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Mixed Autoregressive Model for Spatial Data: A Bayesian Application to Poverty Mapping

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Abstract: Poverty can be defined as the lack of income considered necessary to purchase goods and services in order to maintain a marginal living standard. Its eradication is a global problem especially in developing countries. The objective of this study was to determine the socio economic and environmental indicators as well as to produce a predictive map of poverty in Ghana using the Ghana Living Standard Survey (GLSS7) data. To achieve these objectives, a Spatial Mixed Autoregressive (MAR) model was used. Global and Local Moran's I statistics were computed to test for spatial dependence in the data. Prediction of the risk of poverty was made via a Bayesian ordinary Kriging technique. Results of the study indicated that household size, total annual household expenditure, marital status (divorce), location (rural), educational level of household heads (JHS), deplorable roads and ecological Zone (Savanna) were statistically significant. Moreover, the predictive map showed a high positive spatial dependence of poverty across Upper East, Upper West and Northern Regions, with the extremely poor dominating in these areas. The varied characteristics of households that determine poverty levels should be incorporated into policy decisions to ensure that the country's rural and urban areas develop at the same pace.

Keywords: Spatial Mixed Autoregressive Model, Poverty Mapping, Spatial Dependence, Spatial Error Model, Spatial Lag Model, Global and Local Moran's I

1. Introduction

Poverty can be defined in terms of the lack of income considered necessary to purchase goods and services in order to maintain a marginal living standard [1]. That is, an individual's well-being may be linked with the ability to fulfill basic physical and survival needs (typically food) and their ability to choose among other packages of commodities, as evidenced by their income [1, 2]. It can be described from a variety of viewpoints, including, environmental, socioeconomic, geopolitical, and historical.

Ghana has a total land area of 238,535 square kilometers, comprising a wide range of socio-economic regions from coastal savannas to tropical rain forests [3].

According to [4], 37.9% of rural households experienced poverty between 2012 and 2013, while only 10.6% of urban households experienced same. While about 94% of rural poor households work in agriculture, urban households have more opportunities for employment, especially in the informal sector [1].

The seventh edition of the Ghana Living Standards Survey (GLSS7) provides the most recent report of Ghanaian household's poverty patterns. This survey was undertaken in 2016/2017, and covered a nationally representative sample of households interviewed over a twelve-month period. The survey focused on Ghana's income and inequality among households. It also considered the financial assets, availability of services, and human development. These are all linked to the poverty status of households.

According to the GLSS study done in 2005/06, 2012/13, the level of poverty has decreased. In the seven years between 2005/06 and 2012/13, the number of poor people fell by 7.7%. Between 1991/92 and 2005/06, more progress was made in poverty alleviation, with poverty falling by 23.2% points as well as the frequency of extreme poverty halving, from 37 percent in 1991/92 to 18% in 2005/06 (GSS, 2007). However, the inability to meet significant drops in the poverty gap since 2012/13 shows that the first Sustainable Development Goal (SDG) of eradicating poverty by 2030 may not be achieved without a shift in policy direction (GLSS7).

Most researchers frequently ignore the geographical and environmental factors that might have a significant impact on poverty. In ecologically sensitive areas where communities deal with and contribute to various forms of environmental deterioration, poverty is a topic that is frequently emphasized. The majority of these less fortunate households lack social amenities such as access to road and also access to public facilities for instance health care, water as well as education. In investigating such geographical features of poverty and their links to environmental issues, methods that use spatial analysis techniques are required [5].

Poverty mapping is a method of displaying and evaluating indicators of human well-being in a spatial context. Poverty has become a significant tool in analyzing and debating socio-economic issues to be able to find solutions. It has therefore become necessary to identify those variables that lead to poverty, and would ensure that higher policy formulation is based entirely on evidence, with a focus on improving aid, especially humanitarian relief. Based on this, the developing communities must be identified and their distinctive locations must be determined.

The relationship between the dependent variable and the independent variables can be described using a standard linear regression model. However, if the data has a spatial effect, a spatial regression model should be used. This is due to the fact that the independent variables that influence the dependent variable might vary with location [6].

The spatial autoregressive (SAR) model adopted in this study, is a spatial method for describing the correlation between dependent and independent variables by taking spatial impact into account. [7] Introduced a spatial autoregressive (SAR) model that includes the spatial lag and spatial error effects on explanatory variables. This model was established to cater for dependence not only within the dependent variable but also in the independent variables.

This study used a Mixed Autoregressive Model to disaggregate poverty into two components namely spatial lag and spatial error models to determine the factors that influence poverty in Ghana and establish the most likely place with the highest level of poverty. This approach, we believe, will throw more light to identify and solve the problem of poverty in a more holistic manner. The use of poverty maps would help to determine the spatial pattern of poverty within the country. These maps have a wide range of effects on decisions; from poverty alleviation programs to humanitarian aid.

2. Data Source and Covariates

In this study, secondary data from the Ghana Living Standard Survey (GLSS 7) was used. The Ghana Statistical Service (GSS) performed the Ghana Living Standards Survey Round Seven (GLSS 7) from October 22nd to October 17th, 2016. It is a household-based research that focuses on economic growth and improving socio-economic features and household well-being.

The survey was national with a sample size of 14,009 households drawn from 1,000 enumeration areas (EAs). A household listing technique was carried out in all of the selected EAs after the EAs were chosen before the main survey. Using Computer Assisted Personal Interviewing (CAPI), the household listing procedure entailed visiting each one of the 1,000 selected EAs and recording all facilities and homes inside the EAs, as well as the locations and names of the heads of the households. The indicated households were used as the sampling frame for the systematic sampling approach in the 2nd phase selection of households for the survey.

Dependent and independent variables were included in the study as shown in Table 1.

Table 1. *Contents of GLSS 7 data.*

Variables	Description
HHS	Household size
GEN	Gender
AGE	Age
MAS	Marital status
LOC	Location
ECA	Economic activities
MAO	Main occupation
TEE	Total expenditure on education
TAH	Total annual household expenditure
TEHN	Total expenditure on housing
THE	Total expenditure on health
ELH	Educational level of household heads
DPR	Deplorable roads
ECZ	Ecological zone

3. The Spatial Mixed Autoregressive (MAR) Model

Ordinarily, the relationship that exists between dependent variable y and k independent variables $(X_1, \dots, X_k)$ is specified by a standard linear regression model. The general linear regression model describes a structural association between y_i (the response variable measured at location i) and $X_{1i}, \dots, X_{ki}$ (the independent variables measured at location i). That is,

$$y_i = \beta o + \beta_1 X_{1i} \dots + \beta_k X_{ki} + \varepsilon_i \quad (1)$$

where $\beta_0, \dots, \beta_k$ are the coefficients of the regression model and ε represents the error component.

In this classical regression formulation, the mean of the error component is zero, that is $E(\varepsilon_i) = 0$, for all i and they are distributed independently. This formulation assumes that the model is homoscedastic as well as serially uncorrelated. In matrix notation (1) can be written as

$$y = X\beta + \varepsilon \tag{2}$$

X is a matrix of observations on the k independent variables with dimensions $(n \times (k+1))$, y and $\boldsymbol{\varepsilon}$ are $n \times 1$ vectors and β is a $(k \times 1)$ vector. The error component has mean zero, that is $E(\varepsilon_i) = 0$ and $E(\varepsilon\varepsilon^T) = I$ (where I is the identity matrix).

When dealing with geo-located observations, spatial dependence might occur because of Tobler's First Law of Geography: if the interrelation between entities increases with proximity in the real world, then representation in geographic space and assessment using spatial analyses techniques are appropriate [8, 9].

As a result, the estimating method that explicitly addresses spatial dependence by including spatially lagged dependent and independent variables cannot be overemphasized.

The spatial regression model, which allows us to show that there are regional implications among Ghanaian settlements is important since the percentage of residents who are unable to acquire two meals each day depends on both the averaged values of the response and explanatory factors in neighbouring areas as well as the value of its own explanatory variables. The baseline for poverty in this study is the proportion of families in each settlement that cannot obtain two meals each day.

When the state of a system consists of n locations, then

$$y_i = (y_1, \dots, y_n), \tag{3}$$

where y_i denotes the value of characteristic y at specific location i.

When change of state in the system is caused by spatial features of the characteristic in a spatial process, equation (3) becomes

$$y_i = f\left(\{y_j\}_{j\varepsilon N(i)}\right) \tag{4}$$

where N(i) refers to the regions surrounding i. Spatial dependence can span a wide range of lags and take on a variety of functional forms (f) [9].

The formulation includes a function of the dependent variable observed at other places to give

$$y_i = g(y_{Ji}, \theta) + X_i^T\beta + \varepsilon_i, \tag{5}$$

where J_i comprises all of the nearby locations j of i, with $j \neq i$ (Neighbor relationships are symmetrical). The variable g is usually made simpler by using a spatially weighted matrix. The neighboring location set for every household is defined in the spatially weighted matrix, W, which is n x n positive structure. In the spatial weights matrix, the relations between households (row) i as well as column j indicates elements of non-zero matrix (W_{ij}). The elements of the diagonal of the spatial weight matrix w_{ii}= 0 since self-neighbors are not included.

The row-standardized representation of the weights matrix is often used, with weights ${W_{ij}}^s = \frac{w_{ij}}{\sum_j w_{ij}}$ to make it easier to interpret the weights as creating an average of nearby locations in the spatial lag operator, $\sum_j W_{ij}Z_j$ [10].

Spatial lag and spatial error dependence are two key ways in which spatial dependence can be introduced into equation (5).

A mixed autoregressive (MAR) model, which incorporates both the spatial error model and spatial lag, is a specialized case of a spatial autoregressive (SAR) model [11]. It takes the form

$$y_i = \rho \sum_i^M W_{ij}\, y_i + {X_i}^T\beta + \varepsilon_i \tag{6}$$

where ρ is the coefficient of the spatial autoregressive model and ε_i as the error term which are distributed identically and independently. Equation (6) can be expressed in matrix form as

$$y = \rho W y + X\beta + \varepsilon \tag{7}$$

where W is a row standardized spatial weights matrix referred to as spatial lag.

To deal with the possible effect of endogeneity, we rewrite equations for all observations in a reduced form as

$$y = (I - \rho W_1)^{-1} X\beta + (I - \rho W_1)^{-1}\varepsilon \tag{8}$$

Equation (8) denotes a model with a spatially linked error pattern that is nonlinear in both ρ and β. Given equation (7) and the error term defined as $\varepsilon = \rho W\varepsilon + u$, the spatial error model is given as

$$y = X\beta + (I_n - \rho W_1)^{-1} u \tag{9}$$

The model described in equation (9) can be expanded to a mixed autoregressive model (MAR) which was constructed by WX and enables for explanatory variables from nearby observations. The mixed autoregressive model takes into account spatial autocorrelation in both the error and response variables. It makes use of the fact that a spatial error model could also be represented in spatial lag form. So

$$(I_n - \rho W_1) y = X\beta + WX_\gamma + \varepsilon \tag{10}$$

simplifies to

$$y = (I - \rho W_1)^{-1} X\beta + (I - \rho W_1)^{-1} WX_\gamma + (I - \rho W_1)^{-1}\varepsilon \tag{11}$$

when the value of y is provided, the minimal effect of independent variables from nearby households on the dependent indicator y is measured by the k x 1 parameter vector. When you multiply X by W, you get "spatially lagged" of the independent indicators, which are averages of surrounding data [12]. In this study, W is built in such a way that the five closest neighbors can influence each other.

Similar values tend to be close together when the spatial autocorrelation is positive, while the opposite is true when the value is negative within a particular distance. This measures the spatial dependency (similarity and dissimilarity) of surrounding households. The relevance of the similarity or dissimilarity of surrounding communities for the entire nation is indicated by Global Moran's I. Neighbors with similar and dissimilar locations is determined by the Local

Moran’s I as well as the stability of a settlement's similarity to its neighbors [13]. Both Global and Local Moran's I were computed using GeoDa, a spatial data analysis software, and the R programming language was used general data analysis. The Global Moran's I is used to measure the global spatial autocorrelation and local Moran’s I to measure the spatial autocorrelation of a specific location.

4. Bayesian Estimation, Prediction and Mapping

The Ordinary Least Squares (OLS), Maximum Likelihood Estimation (MLE) and other similar methods in spatial regression have drawbacks. Inefficient estimates and incorrect statistical inference result due to the presence of spatial dependence in the data.

So Bayesian parameter estimation was employed. Ordinary kriging was used to predict and map poverty at unsampled locations across the country. Ordinary kriging enables the estimation of values of a certain geo-referenced environmental feature at several unsampled locations using sampled point data and based on Tobler’s first law of geography [14].

5. Results and Discussion

5.1. Distribution of the Dependent Variable

The histogram (Figure 1) displays the distribution of poverty status of the various regions in Ghana. The graph indicates a positively skewed distribution of the poverty index. The mixed autoregressive model is robust in terms of using asymmetric data, with this; the analysis was conducted without data transformation.

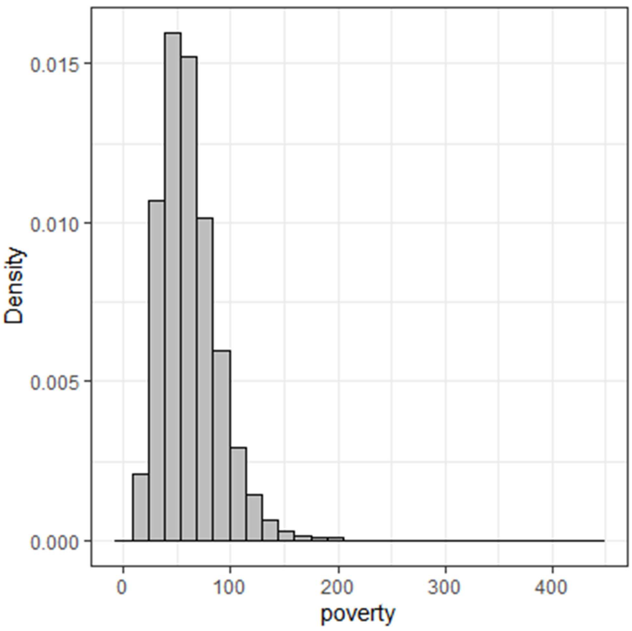

Figure 1. *Distribution of the dependent variable.*

5.2. The LISA Box Plot

Figure 2 is the local Moran’s I box plot for the response variable, which indicates that the data has some outliers which are observed to be beyond the upper quartile.

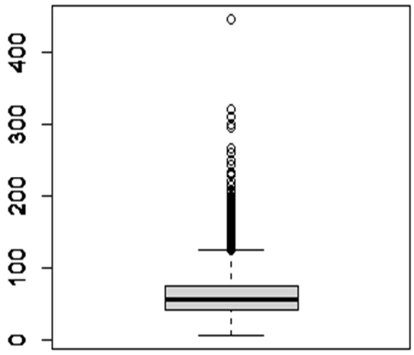

Figure 2. *Local Moran’s I box plot.*

5.3. The LISA Scatter Plot

Figure 3 illustrates a LISA scatter diagram with a positive spatial autocorrelation. The value 0.4065 is the Moran's I statistic which indicates that there is similarities among household settlements. Households in the first quadrant have a high poverty risk with their surroundings. Households in the second quadrant have a low poverty risk with their surroundings, Households in the third quadrant have a low poverty risk with their surroundings and Households in the fourth quadrant have a low risk of poverty with their surroundings.

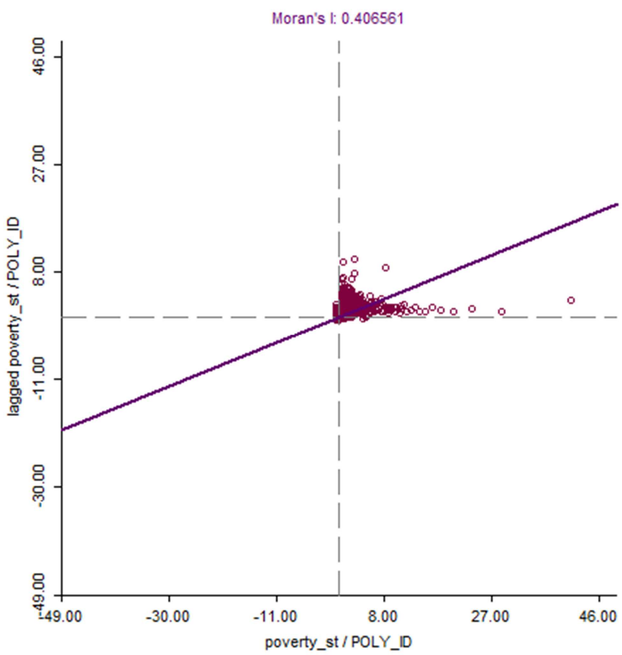

Figure 3. *LISA Scatter Plot.*

5.4. Spatial Autocorrelation Analysis of Households

Table 2 displays residuals of the spatial autocorrelation by the use of the Moran's I test for the various regions with their corresponding sampled household size. Bono Ahafo Region, Central Region, Greater Accra Region, Northern Region, Western Region and Volta Region representing a total sample households of 1317, 1317, 1392, 1403, 1331 and 1367 respectively indicating a positive spatial dependence with neighbouring regions whilst Ashanti region, Eastern region. This might be due to the proximity of household settlements to each other in the respective regions. Upper West region and Upper East region with a total household sample of 1734, 1394, 1361 and 1331 respectively indicating a minimal spatial dependence among neighbouring regions.

Table 2. *Moran's Statistic for the various regions of Ghana.*

Region	Total sample households	Statistic
Ashanti region	1734	-0.00278
Bono Ahafo region	1317	0.00110
Central region	1317	0.0125
Eastern Region	1394	-0.00673
Greater Accra region	1392	5.785
Northern region	1403	0.02263
Upper West region	1361	-0.0306
Upper East region	1393	-0.01174
Western Region	1331	0.01767
Volta Region	1367	0.0107

Source: (GLSS7, Survey)

Global Moran's I was used to quantify the spatial dependence with the neighborhoods. The Moran's I statistic was 0.1412250 indicating positive spatial dependence among neighboring regions.

The variogram (Figure 4) has a spatially upward trend showing lag-dependence in poverty. As a result, the covariance parameters are likely to display a high variation among neighbouring households.

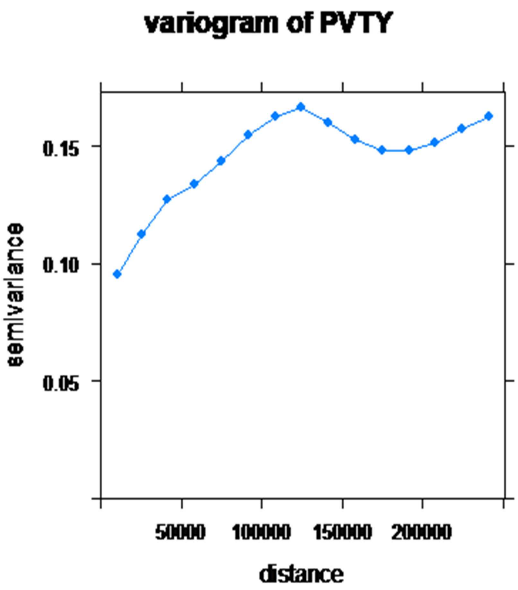

Figure 4. *The Variogram Plot.*

The lag component of the model was used to analyze the data. Results of Table 3 shows that the spatial lag parameter rho (0.0343) is significant. This means that, there is a positive likelihood of nearby household settlements to be affected by poverty. From the table, household size, total annual household expenditure, marital status (divorce) and the location (rural) are the possible factors that cause poverty, household size being the largest.

Table 3. *Spatial Lag Model.*

	Estimate	Std. Error	Z value	Pr(>|z|)
Intercept	3.2901e-01	3.9050e-02	8.4254	2.2e-16
HHS	5.2641e.02	1.4708e-03	35.7913	2.2e-16
TAH	-1.2572e-05	3.7968e-07	-33.1111	2.2e-16
Factor(MAS)2	-6.8933e-02	2.8549e-02	-2.4146	0.01575
Factor(LOC)2	-1.8596e-01	1.1896e-02	-15.6316	2.2e-16
Rho= 0.034385 LR TEST VALUE= 3.9537 p-value=0.046769				
Asymptotic standard error=0.017265				
z-value=1.9916				
p-value =0.046416				
Log likelihood =-2472.837 for Lag model				
ML residual variance (σ^2, σ) = 0.11601,0.3406 Number of observation =14009 Number of parameter estimated=33				
Lm test for autocorrelation: 5.328 p-value: 0.020986				

Table 4 gives results for the direct (or local) effect, indirect (or spillover) effect and total effect (or sum of the direct and indirect effects) for the Lag model. From the table Household size predicts a positive risk of poverty on neighbouring settlements and also has a positive effect among the neighbouring households. Total annual household expenditure and location (rural) predicts a low poverty on neighbouring settlements and also has low impact among the neighbouring households. Also, the marital status (divorce) predicts low poverty on neighbours but has a positive impact among the neighbouring households.

Table 4. *The Spatial Lag Effect.*

	Direct	Indirect	Total
HHS	5.2641e-02	1.864033.e-03	5.451521e-02
TAH	-1.2572e-05	-4.451652e-07	-1.301923e-05
Factor(MAS)2	-6.8933e-02	2.440956e-03	-7.138779e-02
Factor(LOC)2	-1.8596e-01	-6.584941e-03	-1.925821e-01

Table 5 shows results of the spatial error model. The spatial error variable (lambda =0.012068) is high and statistically significant. This implies that neighbouring household settlements that are affected by poverty are uncorrelated due to certain level of poverty which varies among households.

Table 5. *The Spatial Error Model.*

	Estimate	Std.Error	Z value	Pr(>|z|)
Intercept	3.2901e-01	3.8278e-02	9.0211	2.2e-16
HHS	5.2828e.02	1.4682e-03	35.9816	2.2e-16
TAH	-1.2627e-05	3.7887e-07	33.3288	2.2e-16
Factor(MAS)2	-6.8795e-02	2.8560e-02	-2.4088	0.016006
Factor(LOC)2	-1.9665e-01	1.0679e-02	18.4157	2.2e-16
Lambda = 0.012068 LR test = 0.35571 p-value=0.04509				
Asymptotic standard error: 0.020008 z-value=0.60318 p value=0.04239				
Wald statistics = 0.36383 p value= 0.04239				
Log likelihood = -2474.636 for error model				
ML residual variance (σ^2, σ) = 0.11608,0.3406 Number of observation =14009				
Number of parameter estimated=33				

Table 6 displays results of the mixed autoregressive model. From the table, the model reveals household size, total annual household expenditure, marital status (divorce), location (rural), educational level of household heads (JHS), deplorable roads (Yes) and ecological Zone (Savanna) are significant socio-economic determinants of poverty among households. The spatial regression parameter estimate (rho), that is 0.12214 shows a positive impact on poverty and extremely significant to poverty.

The size of a household has a positive impact on poverty and is a statistically significant determinant. Increased household size has a higher risk of poverty to household settlements.

Ghana Population and Housing Census survey (2010) report indicated that, the dependent population thus individuals aged less than fifteen (15) years and individual who are more than sixty-four (64) years accounted for forty-four percent of the total population. Almost twelve (12) percent of the total populations are unemployed among the active labor force. Due to this, heads of households with lesser household size will be capable of supporting their family members. A home with a large household size is more likely to be poor than one with a smaller size, according to [15].

Being poor is more prevalent if you live in a rural location. This implies that, household settlements in the rural locations experience poverty due to inadequate social amenities, infrastructural facilities etc. [16] indicated that, the level of poverty in the rural location represented for more than eighty percent of Ghana's poverty level. In comparison to urban incomes, rural incomes appear to be poor. In Ghana, rural-urban migration is higher because availability of jobs is higher in urban locations than in rural locations. In addition, the disparity in development between urban locations and rural locations makes it harder for households in rural locations to rise over the poverty line. Urban areas are primarily linked to recreational and educational facilities, as well as quality healthcare, telecommunications, including financial institutions, all of which contribute to urban people' human resource benefit in terms of gaining high-paying jobs. Rural communities are unable to accumulate capital due to a lack of loan facilities. The probability of households in the urban locations to be non-poverty is higher than those in rural locations.

The marital status of household heads who are divorced are poor which is statistically significant determinant of poverty. The deplorable nature of a road in an area has a positive correlation to poverty as indicated in Table 6. There is a significant correlation between ecological zone (savanna) and poverty.

Also, the total annual household expenditure on food consumption has an extremely positive correlation to poverty. According to [17], expenditure on food contributed for 40% of total expenditure on households, with the imputed value of household-produced food accounting for another 10.5 percent.

Moreover, the Lag component of the mixed autoregressive model identifies the household size, total annual expenditure of household, marital status (divorce), ecological zone (forestry and savanna areas) and the educational level of household heads as statistically significant determinant which is likely to have a direct effect on neighbouring household settlements.

Table 6. *The Mixed Autoregressive Model.*

	Estimate	**Std. Error**	**Z value**	**Pr(>|z|)**
Intercept	4.0076e-01	9.6042e-02	4.1727	3.009e-05
HHS	5.1834e-02	1.4792e-03	35.0424	2.2e-16
AGE	-1.3017e-04	2.3882e-04	-0.5450	0.58732
TAH	-1.2458e-05	3.8284e-07	-32.5398	2.2e-16
THE	-2.0771e-05	1.3198e-0.-5	-1.5738	0.115541
factor(GEN)2	9.3948e-03	8.1902e-03	1.1471	0.251349
factor(MAS)2	-6.3148e-02	2.8453e-02	-2.2194	0.0001471
factor(MAS)3	-3.4551e-02	2.8403e-02	-1.2164	0.223816
factor(MAS)4	2.7494e-04	9.0635e-03	0.0303	0.975800
factor(MAS)5	1.5142e-03	2.2368e-02	0.0677	0.946029
factor(MAS)6	-3.0072e-02	1.6244e-02	-1.8513	0.064131
factor(LOC)2	-1.3864e-01	1.7990e-02	-7.7065	0.0002482
factor(ECA)2	2.0372e-02	2.1532e-02	0.9461	0.344097
factor(ECA)3	1.8087e-02	1.1782e-02	1.5351	0.124761
factor(MAO)2	-1.0469e-02	3.8916e-02	-0.2690	0.787917
factor(MAO)3	9.7196e-03	5.0593e-02	0.1921	0.847654
factor(MAO)4	-2.9705e-02	5.3120e-02	-0.5592	0.576014
factor(MAO)5	-2.1942e-03	3.3918e-02	-0.0647	0.948421
factor(MAO)6	9.7233e-03	3.4348e-02	0.2831	0.777116
factor(MAO)7	1.3393e-02	3.4842e-02	0.3844	0.700683
factor(MAO)8	9.3209e-04	4.0239e-02	0.0232	0.981520
factor(MAO)9	1.2883e-02	3.8799e-02	0.3320	0.739854
factor(ELH)2	-4.8430e-03	2.3307e-02	-0.2078	0.835390
factor(ELH)3	3.9134e-02	2.2399e-02	1.7472	0.080607
factor(ELH)4	3.7536e-03	1.9502e-02	0.1925	0.847372
factor(ELH)5	-1.7971e-02	2.0723e-02	-0.8672	0.385831
factor(ELH)6	2.1933e-03	5.3838e-02	0.0407	0.967504

	Estimate	Std. Error	Z value	Pr(>|z|)
factor(ELH)7	1.0526e-02	1.0526e-02	1.0202	0.0411957
factor(DPR)1	-2.0099e-02	8.1651e-03	-2.4616	0.013833
factor(ECZ)2	-1.3347e-02	1.9363e-02	-0.6893	0.490631
factor(ECZ)3	-4.1803e-02	2.4013e-02	-1.7408	0.0346635
lag.HHS	1.3964e-02	3.5819e-03	5.5050	3.691e-08
lag.AGE	5.4298e-04	5.7676e-04	0.9414	0.346485
lag.TAH	6.2312e-07	8.9113e-07	0.6992	0.0392409
lag.THE	-1.5911e-05	3.0229e-05	-0.5264	0.598639
lag.factor(GEN)2	7.8817e-03	1.9586e-02	0.4024	0.687375
lag.factor(MAS)2	-1.0521e-01	6.6902e-02	0.0109	0.0104131
lag.factor(MAS)3	-2.3981e-02	6.5866e-02	-0.3641	0.715787
lag.factor(MAS)4	-9.9117e-04	2.1287e-02	-0.0466	0.962861
lag.factor(MAS)5	-1.5044e-02	5.2902e-02	-0.2844	0.776127
lag.factor(MAS)6	-4.8449e-03	3.8453e-02	-0.1260	0.899736
lag.factor(LOC)2	5.8366e-02	1.4302e-02	4.0810	4.485e-05
lag.factor(MAO)2	-5.6572e-02	9.5443e-02	-0.5927	0.553364
lag.factor(MAO)3	-1.1214e-02	1.2176e-01	-0.0921	0.926622
lag.factor(MAO)4	5.9803e-02	1.2746e-01	0.4692	0.638946
lag.factor(MAO)5	4.8081e-02	8.2259e-02	0.5845	0.558880
lag.factor(MAO)6	1.4112e-02	8.3586e-02	0.1688	0.865924
lag.factor(MAO)7	8.8650e-02	8.5525e-02	1.0365	0.299952
lag.factor(MAO)8	6.8324e-02	9.8763e-02	0.6918	0.489060
lag.factor(MAO)9	-5.4892e-02	9.2419e-02	-0.5940	0.552544
lag.factor(ELH)2	1.6710e-01	5.5562e-02	3.0074	0.1876429
lag.factor(ELH)3	4.5201e-05	5.2739e-02	0.0009	0.0306885
lag.factor(ELH)4	9.1630e-02	4.5720e-02	2.0042	0.045052
lag.factor(ELH)5	2.0394e-02	5.0311e-02	0.4054	0.685215
lag.factor(ELH)6	-2.0247e-01	1.2730e-01	-1.5905	0.0236959
lag.factor(DPR)1	5.4794e-02	1.9256e-02	4.1233	3.735e-05
lag.factor(ECZ)2	-1.4207e-01	3.1853e-02	-4.4603	2.2e-16
lag.factor(ECZ)3	-1.9059e-01	3.4847e-02	-5.4693	2.2e-16
Rho= 0.12214 LR test value= 81.086 p-value: < 2.22e-16				
Asymptotic standard error= 0.013711 z-value= 8.9079 p-value:= < 2.22e-16				
Wald statistic= 79.351 p-value= < 2.22e-16 Log likelihood= -4966.308 for mixed model				
ML residual variance (σ^2,σ)= (0.11867, 0.34448) Number of parameters estimated: 63				
Number of observations: 14009 AIC: 10142 (AIC for lm: 10063)				

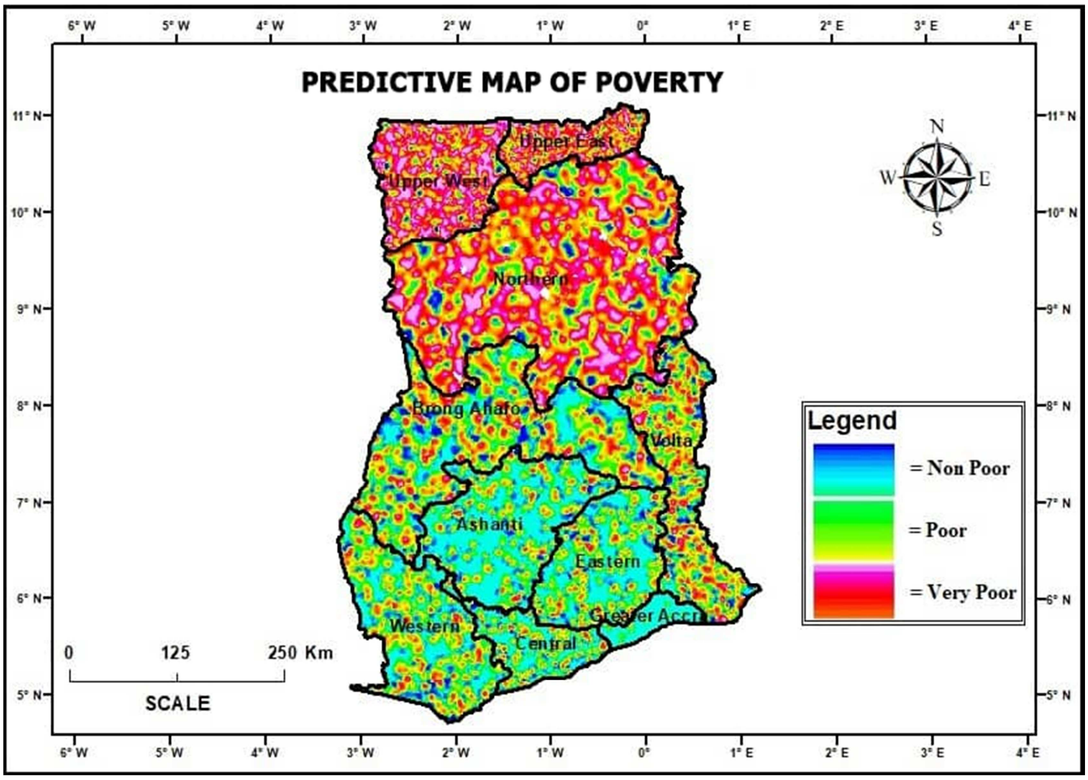

Figure 5. *Predictive Map of Poverty.*

Figure 5 displays a predictive map of poverty which represents poor (blue), non-poor (green) and very-poor (red). The map displays a poverty map of prediction to identify poverty severity region in Ghana. The map (Figure 5) shows that, the three (3) Northern sector which includes; Upper east Region, upper west Region and Northern Region have a greater possibility of high poverty severity among households with a few non –poor households found within Northern region, and extremely high level of severe poverty (very poor) in upper east region and upper west region.

Furthermore, households among Ashanti region, Eastern region and Greater Accra region are likely to be non-poor. Also, Bono Ahafo region, western region and central region predict a few households as very poor and quite marginal number of households as Non poor.

6. Summary, Conclusion and Recommendation

6.1. Summary of Findings

The main purpose of this study is to fit a mixed autoregressive model for poverty mapping. The findings identified determinants which have direct correlations to poverty.

Firstly, the size of a household has a positive impact on poverty and is a statistically significant determinant. A home with a large household size is more likely to be poor than one with a smaller size, according to [15]. Rural location is also a statistically significant determinant of poverty. This might be due to lack of social amenities, infrastructural facilities and other educational institutions. The marital status of household heads who are divorced are poor which is statistically significant determinant of poverty. The total annual household expenditure on food consumption has an extremely positive correlation to poverty.

Moreover, the predictively poverty map portrays the three (3) Northern sector which includes; Upper east Region, upper west Region and Northern Region have a greater possibility of high poverty severity among households with a few non – poor households found within Northern region, and extremely high level of severe poverty (very poor) in upper east region and upper west region.

Moreover, the mixed autoregressive model has an AIC of 4996.5 and the generalized linear model has an AIC of 4998.4. The mixed autoregressive model internally compares the AIC to the Generalized linear model (Glm) been fitted to select the best model since it has a lower AIC comparatively to the generalized linear model.

6.2. Conclusion

The study reveals household size, total annual household expenditure, marital status (divorce), location (rural), educational level of household heads (JHS), deplorable roads (yes) and ecological Zone (Savanna) are statistically significant socio-economic determinants of poverty severity among households settlements. According to [18], most researchers use ignores the environmental variable, which has been proved significant in this study.

6.3. Recommendation

The varied characteristics of households that determine poverty levels should be considered carefully in policy decisions and development aid organizations.

The government should concentrate on improving its domestic mobilization operations, including its administrative and expenditure monitoring equipment, in order to promote effective resource allocation, understanding that the state bears the primary responsibility for economic development.

In order to encourage evidence-based policies that prevent failed policy, developing countries must build peer learning as well as information sharing mechanisms in addition to monetary resources.

Government should enhance massive infrastructural projects in rural locations such as Roadways, education, and recreational facilities should really be prioritized to ensure that the country's rural and urban areas develop at the same pace.

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