Exploring the spatial variation of food poverty in Ecuador

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Abstract

We examine the geographic dimensions of food consumption in Ecuador, which has one of the highest rates of chronic infant undernutrition in Latin America. We use statistical and spatial analyses to examine the distribution of

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food consumption and food poverty and to test and generate hypotheses of food poverty estimates at the district level. Results show that the food poor are concentrated in certain locations with a significant cluster identified in the central Andean region. Geographically weighted regression shows that the processes underlying food poverty in Ecuador are also spatially variable. While our results lend support for nationwide land tenure reforms, in the central Andes these must take into account productivity constraints and communal ownership. Improvements in transport infrastructure will likely decrease levels of food poverty country-wide but could be most beneficial in the extreme south and in the province of Esmeraldas. Investment in rural enterprise development should be encouraged in all regions.

Keywords: Food security; Agricultural productivity; Market access; Rural income generation; Indigenous communities; Ecuador

Introduction

Ecuador, Guatemala, Honduras and Haiti are among the countries in Latin America with the highest rates of chronic infant undernutrition (FAO, 2003). Figures for Ecuador show undernutrition rates of 34% in 1986, 26.5% in 1998 [1](Larrea et al., 2001) and 23% in 2004 [2](CEPAR, 2005). The long-term effects of infant undernutrition on health, educational attainment and capacity to work have been well documented (Steckel, 1995, Grantham-McGregor et al., 2000, Fogel, 2001, Semba and Bloem, 2001). In Ecuador, a country with high social inequality[3] (Larrea and Kawachi, 2005) and 62% of the population falling below the poverty line in 1998, pronounced social, regional and ethnic disparities in the distribution and consumption of food are to be expected.

Policies aimed at reducing inequality and improving nutrition must be based on detailed studies documenting these disparities and identifying their causes. Information for policy formulation and targeting is needed to optimally deploy direct aid, development or research resources. Hentschel et al. (2000) demonstrated a theoretical reduction in resource leakage and greater coverage using a geographically targeted implementation of a pro-poor energy subsidy. Reductions in food poverty are likely to be achieved by the implementation of a range of interventions, rather than a direct cash transfer to recipients. Targeting the range of possible interventions that are not direct aid is inherently more difficult because the benefits are often limited to certain locations, sectors of the economy or demographic groups. The utility of information that improves targeting of public goods is therefore more difficult to quantify.

Analyses based on household surveys, which are representative for a few regions (e.g. Datt and Jolliffe, 1999), often fail to reveal the location of the population affected. On the other hand, qualitative assessments of limited geographical extent (e.g. Hentschel et al., 1996) do not allow a country-wide investigation of the causes of inadequate food consumption and undernutrition. Other studies addressing these problems by combining survey and census data

(Larrea et al., 1996, Hentschel et al, 2000) lack consideration of geographic and environmental factors. Our experience in Ecuador suggests that poor accessibility to markets and services and environmental constraints to agriculture have negative impacts on wealth and food security outcomes. Petrucci et al. (2003) deal with some of these issues for Ecuador but use data aggregated to county level, potentially hiding interactions at the household level.

A spatial analysis framework offers advantages over tabular analysis. The visualization of the estimates in map form is an efficient medium for planning responses to food poverty. Spatial statistics can quantify and clarify patterns seen in maps. A spatial framework allows for incorporating spatially continuous environmental variables in the analysis. Explicit spatial analyses take into account the local nature of relationships between food poverty and its determinants.

Data

Food poverty indicators

We calculated food consumption at the household level using small area estimation (SAE) techniques (Larrea, 2005)[4.] We created models of food consumption using data from the 1998 Living Standards Measurement Study

(LSMS) survey (INEC and World Bank, 1998) and the 2001 Ecuadorian national population census (INEC, 2001). These data were aggregated and food poverty indicators constructed for 990 districts (*parroquias*), a far finer resolution than currently published statistics[5]. Poverty indicators are measures of district-level household food consumption with respect to a specific poverty line (Lanjouw, 1998). Two studies give differing monetary values of the food poverty line in Ecuador. One study estimates the cost of a basic basket of food goods as 173,050 sucres per fortnight, which in 1998 represented US$2.2 per day (World Bank, 1996). An alternative study (Parandekar and Brborich, 1999), gives a value of 132,150 sucres per fortnight for the basic basket of goods (US$1.7 per day). We calculated the Foster-Greer-Thorbecke (FGT) family of poverty indicators, including the headcount ratio, the poverty gap and poverty severity (Foster et al., 1984) for both the higher and lower food poverty lines.

Potential factors related to food poverty

Together with a panel of food security experts in Ecuador, we developed a list of potential determinants of food poverty (Farrow et al., 2002). The panel identified key factors that have a hypothetical association with food poverty. These include social capital, agricultural productivity (climate, soil, management and tenure), labour market structure and access to markets.

A study resulting in a nutritional profile of Ecuador (ODEPLAN-FAO, 2001) suggests that social capital and the culture of a locality influence the access to a diversity of food products and a diverse diet. Indicators of social capital have not been formally defined for Ecuador. While limited local studies investigate the role of social capital (Bebbington and Perreault, 1999), nationwide data on density of voluntary organizations (Putnam, 1993) or of social networks (e.g. Paldam, 2000) are lacking. Our analysis used a proxy variable for social cohesiveness—the percentage of each district's population classified as indigenous. Historic discrimination and social exclusion has limited the livelihood opportunities of indigenous people in Ecuador. Indigenous communities, however, have maintained a strong sense of identity. In recent decades a conversion has been made to full political participation (Larrea and Montenegro, 2005).

Access to water is potentially an important determinant of rural food poverty (Rosegrant et al., 2002, GWP, 2003) since improved agricultural productivity can increase farm incomes and lower prices for consumers (de Janvry and Sadoulet, 2000). We hypothesize that areas suffering regionally from drought and locally from water stress will be unable to support sufficient production to ensure adequate food consumption. For rainfed agriculture we have developed an index of water availability calculating the number of consecutive dry months (Fig. 1) where monthly precipitation less than 60 mm is considered dry due to crop growth limitations (Peter Jones, personal communication, 2003). The number of farms with irrigation and the total amount of land irrigated were recorded in the 2000 agricultural census (INEC, 2000). We acknowledge, however, that farms with irrigation may face restriction on their use of water resources (Cremens et al., 2005). Irrigation data have been published for most counties in Ecuador. Given the lack of data at the district level, we assume that each district has the same value as the county to which it belongs.

Elevation and slope are proxies for temperature and management constraints on agricultural productivity. In some very high zones (*paramos*), we encounter particularly fragile agro-ecosystems associated with elevated concentrations of poverty. In Ecuador, the resolution of altitude data is currently far finer than for temperature. Slope is generally expected to have a greater impact on food poverty than altitude. We calculated summary statistics of altitude and slope for each district from the Shuttle Radar Topographic Mission (SRTM) data set modified by CIAT (Jarvis et al., 2004).

Soil quality is another constraint on agricultural productivity and presents significant spatial variation within districts and even within plots (Dercon et al., 2003). We use maps of potential for agriculture, whose classes explicitly incorporate soil quality information and limitations (BID-CONADE, in Alianza Jatun Sacha-CDC Ecuador, 2003). Potential agriculture classes are classified into suitability for pasture, crops, productive forest and natural areas (default). Actual land use, compiled from various sources from the 1990s (Alianza Jatun Sacha-CDC Ecuador, 2003), is also categorized in terms of percentage crop, pasture, productive forest, natural areas and non-vegetative land use.

Deteriorating soil quality and land degradation is often the result of inappropriate land use decisions. These short-term decisions may be forced upon land managers in order to escape poverty. For each class of actual land use, we determine if it was cultivated in an appropriate location given the potential of the soil. We conclude by producing summary statistics of productive land use suitability for each district.

Land tenure inequality, and as a consequence the large number of farmers without land or with less than 5 ha, is potentially related to low levels of food consumption. Data on legal status of agricultural land were made available at the county level for much of the country (INEC, 2000). Equality indicators, such as the GINI coefficient of farm size, are not formally published for sub-national administrative levels.[6] But these have been calculated for counties using data available on farm sizes (Manuel Chiriboga, personal communication, 2005)[7.] As with data on irrigation, we assume that districts will have the same values for these variables as the counties.

The agricultural sector is often characterized by lower incomes relative to other components of the national workforce (Elbers and Lanjouw, 2001). Districts with high proportions of agricultural workers are likely to have higher levels of food poverty. Agricultural workers receiving a regular wage may be less vulnerable than informal day labourers. Salaried workers may receive ancillary benefits such as limited health insurance that will improve welfare levels. We therefore expect districts with greater proportions of salaried agricultural workers to have lower levels of food poverty than those with non-salaried agricultural workers. The employment characteristics of household members were explanatory variables in the original SAE models (Larrea, 2005), raising concerns about the potential for endogeneity in subsequent modelling. Elbers et al. (2005) suggest, however, that the use of estimates aggregated to community level as the dependent variable does not preclude subsequent regression analyses.

Access to markets is an important prerequisite for rural income generation and can improve nutrition by providing access to a wider variety of foodstuffs than would be possible from on-farm consumption alone. Jacoby (2000) showed that an improvement in access generally benefits the whole population. We would therefore expect districts with better access to markets to have higher mean food consumption and lower levels of food poverty. We produced indices of accessibility to four market types. National markets are the three biggest cities—Guayaquil, Quito and Cuenca. Regional markets are based on traditional markets in the Andes with others selected for the coastal and Amazon regions (Patricio Martinez, personal communication, 2003). Provincial markets are the capital city of each province (Fig. 2). Local markets are the major populated place in each district[8].

Methods

Spatial structure of food poverty

Tobler (1970) proposes the first law of geography as “everything is related to everything else, but near things are more related than distant things”. While this “law” is not universally true[9], an assumption of association between neighbouring observations can guide our investigation of the spatial structure of food poverty. Measures of spatial association can help us discover patterns in food consumption that are hidden or difficult to discern from raw data. Our method addresses whether food poverty is distributed randomly throughout the country, whether it exhibits a high degree of spatial autocorrelation and whether it is spatially clustered.

The spatial representation of districts we used in this analysis is the polygon centroid (Jenness, 2001). To analyse the distribution of food poverty in Ecuador we first utilized semi-variograms choosing intervals of 5 km. Semi-variograms are used extensively in geo-statistics and present a graphical representation of variance that can aid the analysis of patterns of food consumption[10]. The interpretation of the semi-variogram for mean consumption per person per district (Fig. 3) shows spatial dependence up to 100 km. The intercept of the variogram (nugget variance) is moderately high and approximately one-third of variation is not accounted for between districts. We discover similar levels of spatial association for all our indicators of food poverty. The semi-variograms suggest that food consumption and food poverty values are geographically clustered as opposed to randomly distributed.

We measured spatial autocorrelation in our food poverty indicators using Moran’s I statistic (Moran, 1950, Sawada, 1999). Values of Moran’s I varied between 0.354 and 0.447 (Table 1) for all districts. Positive spatial autocorrelation was significant although not always large on account of skewness. Local Indicators of Spatial Autocorrelation [11](LISA)—in this case Moran's I—showed outliers of significant negative spatial autocorrelation located in clusters of significant positive spatial autocorrelation. Many of these outliers represent the principal (often urban) district in each county. When these districts are excluded from the data set, we see increases in spatial autocorrelation and food poverty (Table 1).

Given that food poverty in Ecuador is non-random, we used the Geographical Analysis Machine (GAM; Openshaw, 1987) to seek and visualize significant clusters of people below the food consumption poverty line. GAM searches for cases that are significantly different from the expected (global) incidence of food poverty using a Monte Carlo simulation in a multi-scale moving window to measure the persistence of clusters at different scales. One cluster of districts is easily identified (Fig. 4). This cluster has at least three foci, one in central Chimborazo, a second in western Tungurahua and the third in central Cotopaxi. These clusters correspond with those identified using LISA statistics.

Testing hypotheses using regression models

The existence of spatial autocorrelation in our dependent variable, and the possibility of non-stationarity in the processes that cause food poverty (Brunsdon et al., 1996), limit the inferential power of ordinary least squares (OLS) regression. Geographically weighted regression (GWR) is an alternative and is commonly used to overcome the limitations caused by spatial dependency (Miron, 1984, cited in Fotheringham et al., 2002).

We ran models using available data at the district scale, even though variables for land tenure and irrigation were only available at the county scale. We acknowledge the potential introduction of artificial spatial auto-correlation in some of our independent variables, as well as possible problems of ecological fallacy (Robinson, 1950). Nevertheless, by running the models using district-level information we were able to distinguish between urban and rural areas and take full advantage of the fine resolution of the micro-scale food poverty data. The models were developed using all independent variables for seven dependent variables (see Table 2). We analysed the correlation between our independent variables to eliminate those that showed collinearity (Table 2). In the case of the accessibility indices for district, provincial, regional and national markets, we tested each index individually in all regression models, selecting the index that explained most variance. We calibrated all models using version 3 of the GWR software (Fotheringham et al., 2004). We weighted valid data points aspatially according to the natural logarithm of population of each district and rescaled so that the sum of the weight variable is equal to the sample size (670).

Regression model results

The adjusted R^2 increases and ANOVA F-tests confirm that the GWR models explain significantly more variance than the global models (Tables 3-5). The food poverty gap (FGTI, Table 4) and food poverty severity (FGT2, Table 5) models appear to be better defined than the food poverty headcount ratio (FGT0) and mean consumption (MEANY) models (Table 3). An analysis of the local pseudo R^2 shows that despite small differences between models all areas except the northern Amazon are better explained using local rather than global models. In addition, certain regions in Ecuador are better explained than other zones. The provinces of El Oro and Cotopaxi (Fig. 5) for instance are consistently well explained, while the local pseudo R^2 values for counties in the northern sierra and the provinces of Azuay and Morona Santiago show only marginal improvements over the global R^2 values.

When we examine the coefficients of the “independent” variables, we can take into account both the global and the local model results. Variables that are significant in explaining variance in the global models but show little spatial variability are likely to be significant in most locations. Variables that are both significant in the global regression model and display significant spatial variation are likely to be significant in most locations but the strength of the relationship is less strong in some specific regions. Variables that are insignificant in the global models but which show significant spatial variation are likely to be positively significant in some areas but negatively significant in others. These cases merit special attention.

The percentage of the population who class themselves as indigenous (INDIG) has a significant positive association with all the food poverty indicators and a negative association with MEANY. The variable also displays significant spatial variability in nearly all models. Mapping the local values of significance of this parameter confirms that all areas reflect the global model except the southern provinces of El Oro and Loja and a few remote Amazonian districts.

Our climatic variable (MN_DRY) shows significant spatial variability in all seven models. The significance of determination of dry months on food poverty is strongest in the central Andean region (Fig. 6). Semi-arid coastal areas benefit from alternatives to agriculture such as fishing and tourism but even with the inclusion of a coastal dummy variable (COASTAL) the effect of climate in these areas is either insignificant or negatively significant. The proportion of farms that have irrigation equipment (PR_RIE1) is not significant for either FGT0 or MEANY. Irrigation is moderately significant in the global models of FGT1 and FGT2 as well as displaying considerable spatial variability. This variable shows a negative association with inequality in the central Andes and a positive association in the southern coast and highlands and much of the central Amazon region.

Mean slope per district (MN_SLP) shows a significant positive association with FGT1 and FGT2 in all Ecuador but the relationship with FGT0 or MEANY is insignificant. There is no significant spatial variability in any of the models. Land use suitability (MN_SUIT) shows significant spatial variability in four of the seven models. As expected, we see a negative relationship between suitability and poverty in the central Andes, coast and Amazon; however, this association is reversed in the northern Andes and Amazon (Fig. 7).

The proportion of individually owned land (PR_IND2) is insignificant in all global models but shows some spatial variability. Fig. 8 shows two areas where the proportion of land owned by individuals is negatively associated with food poverty. The GINI coefficient of farm size is highly significant in the global regression but shows little spatial variability. A reduction in GINI is related to a reduction in food poverty; this relationship is strongest with FGT0 but weakens in the FGT2 models.

Our two agricultural employment variables are highly significant in all the global models and show significant spatial variation. We find a cluster of districts in the provinces of Azuay and Cañar, southern Chimborazo, eastern Guayas and parts of Morona Santiago that do not show a strong association between the percentage of the workforce (AGR_WF) in agriculture and food poverty. In the case of the percentage of salaried agricultural workers (SAL_AGR), the relationship between salaried workers and food poverty is strong in two areas—the northern Andes and northern Amazon (from Cotopaxi northwards), and the southern Andes and southern coast (from Cañar southwards). In all other areas, the association is ambiguous.

Accessibility to a provincial capital (MN_AP) is a significant global determinant in all our models. It also displays significant spatial variability in six of the seven models. This suggests that access to markets and services is universally important as a determinant of food poverty in Ecuador but that local variations occur in the strength of this relationship. Districts with significant positive *t*-values are encountered in the provinces of Loja, El Oro, Imbabura and Esmeraldas. Meanwhile a few districts in the provinces of Los Rios and Cotopaxi display an inverse relationship (Fig. 9).

Discussion and conclusions

Results show that community levels of food consumption and food poverty are not distributed randomly throughout Ecuador. Clusters of food poverty may require collective or structural interventions that benefit communities rather than individuals, such as improvements in transport infrastructure or the creation of special development zones. Our results could benefit organizations wishing to apply successful interventions to places with similar food poverty conditions. We have used these results directly within CIAT to highlight the uneven distribution of some of CIAT's research efforts in Ecuador. A survey of local committees of agricultural research (CIALs) [12] showed that food poverty was not a major determinant in their location despite CIAT's mandate to reduce poverty through agricultural research.

A number of studies (e.g. Bigman et al., 2000; Petrucci et al., 2003) have used community level data to improve the estimation of the absolute value and the distribution of food poverty indicators, especially when household-level data are not available. Here we were more interested in how community and broad-scale (large area) variables are related to levels of food poverty, with the ultimate aim of identifying driving forces and subsequent opportunities for interventions to reduce food poverty. We were particularly interested in testing a number of hypotheses, defined a priori by local experts outside a formal conceptual framework. Our analysis sought to generate new hypotheses guided by the results of our GWR models. We ran models for two different food poverty lines. The spatial patterns of significant parameters are fairly insensitive to the poverty line chosen. We found greater differences in spatial patterns between welfare indicators. The outputs of these models, visible in map form, show that the processes that determine food poverty are spatially non-stationary. This has implications for the design of policies to reduce food poverty and suggests that each cluster of food poverty will require different classes of interventions. We see that generally the models appear better defined for the southern and central coastal region than for districts in the Amazon. This implies that we could have chosen a different set of potential factors, or that the data were not reliable or entirely representative for those latter remote areas.

The proportion of the population classified as "indigenous" is universally associated with higher levels of food poverty and lower levels of food consumption. Higher levels of food poverty are found in places with greater concentrations of indigenous compared to non-indigenous people. An exception is some Amazonian districts, characterized by high proportions of indigenous people that were poorly surveyed in the 1998 expenditure survey. District data on consumption and poverty may not reflect well their food security situation. Our analysis confirms other studies, which suggest that, despite high levels of social capital, being of indigenous descent limits opportunities for improving livelihood. Targeting of interventions should address discrimination experienced by indigenous communities.

The experience of food security experts in Ecuador and the findings of past research suggest that poor access to water will result in higher levels of food poverty. This is broadly the case in Ecuador but some areas show results contrary to our hypotheses—areas where we observe a negative association between drought and food poverty but where the effect of irrigation and coastal income sources are insignificant. These particular variables are interesting in the context of the location of clusters of food poverty (see under Methods) in the central Andes. Targeted investment in drought-tolerant varieties of crops such as maize, rather than irrigation development, might be worth considering in this region.

Our panel of food security experts in Ecuador expected the appropriate use of land to be universally associated with lower levels of food poverty. But this factor varied across the country. We expected that, *ceteris paribus*, districts with a greater area used appropriately would have higher food consumption, lower food poverty rates and greater equality. In some areas, this is the case but for many parts of northern Ecuador we find large areas supposedly used inappropriately but with low levels of food poverty (such as the province of Sucumbios). These areas are largely dedicated to the cultivation of crops and pasture despite severe limitations. The patterns we observe may be because the exploitation of soil resources has yet to have negative impacts on productivity. These areas in the northern Amazon were colonized relatively recently. Plots are larger than in other parts of Ecuador (Murphy et al., 1997) enabling settlers to engage in extensive forms of agriculture, notably cattle ranching. Alternatively, the influence of oil production in these provinces may be enhancing district levels of food consumption and reducing food poverty.

The influence of the cut-flower industry may partly explain the negative association with the proportion of land owned individually and food poverty in the north of Ecuador. The county of Cayambe has the lowest proportion of land owned by individuals and contains the districts with the highest food poverty rates in the province of Pichincha. Information on land ownership at the district level—rather than assuming the county value is representative for all districts—would improve this analysis. A more general indicator of land tenure structure is the GINI coefficient of land ownership. This is a significant factor in all the models and the association is as we expected given previous research, which found productivity to be lower on smallholdings (World Bank, 1996). Our results concur with those of Hentschel and Waters (2002), suggesting that land reform might be an appropriate policy route for reducing food poverty. However, the ownership of land by individuals, as opposed to corporate or communal ownership, may not deliver lower levels of food poverty. Land reform therefore must take into account the minimum amount and quality of land in each holding, economies of scale and the marketing power of cooperatives or informal groups of producers.

The results of the regression analysis suggest that employment in agriculture is associated with higher levels of food poverty. Poverty rates are lower in communities where many agricultural workers receive salaries compared to localities where informal agricultural employment predominates. Districts with high proportions of salaried workers are found predominantly in the banana growing province of El Oro, sugar cane plantations in eastern Guayas Province and the cut-flower districts north-east of Quito. Our analysis supports the idea (de Janvry and Sadoulet, 2000) that the promotion of agro-enterprises may be a more successful route out of food poverty than dependence on smallholder farming. Policies that aim to improve transport infrastructure, to increase appropriate investment in inputs and to lend financial and technical assistance will likely promote the creation of small agro-enterprises (ODEPLAN - FAO, 2001).

Our analysis confirms that greater access to markets is associated with lower levels of food poverty. Access to local district-level markets is not a significant variable. Access to provincial capitals proved to be significant. Provincial capitals and local markets have different functions. More significant commerce and income-producing activity occurs at provincial markets. Spatial patterns of coefficients that suggest that policies focused on improving access to provincial markets, for instance by investing in the transport infrastructure, would benefit all areas of Ecuador. But these policies could have greater influence in the southern Andes and north-western Ecuador. The negative relationship between time to provincial capitals and food poverty in central Ecuador may be because large towns that are important regional markets but not provincial capitals were not accessibility target locations.

Our results suggest that the processes associated with food poverty do not reflect the traditional Andes, Coast and Amazon regions of Ecuador. The provincial level is a more appropriate scale of analysis than the region. Our ability to assess different policy options at the provincial level is relevant given the trend towards decentralization in Ecuador. The food poverty maps also serve as a baseline against which future interventions can be judged for evidence of impact.

This study demonstrates that explicit consideration of geographic and environmental factors helps us better understand the patterns and processes linked to food poverty. A spatial analysis framework both allows the incorporation of environmental variables and helps reveal patterns from socio-economic data. As a consequence, policies and interventions can be targeted to specific areas and can be tailored to the specific combination of factors that are linked to food poverty.

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[1] As measured by children (< 2 years old) below international standards of height for age.

[2] As measured by children (< 5 years old) below international standards of height for age.

[3] In 1998, the GINI coefficient for total consumption was calculated as 0.468.

[4] See also Moreano et al., 1994, Larrea et al., 1996, Hentschel et al., 2000, Petrucci et al., 2003 for a discussion of this technique applied to Ecuador, Elbers et al, 2003 for an in-depth discussion of methodology and Fujii et al., 2002 for a study that applies the technique to nutritional data.

[5]Food poverty indicators are not published for Ecuador but the proportion of food consumption as part of total consumption is published for urban and rural sectors: available at http://www.inec.gov.ec/interna.asp?inc=enc_tabla&idTabla=243

[6] The national GINI coefficient of land ownership was 0.81 in 2000 (Chiriboga 2005, unpublished document).

[7] Many other variables in the 2000 agricultural census (INEC, 2000) were not published for sparsely populated counties where data confidentiality issues arose. Data for the province of Bolivar are currently unavailable from the source website.

[8] Calculated using CIAT's Accessibility Analyst (Farrow and Nelson, 2001).

[9] See Smith (2004) as part of a forum discussing Tobler's First Law.

[10] We use semi-variograms to visualize potential spatial dependency rather than as an input to interpolation to create a food poverty surface.

[11] Calculated using GeoDa software http://geoda.uiuc.edu/default.php

[12] Comités de Investigación de Agricultura Local.

Figure Legends

Fig. 1. Consecutive months with less than 60 mm precipitation

Fig. 2. Accessibility to provincial capitals

Fig. 3. Isotropic variogram of *ln*(mean consumption)

Fig. 4. Clusters of food poverty headcount ratio (higher food poverty line) using the Geographical Analysis Machine

Fig. 5. Provinces of Ecuador: 01 Azuay, 02 Bolívar, 03 Cañar, 04 Carchi, 05 Cotopaxi, 06 Chimborazo, 07 El Oro, 08 Esmeraldas, 09 Guayas. 10 Imbabura. 11 Loja.12 Los Rios, 13 Manabí, 14 Morona Santiago, 15 Napo, 16 Pastaza, 17 Pichincha, 18 Tungurahua, 19 Zamora Chinchipe, 21 Sucumbios, 22 Orellana

Fig. 6. Significance of mean number of consecutive dry months per district (MN_DRY) using geographically weighted regression where FGT2_H is the dependent variable

Fig. 7. Significance of mean area of land that is being used appropriately (MN_SUIT) using geographically weighted regression where FGT_0L is the dependent variable

Fig. 8. Significance of individual ownership of land per district (PR_IND2) using geographically weighted regression where FGT0_L is the dependent variable.

Fig. 9. Significance of access to provincial capitals (MN_AP) using geographically weighted regression where FGT1_L is the dependent variable.

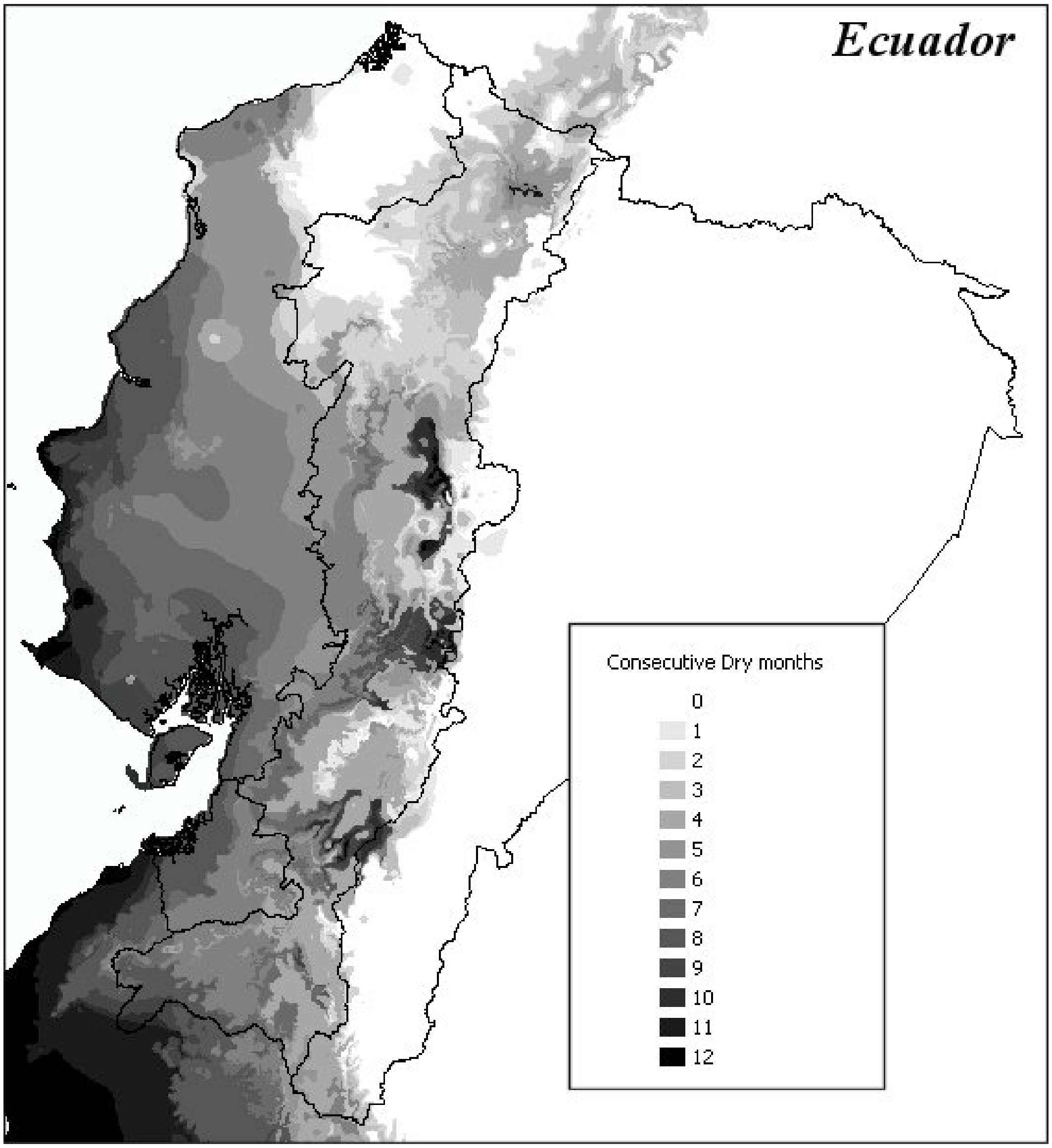

Fig. 1

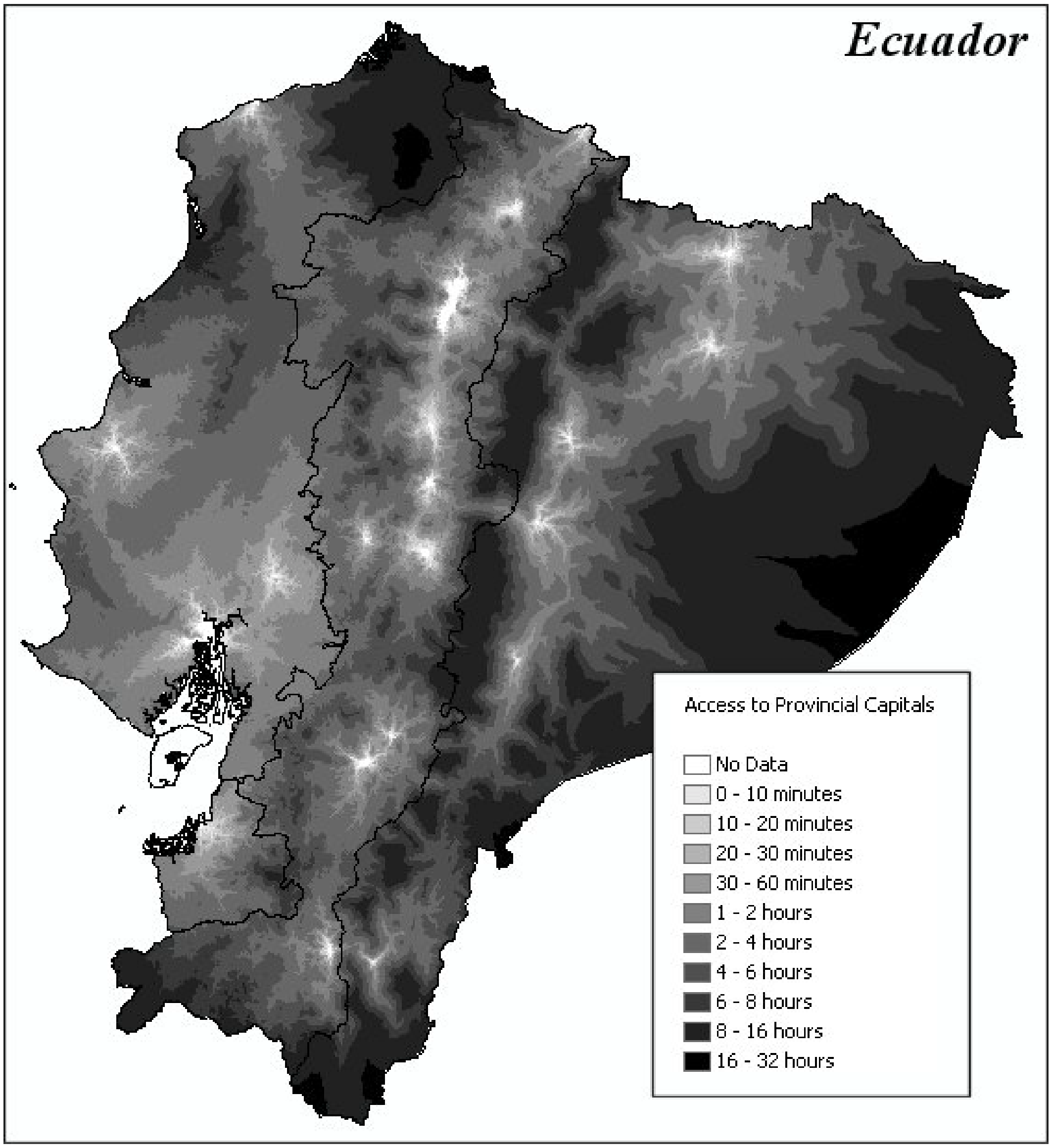
Ecuador
Access to Provincial Capitals
No Data
0 - 10 minutes
10 - 20 minutes
20 - 30 minutes
30 - 60 minutes
1 - 2 hours
2 - 4 hours
4 - 6 hours
6 - 8 hours
8 - 16 hours
16 - 32 hours

Fig. 2.

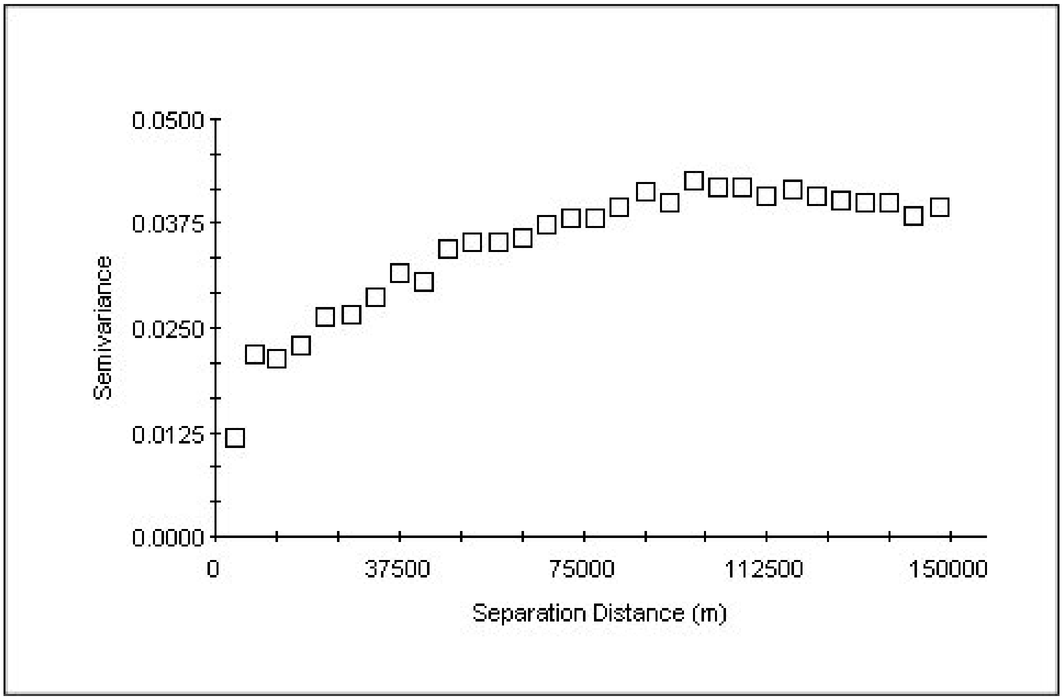
0.0500
0.0375
0.0250
0.0125
0.0000
Semivariance
0
37500
75000
112500
150000
Separation Distance (m)

Fig. 3.

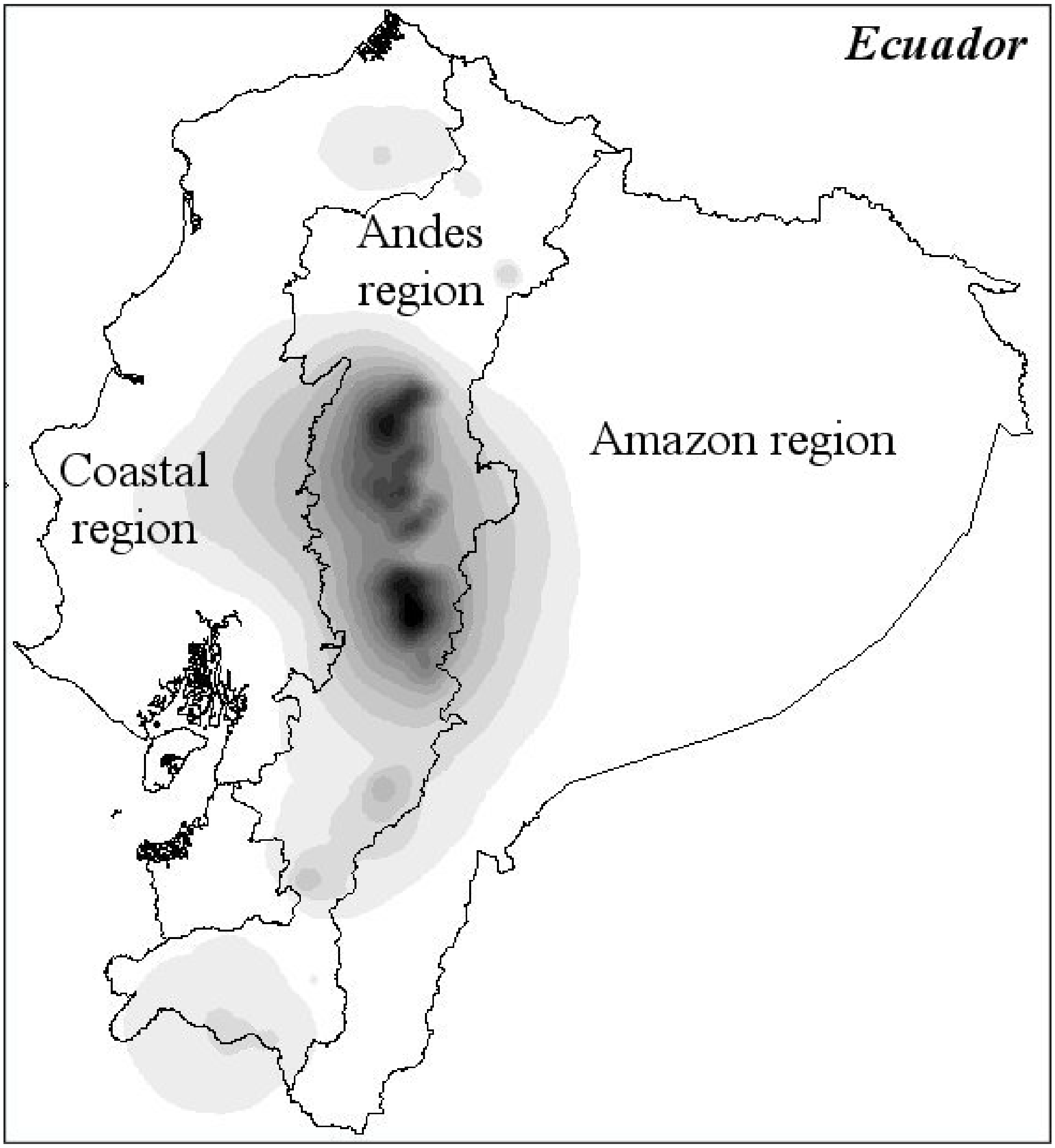

Fig. 4.

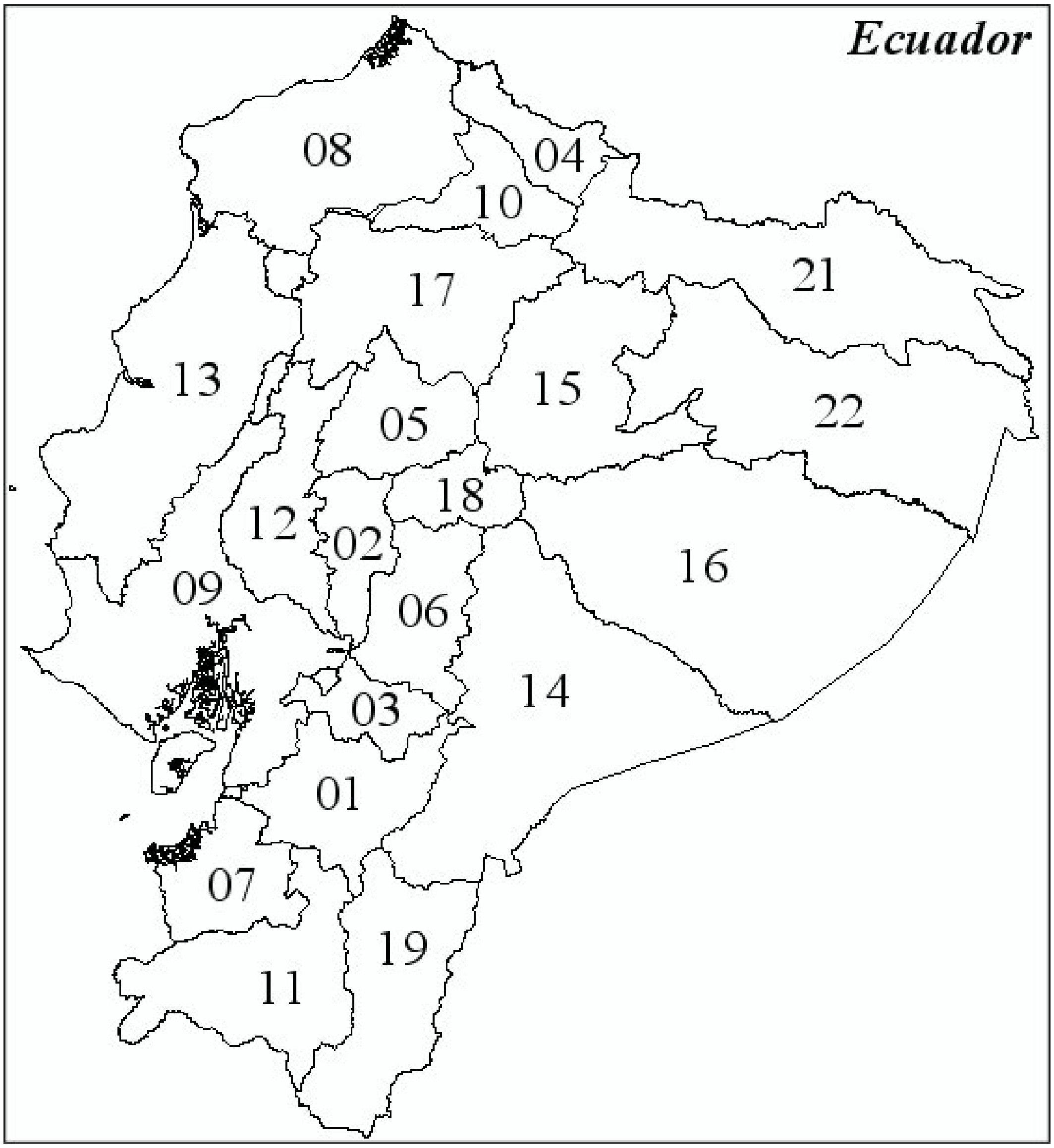

Fig. 5.

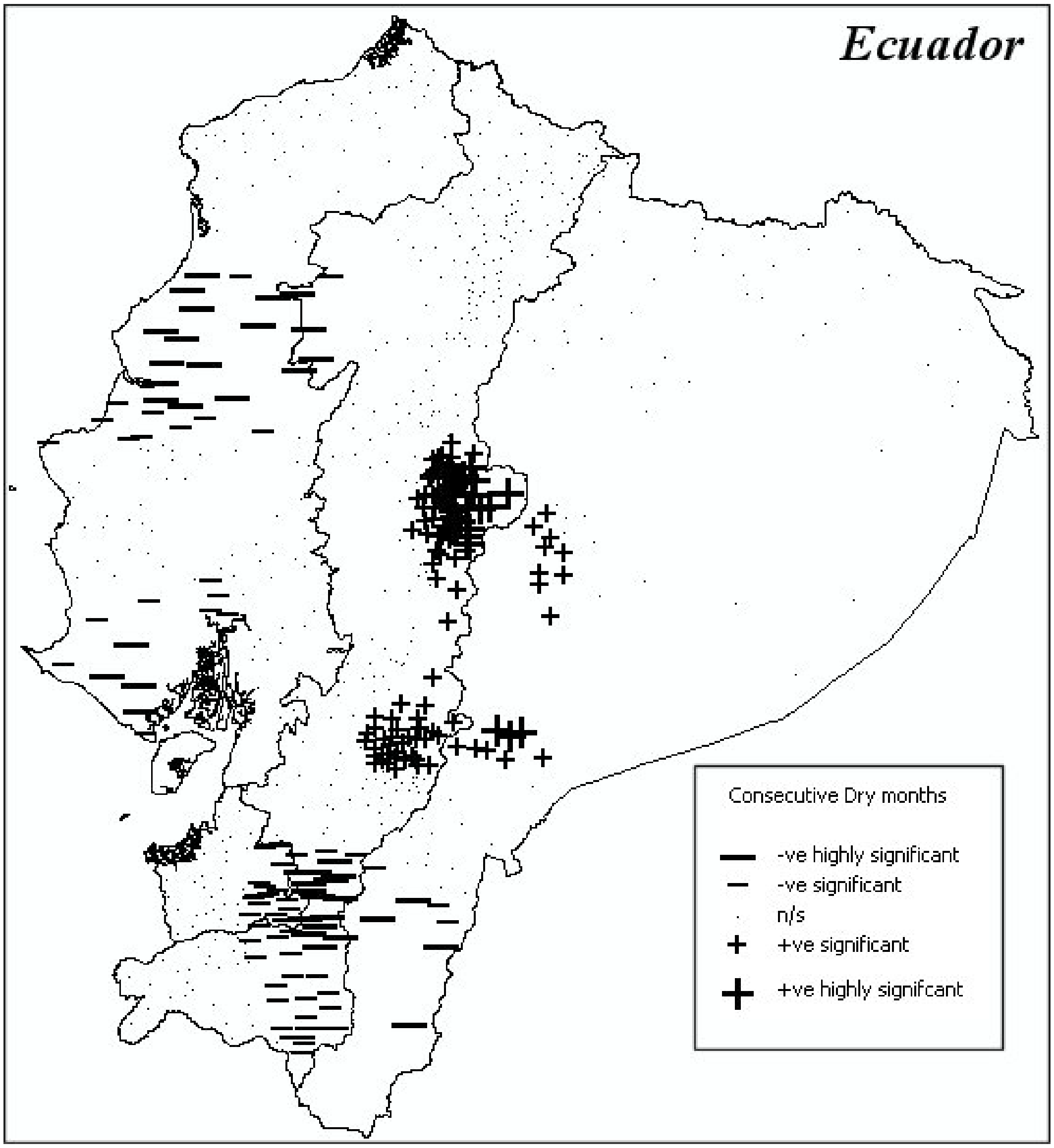
Ecuador
Consecutive Dry months
-ve highly significant
-ve significant
n/s
+ve significant
+ve highly signifcant

Fig. 6.

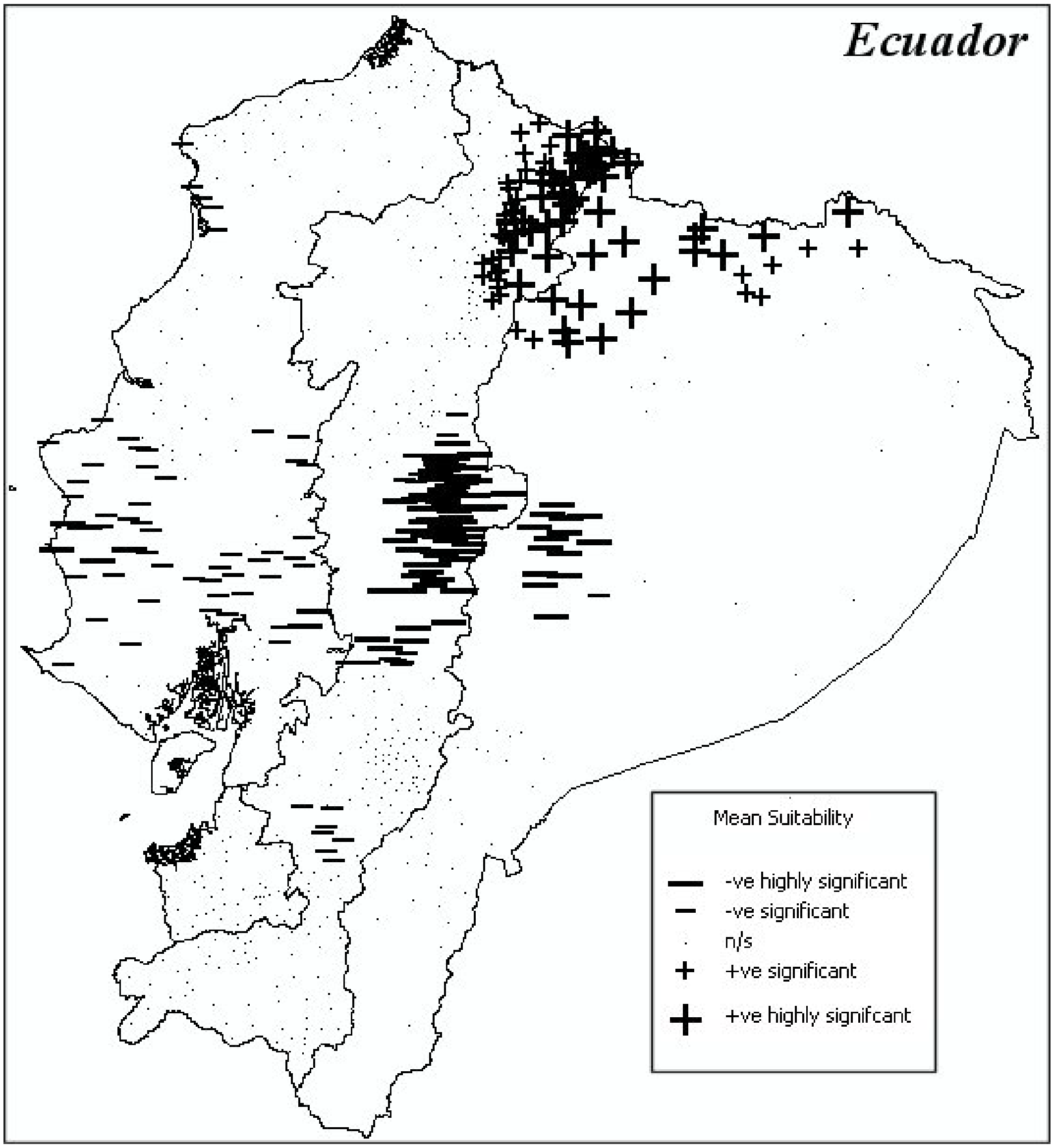
Ecuador
Mean Suitability
-ve highly significant
-ve significant
n/s
+ve significant
+ve highly signifcant

Fig. 7.

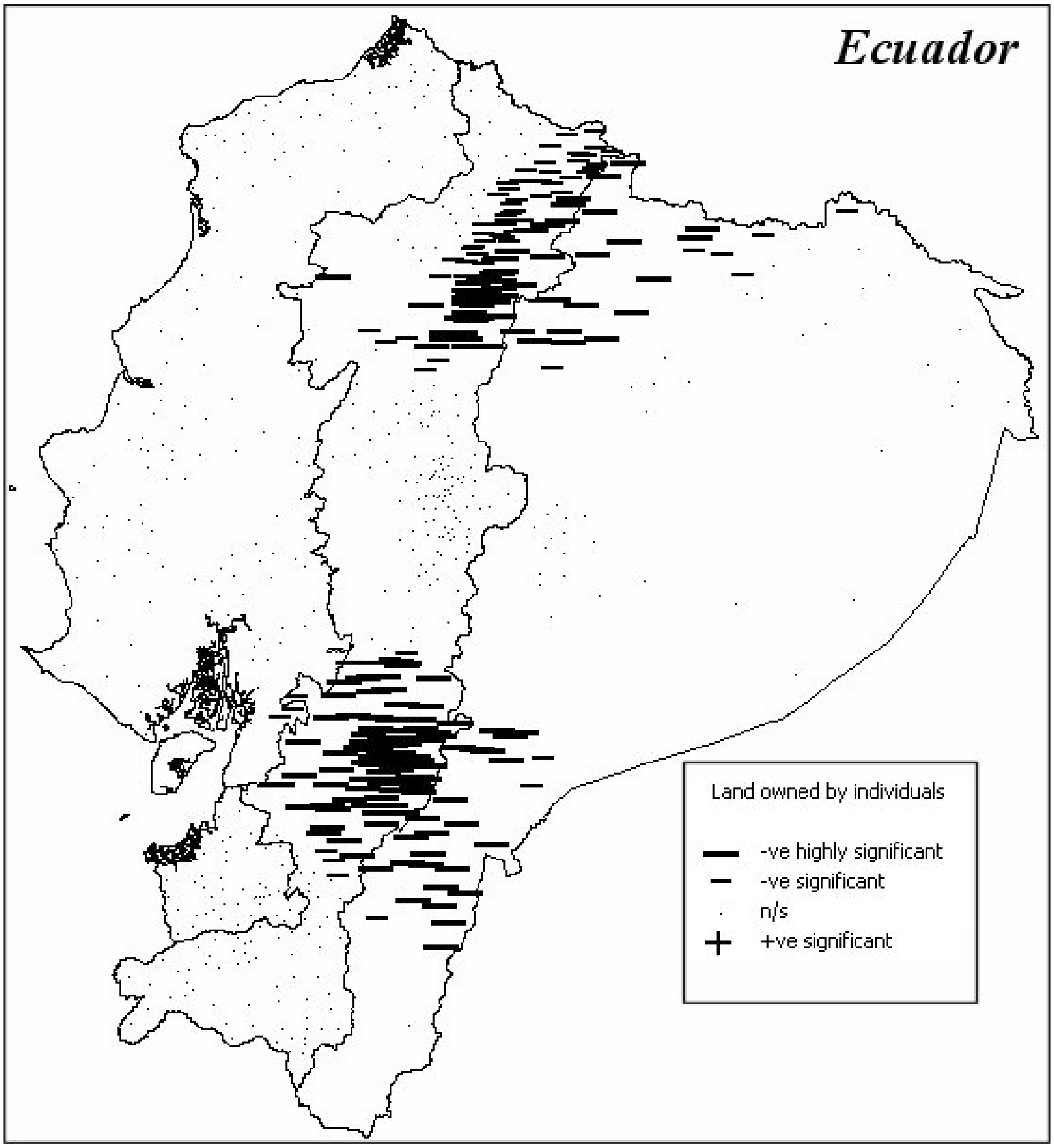
Ecuador
Land owned by individuals
-ve highly significant
-ve significant
n/s
+ve significant

Fig. 8.

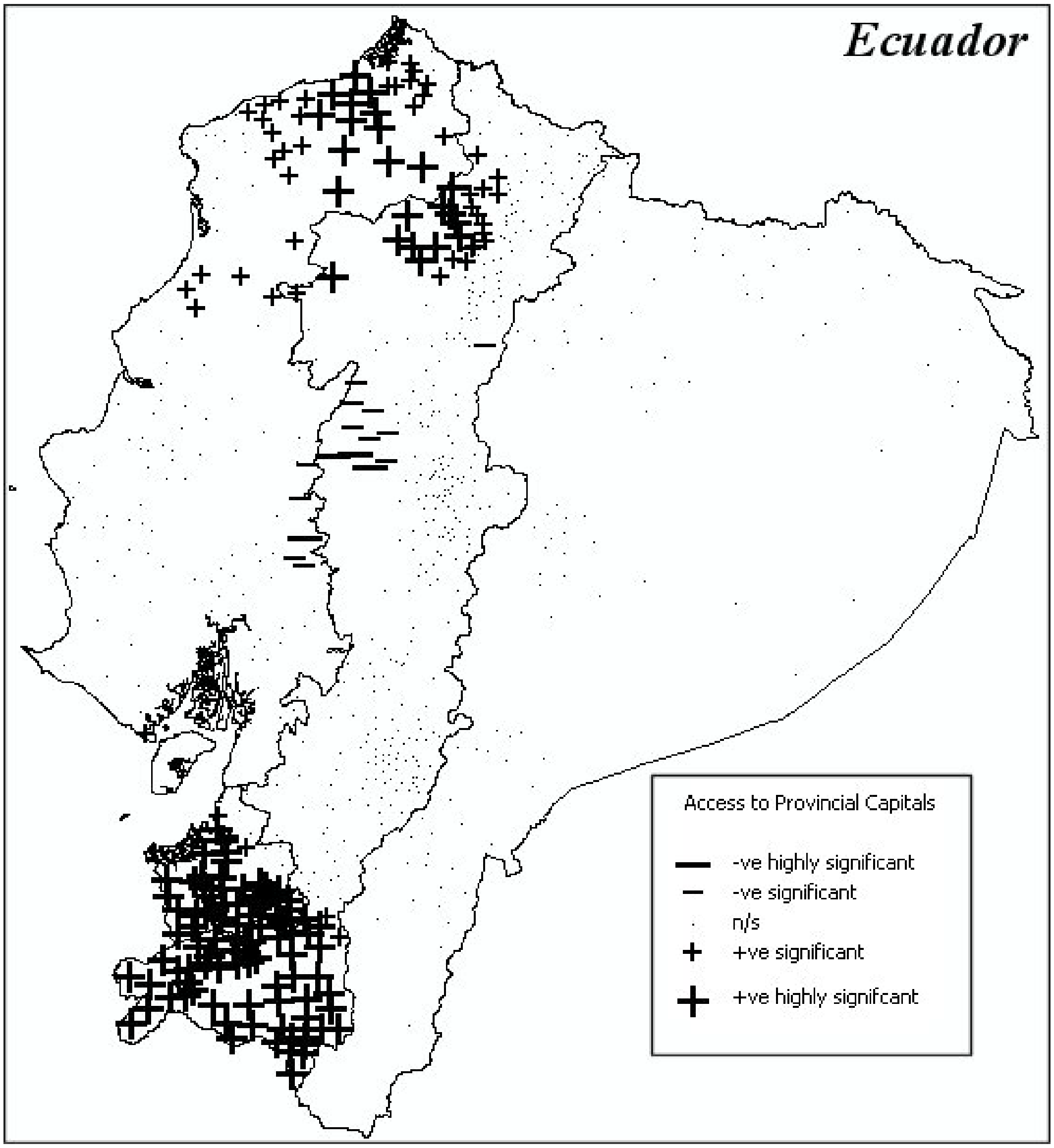
Ecuador
Access to Provincial Capitals
-ve highly significant
-ve significant
n/s
+ve significant
+ve highly signifcant

Fig. 9.

Table 1
Descriptive statistics for food poverty indicators

Data set	Mean food consumption	Headcount ratio (higher poverty line)	Food poverty gap (higher poverty line)	Food poverty severity (higher poverty line)
Statistic – all				
Mean (n = 990)	135827	0.771	0.333	0.180
SD	27017	0.108	0.086	0.061
Skewness	0.58	-0.81	0.07	0.48
Moran's I	0.354**	0.363**	0.440**	0.447**
Statistic – rural				
Mean (n = 777)	129998	0.797	0.35	0.190
SD	24828	0.093	0.081	0.060
Skewness	0.74	-0.9	0.03	0.41
Moran's I	0.5**	0.551**	0.538**	0.515**

** significant at $p \leq 0.01$ level.

Table 2
District level regression variables (n = 670)

Variables	Description	Units	Min.	Max.	Mean	SD
Dependent						
FGT_0H	Headcount ratio using the higher food poverty line	%	45.74	97.90	79.79	9.29
FGT_0L	lower food poverty line	%	29.00	94.00	63.37	12.52
MEANY	Mean food consumption per person per fortnight	Sucres	59089.94	248777.88	129270.50	24319.20
FGT_1H	Food poverty gap using the higher food poverty line	%	15.21	66.45	34.83	8.32
FGT_1L	lower food poverty line	%	7.00	57.00	23.21	7.73
FGT_2H	Food poverty severity using the higher food poverty line	%	6.12	49.25	18.85	6.20
FGT_2L	lower food poverty line	%	2.00	40.00	11.29	4.88
Independent						
MN_DRY	Mean value of consecutive dry months	Months	0.00	11.55	4.28	2.82
PR_RIE1	Proportion of productive units with irrigation	Ratio	0.00	0.92	0.25	0.23
COASTAL	Dummy variable for districts with coastline (benefiting from fishing and tourism)	Binary	0	1	0.05	0.23
MN_SLP	Mean slope	Degree	0.52	29.13	12.49	6.78
MN_SUIT	Mean value of land use suitability	% (* 10)	0.00	758.84	182.73	161.46
PR_IND2	Proportion of productive area owned by individuals	Ratio	0.00	1.00	0.81	0.16
GINI	GINI coefficient of land ownership	Ratio	0.31	0.94	0.73	0.12
AGR_WF	Percentage of workforce in agriculture	%	0.84	95.79	64.19	20.70
SAL_AGR	agricultural workforce with salary	%	0.00	84.18	20.29	17.83
INDIG	population classed as indigenous	%	0.00	100.00	17.73	27.26
MN_AP	Mean value of time to the nearest provincial capital	Hours	0.14	17.17	3.30	2.76

Table 3

Geographically weighted regression model summaries[a]: food poverty headcount ratio for higher (FGT0_H) and lower (FGT0_L) food poverty lines and mean food consumption model (MEANY) (n = 670)

Parameter	FGT0_H			FGT0_L			MEANY		
	Global estimate	Global *t*-value	Spatial variability of parameters *P*-value	Global estimate	Global *t*-value	Spatial variability of parameters *P*-value	Global estimate	Global *t*-value	Spatial variability of parameters *P*-value
Intercept	49.074	13.40**	0.00**	31.758	6.68**	0.01*	213191	21.33**	0.00**
INDIG	0.049	4.42**	0.08	0.106	7.44**	0.01*	-144	-4.81**	0.00**
MN_DRY	0.145	1.19	0.04*	-0.079	-0.50	0.01*	-459	-1.38	0.01*
PR_RIE1	1.681	1.17	0.08	2.931	1.57	0.09	-7355	-1.87	0.01*
COASTAL	-1.466	-1.14	0.09	-2.687	-1.61	0.11	1127	0.32	0.13
MN_SLP	-0.036	-0.72	0.23	0.046	0.70	0.30	-64	-0.46	0.39
MN_SUIT	-0.001	-0.85	0.00**	-0.003	-1.48	0.01*	3	0.69	0.02*
PR_IND2	3.368	1.61	0.00**	1.585	0.58	0.00**	-8416	-1.47	0.00**
GINI	18.776	5.84**	0.08	19.321	4.63**	0.18	-53433	-6.09**	0.07
AGR_WF	0.232	15.80**	0.00**	0.262	13.81**	0.00**	-554	-13.85**	0.00**
SAL_AGR	-0.153	-8.29**	0.09	-0.221	-9.26**	0.01*	371	7.39**	0.08
MN_AP	0.439	3.81**	0.02*	0.546	3.66**	0.00**	-1111	-3.53**	0.11
	AB = 177 nearest neighbours GR adjusted R^2 = 0.45 GWR adjusted R^2 = 0.70 ANOVA *F*-value = 8.55			AB = 177 nearest neighbours GR adjusted R^2 = 0.49 GWR adjusted R^2 = 0.73 ANOVA *F*-value = 8.53			AB = 172 nearest neighbours GR adjusted R^2 = 0.41 GWR adjusted R^2 = 0.68 ANOVA *F*-value = 8.41		

* significant at $p \leq 0.05$, ** at $p \leq 0.01$ level.

[a] AB, adaptive bandwidth; GR, global regression; GWR, geographically weighted regression.

Table 4
Geographically weighted regression model summaries[a]: food poverty gap for higher (FGT1_H) and lower (FGT1_L) food poverty lines (n = 670)

Parameter	FGT1_H			FGT1_L		
	Global estimate	Global *t*-value	Spatial variability of parameters *P*-value	Global estimate	Global *t*-value	Spatial variability of parameters *P*-value
Intercept	17.508	5.63**	0.06	10.641	3.70**	0.07
INDIG	0.094	10.09**	0.00**	0.099	11.59**	0.00**
MN_DRY	-0.129	-1.24	0.00**	-0.179	-1.88	0.00**
PR_RIE1	2.518	2.06*	0.04*	2.566	2.27*	0.00**
COASTAL	-1.628	-1.49	0.19	-1.441	-1.43	0.18
MN_SLP	0.088	2.04*	0.39	0.115	2.88**	0.37
MN_SUIT	-0.002	-1.48	0.04*	-0.002	-1.61	0.06
PR_IND2	-0.212	-0.11	0.04*	-1.157	-0.70	0.13
GINI	10.204	3.74**	0.21	7.156	2.84**	0.12
AGR_WF	0.147	11.83**	0.00**	0.114	10.00**	0.00**
SAL_AGR	-0.139	-8.90**	0.00**	-0.125	-8.69**	0.00**
MN_AP	0.328	3.35**	0.00**	0.265	2.93**	0.00**
	AB = 170 nearest neighbours			AB = 168 nearest neighbours		
	GR adjusted R^2 = 0.0.51			GR adjusted R^2 = 0.0.52		
	GWR adjusted R^2 = 0.74			GWR adjusted R^2 = 0.74		
	ANOVA *F*-value = 8.39			ANOVA *F*-value = 8.38		

* significant at $p \leq 0.05$, ** at $p \leq 0.01$ level.
[a] AB, adaptive bandwidth; GR, global regression; GWR, geographically weighted regression.

Table 5
Geographically weighted regression model summaries[a]: food poverty severity for higher (FGT2_H) and lower (FGT2_L) food poverty lines (n = 670)

Parameter	FGT2_H			FGT2_L		
	Global estimate	Global *t*-value	Spatial variability of parameters *P*-value	Global estimate	Global *t*-value	Spatial variability of parameters *P*-value
Intercept	8.746	3.78**	0.07	4.805	2.62**	0.17
INDIG	0.082	11.83**	0.00**	0.070	12.87**	0.00**
MN_DRY	-0.143	-1.87	0.00**	-0.137	-2.25*	0.00**
PR_RIE1	2.158	2.37*	0.00**	1.852	2.57*	0.00**
COASTAL	-1.168	-1.44	0.18	-0.880	-1.37	0.16
MN_SLP	0.095	2.98**	0.37	0.088	3.46**	0.36
MN_SUIT	-0.001	-1.41	0.06	-0.001	-1.10	0.13
PR_IND2	-0.997	-0.75	0.12	-1.109	-1.06	0.16
GINI	5.717	2.82**	0.18	3.535	2.19*	0.17
AGR_WF	0.089	9.69**	0.00**	0.057	7.86**	0.00**
SAL_AGR	-0.097	-8.37**	0.00**	-0.072	-7.82**	0.00**
MN_AP	0.226	3.12**	0.00**	0.170	2.96**	0.00**
	AB = 170 nearest neighbours GR adjusted R^2 = 0.0.51 GWR adjusted R^2 = 0.74 ANOVA *F*-value = 8.47			AB = 170 nearest neighbours GR adjusted R^2 = 0.0.51 GWR adjusted R^2 = 0.74 ANOVA *F*-value = 8.31		

* significant at $p \leq 0.05$, ** at $p \leq 0.01$ level.
[a] AB, adaptive bandwidth; GR, global regression; GWR, geographically weighted regression.