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Why the Poor in Rural Malawi Are Where They Are: An Analysis of the Spatial Determinants of the Local Prevalence of Poverty

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Abstract

We examine the spatial determinants of the prevalence of poverty for small spatially defined populations in rural Malawi. Poverty prevalence was estimated using a small-area poverty estimation technique. A theoretical approach based on the risk chain conceptualization of household economic vulnerability guided our selection of a set of potential risk and coping strategies—the determinants of our model—that could be represented spatially. These were used in two analyses to develop global and local models, respectively. In our global model—a spatial error model—only eight of the more than two dozen determinants selected for analysis proved significant. In contrast, all of the determinants considered were significant in at least some of the local models of poverty prevalence. The local models were developed using geographically weighted regression. Moreover, these models provided strong evidence of the spatial non-stationarity of the relationship between poverty and its determinants. That is, in determining the level of poverty in rural communities, where one is located in Malawi matters. This result for poverty reduction efforts in rural Malawi implies that such efforts should be designed for and targeted at the district and subdistrict levels. A national, relatively inflexible approach to poverty reduction is unlikely to enjoy broad success.

Key words: spatial regression, poverty determinants, poverty mapping, Malawi

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1. Introduction

In seeking a better understanding of the determinants of local levels of poverty in rural Malawi, we directed our research toward identifying key spatially explicit determinants of differing levels of poverty incidence in local areas in rural Malawi. Such an understanding could effectively guide the efforts of government and others to help communities attain higher levels of welfare. Note that our focus here is not on individuals and households. Rather, the emphasis is on the local areas within which rural Malawians are primarily carrying out their livelihoods. This research is undertaken on the assumption that certain agroecological and aggregate social characteristics of the area of residence of an individual or household are important determinants of whether individuals or households will attain an adequate level of welfare to meet their basic needs. In essence, where an individual lives should tell us something about the quality of life that individual enjoys. This local-scale understanding, if coupled with knowledge of how individual, household-specific, and broader national and subnational factors affect household welfare, will contribute to the success of policymakers and program implementers in their efforts to enable rural Malawians to improve their quality of life.

We identify those characteristics of the local context that produce the outcome of lower welfare and higher poverty levels in rural Malawi, or vice versa, through a quantitative analysis of the key determinants of the prevalence of poverty in more than 3,000 small areas across rural Malawi. Potential key determinants of the poverty headcount are identified using a theoretical approach based on the risk chain, whereby the welfare level of a household or individual is a function of the risks to economic well-being faced and the coping strategies a household or individual can call upon in the face of such risks. Notably, since the focus is on the rural, primarily agricultural population of Malawi, agroecological and agricultural production and marketing factors constitute many of the determinants, or independent variables, examined here. We employ quantitative spatial data analysis methods to examine the spatial determinants of aggregate local poverty: (1) a spatial error model that takes into account the spatial dependency in the data used in the analysis, and (2) a geographically weighted regression procedure that describes a spatially varying relationship between the determinants considered and the local prevalence of poverty. The two different methods provide contrasting insights into the nature and strength of the links between key determinants and poverty prevalence depending on the analytical spatial frame of reference.

Our focus on small, local populations of rural Malawi, rather than all of Malawi, is meant to simplify the analysis somewhat. The principal livelihood strategies employed by virtually all rural Malawian households are based on agriculture or the use of other natural resources. Agroecological conditions are important elements of these livelihoods and of the risk chains in which they are enmeshed, both as sources of risks and as resources to draw upon in responding to shocks. In contrast, with more diverse livelihood strategies being pursued by urban households, we expect that a much broader range of risk and coping variables would need to be included to adequately capture the determinants of poverty prevalence in urban neighborhoods.

At the outset, it is important to state the definition of welfare and, consequently, of poverty that we use. As is common with much economic research on poverty and welfare, here welfare is quite narrowly defined as the level of consumption of an individual or household (Deaton and Zaidi 2002). The welfare and poverty content of our analysis is based on the computation of a welfare measure for each individual or household in the 1997–98 Malawi Integrated Household Survey (IHS) sample. To determine whether an individual or household is poor or not, the welfare measure is compared to a poverty line. The poverty line used is a cost of basic needs poverty line that incorporates the daily basic food and nonfood requirements of Malawians. The welfare measure for an individual or household is then evaluated against the poverty line: if the reported per capita total daily consumption is above the poverty line, that individual or household is considered to be nonpoor; if below, poor (Benson, Machinjili, and Kachikopa 2004).

Notably, the basic food requirements are tied to the recommended daily calorie requirements for individuals, as determined by human nutritionists. About 80 percent of the value of the "basket" of basic items in the poverty lines used for rural Malawians consists of food. For the weighted rural sample of the IHS as a whole, 73.5 percent of the value of their consumption is food (PMS 2000). From an analytical standpoint at least, in rural Malawi the poor are food insecure and the food insecure will be poor. Conceptually, poverty and food insecurity are very similar for rural Malawians. Consequently, the analysis here is as relevant to issues of household food insecurity in rural Malawi as it is to poverty.

The structure of this paper is as follows: in the next section, we present the theoretical understanding that guides the analyses—the risk-chain concept to understand how households cope (or fail to cope) with shocks to their economic well-being. The third section describes in detail the various methods and tools used in the research. We give details on the poverty mapping method by which the dependent variable was estimated, the construction of the aggregated enumeration area geography for this analysis, the assembling of the analytical data set, and the sequence of spatial data analysis methods employed. The results of the two spatial data analyses—the spatial error model and the geographically weighted regression procedure—are presented in section five. In the final section, we consider the explanatory power of the analysis here. In particular, we reflect upon the value of the results obtained from an applied perspective. What new understandings might be drawn from the analyses to guide action taken to assist Malawi's rural poor?

2. Vulnerability to Poverty—The Risk Chain

We seek to identify important determinants of the prevalence of poverty among relatively small local populations of 2,000 to 4,000 persons living in 500 to 1,000 households in rural Malawi. The research is intended to derive and apply appropriate and effective poverty reduction policies and programs to reduce the overall prevalence of poverty. While not all of the poverty determinants identified through this research will be amenable to change, by undertaking efforts to change those that are amenable in a manner that would reduce the deleterious effects and enhance the beneficial effects each has on household or individual welfare, progress can be made in improving the welfare of the population as a whole.[1]

The theoretical understanding that guides our analysis has been drawn from the literature on household economic vulnerability and, in particular, the concept of the risk chain. Vulnerability is usually defined in the economics literature as "having a high probability of being poor in the next period" and is determined by the ability of households and individuals to manage the risks they face (Christiaensen and Subbarao 2001; Dercon 2001). Although vulnerability is a dynamic concept in that it is concerned with the potential future welfare status of individuals and households, it also provides useful insights in accounting for why households and individuals or, as here, aggregations of households are predominantly poor or not poor at a particular point in time. Consequently, we use the risk chain in our research to investigate the determinants of the prevalence of poverty in local areas of rural Malawi.

The risk chain theory is a decomposition of household economic vulnerability: Risk or risky events (shock) → Responses to risk → Outcome in terms of welfare. The level of economic vulnerability of households is dependent on the degree to which they are exposed to negative shocks to their welfare and on the degree to which they can cope with such shocks when they do occur. Their current welfare status—whether they are poor or not—is the outcome. Although it might be described in different ways, the risk chain is a common conceptual framework in a range of subdisciplines, including development and welfare economics, the food security literature, hazards and global climate change research, and in health and nutrition (Alwang, Siegel, and Jørgensen

[1] Ultimately, any poverty reduction policy must lead to change at the household and individual levels. However, in using the results of this analysis to plan poverty reduction activities, it is important not to assume that the nature of the relationships observed here at the local aggregated enumeration area level will be replicated at the level of the household or individual. Doing so would be an example of the ecological fallacy, whereby an analyst erroneously assumes that relationships observed for groups, such as residents in a relatively small rural locale, will necessarily hold for individuals within the group. Poverty reduction program planners can best use the results here in planning for action to change the broader, local conditions within which households and individuals pursue their livelihoods and cope with the economic shocks they face, rather than planning for explicit individual and household level interventions.

2001; Brooks 2003). Here we provide a brief overview of the sorts of components that make up each link in the risk chain.

Risk

The degree of exposure to risky events or shocks to their welfare to which a household or individual is subject is an important consideration in assessing their likelihood of being vulnerable to falling into poverty. These risks may be events that affect the population broadly—covariate risks—or those that affect individuals or households in a more random fashion—idiosyncratic risk. Covariate risks that affect specific areas or broad and, ideally, spatially defined segments of the population are the easiest to bring into a spatial analysis such as ours. Such shocks—epidemics, drought, flooding—can be mapped. Although prevalence and incidence rates do provide some measure of the level of idiosyncratic risks, they are less easily managed analytically within a spatial context than are covariate shocks. Consequently, if the most prevalent shocks faced by households in an area are idiosyncratic, our analysis likely will miss a significant portion of this component of the determinants of household welfare levels and, hence, the local prevalence of poverty. In consequence, the explanatory power of our analyses will be lower than it might otherwise have been.

The nature of the risks that might affect the welfare of individuals and households living in rural areas are quite varied. Hoddinott and Quisumbing (2003) provide a useful inventory that includes natural and environmental, social and political, demographic (life-cycle), health, and economic and market risks. Each of these categories typically will have some covariate risks (e.g., droughts, floods, epidemics, market collapse) and some idiosyncratic (e.g., births, crime, discrimination, business failure).

Responses to Risk, Coping Strategies

Whether a household or individual that is affected by a risky event or shock experiences a decline in their welfare depends on the degree to which the household or individual is susceptible to harm from that shock. Their resilience to shocks depends on whether they have access to necessary resources or assets to cope effectively with the shock so that no lasting damage is done to their well-being. The range of risk management strategies that can be employed by households in the face of shocks is broad. While a comprehensive list of the coping strategies that rural Malawians might employ would be difficult to formulate, a broad asset-based approach does provide an imperfect measure of the likely ability of households and individuals to manage shocks.[2] These assets are building blocks by which households and individuals acquire their livelihoods, work to improve their welfare, and cope with threats to that welfare.

Several qualifications should be highlighted. Most notably, the degree to which individuals and households might effectively employ these assets in coping with shocks is dependent on the institutional and political organization of society. For example, the ability of a woman to exercise a particular coping strategy may be qualitatively different from that of a man because of the nature of the gender organization of a particular society or community. Moreover, it is important to note that some risk factors are also coping strategies. For example, the market can be the source of economic shocks felt by households and individuals in an area and source of risk to their livelihood at the same time as access to the market offers a range of strategies for coping with other shocks to welfare.

Welfare Outcomes

The welfare outcome for a household or individual faced with a negative shock to their economic well-being could be measured in several ways—most commonly, a consumption-based welfare indicator. Child malnutrition rates, food consumption levels,

[2] The "sustainable livelihoods" approach to understanding the many factors that affect the livelihoods of the poor is centered on five asset classes—human capital, social capital, natural capital, physical capital, and financial capital—and provides a useful guide in examining the broad range of assets that households might use to cope with risky events (DfID 1999). One should note that the same set of assets available to a household or community can be used in different ways with different welfare outcomes. However, the analysis here is unable to consider in any thorough manner spatial differences in the livelihood strategies by which similar sets of such assets are employed.

educational attainment, and any manner of human development or "quality of life" indices, and so on, could also be used. In our analyses, we use the aggregate poverty headcount for a local area as our dependent variable.[3]

3. Methods and Data

For this research, we employ a quantitative spatial analysis in which a relatively broad range of independent spatial variables expressed at the scale of the aggregated enumeration area (EA) is used to model the poverty headcount for rural aggregated EAs. The poverty headcount is determined using poverty mapping, small-area estimation methods applied to the population, as enumerated by the 1998 Malawi Population and Housing Census, residing in each aggregated EA. The aggregated EA geography of Malawi was created specifically for this analysis by aggregating the EAs employed in census data collection by the Malawi National Statistical Office to allow for the estimation of poverty measures for Malawi at as local a scale as possible, given the methodology used. In the analysis, 3,004 rural aggregated EAs are used.

A relatively large set of high-resolution agroecological and social spatial data sets have been developed for Malawi, with some specifically developed for this analysis. We used a subset of these as our independent variables, with the choice of variables based on the risk-chain conceptual framework. The candidate independent variables were aggregated to the aggregated EA scale.

Two separate analyses were then conducted to investigate the spatial determinants of the local prevalence of poverty in rural Malawi. Initially, an Ordinary Least Squares (OLS) regression was done. However, as spatial autocorrelation was present in the OLS model, a spatial error model that corrected for the autocorrelation was used to refine this

[3] In this report, we use poverty headcount and the prevalence of poverty interchangeably. This measure also may be referred to as p0 or FGT_0. All mean the proportion of the population whose level of welfare is below the poverty line. Formally, the poverty headcount is one of the three most commonly used Foster-Greer-Thorbecke poverty measures—the other two being the depth of poverty measure (p1) and the severity of poverty measure (p2) (Foster, Greer, and Thorbecke 1984).

analysis. This analysis was undertaken at a global scale, whereby a single model was computed for all of rural Malawi. In contrast, the second analysis, a geographically weighted regression, provides a local analysis of the spatial determinants of poverty prevalence by computing separate models for all 3,004 aggregated EAs in our data set.

Poverty Mapping

The dependent variable for our analysis, the poverty headcount for rural aggregated EAs, was computed using the poverty mapping methods developed primarily by Elbers, J. Lanjouw, and P. Lanjouw (2000; 2003).[4] Poverty mapping involves, first, discovering relationships between household and community characteristics and the welfare level of households as revealed by the analysis of a detailed living standards measurement survey (LSMS). Second, one then applies a model of these relationships to data on the same household and community characteristics contained in a national census in order to determine the welfare level of all households in the census. The resulting estimates of aggregate welfare and poverty derived can be spatially disaggregated to a much higher degree than is possible using survey information, providing an enhanced understanding of the spatial dimensions of poverty. A critical strength of this method is that estimates are provided of the error in the calculated poverty measures.

A poverty map for Malawi was completed in early 2002 based upon the 1997–98 Malawi Integrated Household Survey and the September 1998 Malawi Population and Housing Census. Twenty-three separate strata models were developed to construct the poverty map, one for each of the 22 IHS analytical strata (made up of 11 single districts, 7 groupings of districts, and the 4 urban areas of Malawi), together with an additional stratum made up of EAs that, although found in rural areas, are urban in character.

[4] Elbers, J. Lanjouw, and P. Lanjouw (2005) assess the use of imputed welfare estimates, particularly those from poverty mapping analyses, in regression analyses. Some caution in the interpretation of significance levels of coefficients is necessary when such estimates are used, as here, as the dependent variable for a model: one should be somewhat conservative in the interpretation of significance. However, they find that such estimates can be used as independent variables in regressions in a relatively straightforward manner, as in the use of the GINI variable in the analysis here.

These are described in Benson et al. (2002). For the 23 models, the mean adjusted R^2 is 0.380 and ranges from 0.248 to 0.594. Overall, the headcounts from the poverty mapping analysis are comparable to those of the IHS poverty analysis. Nationally, the headcount differs by one percentage point, with the poverty mapping analysis estimating a slightly lower proportion of the population to be poor: 64.3 percent. As one moves to the more local scale of the district, the differences between the IHS poverty analysis and the poverty mapping results are greater.

New Analytical Geography

In the initial poverty mapping analysis, estimates were made for the subdistrict Traditional Authorities (TA) and urban wards geography. These are the most commonly recognized subdistrict spatial units. A finer level of analysis of the recently established local government wards was also done. The developers of these poverty mapping methods have demonstrated that reliable poverty estimates can be generated for quite small populations. While the desired minimum level of statistical precision in the poverty and inequality estimates produced through the poverty mapping exercise will determine the minimum population size one might use, early assessments of the minimum population threshold to which poverty mapping methods could reasonably be applied were as low as 500 households (Elbers, J. Lanjouw, and P. Lanjouw 2000).

We sought to exploit this feature of poverty mapping at as local a level as possible. The enumeration area in Malawi, with an average household population of about 250 households is too small a population group for reliable use of poverty mapping. (See Table 1 for descriptive statistics on the population and poverty headcount estimates for various spatially defined populations in Malawi.) Consequently, we developed a new analytical geography for Malawi by agglomerating EAs into units with populations just above what was then viewed to be the minimum population threshold for poverty mapping of 500 households.[5] A digital map of the EAs used for the 1998 Census by the Malawi National Statistical Office had been developed. Using household population data for each EA from the census, we defined the aggregated EAs. Maps of the initial EAs and resultant rural aggregated EAs are presented in Figure 1.[6] The new spatial units respected the boundaries of the poverty mapping strata to enable the application of the poverty mapping models to households resident in the aggregated EAs.

Table 1—Characteristics of the population and standard error for estimated poverty headcount for various analytical geographies for Malawi

	IHS poverty analysis	Poverty mapping analysis					
Geography	**Districts and urban centers**	**Districts and urban centers**	**Traditional authorities and urban wards**	**Local government wards**	**Enumeration areas**	**Aggregated enumeration areas**	**Rural aggregated EAs analyzed**
Number of spatial units	29[a]	31[a]	351	848	9,218	3,473	3,004
Mean individual population	342,547	320,447	28,302	11,714	1,078	2,860	2,808
Mean household population	78,408	73,350	6,478	2,681	247	655	641
Median household population	74,860	70,792	4,174	2,357	240	635	630
Poverty headcount, mean standard error (%)	5.37	3.94	6.34	6.24	--	8.19	8.19
Poverty headcount, median s.e. (%)	4.01	3.77	5.14	5.44	--	7.37	7.33
Mean ratio of standard error to point estimate	0.087	0.064	0.134	0.116	--	0.146	0.143
Median ratio of standard error to point estimate	0.074	0.061	0.089	0.087	--	0.115	0.109

Note: Population data is from the 1998 Malawi Population and Housing Census. In the poverty mapping analysis, no poverty estimates were computed for enumeration areas.

[a] The recently created Balaka and Likoma Districts were not included in the sampling structure of the 1997-98 Integrated Household Survey, so poverty estimates cannot be computed for these districts from the survey. However, poverty estimates were made for these districts in the poverty mapping exercise.

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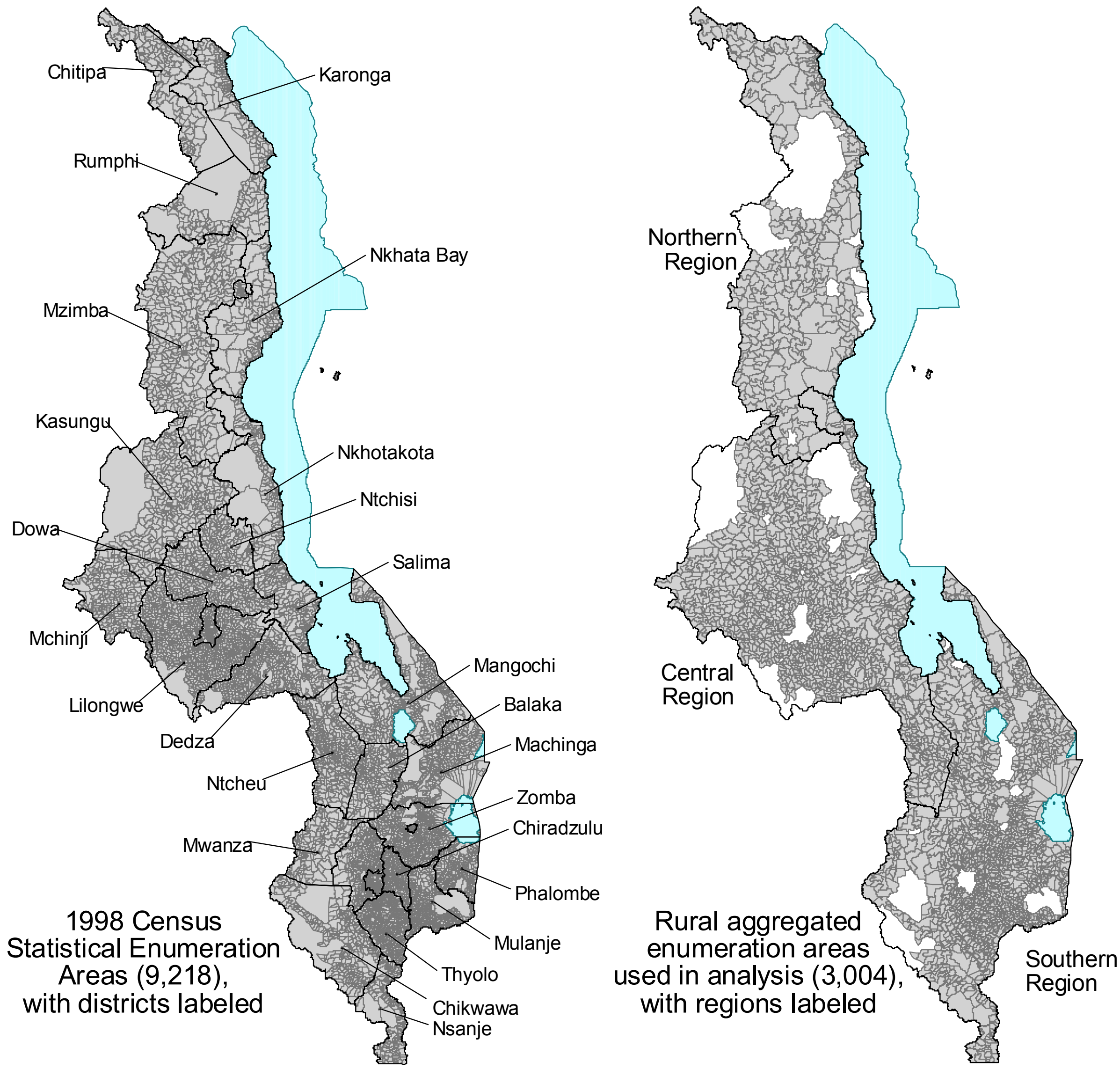
[5] A later assessment in several countries in which poverty maps have been developed led to an upward revision in this threshold, but it still shows reasonably precise poverty headcount estimates for populations down to about 1,000 households (Demombynes et al. 2002). Given the lower explanatory power of the poverty mapping models for Malawi relative to the models used in these other countries, the minimum population size to which one can reasonably apply the poverty mapping methodology in Malawi likely is greater, possibly even considerably greater, than 1,000 households. That said, the trend in mean and median standard errors for the poverty headcount presented in Table 1 does not show a sharp discontinuity as one examines increasingly smaller divisions of the population.

[6] Note that neither the EA nor the aggregated EA geographies are recognized as administrative units. Although the boundaries of the EAs do respect administrative boundaries at broader scales, they serve no administrative functions but are established by the Malawi National Statistical Office purely for data collection purposes.

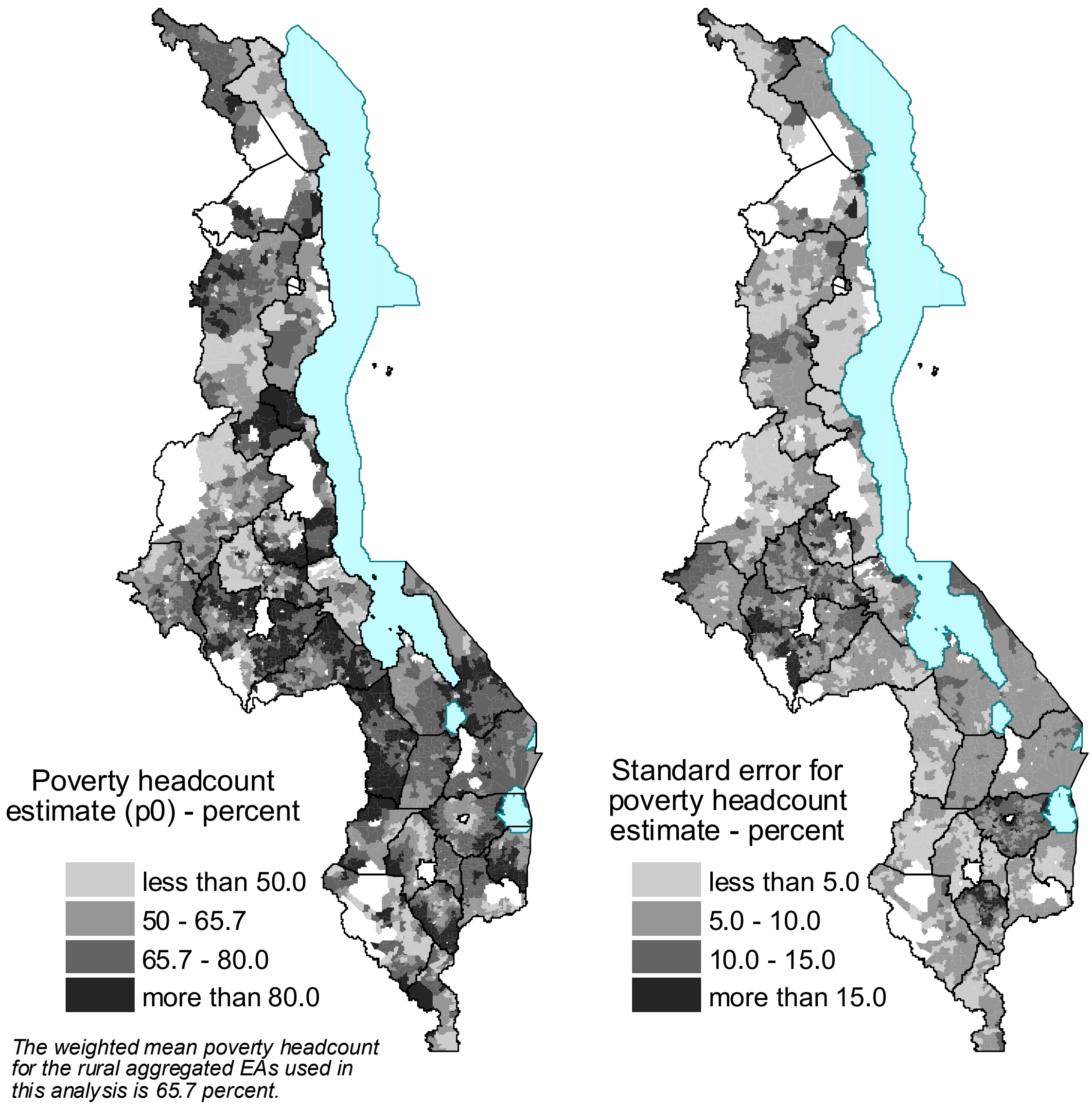
Figure 1—Maps of enumeration areas and rural aggregated enumeration areas used in the analysis



The 3,004 aggregated EAs used in the analysis exclude aggregated EAs from the four major urban centers of Malawi, all forest reserves and national parks, and some rural areas in Nkhata Bay District for which agricultural production data were missing. Urban areas in rural zones are included in the analysis, as it is expected that agriculture will remain the dominant livelihood strategy for the population in these smaller urban centers.

The estimated poverty headcount and standard errors for the poverty headcounts for the rural aggregated EAs used in the analysis here are portrayed in Figure 2. While the mean 95 percent confidence interval is ± 16.0 percentage points, 10 percent of all rural aggregated EAs have a confidence interval exceeding ± 25.5 percentage points, and the confidence interval for 20 percent exceeds ± 21.1 percentage points. However, while

Figure 2—Poverty-mapping poverty headcount (p0) estimate and standard error of p0 estimate for rural aggregated enumeration areas



recognizing the presence of these large numbers of outliers, the error terms for a majority of the estimates are reasonable. The average ratio of the standard error of the poverty headcount to the point estimate is 0.143, with a median ratio of 0.109.

Selection of Independent Variables

Potential determinants of the level of the prevalence of poverty in rural aggregated EAs are the independent variables for our analysis. Earlier we described the risk chain that guided our selection of independent variables. Moreover, a necessary characteristic of potential independent variables is that they could meaningfully be aggregated and display variation across the country at this scale. Not all risks faced or coping strategies employed by households in rural Malawi can be mapped in this way; those that could not are excluded from our analysis.

The independent variables were selected as follows. Guided by the risk chain framework, all available spatial data sets for Malawi were examined to create a subset of potential independent variables for use in the analysis. Several statistical analyses were then carried out to develop as parsimonious a set of variables as possible. Initially, covariance matrices were computed for all of the variables. Where high levels of correlation were found between two variables, one was selected for inclusion in the analysis based on the relative ease of interpreting the nature of the relationship between the variable and the dependent variable. After the initial set of independent variables was trimmed in this manner, the remaining variables were used in a multivariate OLS regression, and post-regression diagnosis was used to further assess multicollinearity.

The 26 independent variables selected for the analysis are described in Table 2, with descriptive statistics in Table 3. They are categorized by their general nature and a priori assessments are provided both as to the position that the characteristic is assumed to play in the risk chain of economic vulnerability and as to the nature of the relationship between the level of the independent variable and the level of poverty prevalence in a rural aggregated EA—positive if a higher value for the variable implies a greater

Table 2—Independent variables for analysis of spatial determinants of poverty prevalence in rural aggregated enumeration areas

Name	Definition	Assumed risk chain link position	Assumed relationship to poverty prevalence	Source
Agroclimatological				
CLIOPT5PRE	Average rainfall (mm) in 5 mo. following precip. to potential evapotranspiration ratio triggered plant date	risk	negative	Malawi, AWhere – ACT3.5, Mud Springs Geographers, Inc. (2003)
CVRAIN	Avg. rainfall coefficient of variation during rainy season (Dec.-Mar.), percent, [100 * (standard dev. / mean)]	risk	positive	Analysis of data from over 250 rainfall recording stations.
HIRAIN9798	In highest quintile of rainfall deviation from long-term mean in 1997-98 season (0/1) – much higher rainfall than average.	risk	unknown or negative	Interpolated surface derived from Malawi Meteorological Services rainfall data
LORAIN9798	In lowest quintile of rainfall deviation from long-term mean in 1997-98 season (0/1)	risk	positive	Interpolated surface derived from Malawi Met Services rainfall data
Natural hazards				
FLOOD	Dominant soils subject to flooding (0/1)	risk	positive	Soils and physiography map
STEEP	Steep slopes common (0/1)	risk	positive	Soils and physiography map
Agriculture and livelihoods				
SOLGOODD	Dominant soils have relatively good agricultural potential, based on FAO soil classification (0/1)	risk/coping	negative	Soils and physiography map
AVMZYLD	Mean maize yield (kg/ha), 1995/96 to 1999/2000	risk/coping	negative	Min. of Ag. crop estimates.
CVMAIZE	Maize yield coefficient of variation, 1995/96 to 1999/2000, [100 * (standard deviation / mean)]	risk	positive	Ministry of Agriculture crop estimates.
CROPDIVERS	Percent cropped area not in staple crop	risk/coping	negative	Min. of Ag. crop estimates.
PCT_NOT_FA	Percent of workers whose principal economic activity is not in agriculture	risk/coping	negative	1998 Population and Housing Census analysis.
Access to services				
HOSP_HR	Avg. travel time (hr) to nearest hospital. Proxy for district-level services.	coping	positive	GIS analysis using roads, health facilities, & land use.
GAZ_AREA_H	Avg. travel time (hr) to major forest reserve or nat'l park – proxy access to common property resources.	coping	positive	GIS analysis using roads, EA, & land use.
MKT_ALL_HR	Avg. travel time (hr) to nearest sub-district market center	coping	positive	GIS analysis of roads & land use with hierarchical market listing.
MKT_1_HR	Avg. travel time (hr) to nearest of the six major regional markets of Malawi – Blantyre, Lilongwe, Mzuzu, Zomba, Kasungu, and Karonga.	coping	positive	GIS analysis using roads, urban center, & land use coverages.
RD_WT_PAV	Average weighted road density (m/km^2), weighted by potential speed on different qualities of road	coping	negative	GIS analysis using roads coverage.
Demography				
MSXRT20_49	Sex ratio (modified) for ages 20 to 49 years, [(no. men per 100 women) – 100]	coping	negative	1998 Census analysis.
DEPRATIO	Dependency ratio, [total aged under 15 and over 65 years divided by total pop.]	coping	positive	1998 Census analysis.
FEMHHH	Percentage of households headed by women	coping	positive	1998 Census analysis.
POPDENS	Population density, [persons/km^2]	risk/coping	unknown	1998 Census analysis.
Education				
SEXDIFF_LI	Literacy rates differences between adult men and women, percent	coping	positive	1998 Census analysis.
MAXED	Mean maximum educational attainment level in households (years of school completed)	coping	negative	1998 Census analysis.
Other				
ORPH_PREV	Percent of those aged 14 years or less having at least one parent dead – proxy for general health status, adult mortality, level of child care	risk/coping	positive	1998 Census analysis.
GINI	Gini coefficient of consumption inequality	risk/coping	unknown	Poverty mapping analysis.
CHEWA_YAO	Percent of population with Chichewa, Chinyanja, or Chiyao as mother-tongue – proxy for matrilineality	coping	unknown	1998 Census analysis.
OLDPARTY	Parliamentarian from historical ruling party elected from area in 1999, the Malawi Congress Party (0/1)	coping	negative	1999 election results and map of parliamentary constituencies.

Note: The notation (0/1) in the variable definition indicates that the variable is a binary, dummy variable. A negative relationship to poverty prevalence indicates that increases in the determinant's value should lead to a reduction in poverty prevalence.

Table 3—Analytical variables—descriptive statistics (n = 3,004 rural aggregated enumeration areas)

Variable	Mean	Standard Deviation	Minimum	Lower quartile	Median	Upper quartile	Maximum
Dependent variable							
FGT_0	0.661	0.168	0.062	0.547	0.689	0.788	0.987
Independent variables							
CLIOPT5PRE	913	172	609	801	863	979	1912
CVRAIN	24.5	2.8	15.9	22.8	24.7	26.4	36.2
HIRAIN9798	0.200	0.400	0	0	0	0	1
LORAIN9798	0.200	0.400	0	0	0	0	1
FLOOD	0.046	0.210	0	0	0	0	1
STEEP	0.204	0.403	0	0	0	0	1
SOLGOODD	0.527	0.499	0	0	1	1	1
AVMZYLD	1381	333	664	1164	1308	1549	2470
CVMAIZE	24.9	10.6	5.9	17.5	23.5	30.9	63.1
CROPDIVERS	0.443	0.127	0.000	0.344	0.443	0.532	0.808
PCT_NOT_FA	16.3	18.0	0.1	4.8	9.7	19.6	99.4
HOSP_HR	0.90	0.65	0.00	0.50	0.77	1.16	9.37
GAZ_AREA_H	1.57	0.92	0.00	0.89	1.50	2.08	9.47
MKT_ALL_HR	0.77	0.61	0.01	0.42	0.66	0.96	11.60
MKT_1_HR	1.94	1.07	0.05	1.15	1.78	2.62	13.44
RD_WT_PAV	3286	1989	0	2002	2995	4120	18387
MSXRT20_49	-10.9	15.4	-49.6	-20.7	-13.1	-4.0	155.2
DEPRATIO	0.484	0.028	0.321	0.469	0.487	0.503	0.568
FEMHHH	32.8	12.2	0.0	24.3	31.6	39.9	84.0
POPDENS	256	521	2	95	165	261	14924
SEXDIFF_LI	21.6	8.3	-3.7	16.1	21.7	27.0	51.3
MAXED	5.1	1.5	1.1	4.1	5.0	5.9	10.6
ORPH_PREV	7.5	3.4	0.3	4.9	7.0	9.6	39.2
GINI	0.352	0.055	0.116	0.316	0.339	0.379	0.671
CHEWA_YAO	81.7	31.6	0.0	84.4	97.8	99.5	100.0
OLDPARTY	0.354	0.478	0	0	0	1	1

prevalence of poverty, negative if otherwise. Note that several of the variables were judged to be both risk factors and coping factors. For example, good agricultural soils imply lower risk of crop failure and more reliable recovery from a shock to household welfare. For several variables, the assumed relationship between the level of the independent variable and that of the dependent variable is not clear a priori.

Several of the independent variables require additional comment:

- The GINI variable, just like the poverty headcount dependent variable, is a product of the poverty mapping exercise. However, we argue that this variable is relatively independent of the poverty headcount measure since it describes the distribution of welfare across the population and is not tied to the poverty line in any way. The relationship of the Gini coefficient to poverty prevalence is unclear.

- The CHEWA_YAO variable serves as a proxy for matrilineality, as the Chewa and the Yao are the largest matrilineal ethnic groups in Malawi. As Watts and Bohle note in their discussion of the space of vulnerability, "vulnerability is a multilayered and multidimensional social space defined by the determinate political, economic, and institutional capabilities of people in specific places at specific times" (1993, 46). Inheritance patterns and the property rights inherent in them are among the social institutions that may have developed, among other reasons, as a way to enhance the ability of the population to cope with economic shock. This variable assesses whether this is indeed the case or, given social trends in recent generations that favor patrilineal systems, whether there might now be evidence that the matrilineal inheritance system is now dysfunctional in safeguarding household and individual welfare.
- In the same vein, the OLDPARTY variable points to the role of the political organization of Malawi as a characteristic of economic vulnerability. The Malawi Congress Party (MCP), while not in power at the time of the survey and census, held power in Malawi from the time of independence from Britain in 1964 until 1994. Those areas of the country that continued to support the MCP at elections five years after the party fell from power may have been motivated by the perception that they have derived welfare benefits in the past from their support of the party, benefits that they feel would not be sustained under the leadership of the new ruling party. Consequently, a negative sign is anticipated, reflecting a relatively lower level of poverty in these areas due to the past benefits accrued from supporting the MCP when the party was in power.

Several issues relating to these independent variables should be highlighted. First, economic vulnerability is a dynamic concept, in that it reflects the potential impact on household and individual welfare of agroecological and socioeconomic shocks now and in the future. In contrast, poverty status is a static concept, representing the welfare state of a household or individual at a particular point in time. Our dependent variable is a static poverty measure based on two cross-sectional data sets, the 1997–98 Malawi IHS and the 1998 Census. Moreover, many of the spatial data sets that we employ to account for the determinants of aggregate poverty are themselves cross-sectional and static. Incorporating temporal elements into spatial variables is challenging. What we have done is to specifically include spatial variables that either measure the annual variability in a phenomenon or compare the level of a factor at the time of the IHS survey and the Census to its long-term mean. However, we were only able to do so for crop yields and for rainfall. Overall we cannot claim that our analysis provides any substantive insights on how spatial variables might be altered to reduce the degree of vulnerability within which households in these rural aggregated EAs pursue their livelihoods. The principal contribution that this analysis makes is to identify spatial factors that explain some of the variation in aggregate welfare outcomes. To better understand the mechanisms by which these factors contribute to or alleviate household economic vulnerability, they would need to be examined within a dynamic context in which household welfare is traced through time.

Second, the exogeneity of all of the independent variables selected is questionable. Endogeneity arises at two levels. First, some of the independent variables are likely collinear with independent variables used in some of the poverty mapping models that estimate the dependent variable. Moreover, poverty status, even when narrowly defined based on a consumption measure as here, is implicated in the effectiveness with which households can cope with economic shock. To some extent the levels of several of the independent variables are influenced by the relative number of poor individuals who reside in an aggregated EA.

Third, in this spatial analysis we draw on data that were developed at several different scales. Pulling data from different scales in an analysis poses the risk of committing the ecological fallacy of drawing inferences about smaller analytical units from the aggregate characteristics of groups of those units. The aggregate group characteristic may mask the heterogeneity in that characteristic for the individual units making up the group. As a rule of thumb, one might avoid the ecological fallacy by only undertaking analysis and drawing inferences at the broadest scale from which the analytical data were acquired. For the analysis here, we are fortunate to have an extensive set of spatial data for Malawi, which was collected at a more local scale than that of the aggregated EA. However, the agricultural production data are an exception. Differences in crop production in neighboring aggregated EAs are hidden here, so any inferences drawn on the relationship between agricultural production and poverty prevalence will necessarily have some error associated with the aggregated quality of the underlying data.

Finally, the quality of the data from which these variables were constructed is not uniformly high. While, given the large number of sample points, any outliers probably will not strongly affect the results obtained, they do signal caution. Furthermore, the dependent variable itself is drawn from a survey data set that requires care in analysis.

Analytical Methods

Analysis of the spatial determinants of the prevalence of poverty in rural aggregated EAs involved using two different statistical analyses to estimate the prevalence of poverty as a function of spatial variables selected on the basis of the risk chain conceptual framework of economic vulnerability. The first, using a spatial regression model, produces a global model that assumes that a single multivariate relationship determines the level of poverty prevalence across all rural aggregated EAs in Malawi. The second, using the geographically weighted regression (GWR) technique, generates local models of the determinants of poverty prevalence for each rural aggregated EA.

Spatial Regression Models

A spatial regression model was developed following an assessment of the results of an Ordinary Least Squares (OLS) regression. In brief, the OLS regression model takes the form

$$Y = X\beta + \varepsilon,$$

where Y is a vector of observations on the dependent variable, X is a matrix of independent variables, β is a vector of coefficients, and ε is a vector of random errors. Using OLS, we initially developed a single global model of the relationship between the dependent variable and the independent variables. However, one must accept a broad set of assumptions in order to make valid use of an OLS regression procedure.[7] Only if these assumptions are met can one be assured that the estimates generated are unbiased and efficient (minimum variance). A critical concern in the analysis here is the violation of the assumption that the error terms not be correlated with each other. One way in which the error terms may be correlated is spatially, as evidenced by observations from locations near to each other having model residuals of a similar magnitude. The Moran's I statistic is used to assess spatial autocorrelation in the residuals.

When spatial autocorrelation is present in the data, the OLS results will be biased, inefficient, and, thus, invalid. In order to control for it, a variable representing the spatial dependency of the dependent variable can be inserted into the model as a supplementary explanatory variable. The most common way in which this is done is to use the spatial lag of the dependent variable. The spatial lag variable is the weighted mean of a variable for neighboring spatial units of the observation unit in question. For the dependent variable, the spatial lag variable is generally written as Wy, where W is the spatial weights matrix that identifies neighboring spatial units.[8]

We can conceptualize the spatial dependence in the regression model as manifesting itself in two different ways. First, the spatial dependence could be judged to

[7] Kennedy (1985, Ch. 3) has distilled these assumptions down to five: (1) The dependent variable has a linear relationship with the independent variables. (2) The expected value of the error term is zero. (3) The error terms all have the same variance and are not correlated with each other. (4) Observations on the independent variables can be considered fixed in repeated samples. (5) The number of observations is greater than the number of independent variables, and there are no exact linear relationships between the independent variables.

[8] The use of a spatial lag term for spatial regression is similar in some respects to the use of a serially autoregressive term for the dependent variable—y_{t-1}—on the right-hand side in time-series analysis.

be a result of the level of the dependent variable in a neighboring area affecting the level of the dependent variable in the area in question. That is, the prevalence of poverty in one rural aggregated EA will directly affect the prevalence of poverty in a neighboring aggregated EA. Such a relationship is modeled as a *spatial lag model*:

$$y = \rho W y + X\beta + \varepsilon,$$

which is similar to the OLS equation described above, with the addition of the Wy spatial lag of the dependent variable, which takes the coefficient ρ, the spatial autoregressive parameter.

Alternatively, the spatial dependence can be attributed to the error term of the model. That is, the error term for the model in one aggregated EA is correlated with the error terms in its neighbors, as might occur due to a missing spatial variable for the model that affects an aggregated EA and its neighbors in a similar manner (Anselin 1992). Such a relationship can be modeled as a *spatial error model*:

$$y = X\beta + \varepsilon, \text{ where } \varepsilon = \lambda W\varepsilon + \varepsilon.$$

Here, the error term is disaggregated into the spatial lag of the error term of neighboring aggregated EAs and the residual error term for the spatial unit in question. The spatial lag term on the error, $W\varepsilon$, takes the coefficient λ, the spatial autoregressive parameter for this model.

Although they result from different interpretations of the spatial processes accounting for the spatial autocorrelation, in practice, there is usually very little difference between the two spatial models. In order to choose which one to use, a Lagrange Multiplier test is used to assess the statistical significance of the ρ and λ coefficients in each model, respectively. Where spatial autocorrelation is likely, usually the result of the test on each will be significant. The preferred model in such a case is the one with the highest Lagrange Multiplier test value (Anselin and Rey 1991).

Before turning to the second analytical method employed, we should point out that the choice of spatial weights matrix used in the analysis is an important analytical decision. There is little formal guidance as to how the choice should be made (Anselin 2002). Here we simply undertook a sensitivity analysis of the results obtained using different weighting schemes and made our choice—a first-order Queen's contiguity-based weighting matrix—based on the resultant explanatory power of the model and the ease of interpretation of the results in light of the spatial weighting scheme.

Geographically Weighted Regression

In using the spatial regression and the OLS models, we assume that the underlying spatial process accounting for the estimated poverty headcount levels in rural aggregated EAs in Malawi is the same across the country. That is, the relationship is *spatially stationary*, and, accordingly, the coefficients for a quantitative model of the relationship are assumed to be independent of location and do not vary across space. Such an assumption might be reasonable when one is considering physical processes that are governed by universal physical relationships. However, at least at the generalized level of our analysis, few social processes will be found to be so constant over space (Fotheringham, Brunsdon, and Charlton 2002, 9). The generalized, global regression models will hide this potential heterogeneity, or *spatial nonstationarity*, in the determinants of the prevalence of poverty.

The geographically weighted regression (GWR) method provides a way to assess the degree to which the relationship between the potential determinants and the prevalence of poverty varies across space. The method produces local, rather than global, models of the relationship for each rural aggregated EA in our data. This is done by constructing a spatial weighting matrix and running a spatially weighted regression for each rural aggregated EA.

The global OLS regression model described earlier can be rewritten as

$$y_i = a_0 + \Sigma_j x_{ij} a_j + \varepsilon,$$

where y is the dependent variable, x is the independent variable, a is the regression coefficient (a_0 being the constant), i is an index for the location, j is an index for the independent variable, and ε is the error term. This can be reworked as a local regression model to become

$$y_i = a_{0i} + \Sigma_j \, x_{ij} \, a_{ij} + \varepsilon,$$

in which location dependent coefficients are estimated (Minot, Baulch, and Epprecht 2003, 15).

For each location, the neighboring observations used to estimate the model are chosen and the importance of each for the estimation procedure is weighted using a distance-based spatial weights matrix. Typically, a Gaussian distance decay function will be employed to weight neighboring observations. The size of the neighborhood to which the spatial weight matrix applies can be a fixed distance (bandwidth) or, alternatively, can be based on k-nearest neighbors with a varying, adaptive bandwidth applied to the weighting function.[9] The optimal bandwidth or k for the spatial weights matrix is determined using iterative statistical techniques. Note that the distance between spatial units is the distance between their center points.

Where there are many observation points and independent variables, the GWR procedure provides a deluge of information. For each spatial unit, R^2 values, constants, coefficients and t-statistics for each independent variable, residuals, and influence statistics are produced. Indeed, one of the key challenges in employing the GWR method is information management. This is most efficiently done using maps.

One can also assess the spatial nonstationarity of the relationship of each independent variable to the dependent variable to determine whether the GWR method offers any improvement over a global regression model. A Monte Carlo simulation

[9] The Gaussian distance decay function is computed as $w_{ij} = \exp[-½(d_{ij}/b)^2]$, where i is the regression point, j is observation points around i, d is the distance from i to j, and b is a critical distance – the bandwidth. For the adaptive bandwidth spatial weights matrix, a bi-square function is used so that $w_{ij} = [1 - (d_{ij}/b)^2]^2$ if j is one of the k^{th} nearest neighbors of i and b is the distance from i to the k^{th} nearest neighbor, but $w_{ij} = 0$ otherwise (Fotheringham, Brunsdon, and Charlton 2002, 56–59).

procedure is used in which the variability in the observed GWR estimates for the spatial units are compared to the variability of the GWR results from a large number of random allocations of the analytical data across the units. Where one finds a significant difference between the variability of an observed estimate from those computed using the randomized data, spatial nonstationarity for that particular independent variable is indicated (Fotheringham, Brunsdon, and Charlton 2000, 126-128).

Spatial autocorrelation and the use of spatial lag variables to control for the autocorrelation does not come into GWR analysis, making the results somewhat easier to interpret in this regard. Spatial autocorrelation is not ignored. However, rather than controlling for spatial dependency, the GWR analysis attempts to explain the nature of this spatial dependence as part of the local analysis. Fotheringham, Brunsdon, and Charlton note that “the calibration of local rather than global models reduces the problem of spatially autocorrelated error terms by allowing geographically varying relationships to be modeled through spatially varying parameter estimates rather than through the error term (2002, 114–115).” The spatial autocorrelation becomes part of what the local GWR model explains.

4. Results

Spatial Regression Model

Our first step was to undertake an OLS regression of the poverty headcount for each of the 3,004 rural aggregated EAs on the set of independent variables presented in Table 2. The adjusted R^2 for the OLS model is 0.2856, indicating that much of what determines the level of poverty found in these aggregated EAs goes unexplained by this model. However, the validity of the OLS model is called into question due to spatial autocorrelation in the residuals for each aggregated EA from the OLS regression. The Moran’s I statistic for the OLS regression residuals using a first-order Queen’s spatial weights matrix is 0.5392, $p \leq 0.001$.

A spatial regression model was used to control for the spatial autocorrelation. To choose which model of spatial dependence should be used—a spatial lag or a spatial error model—we tested the significance of the spatial autoregressive parameter for each model. Results for both the normal and the robust Lagrange Multiplier tests for both models are presented in Table 4. Although both models exhibit significant spatial dependence, the model with the highest test statistic should be used: in this case, the spatial error model has the higher statistic for both the normal and robust tests.[10]

Table 4—Diagnostic tests for nature of spatial dependence in poverty prevalence in rural aggregated enumeration areas in Malawi

Test	Value	Prob.
Spatial-lag model		
Lagrange Multiplier	2232.2	0.0000
Robust LM	69.2	0.0000
Spatial error model		
Lagrange Multiplier	2282.9	0.0000
Robust LM	119.8	0.0000

Spatial weights matrix: 1st order Queen's, row-standardized.

The spatial error model of the determinants of the prevalence of poverty for rural aggregated EAs in Malawi is shown in Table 5. The explanatory power of the model increases considerably over the OLS regression, with an R^2 of 0.678l. The spatial autocorrelation is much reduced—the Moran's I statistic having dropped considerably from 0.5392 to 0.0334. However, this statistic remains significant at the $p \leq 0.01$ level. Eight independent variables are significant. As expected, the λ coefficient for the spatial lag of the error is highly significant with a t-statistic that is an order of magnitude larger than the next largest.

From an econometric standpoint, spatial regression models deal with the nuisance caused by spatial autocorrelation. In this case, we used a first order Queen's spatial

[10] The spatial regression models were developed and assessed using GeoDa 0.9 software (Anselin 2003).

Table 5—Results of spatial error maximum-likelihood estimation model on the determinants of poverty prevalence for rural aggregated enumeration areas in Malawi

Variable	Coefficient	Standard error	z-statistic	Probability
Constant	0.37336	0.09399	3.97219	0.00007
λ - LAMBDA	0.79898	0.01240	64.45346	0.00000
CLIOPT5PRE	0.00005	0.00004	1.47527	0.14014
CVRAIN	0.00228	0.00262	0.86813	0.38533
HIRAIN9798	-0.02429	0.01231	-1.97327	0.04846
LORAIN9798	-0.01531	0.01155	-1.32620	0.18477
FLOOD	-0.00297	0.01026	-0.28968	0.77206
STEEP	0.00257	0.00601	0.42705	0.66934
SOLGOODD	0.00171	0.00552	0.30937	0.75704
AVMZYLD	0.00003	0.00001	2.34613	0.01897
CVMAIZE	0.00006	0.00042	0.14645	0.88357
CROPDIVERS	-0.13085	0.03977	-3.29023	0.00100
PCT_NOT_FA	-0.00171	0.00022	-7.83898	0.00000
HOSP_HR	0.02158	0.01526	1.41423	0.15730
GAZ_AREA_H	-0.00739	0.00898	-0.82355	0.41019
MKT_ALL_HR	0.00906	0.01430	0.63321	0.52660
MKT_1_HR	-0.00063	0.00999	-0.06270	0.95001
RD_WT_PAV	0.00000	0.00000	-0.11647	0.90728
MSXRT20_49	0.00015	0.00022	0.66903	0.50348
DEPRATIO	0.64136	0.09686	6.62166	0.00000
FEMHHH	0.00040	0.00022	1.78551	0.07418
POPDENS	-0.00001	0.00000	-1.71496	0.08635
SEXDIFF_LI	0.00011	0.00028	0.40414	0.68611
MAXED	-0.00720	0.00260	-2.77261	0.00556
ORPH_PREV	0.00128	0.00071	1.79468	0.07271
GINI	-0.34611	0.04953	-6.98783	0.00000
CHEWA_YAO	0.00054	0.00017	3.16258	0.00156
OLDPARTY	-0.01505	0.01325	-1.13621	0.25587

Dependent variable: FGT_0 Number of observations: 3004

No. of variables: 27 + spatial error lag, which takes λ coefficient

R-squared: 0.6777 Akaike information criterion: -5014.12

Note: Shaded cells in the Probability column are significant at the $p \leq 0.05$ level.

weight matrix to create the spatial lag of the error term to control for spatial autocorrelation at quite a local scale of neighboring aggregated EAs. Other spatial weights matrices will give differing results. Having removed this nuisance of local spatial autocorrelation, the results of our model identify those spatial variables that have a strong relationship to the prevalence of poverty across all of the rural aggregated EAs considered. The results also indicate those variables whose relationship to poverty prevalence is more consistent at a broader scale than the contiguous aggregated EAs specified by the first order Queen's spatial weight matrix. However, in this analysis, we lose information on both real and spurious associations between the independent variables and the dependent variable, which operate at the spatial scale of first-order neighboring aggregated EAs and not at broader scales. Any such information is captured by the coefficient for the spatial lag variable.

Here we review the coefficient estimates by classes of independent variables, comparing our results to our a priori assumptions.

- For the agroclimatological variables, only the dummy variable specifying that the rainfall in the 1997–98 season was much higher than normal is just significant at the $p \leq 0.05$ level and is associated with a somewhat lower prevalence of poverty. Higher yields due to increased rainfall during the period of the IHS survey may be reflected in higher consumption levels and, thus, higher welfare measures and lower poverty in these aggregated EAs.
- Neither of the natural hazard variables—floods or steep slopes—is shown to be significant. This is somewhat puzzling. However, the spatial distribution of areas with steep slopes displays considerable clustering; that is, steep areas neighbor other steep areas. The spatial lag of the error term may remove from the model information on the effect of slope on local poverty prevalence.
- For the agriculture and livelihood variables, average maize yield is a significant determinant of poverty prevalence. However, contrary to expectations, the coefficient is positive, implying that areas with higher maize yields on average will have higher levels of poverty. This may be a result of in-migration and consequent small landholding sizes in these areas of high agricultural potential. Alternatively, relatively large numbers of poor workers may account for higher poverty headcounts in high-potential tobacco areas, where tenants or wage laborers produce the tobacco on estates. The variables for crop diversity and the importance of nonagricultural economic activities are also significant.

- All variables for access to services are insignificant. However, our interpretation of this result for policymaking purposes should be cautious. Most consumption-based welfare measures, such as those used in the poverty analysis that underlies this research, do not capture the public goods and access to services dimensions of welfare very well, since they are focused quite narrowly on private household consumption (Deaton and Zaidi 2002, 17).[11]
- Of the demography variables, only the dependency ratio variable is a significant determinant of poverty prevalence within the spatial error model.
- For the educational determinants, average maximum educational attainment is a significant determinant of poverty prevalence, while sex differences in adult literacy is insignificant.
- For the other group of variables, the prevalence of orphans and the political party affiliation variables are shown not to be important. However, the Gini coefficient of consumption inequality and the CHEWA_YAO proxy for matrilineality are significant. Higher consumption inequality is shown to result in a lower prevalence of poverty. The matrilineality proxy is positive, indicating higher levels of poverty when a greater proportion of the population in an aggregated EA follows a matrilineal inheritance system.

The policy implications that we can draw from these results are relatively few and not surprising. Policymakers and poverty reduction program designers should consider efforts in the following areas:

- Irrigate to assure adequate moisture for crops. However, the economics of irrigation in smallholder agriculture in Malawi pose an important and possibly insurmountable challenge to profitably employing irrigation.
- Encourage crop diversification and rural nonfarm livelihood strategies.

[11] We are grateful to our reviewer for highlighting this point.

- Reduce the number of dependents in households or reduce the burden of care those dependents impose on workers in a household through programs targeted at children and the elderly or their caregivers.[12]
- Educate the population to the highest level feasible.[13]

It is unclear what actions could be taken in light of the significant, but positive association between average maize yields and poverty levels and the significant GINI and matrilineal variables, beyond simply being aware that these factors may interact with whatever other actions are taken, complicating them somewhat or forcing modifications if the other strategies are to be effective.

Geographically Weighted Regression

As we pointed out earlier, the spatial error model is a global model of the spatial determinants of rural poverty prevalence in Malawi. We now present the results of the geographically weighted regression (GWR) analysis that allows for spatially varying relationships between rural poverty prevalence and these same spatial determinants across the country.[14]

We used the same dependent and independent variables as in the previous analysis and an adaptive bandwidth spatial weighting scheme of the 347 nearest neighbors to each aggregated EA to run the GWR regression. This spatial weighting

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[12] This result reflects the close correlation between a high dependency ratio within a household and that household being in poverty. While there is theoretical merit to this relationship, it also reflects the mechanics of the poverty analysis used. The welfare measure is computed on a per capita basis, rather than an adult equivalent basis. An important consequence is that households with children are more likely to be judged poor on a per capita basis than they would be if their welfare level was measured on an adult equivalent basis.

[13] No guidance can be provided as to whether specific individuals within a household should be targeted within the population for education when resources are limited. The choice of mean maximum household education level as the education variable was made on the assumption that higher educational attainment by a single household member, regardless of his or her relationship to the household head, would raise the consumption levels for all household members. However, this assumption is open for debate. See Jolliffe (2002) for a detailed discussion.

[14] The geographically weighted regression models were developed and assessed using GWR 3.0 software. See Fotheringham, Brunsdon, and Charlton 2002, Chapter 9.

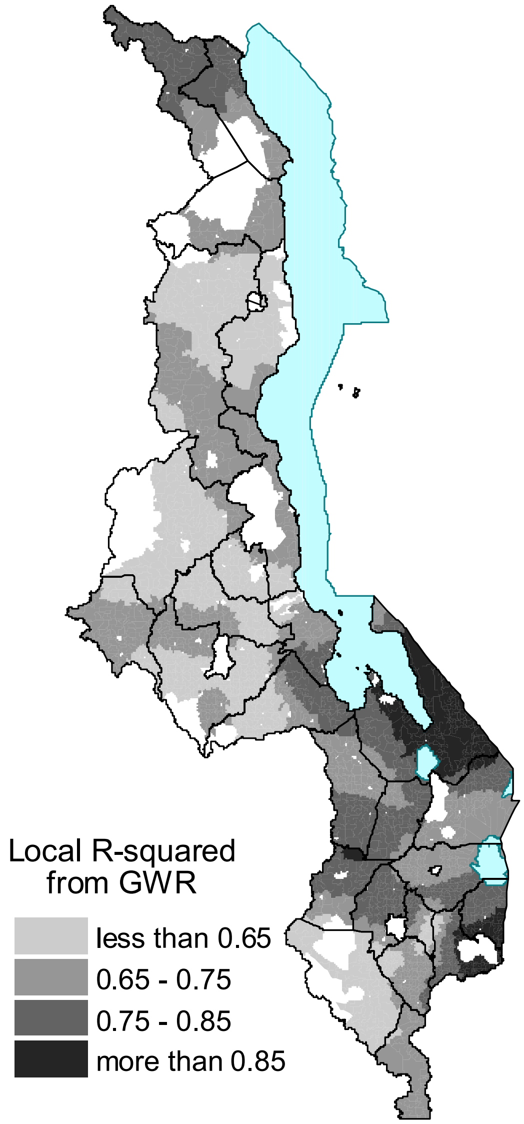
scheme for the analysis was chosen using an optimization procedure that identifies the scheme that minimizes the Akaike Information Criterion (AIC) for the model (Fotheringham, Brunsdon, and Charlton 2002, 212). The global adjusted R^2 for the GWR is 0.6993 (unadjusted, 0.7452), which is a considerable improvement over the OLS regression (0.2856) and a small improvement over the spatial error model (0.6777, unadjusted). The Moran's I-statistic for the residuals of the GWR model is 0.1710, which is significant at the $p \leq 0.001$ level. While this level of spatial autocorrelation is much lower than that of the OLS regression (0.5392), it is higher than that of the spatial error model (0.0334). The effect of spatial autocorrelation on the parameter estimates of the GWR models cannot be wholly ignored.

Figure 3 presents the local R^2 statistic for each rural aggregated EA. It was hoped that this pattern would shed some light on missing determinants for inclusion in our model. Those areas with the lowest R^2s are relatively diverse agroecologically and do not have any obvious socioeconomic commonalities. No missing spatial variables for the model are immediately apparent from this pattern. The model performs best around Mt. Mulanje in the southeast, in the smallholder subsistence areas bordering Mozambique, and in parts of the southern lakeshore. However, again, we see no obvious similarities between these specific areas.

Turning to the specific estimates of the strength and nature of the local relationship between determinants of poverty and the prevalence of poverty in rural aggregated EAs, we find that standard presentations of regression results are difficult to make because each variable will have 3,004 separate coefficients. Table 6 describes the distribution of the coefficients for all independent variables.

The model results of the GWR can be interpreted in two ways. Those interested in a particular local area in rural Malawi might use the complete model results for that place to get a multivariate understanding of key local determinants of the level of poverty. We do not do that here. Rather, we consider for each determinant variations

Figure 3—Local R^2 from the geographically weighted regression of the determinants of poverty prevalence for rural aggregated enumeration areas in Malawi



across rural Malawi in the relationship between the determinant and local levels of poverty—positive or negative. In this way we can try to develop hypotheses on why the global patterns suggested in the spatial error model are not necessarily replicated in the GWR analysis, what might account for counterintuitive spatial patterns in the parameters, and how this analysis might inform efforts to aid households and individuals raise their welfare levels.

Table 6—Descriptive statistics of the coefficients for each independent variable for the geographically weighted regression model of the determinants of poverty prevalence for rural aggregated enumeration areas (EAs) in Malawi (n = 3,004)

Variable	Minimum	Lower quartile	Median	Upper quartile	Maximum	Percent of rural aggregated EAs with significant coefficient	
						Negative	Positive
Constant	-1.94981	-0.33394	0.10816	0.77342	2.89514	15.3	22.5
CLIOPT5PRE	-0.00063	-0.00006	0.00010	0.00024	0.00284	9.0	34.8
CVRAIN	-0.04102	-0.00633	0.00575	0.01658	0.04435	11.0	31.4
HIRAIN9798	-0.32874	-0.06148	-0.01496	0.00000	0.32003	25.0	4.1
LORAIN9798	-0.32573	-0.08776	-0.01043	0.01650	0.47181	30.7	11.8
FLOOD	-0.17801	-0.02738	0.00000	0.02224	0.45353	11.2	4.8
STEEP	-0.24000	-0.00776	0.00730	0.02696	0.32526	0.2	15.8
SOLGOODD	-0.52372	-0.02072	0.00116	0.01985	0.30624	10.9	12.7
AVMZYLD	-0.00033	-0.00003	0.00006	0.00019	0.00057	15.7	42.1
CVMAIZE	-0.00922	-0.00224	-0.00008	0.00379	0.01634	24.5	26.8
CROPDIVERS	-1.74229	-0.27547	-0.04368	0.12295	1.46350	24.8	16.0
PCT_NOT_FA	-0.00587	-0.00249	-0.00153	-0.00103	0.00232	50.7	0.1
HOSP_HR	-0.33748	-0.01792	0.05296	0.10709	0.34218	10.9	43.3
GAZ_AREA_H	-0.33622	-0.03974	-0.00204	0.03655	0.14040	27.6	18.7
MKT_ALL_HR	-0.31533	-0.07275	-0.02747	0.01997	0.40941	26.5	12.4
MKT_1_HR	-0.36103	-0.04106	-0.00706	0.03964	0.15979	18.5	19.8
RD_WT_PAV	-0.00002	-0.00001	0.00000	0.00000	0.00003	14.1	4.4
MSXRT20_49	-0.00248	-0.00070	-0.00001	0.00067	0.00296	2.5	7.6
DEPRATIO	-1.01700	0.20705	0.50681	0.84924	1.90329	0.4	33.6
FEMHHH	-0.00334	-0.00055	0.00026	0.00103	0.00438	7.6	11.1
POPDENS	-0.00018	-0.00006	-0.00002	0.00000	0.00014	17.6	3.5
SEXDIFF_LI	-0.00486	-0.00044	0.00037	0.00118	0.00343	1.7	6.3
MAXED	-0.10897	-0.03926	-0.01032	0.01797	0.06743	41.1	23.3
ORPH_PREV	-0.01149	-0.00107	0.00136	0.00277	0.01066	1.2	4.6
GINI	-1.48925	-0.85225	-0.28509	0.10171	1.19286	44.8	10.8
CHEWA_YAO	-0.01535	-0.00069	0.00029	0.00118	0.00913	5.8	8.8
OLDPARTY	-0.90323	-0.03388	0.00000	0.01500	0.39417	14.7	11.4

In Figure 4 (4a to 4e), we present partial results for the GWR analysis—the t-statistics for the GWR model intercepts, and two maps for each of the 26 independent variables in the model. The top map in each pair is of the value of the independent variable, while the bottom map portrays the statistical significance of the t-statistic and sign of the coefficient for the variable across rural aggregated EAs. In the lower map, a three-category legend is used with legend category breaks at the t-value of ± 1.96 ($p \leq 0.05$) levels. Maps of the value of the actual coefficients from the local models for

Figure 4a—Maps of independent variables and t-statistics for each from geographically weighted regression analysis of the determinants of poverty prevalence for rural aggregated enumeration areas in Malawi

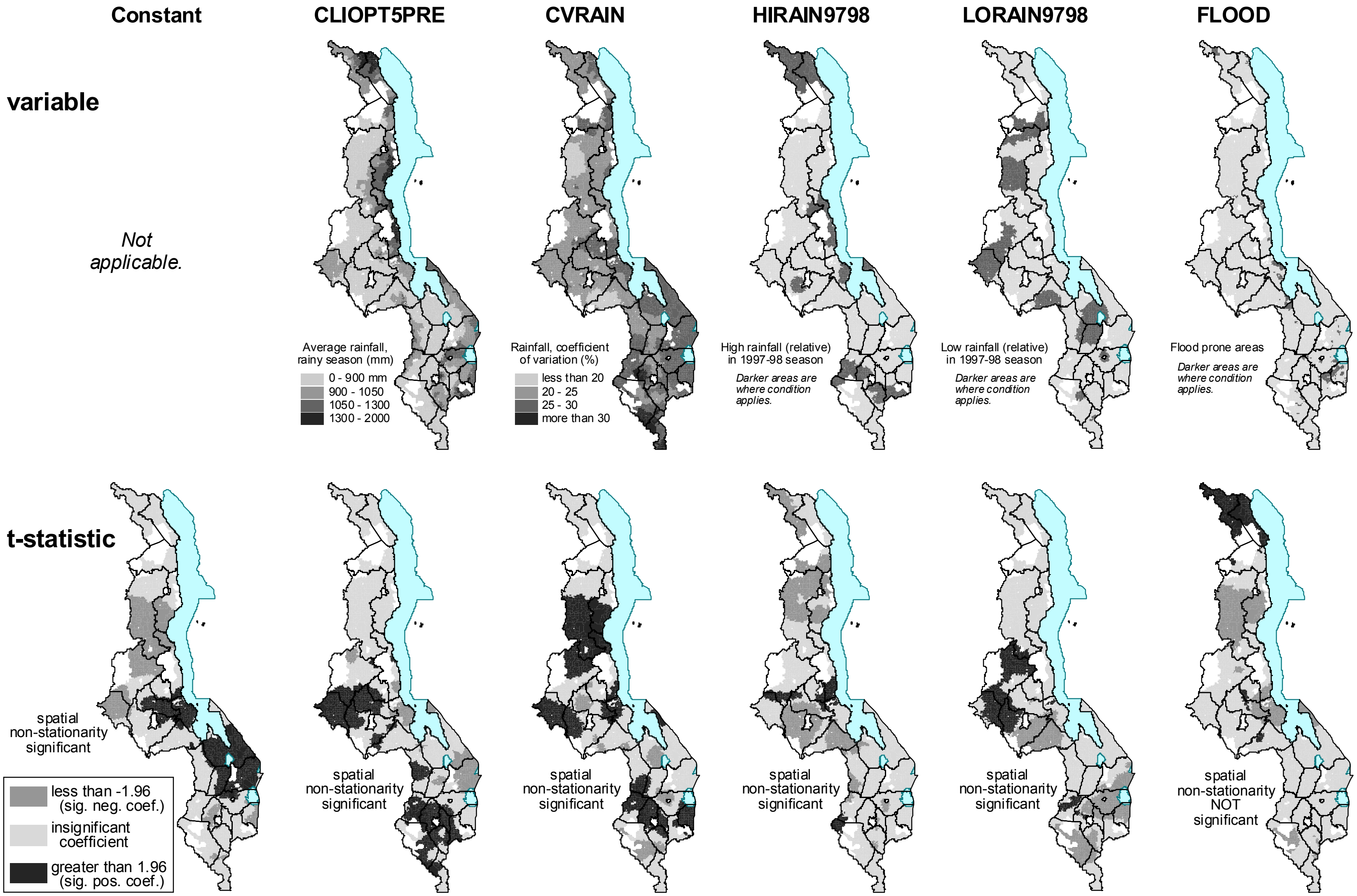


Figure 4b—Maps of independent variables and t-statistics for each from geographically weighted regression analysis of the determinants of poverty prevalence for rural aggregated enumeration areas in Malawi (continued)

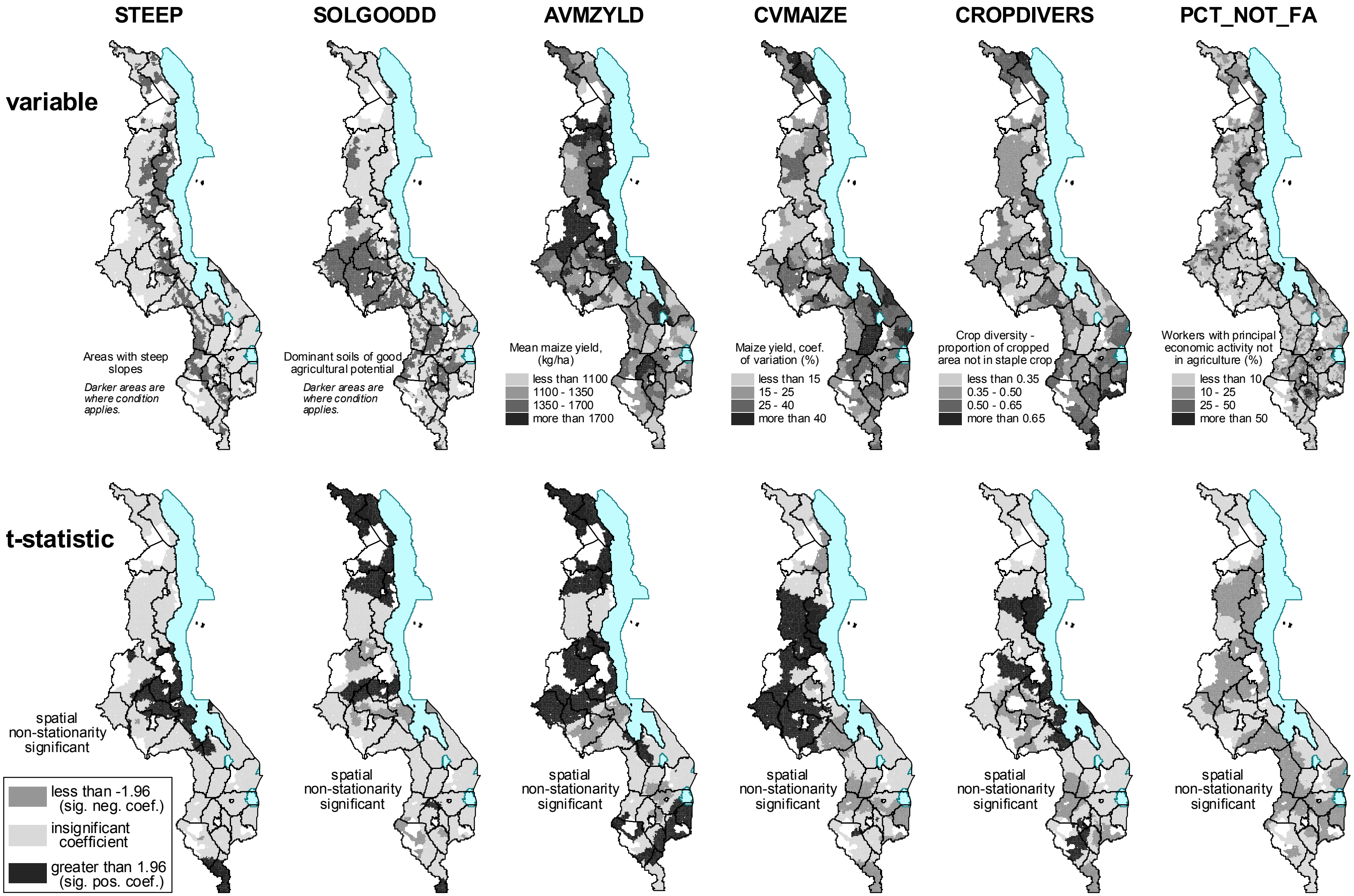


Figure 4c—Maps of independent variables and t-statistics for each from geographically weighted regression analysis of the determinants of poverty prevalence for rural aggregated enumeration areas in Malawi (continued)

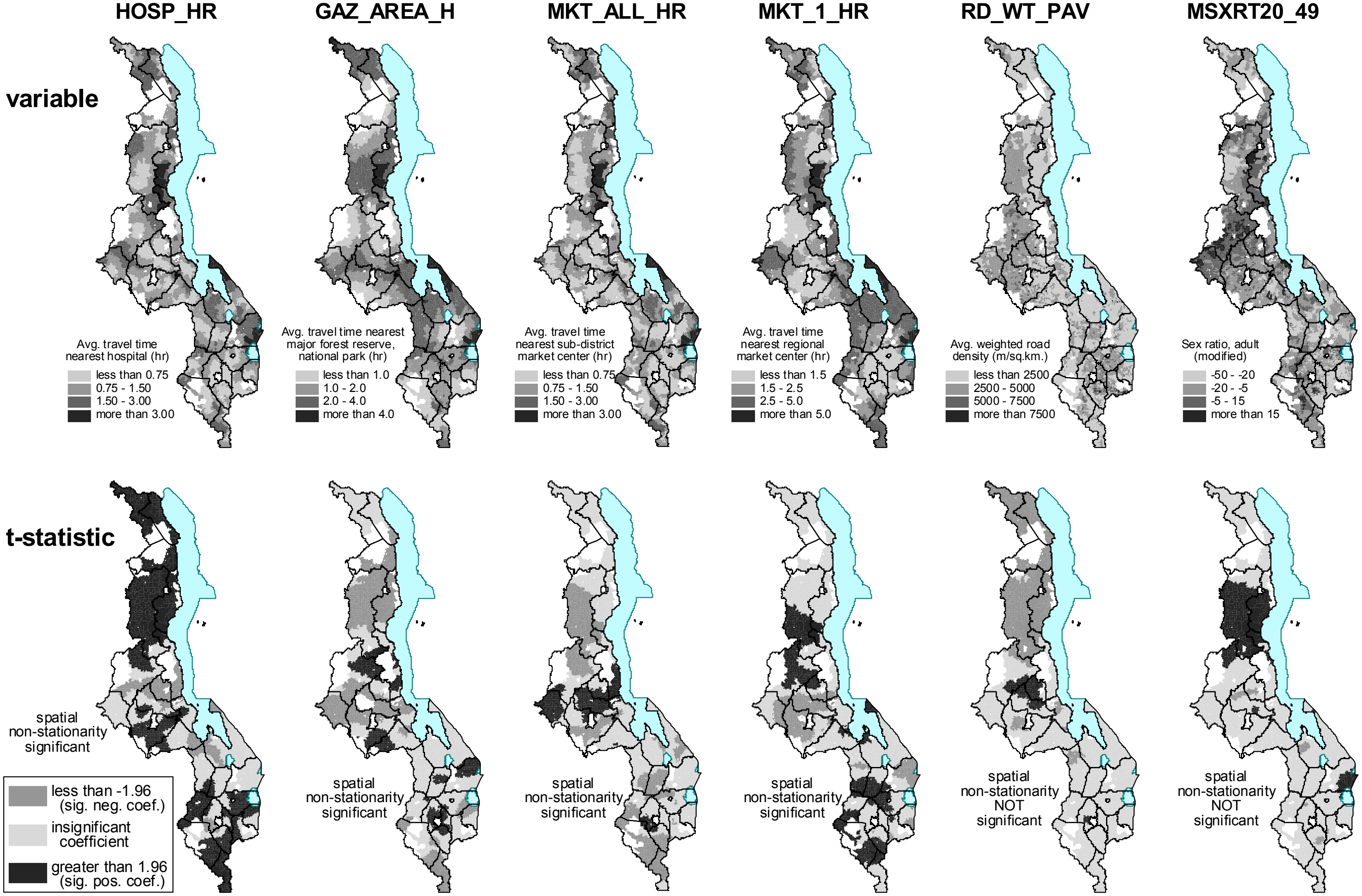


Figure 4d—Maps of independent variables and t-statistics for each from geographically weighted regression analysis of the determinants of poverty prevalence for rural aggregated enumeration areas in Malawi (continued)

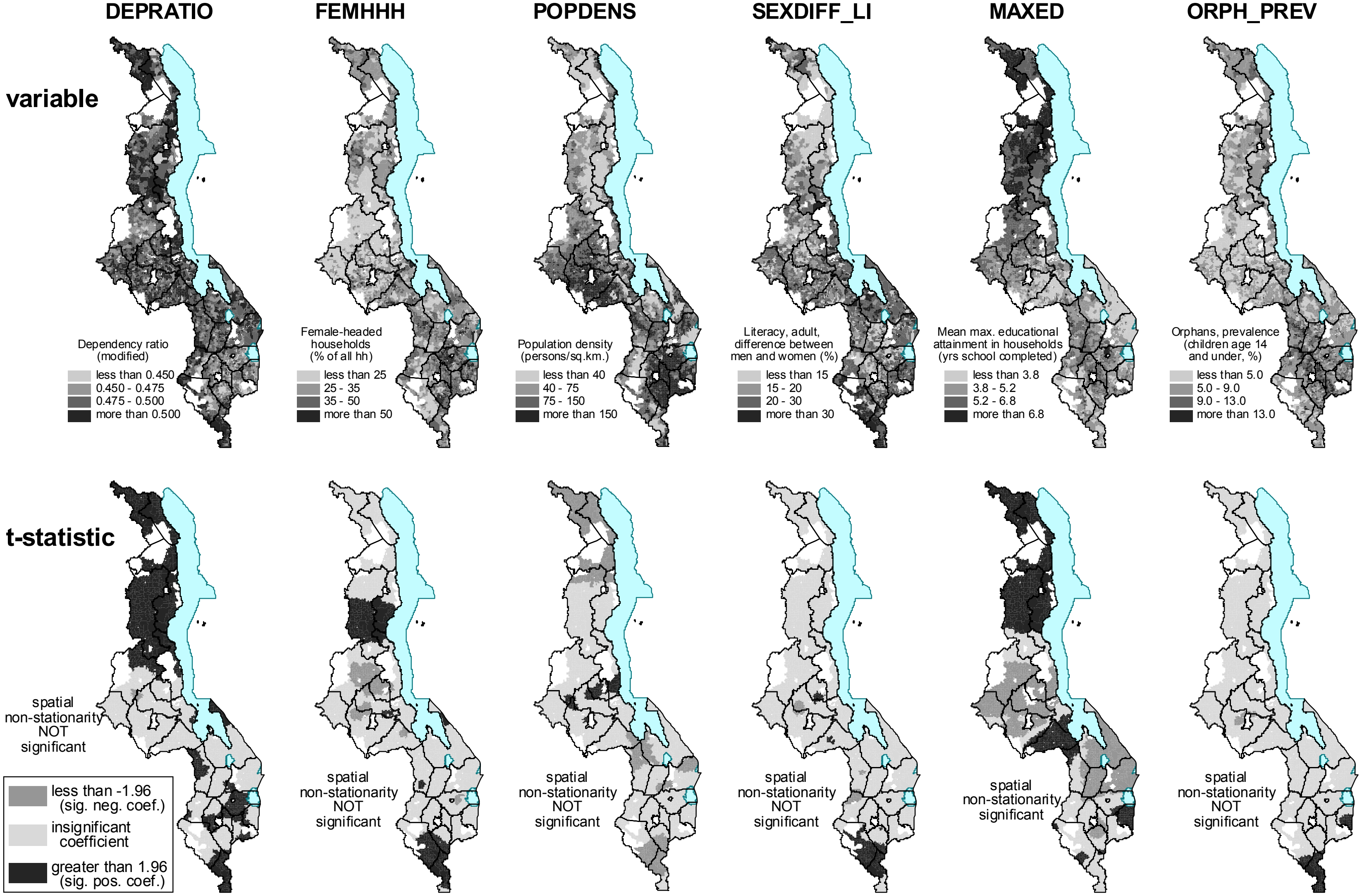
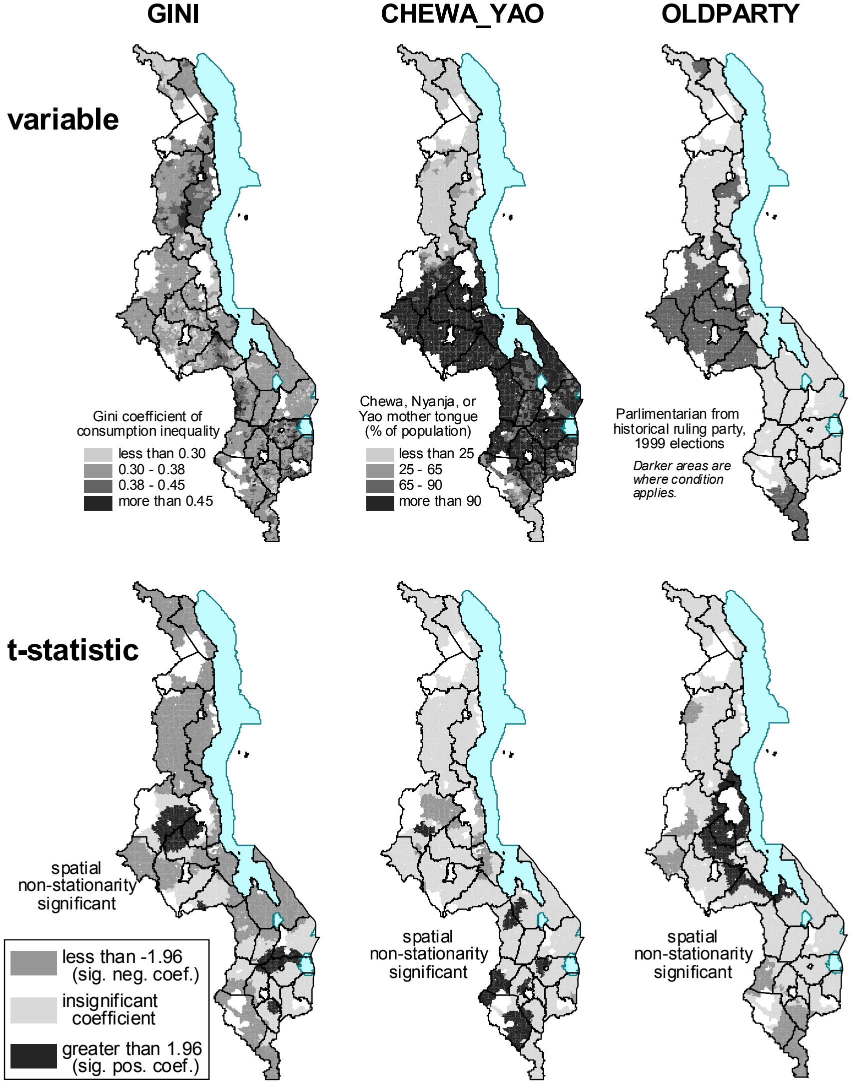


Figure 4e—Maps of independent variables and t-statistics for each from geographically weighted regression analysis of the determinants of poverty prevalence for rural aggregated enumeration areas in Malawi (continued)



each independent variable are not provided. Although results are mapped for all independent variables, in the interest of space, the results for only five of the independent variables are discussed here. These variables—average maize yield, percent of workers not in farming, travel time to hospital (and other district center services), mean maximum educational attainment level in households in the aggregated EA, and the Gini coefficient of consumption inequality—are chosen either because they were shown to be important determinants in the global spatial error model, or, as in the case of the insignificant hospital access variable, they represent a common approach to poverty reduction, such as improving access to services.

The GWR model intercept term shows how the local prevalence of poverty will differ from the overall mean when all of the independent variables are held constant. Just as the local R^2 map might point to missing variables, so too does the map of the intercept. Somewhat lower levels of poverty than can be explained by the determinants in our model are found in a band running along the upland plateau area from Mchinji District through central Mzimba and down to the lakeshore. The upland plateau area is notable for being quite productive agriculturally, with tobacco being an important component of the rural economy, grown by smallholders and commercial estates alike. Although tobacco is not directly included in our determinants, the general level of agricultural productivity in the area is. Areas of higher than expected poverty are found in the southern lakeshore, Salima District, and in the hills of Dowa District. The southern lakeshore area corresponds with those areas that are noteworthy for low general levels of educational attainment (see the top MAXED map in Figure 4d). However, this factor is included in our model, so the spatial pattern of the constant term raises as many questions as it answers.

We turn now to the five determinants selected for further discussion. As should be expected, the four that were significant in the global model have significant coefficients over much of the country. However, examining each in turn shows that the results of the global model mask considerable heterogeneity in the nature of the relationship between the determinant and the estimated poverty prevalence in small rural populations.

- Higher average maize yields, AVMZYLD, (see the map in Figure 4b) tend, nonintuitively, to result in higher poverty levels. This pattern was seen in the global model. Exceptions to this pattern are found near Lilongwe, Zomba, and Blantyre urban centers, where urban food market demand probably enhances the value of the crops produced and, hence, the welfare benefit farmers derive from higher productivity.
- The variable on nonagricultural economic activities, PCT_NOT_FA, (see the map in Figure 4b) shows a relatively consistent pattern nationally of lower prevalence of poverty with higher levels of nonagricultural activity; in very few areas does greater participation by the local population in nonagricultural economic pursuits result in a higher prevalence of poverty.
- The access to hospital and other district services variable, HOSP_HR, (Figure 4c) highlights the poverty effects of poor access in northern Malawi, in particular, as well as in Lilongwe District and in some areas of the Southern Region. In comparison to the other access variables analyzed, this variable is significant over most of rural Malawi, suggesting that access to district level services is the most critical form of access to services necessary to enhance aggregate welfare in communities across rural Malawi. However, this pattern of association of inaccessibility to district-level services with higher poverty is not uniform. There are areas, such as Ntchisi District, where improved access is associated with higher poverty prevalence. Accounting for these anomalies would require additional research.
- Education is frequently advocated as a cure for poverty. Consequently, it is not surprising to find that the MAXED variable (Figure 4d) was significant with a negative sign in the global spatial error model. However, here in the local analysis, considerable variation is seen in the nature of the relationship. In the north of the country, in particular, the association between education and poverty is strong and positive. This implies that the relatively well-educated population here is unable to derive any significant welfare benefit from the knowledge they have gained, and

education is not sufficient in itself to reduce poverty. Dedza, northern Ntcheu, and Phalombe districts also have significant positive coefficients for the MAXED variable. However, in contrast to the northern districts, the general educational level in these areas is considerably lower. This suggests that the population there may be responding to disincentives to education, but what these might be is unclear from this analysis. In broad areas elsewhere, however, higher general levels of education are shown to be an important factor in reducing the local incidence of poverty.

- Finally, concerning consumption inequality, the GINI maps in Figure 4e show a broad global pattern of a negative association with poverty levels over most of the country. However, there are exceptions to this pattern, most notably in the mid-altitude areas of Kasungu, Ntchisi, and Dowa Districts, where tobacco estates are common. The findings may reflect a sharp polarization in the distribution of consumption between a small group of wealthy estate owners and a large population of considerably poorer estate workers and tenants. However, similar estates are found in neighboring Lilongwe, Mchinji, and South Mzimba Districts, where the dominant association is negative. The use as dependent variables of the depth (p1) and severity (p2) poverty measures, which, in contrast to the poverty headcount (p0) measure used here, incorporate information on the distribution of consumption within a population, likely would provide a better understanding of the varying nature of the relationship between consumption inequality and general welfare levels across rural Malawi.

The results of the spatial nonstationarity assessment for all of the independent variables in our GWR model are presented in Table 7. Of the 26 independent variables, 18 are shown to have a statistically significant probability of being spatially nonstationary. It is primarily the demographic variables that are shown to be spatially stationary. This is an interesting result, given our earlier assertion that social processes, in contrast to physical processes, can be expected to be spatially nonstationary. However, it should be noted that, except for the dependency ratio variable, the strength of the relationship of these spatially stationary variables in the global spatial error model is estimated to be quite weak. These results provide strong support for the use of local models of the determinants of poverty prevalence in designing poverty reduction policies and programs in rural Malawi.

Table 7—Test for spatial nonstationarity in the coefficients of the determinants of poverty prevalence in rural Malawi, based on Monte Carlo simulation of the geographically weighted regression analysis

Variable	p-value	significance	Variable	p-value	Significance	Variable	p-value	Significance
Constant	0.00	**	CVMAIZE	0.00	**	DEPRATIO	0.46	ns
CLIOPT5PRE	0.00	**	CROPDIVERS	0.00	**	FEMHHH	0.09	ns
CVRAIN	0.00	**	PCT_NOT_FA	0.00	**	POPDENS	0.06	ns
HIRAIN9798	0.00	**	HOSP_HR	0.00	**	SEXDIFF_LI	0.89	ns
LORAIN9798	0.00	**	GAZ_AREA_H	0.00	**	MAXED	0.00	**
FLOOD	0.09	ns	MKT_ALL_HR	0.00	**	ORPH_PREV	0.75	ns
STEEP	0.00	**	MKT_1_HR	0.00	**	GINI	0.00	**
SOLGOODD	0.00	**	RD_WT_PAV	0.20	ns	CHEWA_YAO	0.00	**
AVMZYLD	0.00	**	MSXRT20_49	0.81	ns	OLDPARTY	0.00	**

Notes: 100 simulations run. ** = significant at $p \leq 0.01$ level; * = significant at $p \leq 0.05$ level; ns = not significant.

Whether the relationship of the determinant to the local prevalence of poverty is spatially stationary or not in Table 7 strongly influences the guidelines for action that can be drawn from the GWR analysis. If it is stationary, as is the case for most of the demographic variables and, most notably, for the road density variable (RD_WT_PAV), then a single approach to modifying local conditions for these variables can be adopted nationally. For the other spatially nonstationary determinants, geographically targeted approaches to change local conditions so that they are more conducive to reducing the general level of poverty will need to be used. Which approach is used in a particular locale will depend upon the relationship between the determinant(s) addressed by a particular action or set of actions and poverty prevalence, which will vary from one locale to another. For example, as shown in the t-statistic map for MAXED in Figure 4d, efforts to improve general levels of educational attainment will be of greater value in reducing poverty in the southern lakeshore area and in the northern districts of the Central Region than in places where the model shows a perverse and puzzling positive association between educational attainment and the prevalence of poverty. Similar guidance could be drawn from the maps of many of the other independent variables.

Clearly, the results of the GWR analysis of the local determinants of the prevalence of poverty could be extended into any of a range of analyses. Here we have attempted to draw some initial, readily apparent conclusions. As noted, many of these conclusions should be subjected to further examination and analysis to determine whether they hold.

5. Conclusions

In this research, we examined the spatial determinants of the prevalence of poverty for small, spatially defined populations in rural Malawi. A theoretical approach based on the risk chain conceptualization of individual and household economic vulnerability guided our selection of an extensive set of potential risk and coping strategies that could be represented spatially. These were used in analyses to develop both global and local models of the prevalence of poverty.

The methods provide somewhat different results.

- The spatial error model that controls for the spatial autocorrelation present in an OLS model produced global results that one might use with confidence. The set of determinants shown to be significant is relatively restricted. For several of these, the nature of their relationship to the prevalence of poverty was in line with expectations. However, a few other determinants for which we did not have any strong theoretically based expectations were shown to be significant. Finding out why these determinants are significant in the model remains a challenge. Finally, the variable for average maize yields is significant, but the nature of its relationship to the dependent variable is counter to expectations.
- The GWR analysis produced an almost overwhelming amount of information on local relationships between the determinants and the local poverty headcount. From a

spatial perspective, these results are the most intriguing, providing strong evidence of a spatially varying model of the determinants of poverty prevalence in rural Malawi. By examining the model of the prevalence of poverty for a specific locale, these results could be used to guide actions to reduce poverty at a very local level. Certainly, we found our efforts to draw national generalizations from the spatial patterns of the GWR model parameters challenging.

From the standpoint of guiding broad action to reduce poverty, overall, explanatory power of the analyses proved to be quite low. In the global spatial error model, most of the more than two dozen determinants of the prevalence of poverty that we selected for analysis were not significant. In contrast, most of these determinants were significant in at least some rural areas within the GWR local model. This implies that poverty reduction efforts in rural Malawi should be targeted at the district and subdistrict levels. A national, relatively inflexible approach to poverty reduction is unlikely to enjoy broad success.

Assessing the strength of the spatial association between potential agroecological determinants of poverty in Malawi and the poverty prevalence observed was an important objective of this research. Perhaps more so than with the other determinants considered in our analysis, the agroecological variables provide an unclear picture. We found that locations where nonagricultural livelihood strategies can be widely pursued have fewer poor; this was the strongest relationship observed. We also found that areas where maize yields are higher consistently have higher rates of poverty prevalence. The half dozen or more other agroecological variables examined generally proved to have very weak relationships to the prevalence of poverty.

Very little evidence emerged from the analysis to permit one to convincingly argue that the poor in Malawi are trapped in areas of low agricultural productivity, subject to frequent drought and farming on poor soil. The poor are throughout Malawi, on the best land and the worst land, in areas of relatively high productivity and those of low productivity. Extending this idea, we know that poverty and food insecurity in rural

Malawi are closely linked. The fact that agriculture is shown to be positively associated with poverty also implies that agriculture, if not a source of food insecurity, is not serving as an effective means of reducing food insecurity. Subsistence farming dominates the rural economy of Malawi, but the evidence here is that such farming is not providing a reliable and sufficient livelihood for most. Moreover, this dismal relationship is not found in isolated pockets but is the dominant pattern observed.

Considering other components of the rural economy, we also examined the role of market access or, more broadly, access to services and infrastructure as a spatial determinant of the prevalence of poverty. The results were less clear than we expected, but some insights were gained. The most important determinant in this regard is the variable specified as the travel time to the nearest hospital, which we interpreted as a proxy for access to district-level services. This was generally the strongest of the various access measures assessed. Access to more local services such as at subdistrict markets, or to regional services located at the larger marketplaces and urban centers, was less important as determinants of poverty levels. Enhancing access to district-level services is one policy prescription that emerges from this analysis.

We found support for human capital development, particularly through education, in this analysis. However, the local model shows that the relationship between education and reduced poverty is more complex than we might think. In broad areas of northern Malawi, higher education is associated with reduced aggregate welfare levels and higher poverty. The welfare returns to increased education are not linear in all circumstances. Our findings here point to the need to determine just what circumstances are necessary for increased educational attainment in an area to always result in higher general welfare.

In making use of the results here, we once again must urge caution concerning the ecological fallacy of drawing inferences about smaller analytical units from the aggregate characteristics of groups of those units. Our analysis here deals with aggregates of individuals and households—the populations resident in rural aggregated EAs. The inferences that we can make will be most reliable at the same aggregate level. The aggregate may mask heterogeneity in characteristics of individuals and households that would render any action undertaken on the basis of the analysis here irrelevant or even harmful for the individuals and households targeted. Our analysis is most useful in guiding broad community action and other action at the subdistrict level.

Finally, to be meaningful for this analysis, the independent variables selected must not only be potential determinants of poverty, but also must be mappable and have sufficient variation across rural Malawi. To some degree, the lack of variability in poverty levels across rural Malawi hinders our ability to gain insights into what might determine those levels. The poor are dominant within the population in most rural areas, regardless of how those areas may differ in terms of the determinants of interest.

In considering how to expand this analysis, two aspects should be addressed. First, in this research, we focus narrowly on the prevalence of poverty, to the exclusion of what are arguably somewhat more interesting measures: the depth and severity of poverty. The poverty headcount measure is one-dimensional, simply measuring the number of people living below the poverty line but providing no understanding of whether the welfare status of the poor in an area is desperate or, alternatively, is just below the poverty line. One should expect that the nature of the relationships seen here, where the poverty headcount is the dependent variable, would change as one considers other poverty measures.

Second, we only consider the rural aggregated EA to assess the spatial determinants of poverty prevalence. The primary advantage of the aggregated EA geography is that it allows the computation of poverty measures for spatially defined populations that are about as small as the poverty mapping methodology will allow, possibly even too small. However, the creation of this geography is not without cost. More important, this geography is only used for analytical purposes and not as a spatial unit for the planning of poverty reduction policies and programs. Consequently, an assessment should be made of whether the aggregated EA geography provides any qualitatively different understanding of the spatial determinants of poverty prevalence than could be acquired using a more commonly recognized geography such as the traditional authorities/urban wards or the districts of Malawi. If the geography we use here offers no advantages, it likely has little additional worth. The other geographies are standard, and any analytical results based on them could be applied immediately.

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