Targeting agricultural research to benefit poor farmers: relating poverty mapping to maize environments in Mexico

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Abstract

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We explore approaches for targeting agricultural research to benefit poor farmers. Using small area estimation methods and spatial analysis, we generated high-resolution poverty maps and combined them with geo-referenced biophysical data relevant to maize-based agriculture in Mexico. We used multivariate classification and cluster analysis to synthesize biophysical data relevant for crop performance with rural poverty data. Results show that the rural poor are concentrated in particular regions and under particular circumstances. Formal maize germplasm improvement trials were largely outside the core areas of rural poverty and there was little evidence for direct spillover of improved germplasm. Agro-climatic classification used for targeting breeding is useful but often ignores some important factors identified as relevant for the poor. Combining this method with poverty mapping improves stratifying and targeting crop breeding efforts to meet the demands of resource-poor farmers. We believe this integrated approach will help increase benefits from agricultural research to poor rural communities.

Keywords: Poverty mapping; Maize mega-environments; Targeting crop breeding; Biophysical data; Rural poor; Mexico

Introduction

Poverty alleviation is an important goal in the global development agenda. A high proportion of the poor in developing countries live in rural areas, even in middle-income countries where agriculture remains an important component of their livelihoods. Agricultural research has made a contribution to poverty alleviation but many poor farmers are still not beneficiaries and reaching them should be an important goal to further increase the impact of agricultural research. However, reliance on spillover effects of new technologies is unlikely to solve the problem. A pro-active approach needs to be taken to develop relevant agricultural technology for poor farmers that responds to their needs, performs well in the environments in which they farm and under the management they can apply. This suggests the need for better targeting of agricultural research to reach the poor.

Agricultural research can contribute to poverty alleviation both directly and indirectly (Byerlee, 2000, Hazell, 2003). Direct effects include increasing on-farm production and household food security and reducing market and production risks. Indirect effects include greater agricultural employment, growth in the local non-farm economy and lower food prices. Targeting has become an important component of poverty alleviation programmes used to enhance their efficacy and efficiency. Poverty mapping is an increasingly used tool for targeting these programmes, which usually consist of cash transfers to the poor as well as providing improved access to education and health services (Skoufias et al., 2001, Henninger and Snel, 2002).

Advances in geographical information systems (GIS) and availability of spatial data make feasible the mapping of a combination of agro-ecological and socio-economic variables, such as poverty incidence (Byerlee, 2000). These geographical targeting efforts may be particularly effective if regional disparities are large (Bigman and Loevinsohn, 2003). Therefore, making poverty mapping relevant for the targeting and development of agricultural technology may increase the impact of agricultural research on the poor. Not surprisingly, one conclusion of the 1999 international workshop, "Assessing the impact of agricultural research on poverty alleviation", was the need for more comprehensive mapping, "…if the direct impacts of agricultural research on poverty, the linkages between those direct effects and the well-being of the rural non-farm population, and the poverty-resource degradation linkages are to be clarified in the future" (Pachico et al., 2000, p. 383).

Improved crop germplasm is a key output of agricultural research. Whether or not improved crop varieties benefit poor farmers has been debated (e.g. Lipton and Longhurst, 1989). In theory, improved varieties are scale neutral and should benefit both large- and small-scale farmers (Hazell, 2003). However, the possibility for these spillovers may be more limited if the environments in which better-off and poorer farmers raise crops vary considerably or if the management regimes they use are different. The need for targeting germplasm is well recognized among breeders, and tools have been developed to assist this process. For example, over time, the International Maize and Wheat Improvement Center (CIMMYT) and its partners have developed and refined the concept of global maize mega-environments (MEs). The MEs (homogeneous production environments defined on an agro-climatic basis) help crop breeders manage genotype-by-environment interactions and extrapolate within similar agro-climatic zones (Hartkamp et al., 2000). However, these MEs do not include socio-economic variables that make them more relevant for targeting poor farmers. In particular, poor farmers are generally subsistence farmers, farming in the most challenging edaphic conditions in the ME (e.g. steepest slopes, poorest soils and lowest inputs due to poor access to markets). In addition, poor farmers in Latin America (and Africa) are often indigenous peoples for whom traditions and culture are key determinants of their behaviour.

Mexico as a case study for poverty mapping

Although Mexico is a middle-income country, it has an enormous diversity of environments and socio-economic conditions. Despite its large developed economy, poverty (particularly in rural areas) is still present and remains a national concern. In 2000, 57% of all households were considered poor, while in rural areas this number increased to 70% (CTMP, 2002). Furthermore, the Comité Técnico para la Medición de la Pobreza (CTMP) estimated that, nationwide, 19% of households are under the food poverty line[1] and are considered to be under extreme poverty, rising to 34% in rural areas. According to the latest National Nutrition Survey (Rivera Dommarco et al., 2001), estimates of child malnutrition (stunting) in 1999 were 18% nationwide but with considerable variation among regions and types of communities—32% in rural communities and 11% in urban areas.

In Mexico, members of the relatively large rural population still depend on farming for their livelihoods. Maize is their main staple crop and can be considered the crop of the poor. Mexico is also the centre of diversity and origin for maize. For decades, a major effort has been made to produce improved agricultural technologies, particularly maize germplasm, both in the public sector (including national agricultural research programmes and CIMMYT, which has its headquarters in the country) and more recently from the private sector. Mexico also has available quality data on socio-economic conditions, infrastructure and other common indicators of food security and human welfare. Given these factors, the overall goal was to explore approaches for making poverty mapping relevant for better targeting crop breeding.

Methods

We developed a map of rural poverty in Mexico using the small-area estimation method described by Bigman et al. (2000). We estimated a Multiplicative Heteroskedasticity regression model[2] with data from the 2000 National Survey of Household Incomes and Expenditures (ENIGH 2000) (INEGI, 2001), and using the food poverty line defined by the CTMP (2002)[3]. We chose model variables for their potential relation to human welfare and the fact that they could be directly linked to the national census data. Input data included 3299 households in 184 municipalities across all Mexican states plus the Federal District. We used the developed model to predict the expenditure of the average rural household, as well as its variance, by municipality using data from the XII General Population and Housing National Census 2000 (INEGI, 2002)[4.] Based on these results, we estimated (from communities <2500) the proportion of rural households under the food poverty line by municipality.

We also applied the predictive model for expenditure to community-level data to map monthly per capita expenditure of the average household by community. We estimated these data for 103,635 rural communities (<2500 people) from the National Census of 2000 (INEGI, 2002). We applied non-parametric interpolation, using indicator kriging techniques, to the community-level data to generate rural food poverty probability surfaces, with the food poverty line (US$51.60 per capita monthly expenditure) used as a threshold limit. We classed selected areas with probabilities equal to, or greater than, 80% as high probability rural poverty zones.

While we fully recognize that additional errors will be generated at the community level, given that we estimated the model with data that can only be linked to the municipal (not the community) level, we think exploring the results is worthwhile because they provided a means to link the poverty data to environmental and agro-ecological data relevant for crop breeding. The local nature of biophysical data (e.g. soils, climate and slope) relevant to breeding activities was a major factor in exploring this line of investigation. Recognizing the potential uncertainty in locality-level data, they are used in an illustrative way and only predominant general trends are reported.

To examine the relationship between environmental factors of relevance for crop breeding and rural poverty, we used a modified version of existing CIMMYT maize MEs (Hartkamp et al., 2000). We used six environments, defined on the basis of growing season maximum temperature and rainfall (Table 1). Additionally, we determined information on the major soil types from 1:250,000 soil maps (INIFAP, 1999, unpublished data) and an indication of terrain derived from a slope surface (generated from the digital elevation model of Hijmans et al., 2004).

To explore the relevance and implications of the poverty mapping results to agricultural research organizations, we compared several databases to the occurrence of rural poverty. The databases included the distribution of important crops (maize, wheat and beans) and the locations of formal CIMMYT maize trials. The latter were derived from CIMMYT's International Maize Trial database and mainly represent testing locations of CIMMYT materials requested by collaborators. We also compared commercial agriculture zones for maize, calculated on the basis of high production surplus for the agricultural population per capita, to the poverty results. Municipalities with greater than 1 ton per capita surplus production for the agricultural population were considered commercial, and expert evaluation by CIMMYT scientists supported these designated areas. Additionally, predictive models (climate-based, regression models based on actual measured farmer storage losses) were used to develop maize grain storage loss surfaces under different storage conditions and durations, and so appraise the potential importance of storage losses to the poor.

Finally, to rigorously synthesize the biophysical data relevant for crop performance with the data from poverty mapping, we used a combination of multivariate classification methods for allocating individuals, in this case communities, into homogenous but distinct groups. Biophysical data relevant for crop performance used to form the groups included: (1) average minimum and maximum temperatures during the main cropping season (^{0}C), (2) elevation above sea level (m), (3) ratio of precipitation to potential evapotranspiration during the main cropping season (P/PE) and (4) percentage of slope. For poverty, we used the predicted expenditure of the average household in the community.

We used a sequential classification strategy (after Franco et al., 1997) to form the initial groups by the geometric technique using the Ward (1963) hierarchical method, with an optimal number of clusters determined using the upper tail rule (Wishart, 1987). Next, we used discriminant analysis to reclassify communities among groups using a linear discriminant function together with changes in likelihood as a criterion to obtain the final number of clusters; this was done with the statistical analysis system (SAS), WARD-DISCRIM (SAS, 1996). Once we had established the clusters, we performed canonical discriminant analysis using PROC CAN DISC (SAS, 1996) to evaluate the pattern of diversity within the clusters.

Mapping rural poverty in Mexico

Results from the regression model used to develop the poverty map (Tables 2, 3 and 4) show the statistically significant variables.[5] The results also demonstrated that multiplicative heteroskedasticity cannot be rejected; hence it was important to model the variance of per capita expenditure. These results showed that increased education in the municipality decreases the variance; the proportion of households with poor housing and lack of potable water also has a similar effect. Only the proportion of households with telephone increases the variance.

To test the model's performance, we compared the proportion of rural households in extreme poverty by municipality estimated from the model with the actual fractions measured from the ENIGH 2000 survey data (184 municipalities); we found a highly significant correlation (r = 0.799, p<0.01). Additionally, to assess whether there was a correspondence between the observed ranking of municipalities in terms of poverty with the ranking derived from the model predictions, we calculated the Spearman-rank correlation between both, which also shows a strong and highly significant correlation (Spearman's rho = 0.762, p<0.01). Furthermore, we calculated the average fraction of households below the food poverty line for the observed ENIGH 2000 data and from the model predictions. We found that the national average observed rate was 0.324 compared to 0.415 for the model, which suggests that the model tends to overestimate the fraction of households under the food poverty line. Given the significant correlations between observed and predicted rates, the results suggest that the model provides a reasonable estimate of the trend but has a tendency to overestimate actual rates. Our estimates thus may be an upper bound for the incidence of food poverty. Errors of this type are not unexpected, given data restrictions and the unavoidable use of aggregated census data. Access to household-level census data would almost certainly have improved the estimates. However, given the relatively low aggregation level of the census data (municipality level), the spatial patterns and ranking by poverty rates are likely to be valid (e.g. Minot and Baulch, 2002).

The spatial distribution of the predicted per capita total expenditures for the average rural household per municipality, classified according to the three poverty lines (Fig. 1), shows a non-uniform distribution of extreme rural poverty within Mexico concentrated in southern areas and the Sierra Madre Occidental. The non-poor are predominantly in northern areas, irrigated coastal plains and close to large urban centres or tourist resorts.

We also applied the model estimates to the rural community-level data from the 2000 National Census, with the caveats of this approach noted earlier. Results show a similar distribution to that obtained at the municipality level, with strong concentrations of extremely poor rural communities in the southern half of Mexico and pockets within the Sierra Madre Occidental (Fig. 2). The model predicted 40,879 rural communities as below the food poverty line.

We found a strong correlation between our predicted model results with priority regions defined by the Mexican Department for Social Development (SEDESOL) on the basis of marginality (Skoufias et al., 2001, Davis, 2003). Close to 33,752 (83%) of the predicted extremely poor rural communities occurred within the priority zones defined by SEDESOL—virtually all within either "high" or "very high" marginality municipalities. At the municipality level, the model predicted 1020 municipalities below the food poverty line. In comparison, SEDESOL classified 1314 municipalities as either "high" or "very high" marginality. Of the 1020 predicted food poverty municipalities, 909 (89%) coincided with the highest marginality rankings of SEDESOL.

In addition, an independent CIMMYT socio-economic study from 12 rural communities in the southern states of Oaxaca and Chiapas in 2001 provided access to very detailed household-level expenditure data. The Oaxaca/Chiapas study permitted a comparison between observed and predicted poverty status at the community level, albeit on a very small sample. There was a statistically significant correlation between the observed total per capita expenditure and the predicted one ($r = 0.63$, $p<0.01$), and with respect to their rankings (Spearman's rho = 0.63, $p<0.01$).

Rural poverty and maize production

Unsurprisingly, the distribution of maize production was largely coincident with areas of rural poverty. However, commercial maize production areas were largely outside the predicted areas of extreme rural poverty. Commercial wheat areas showed no coincidence. These results were consistent with the working hypothesis that rural poverty would occur predominately outside commercial farming areas.

In terms of CIMMYT maize MEs, 30,161 (74%) of the predicted food poverty rural localities occurred in just three MEs—wet lowlands, wet upper mid-altitude and highland. The two wet environments have more than adequate growing season rainfall (more than 600 mm for wet mid-altitude and more than 800 mm for wet lowlands for a 5-month season). Highland environments have more variable rainfall; however, comparison of all food poverty rural communities with growing season precipitation revealed that 35,814 (88%) were in areas with over 600 mm. The indication is that most of the predicted extreme rural poor communities are located within relatively high rainfall areas.

In terms of soil types, approximately 18,989 (50%) of the extremely poor rural communities that had available soils data occurred on just three major Food and Agriculture Organization (FAO) soil groups; Phaeozems (usually fertile but can be limited by wind and water erosion), and Regosols and Lithosols (poor, underdeveloped soils). There was a clear tendency for the poorer rural communities to be located on sloping lands (Fig. 3).

Poverty and maize trials

In terms of locations where formal CIMMYT maize trials had been carried out, only 7 of the 158 sites used were actually in high probability rural poverty areas and only 16 of the 158 were within extremely poor municipalities (Fig. 4). In terms of MEs, the three key environments (see previous section) were reasonably well represented as 93 of the 158 sites were within them; however, MEs by definition only take into account climatic variables and not factors such as slope and soils. The disparity in the locations of the trials and where the poor live suggests that the potential for spillovers from germplasm tested in those sites to poor farmers may be limited, unless trials were carried out under managed stress designed to replicate farmer conditions and management practices. The finding is consistent with other studies that have found that while improved maize varieties have been available in Mexico for more than 40 years, diffusion has been limited and only about 20% of the total maize area (mostly commercial) is planted to improved varieties (Morris and Lopez-Pereira, 1999).

Other research has shown that the poor tend to benefit indirectly from improved germplasm rather than by its direct adoption by a process known as creolization. This consists of exposing improved varieties to local farmer conditions and management, continually selecting seed of these varieties for replanting and in some cases promoting their hybridization with landraces (Bellon and Risopoulos, 2001, Bellon et al., 2003). Results suggest that either improved varieties are not well adapted to the conditions and environments of the poor, or they lack the traits preferred by farmers. For example, in a recent survey (CIMMYT, unpublished data, 2003) of 400 households in 20 poor communities in four transects representative of three maize MEs from the central highlands to the lowlands of the Gulf Coast, we found that of 606 maize types planted, only seven were improved varieties. However, 26% of the farmers had experimented with 126 maize types, of which 52 were of improved varieties but only three were retained. The survey results suggest that, while farmers have not adopted improved germplasm, they are interested in experimenting with it but the improved germplasm available seems unsuitable for them.

Current technologies addressing the needs of poor farmers

The preceding section may give the impression that the outputs generated by agricultural research have not benefited the rural poor. However, selected examples indicate that some gains are being made. One race of maize germplasm, Tuxpeño, has been the focus of considerable improvement efforts by CIMMYT researchers and national partners. Adaptation zones, based on agro-climatic parameters, and accession sites for this material were strongly coincident with many areas of high probability rural poverty. In other research, we have shown that poor farmers in areas with a high incidence of poverty in the states of Oaxaca and Chiapas have adopted Tuxpeño improved varieties and that the farmers appreciate some of the traits these varieties provide (Bellon et al., 2003). In addition, post-harvest storage technologies for maize grain (through improved pest-resistant germplasm or physical storage devices, such as metal silos) have high potential as pro-poor technology. Existing farmer experimental sites, used for measuring storage losses, were found to occur in or adjacent to high-probability poverty areas. Based on the results measured at these farmer sites, we used predictive models (climate based) to develop storage loss surfaces for Mexico. A combination of these model surfaces with high-probability poverty areas now forms the basis for priority setting exercises (Fig. 5).

Linking poverty mapping to agro-ecological factors relevant for maize performance

The multivariate classification methods grouped 99,665[6] communities into 15 distinct groups. Canonical discriminant analysis resulted in the first two canonical axes explaining 98% of the total variation. The x-axis is correlated with elevation (σ = -0.09921) and minimum (σ = 0.3468) and maximum (σ = 0.2641) temperatures. The y-axis is correlated with the expenditure of the average household in the community (σ = 0.9361) and P/PE ratio during the main agricultural season (σ = -0.3406). Results indicate that for a given elevation (and hence maize environment) there are communities classified as poor and non-poor. Although intuitive, the classification exercise allows us to identify and map them specifically. Fig. 6 maps two contrasting cluster groups (G4 and G12) in terms of poverty in Central Mexico. These two cluster groups, however, share relatively homogenous biophysical environments (cool, high elevation) and the degree of coincidence with the independently defined highland ME is apparent. This refinement beyond simple biophysical characterization is likely to add value to technology targeting efforts. Furthermore, with these data, the importance of each group can be assessed by the percentage of communities included as well as the population in them. The classification provides an efficient sampling framework to select representative communities for further study, e.g. for livelihoods or risk management surveys.

A surprising finding is the correlation between P/PE (a measure of water availability) and the second canonical axis, which indicates that non-poor communities are located in areas with low water availability. One possible explanation is that non-poor communities are found in areas equipped for irrigation, supporting the previous finding that commercial farms are outside the poverty areas.

Discussion and Implications

Targeting agricultural research to produce and deliver appropriate technologies to poor farmers can enable them to have a better life and escape poverty. Poverty mapping is one potential tool to accomplish this goal; however, it requires modifications to make it relevant for targeting agricultural research. As our results in Mexico demonstrate, the rural poor are not homogenously located across the country but rather are concentrated in particular regions and under particular circumstances. Poverty is concentrated in mountainous and indigenous areas, mainly in central and southern Mexico but also the mountainous regions of north-west Mexico. These "islands" of poverty exhibit specific circumstances such as the presence of indigenous populations, higher rainfall, steep slopes, erodable soils and lack of access to services.

While the concept of agro-climatic classification (e.g. maize MEs) is a useful tool for targeting breeding in terms of climatic variables, it ignores some of the important factors identified as relevant for the poor, such as land slope and soil classification. Clearly, in terms of targeting research for the poor, these factors must be taken into consideration. It should be pointed out that the spatial patterns identified above may reflect a historical process that led to what Mexican anthropologist Aguirre Beltrán (1987) called "regions of refuge," i.e. isolated and difficult-to-access areas into which the expansion of more powerful mestizo and European-descent Mexicans has pushed indigenous peoples since colonial times. Besides these historical patterns, it is clearly more expensive and difficult to bring both private and public goods and services to the inhabitants of these areas because of low population densities and difficult access due to the topography.

Another factor that may exacerbate this pattern is that indigenous peoples have historically suffered from social exclusion and discrimination, having low social status, and hence society in general and governments in particular have easily ignored their voices in the past. This means that the political clout needed to mobilize public investment (and hence the provision of public goods and services, which may also facilitate the supply of private ones to these areas) may have been low, perpetuating a historical pattern of neglect and probably making it even worse. Clearly, this suggests a poverty trap, rooted in a history of social exclusion, which goes beyond the current circumstances faced by the poor in these regions.

A key result of our study is the lack of coincidence between the location of the formal maize trials that CIMMYT and its partners carry out in the country and the locations where the rural poor live. The disparity cast doubts on the potential for spillovers of the germplasm tested in these environments to the locations and conditions of the poor. This disparity is not surprising and should be interpreted carefully. First, most of these trials are conducted in collaboration with national partners for whom alleviating poverty has not necessarily been a primary mandate. The partners largely determine where trials are planted, and favourable accessible flat lands are often preferred sites.

Second, many of these trials are conducted on experimental stations that allow breeders better control of environmental variation and of selection factors, such as abiotic and biotic stresses, which the germplasm in development will face in the target environments. Methodologies for stress breeding on experimental stations have been developed and tested successfully (e.g. Bänziger et al., 2000, Bänziger and Cooper 2001). In contrast, conducting breeding work in farmers' fields is often less efficient because researchers' ability to manage selection factors and control environmental variance are often limited. Building new stations in the regions where the poor live may be feasible but will require additional investments that may not be the best use of scarce resources for agricultural research.

Third, the most effective approach may be a combination of breeding for conditions more relevant to the poor by using researcher-managed, controlled stress environments on experimental stations (which could also include the direct input of farmers in specific stages of the breeding process) plus a network of trial sites in the areas where the poor live, largely handled by farmers using their common management practices. This model, known as "Mother and Baby" trials, continues to be used by CIMMYT and its partners in southern Africa and has proven highly successful (Bänziger and De Meyer, 2002, De Groote et al., 2002), although the targeting of these efforts has not been based on poverty mapping per se.

A poverty mapping effort that combines factors that are relevant for the development and performance of agricultural technology, in this case breeding, should be effective in systematically identifying the important biotic and abiotic stresses faced by the poor, given the biophysical conditions in which they farm and their relative importance. These include the management practices and inputs that the poor use, the traits they value and the priorities they place on these traits, as well as the trade-offs they face. Biophysical conditions encountered by the poor can be identified directly from maps and secondary data (e.g. rainfall and temperature). But identifying, characterizing and prioritizing management practices, level of inputs and crop traits requires direct interaction with poor farmers.

A poverty map is a useful tool for identifying the areas where the poor farm and as a framework for designing and carrying out representative studies to more systematically characterize the management practices, input levels and crop traits in these areas, which based on their importance and distribution should lead to their prioritization. This in turn should allow tailoring the conditions under which formal plant breeding takes place to better reflect the conditions of the target environments, both from an agro-ecological and a management perspective. By quantifying how widespread those conditions are in terms of number of farmers and area planted, one could prioritize the breeding effort across environments, management practices and traits. Clearly, the larger the number of different environments and the smaller each environment may be in terms of number of farmers or area, the more expensive targeting may be, and vice versa. But this is something that cannot be done until a poverty map with relevant crop performance information is developed.

The exercise presented here, linking a poverty map with relevant biophysical data, presents a first approach to developing an improved targeting and priority-setting framework. This should be followed by a systematic characterization of the different environments faced by the poor in terms of required crop traits demanded, management and inputs used, constraints faced and opportunities to access improved technologies if made available. The final characterization should use direct contact with farmers and other participants in the targeted regions. CIMMYT maize scientists are now implementing such an approach in relation to post-harvest storage technologies and demand-driven, targeted trait introgression.[7]

We used Mexico as a case study to explore the relevance of poverty mapping to agricultural research but believe the findings and approaches are more widely applicable. Similar datasets relating to poverty, crop performance and agricultural research are now available in many developing countries, providing opportunities to undertake comparative studies in other regions. The integrated approach outlined in our study is believed to be one way in which to increase the benefits from agricultural research to poor rural communities.

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[1] The CTMP (2002) developed three poverty lines for both rural and urban areas of Mexico (Mexican pesos of 2000, given here in US$ for rural areas). First, the food poverty line (Poverty Line 1= US$51.60/capita/month) refers to the impossibility of obtaining a food basket needed for adequate nutrition, given the consumption patterns of Mexicans, using all available resources. Second, the capabilities poverty line (Poverty Line 2 = US$89.57capita/month) refers to the failure to reach the level of expenditure needed to obtain a reference food basket plus the expenditure needed for health, clothing, housing, transportation and education. Lastly, the assets poverty line (Poverty Line 3= US$111.25capita/month) refers to the inability to obtain the value of the reference food basket plus an estimate of non-food expenditure considered as necessary in general.

[2] We used this regression model, as suggested by Bigman et al. (2000), estimated with LIMDEP (Greene, 1998). The model estimated the log of the ratio of total current expenditure per capita per household per month to the food poverty line (US$51.60) as a function of household size, education and housing characteristics at household level plus an index of accessibility, fraction of indigenous language speakers, percentage of the rural population, population density and climatic data at municipal level and state location. We estimated one national model instead of several sub-national ones that in theory could have addressed the high social and spatial heterogeneity in the country. The latter, however, would have implied dividing the country into sub-national units, which can be seen as arbitrary and would have decreased the number of observations per model. Our single model included dummy variables for all Mexican states, well-recognized political units, with distinct histories, policies and institutions, but allowed use of all available data.

[3] The CTMP applied the poverty lines to the whole country, without adjustments for regional disparities in prices. While ideally one may want to adjust for these disparities, in our study no adjustments were made.

[4] Ideally, one would apply the estimated regression parameters to individual households to predict their consumption or income (e.g. Hentschel et al., 2000). However, we could not do this because we lacked access to household disaggregated data at the national level for Mexico. We chose the method developed by Bigman et al. (2000) because it allowed us to work with available data. Other studies (e.g. Minot and Baulch, 2002) have confirmed the validity of such an approach when use of aggregated data is unavoidable.

[5] The overall estimation of the regression model yielded the following results: Breusch-Pagan LM statistic [13 DF] = 78.5274. Sig. level= 0.00001. Log likelihood function = -2620.979. Restricted log likelihood = -2656.292. Chi-squared = 70.62644, DF = 13, Sig. level = 0.000001. No simple R^2 can be reported because maximum likelihood estimation was used to jointly determine the coefficients in the model and the heteroskedasticity structure.

[6] Mexico has 103,635 communities but some had insufficient data to be included in the analysis.

[7] "Targeted allele introgression" is a methodology, currently under evaluation, which allows the incorporation of valuable traits (such as drought tolerance and storage pest resistance) from elite germplasm into local maize populations and builds on farmers' seed management practices (Bergvinson and Garcia-Lara, 2004).

Figure Legends

Fig. 1. Poverty status, based on predicted total expenditure per capita for municipalities, in relation to poverty lines defined by the Mexican Technical Committee for the Study of Poverty (CTMP, 2002).

Fig. 2. Rural communities under Poverty Line 1 (food) defined by the Mexican Technical Committee for the Study of Poverty (CTMP, 2002).

Fig. 3. Percentage of rural communities predicted to be under Poverty Line 1 (food) or non-poor (using CTMP [2000] definition) by slope class.

Fig. 4. International Maize and Wheat Improvement Center maize trial sites, derived from international testing trials database, in relation to rural poverty areas.

Fig. 5. Predicted maize grain storage damage (after 150 days under small-scale farmer storage conditions) in relation to rural food poverty.

Fig. 6. Example of two contrasting cluster groups (G4 and G12) in terms of poverty, occurring within a relatively homogenous environment, Central Mexico, shown in relation to the independently derived highland maize mega-environment.

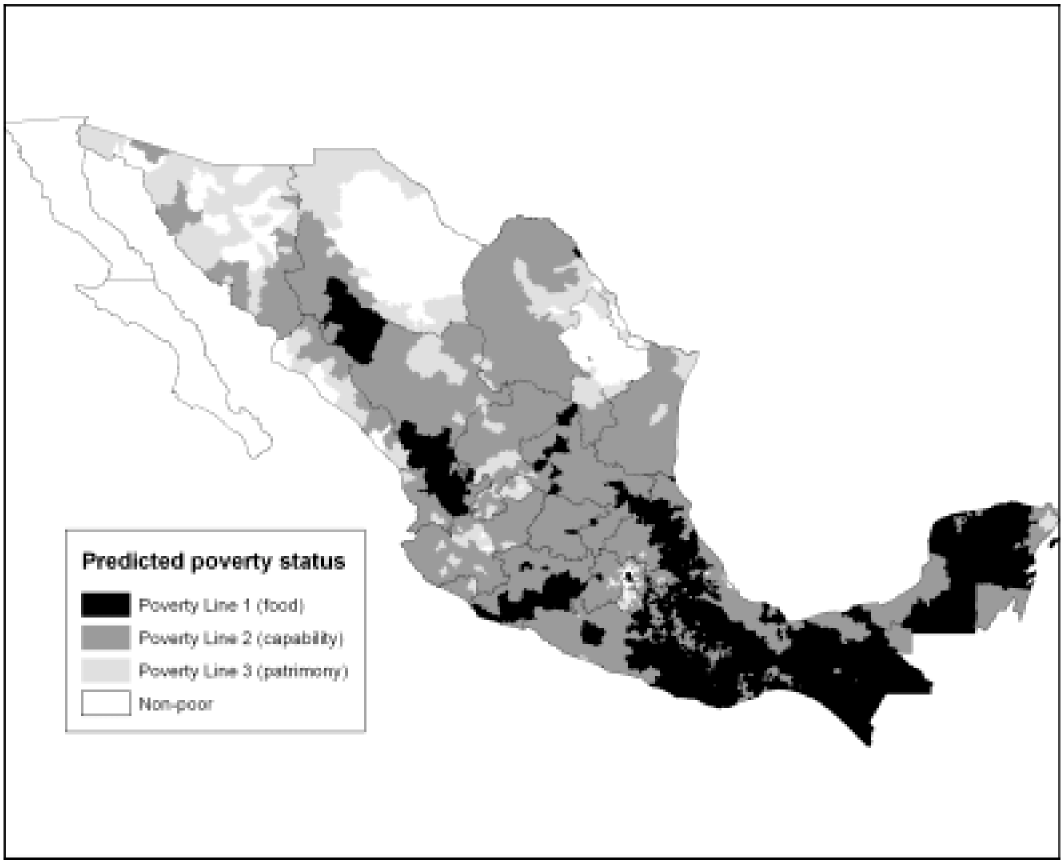

Predicted poverty status
Poverty Line 1 (food)
Poverty Line 2 (capability)
Poverty Line 3 (patrimony)
Non-poor

Fig. 1

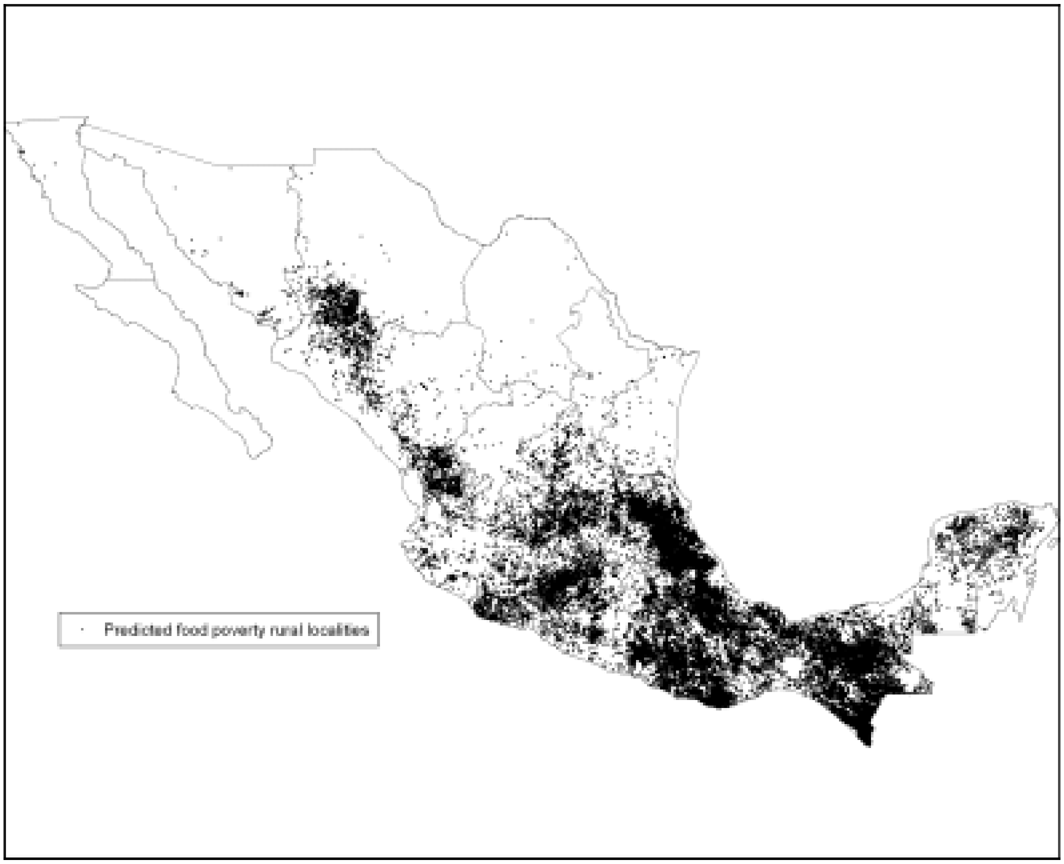


Fig. 2

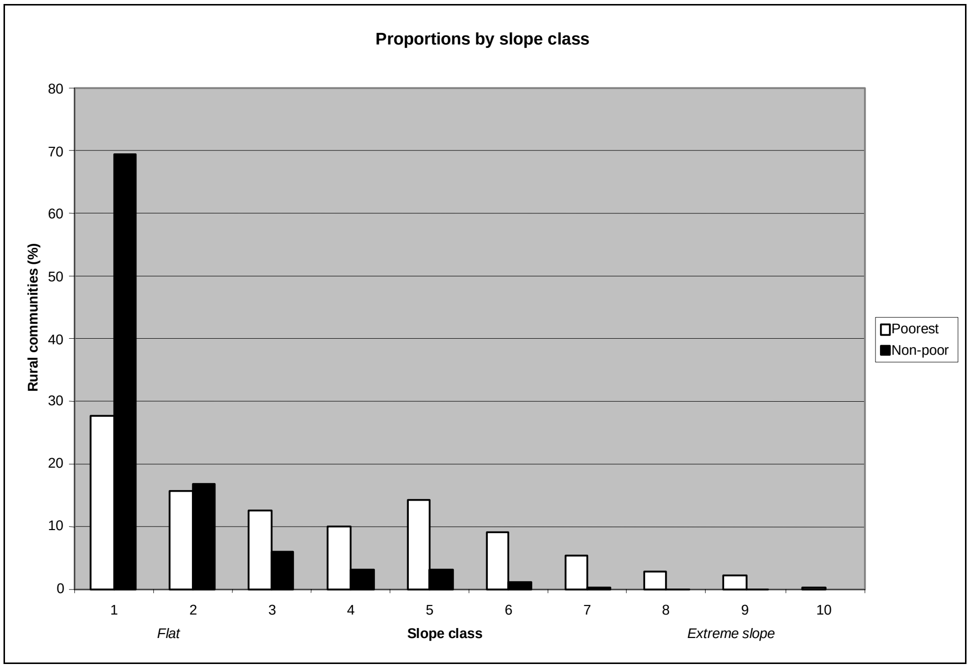
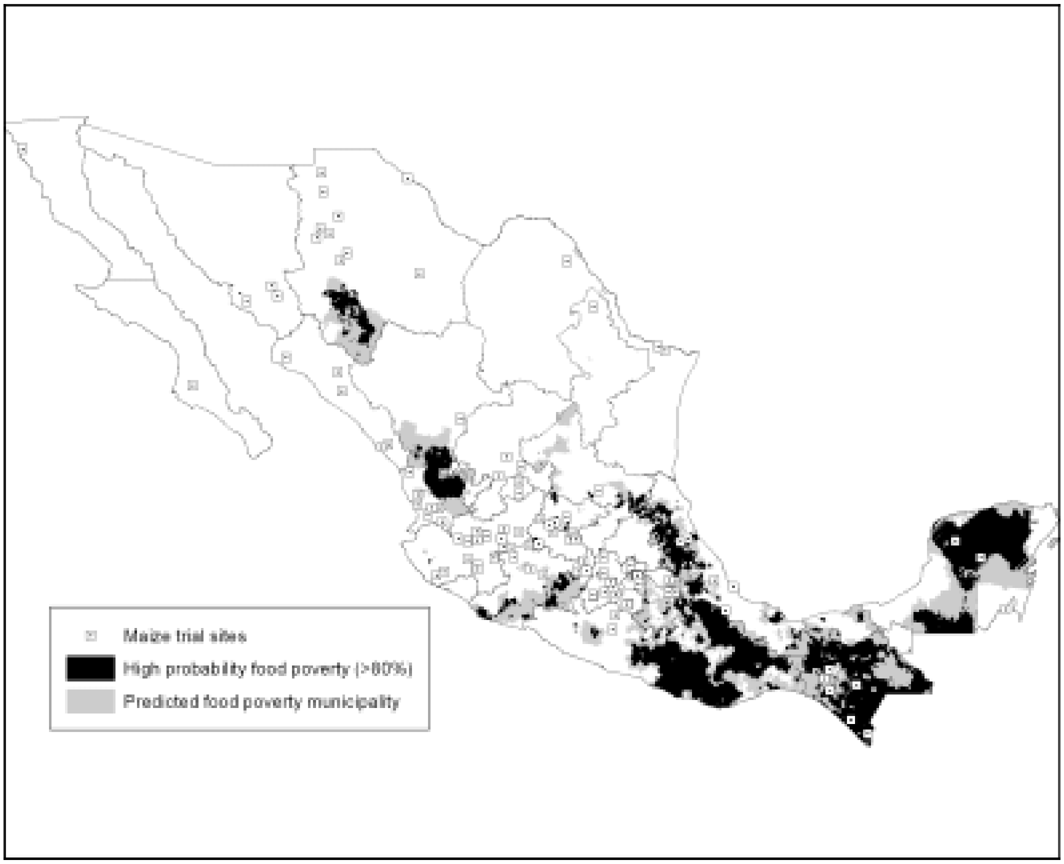

Proportions by slope class
Rural communities (%)
80
70
60
50
40
30
20
10
0
1
2
3
4
5
6
7
8
9
10
Flat
Slope class
Extreme slope
Poorest
Non-poor

Fig. 3



Maize trial sites
High probability food poverty (>80%)
Predicted food poverty municipality

Fig. 4

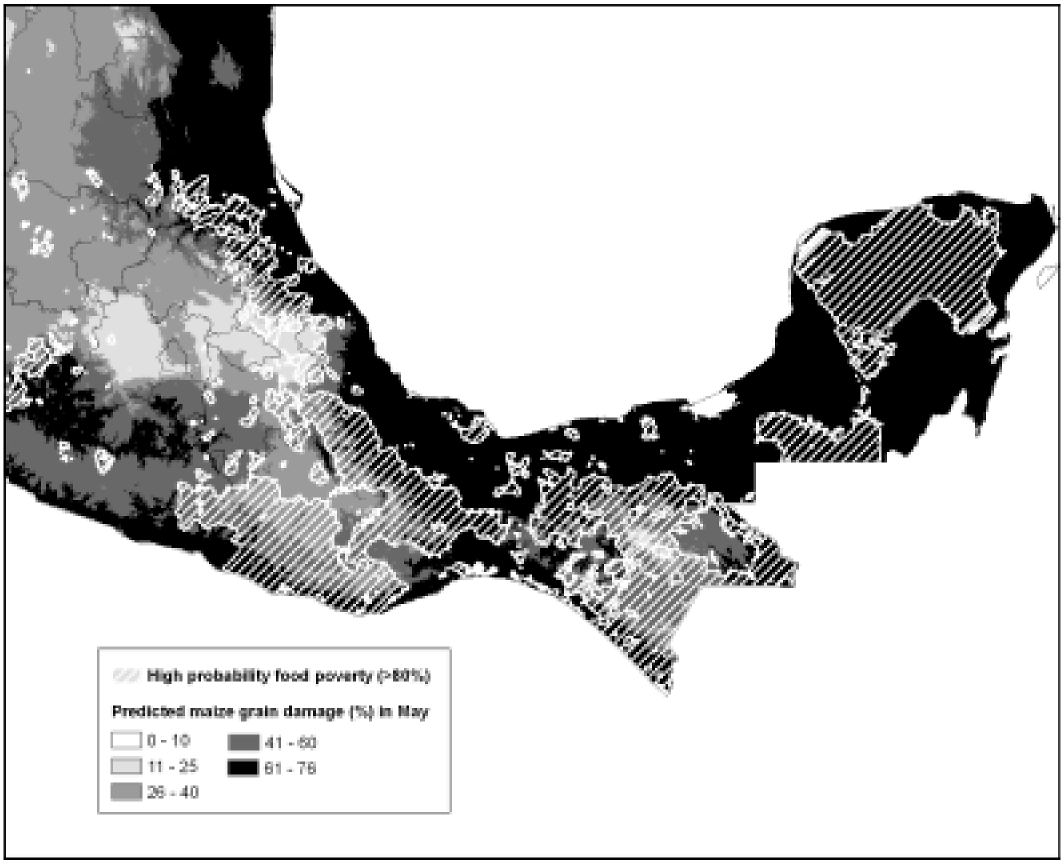

High probability food poverty (>80%)
Predicted maize grain damage (%) in May
0 - 10
11 - 25
26 - 40
41 - 60
61 - 76

Fig. 5

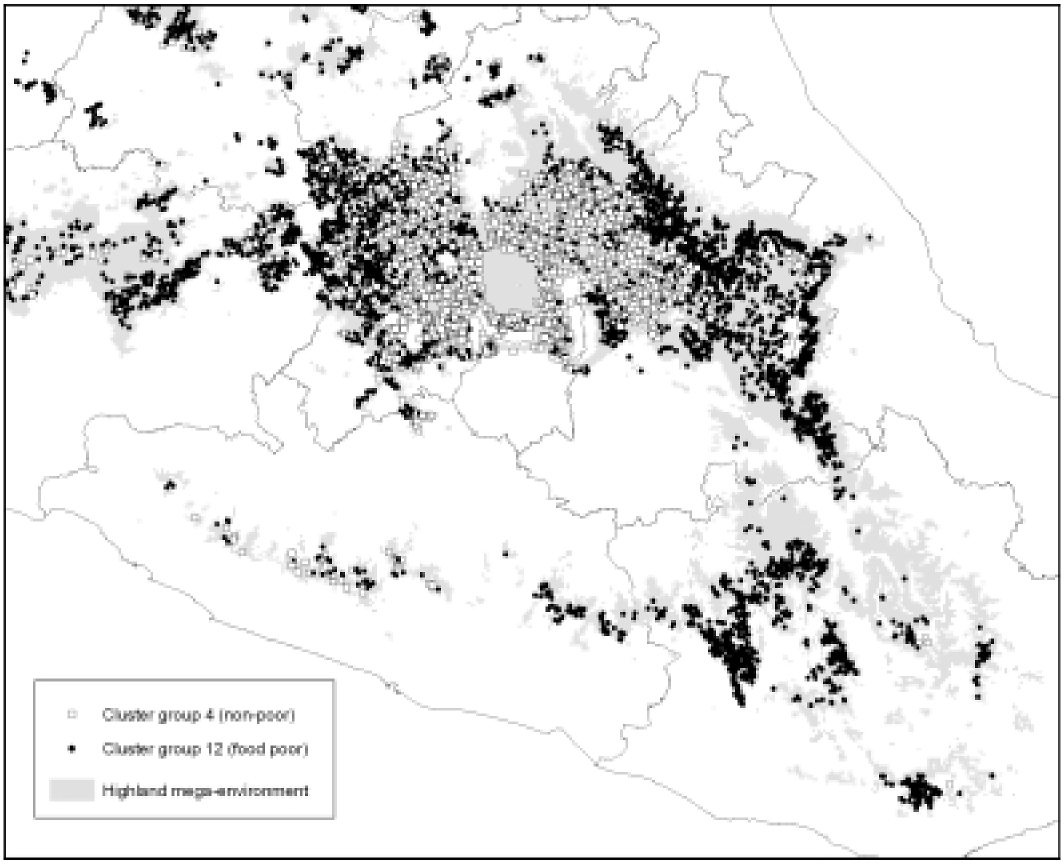

Cluster group 4 (non-poor)
Cluster group 12 (food poor)
Highland mega-environment

Fig. 6

Table 1
Definitions of maize mega-environments based on climatic parameters for a 5-month optimum season (i.e. 5 consecutive months with highest precipitation/potential evapotranspiration ratio)

Maize mega-environment	Precipitation (mm)	Maximum temperature (ºC)
Wet Upper Mid-altitude	>600	>=24 <28
Wet Lower Mid-altitude	>600	>=28 <30
Dry Mid-altitude	>350 <=600	>=24 <30
Wet Lowland	>800	>=30
Dry Lowland	>350 <=800	>=30
Highland	>350	<24 >=18

Table 2
Regression results: Log of the ratio of household per capita expenditure/month to the food poverty line ENIGH 2000[a], household-level factors

Variable	Coefficient	*t*-value[b]
Constant	1.0510	5.01**
Household size	-0.1560	-28.44**
Dwelling with (dummy variable):		
only earth floor	-0.1819	-6.74**
only one room	-0.1214	-5.13**
potable water	0.0280	1.08
sewage	0.2330	10.12**
electricity	0.1905	4.83**
telephone	0.3425	10.34**
No. of household members older than 15 that:		
do not know how to read and write	-0.0322	-2.36*
have some years of elementary education but incomplete	-0.0231	-1.98*
completed elementary education	0.0306	2.27*
have some years of secondary education but incomplete	0.0446	1.79†
completed secondary education	0.0546	3.69**
have post secondary education	0.1723	5.67**

[a] *Source:* INEGI (2001)
[b] † significant at $p = 0.10$, * at $p = 0.05$ and ** at $p = 0.01$ for a 2-tailed *t*-test.

Table 3
Regression results: Log of the ratio of household per capita expenditure/month to the food poverty line ENIGH 2000[a], municipal-level factors

Variable	Coefficient	*t*-value[b]
Fraction of population older than 5 that speaks an indigenous language	-0.2530	-4.40**
Accessibility index[c]	0.0002	2.12*
Minimum temperature	0.0182	1.84†
Maximum temperature	-0.0117	-1.03
Yearly rainfall	-0.0002	-3.01**
Percentage of rural population	-0.0003	-0.80
Population density	0.0002	3.53**
State location (dummy variable)		
Aguascalientes	0.1710	1.35
Baja California	0.2469	1.81†
Baja California Sur	0.3999	2.80**
Campeche	-0.2499	-1.82†
Coahuila	-0.0475	-0.37
Colima	-0.0341	-0.25
Chiapas	-0.3971	-3.09**
Chihuahua	0.1278	0.94
Durango	0.0367	0.29
Guanajuato	-0.1436	-1.21
Guerrero	0.1859	1.48
Hidalgo	-0.0663	-0.57
Jalisco	0.0006	0.01
Mexico	-0.0173	-0.15
Michoacan	-0.1503	-1.28
Morelos	0.1152	0.90
Nayarit	-0.0417	-0.31
Nuevo Leon	0.1790	1.42
Oaxaca	-0.3520	-2.73**
Puebla	-0.3159	-2.56*
Queretaro	-0.0532	-0.44
Quintana Roo	-0.0095	-0.07
San Luis Potosi	-0.1299	-1.06
Sinaloa	0.2308	1.67†
Sonoroa	-0.0027	-0.02
Tabasco	-0.2726	-2.09*
Tamaulipas	-0.0139	-0.11
Tlaxcala	-0.0315	-0.28
Veracruz	-0.1439	-1.23
Yucatan	-0.5150	-3.69**
Zacatecas	0.1334	1.05

[a] *Source:* INEGI (2001)
[b] † significant at $p = 0.10$, * at $p = 0.05$ and ** at $p = 0.01$ level for a 2-tailed *t*-test.
[c] Average travel time in minutes to the nearest urban centres (>2500 persons) for a municipality. A large number indicates inaccessibility and vice versa.

Table 4
Regression results: Log of the ratio of household per capita expenditure/month to the food poverty line ENIGH 2000[a], variance function factors

Variables	Coefficient	*t*-value[b]
Sigma	0.9701	6.82**
Household size (municipality mean)	0.0595	1.29
Dwelling with (fraction for the municipality):		
only earth floor	-0.0879	-0.62
only one room	-0.3270	-2.02*
potable water	-0.2324	-2.05*
sewage	0.1777	1.55
electricity	-0.3496	-1.57
telephone	0.3769	1.73†
No. of household members older than 15 that:		
do not know how to read and write (municipality mean)	0.1929	2.00*
have some years of elementary education but incomplete	-0.3929	-4.05**
completed elementary education	-0.4929	-4.09**
have some years of secondary education but incomplete	0.1470	0.58
completed secondary education	-0.2966	-2.30*
have post secondary education	-1.5759	-5.00**

[a] *Source:* INEGI (2001)
[b] † significant at $p = 0.10$, * at $p = 0.05$ and ** at $p = 0.01$ level for a 2-tailed *t*-test.