</tr>
<tr>
<td>Population</td>
<td>-0.0002954</td>
<td>0.593</td>
</tr>
<tr>
<td>Urban</td>
<td>0.0099031</td>
<td>0.893</td>
</tr>
<tr>
<td>Road</td>
<td>1.373573</td>
<td>2.156**</td>
</tr>
<tr>
<td>Hospital</td>
<td>4.11x10^-6</td>
<td>0.294</td>
</tr>
<tr>
<td>Doctor</td>
<td>-4.30x10^-6</td>
<td>-1.241</td>
</tr>
<tr>
<td>Post office</td>
<td>0.0344091</td>
<td>1.875*</td>
</tr>
<tr>
<td>Distress</td>
<td>-3.255817</td>
<td>-2.684**</td>
</tr>
</tbody>
</table>

Note: * Significant at 10 percent level. ** Significant at 5 percent level.
Log likelihood = -172.79, c_s[0] = 39.08

The poverty consideration (α_literate) is sufficiently large enough to overturn the combined positive effect so that the net effect is negative; that is, \(| \alpha_{\text{literate}} | > | b_{\text{literate}} + s_{\text{literate}} + d_{\text{literate}} | . The coefficient of the landholding variable Landsize has a similar interpretation—that the poverty effects of the smaller landsize more than outweighs the combined effects on credit demand and risk costs. Landsize, however, is not significant at the 10 percent level.

The coefficient of Distress is negative and significant at the five-percent level. NGOs thus are less likely to place branches in high distress locations. Unlike the case of Literate above, it appears that poverty considerations (that are attendant with high level distress) are not strong enough to compensate for the negative effects arising out of conducting business in risk-prone areas. Significantly, this result indicates the inability of even large NGO's, such as BRAC and ASA, to effectively deal with risks.

Overall, the estimated branch placement equation indicates while NGOs appear to respond to poverty, they are more likely to place branches in locations that have favorable infrastructure. They also are less likely to place branches in high distress location.

Client Coverage

Having examined branch placement outcomes of the three NGOs, we now go on to examine factors that influence the client outreach of thana-level
branches. Apart from learning what types of poverty characteristics affect client density, it is also of interest to examine whether any type of decentralization process characterizes geographical distribution of service delivery. As Ravallion and Wodon (1998) point out, in many targeted programs, it may be the case that the headquarters (or the central government) makes a decision on where to place a branch, but subsequently leaves it up to local managers (or local governments) to determine the scale of operation of the established branch. Is this also the case of Bangladeshi NGOs? In this section, we use participation density (Outreach), measured as the number of participants in a specific program per 1,000 people in the thana, as an indicator of client outreach.

The econometric specification of the outreach regression equations is similar to the branch placement equation 11.6, except that the dependent variable Outreach is a continuous but truncated variable: client coverage is observed only in thanas that have branches. The procedure used to correct this sample selection bias is the two-stage Heckman procedure (1979) whereby a Mills ratio—Lamda—computed from the branch placement (logit) equation is used as an additional regressor in the participation density equation and appropriate adjustments are made in the computation of standard errors (Greene 1993). An additional variable Years is used in the outreach equation to control for the fact that client density is expected to increase with years of operation of the branch. Years is the number of years for which the branch has been in operation. However, because Years was not available for PROSHIKA, the outreach equation was estimated using data for BRAC and ASA only, with Years computed as the sum of years that branches of both ASA and BRAC (or both) in the thana had been in operation. The combined outreach equation estimated for ASA and BRAC is presented in table 11.3.

In the outreach equation in table 11.3, only the coefficients of three variables are significant: these are Years, Landsize, and Distress. These variables are discussed below.

- The coefficient of Years is positive and highly significant, indicating that NGO institutions have expanded their client base through time. Indeed if it was the case that Years was the only variable significant in the equation, this would have suggested that, once a branch was placed in a particular location, client coverage was mostly determined without significant reference to local specificities. However, this is not the case since at least two other area characteristics appear to influence outreach.
- Outreach is significantly higher in thanas that have a higher distress index. This result is completely opposite to that of the placement equation, which had indicated that placement rule disfavored high distress
areas. The result thus suggests that though branches are less likely to be placed in high distress areas, once established, they have higher client densities. This is a plausible scenario. First, it may be that demand for special financial services like those provided by the NGO institutions is especially large in these backward, high-risk thanas, especially since these areas are inadequately served by other market-based or government-sponsored organizations. Second, it may indeed be part of institution policy to have higher levels of outreach in relatively more depressed areas. Third, as suggested above, it may also be reflective of partial decentralization in service delivery whereby local branch managers, once the branch is set up, exercise more control in outreach-related decision functions that are more responsive to local conditions. Indeed it is possible that the high-outreach requirements of branches placed in distressed areas may in fact put pressure on NGOs to limit the number of branches operating in such areas.

- Outreach is significantly lower in thanas that have a higher proportion of marginal farmers, as shown by the negative coefficient of Landsize. But it remains unclear whether this result is driven by supply or demand factors. In the second section of this chapter it was noted that a significant proportion of the projects financed by NGOs were off-farm microenterprises engaging in rural trading, food processing, and
handicraft production. If financing off-farm microenterprises (rather than agricultural production) is indeed one of the main objectives of the NGO institutions, then outreach would be responsive not just to the proportion of the population owning less than 0.5 acres of land, but also to the presence of landless wage laborers who are likely to be even poorer.

- Though it was clear from the placement equations that branches were more likely to be established in thanas with better communication and transportation infrastructure, there is no evidence that, once a branch is established, client outreach also responds to infrastructure-related characteristics. This once again suggests discontinuities between the placement and outreach decision functions.

Conclusions and Policy Recommendations

Our analysis indicates that even though the placement of branches of NGO institutions was attentive to poverty considerations, other considerations fared more prominently and branches were more likely to be established in locations that had better access to transport and communication infrastructure. Hence it appears that NGO services are geared more toward the poor who reside in relatively well-developed areas rather than toward the poor in more remote and less developed regions. Client density of the existing branches, however, did not exhibit such a feature and actually tended to be better in less favorable and more distressed locations.

Greater concentration of branches in the better areas may in part be the result of a search for locations where the marginal impact of credit services is the greatest. Typically, accompanying constraints on production or income—such as those imposed by the lack of markets, transportation, or communications—are likely to be less severe in areas that have good infrastructure. For example, loans for financing the production of highly market-dependent outputs, such as production of commercial crops, and other non-farm microenterprises, are less suitable for remote areas. Moreover, banking services become especially risky in remote areas where covariance in household incomes is likely to be very high. In such areas, the high repayment rates necessary to maintain an NGOs’ access to subsidized funds from various agencies are harder to maintain. Furthermore, the unavailability of commercial banks limits financial operations in remote or poor locations. Hence, as suggested in the previous section, NGOs may follow a strategy of placing fewer branches in distressed areas, but with each of these branches serving a larger number of clients.

Simultaneous efforts to reach the poor, to maximize marginal impact of services, and to keep loan delinquency at the minimum introduces consid-
erable tension in service placement decisions of NGOs. Solutions for reducing this tension lie in innovative lending technologies that reduce transaction costs for both lenders and borrowers and increase marginal returns of loans for the poor in disadvantaged locations. We suggest four strategies towards this end. These are: (1) area-specific innovations and differentiations in financial products; (2) performance and location incentives for branch staff; (3) reduction in dependence on branch offices of commercial banks; and (4) increased donor support for expansion of programs in the remote and vulnerable areas.

1. **Area-specific innovations and differentiations in financial products.** A range of area-specific factors affects the demand for different types of loan and savings services. Reducing the cost of credit delivery and increasing the marginal impact of credit on borrowers depends on the extent to which credit and savings services are responsive to area-specific characteristics. However, it is presently the case that financial products of nongovernmental organizations are usually standardized for the entire country. While branch managers have sufficient decision flexibility in managing the headquarters-prescribed array of financial products, they do not have the flexibility to design new financial products or introduce modifications to existing ones. Presumably, headquarter offices do not possess enough information to evaluate the potentials and constraints of service branches. Hence, it is suggested that lower-tier institutions, such as divisional or district offices, be given some flexibility and incentives for modifying existing financial and other services or to introduce new services on a pilot level. Such area-specific modification and innovation may well cover the terms of the credit contract, including spatial differentiation of interest rates.

2. **Performance and location incentives for branch staff.** To improve outreach and cost recovery in bank branches, managers and their staff could receive special incentives for above-average performance. Successful innovations by branch or district managers, as mentioned above, could be especially rewarded. Furthermore, if the presumed self-selection of good managers to urban areas is valid, some form of compensatory payments could be given to managing staff or branch offices that operate in remote areas where access to basic social services and economic infrastructure is lacking.

3. **Reduction in dependence on branch offices of commercial banks.** NGO branches currently depend on a commercial bank office at which funds are deposited and withdrawn. This has the effect of limiting the outreach of the NGOs to those areas where such bank branches exist. Grameen Bank, one of the pioneers of microcredit, has chosen to maintain its own network of branch offices that perform all functions of money transfer between branches and regional offices and headquarters. When other NGO-supported financial systems reach a critical size, they may well follow this example; BRAC, for example, actually plans to develop a rural bank branch network.
of its own. However, for the smaller NGOs, this would not be economical. A solution here may lie in the establishment of subdistrict NGO units in remote areas that act as "NGO bank branches" by mediating between individual branch offices and commercial bank branches. The establishment of such units may well be supported by a consortium of NGOs targeting a particularly vulnerable area, so that the unit services a number of NGOs at the same time. Another possibility is that of mobile banking, where remote branch offices are served by regional or district NGOs or commercial bank offices on a prescribed time schedule. In so far as above-average-skill managers exhibit preference in locating themselves near towns, the system of mobile banking would allow remote branches to be continued to be served by a cadre of qualified managers instead of being "trainee branches." For the borrower or saver, it provides access where it was not available before.

4. Increased government and donor support for expansion of programs in particularly remote and vulnerable areas. The placement of a branch office, the recruitment and training of its personnel, and the formation and training of groups requires considerable up-front investments, especially in remoter areas. However, it is also likely that many remote thanas in Bangladesh that are currently not served have sufficient long-term demand to support total cost of operation. Hence, donor and government support to target selected remote areas, and accelerate expansion of the branch network in these areas, can be in many cases justified, both from the efficiency and equity perspectives.

Note

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References


