Exploring the impact of agriculture and physical geography on poverty in the East Coast of Malaysia: a spatial analysis

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Abstract. Poverty is one of the most significant issues facing humanity in the 21st century. In Malaysia, awareness of poverty was more heavily weighted toward developing a prosperous lifestyle. Hence, the objectives of this study were to explore the spatial pattern of poverty and the effects of agricultural growth and physical geography on poverty in East Coast, Malaysia. Secondary data on the heads of poor households from 2020 were obtained from the e-Kasih database. The dependent variable was the number of poor household heads in each district, which count variable and acts as an indicator for measuring poverty. Therefore, a Generalised Linear Model (GLM) was used. Since a spatial autocorrelation was detected in the model using Moran's I statistic, a Poisson Log Linear Leroux Conditional Autoregressive was fitted to the data. RStudio software was used to analyze the data. The results of this study indicate that the variables of the number of people without education, number of female heads of households, number of government servants, total land area for cash crops, and slope significantly influence the number of poor household heads in each district. The estimated poverty risk in each district was measured. ArcMap software created the poverty distribution map in Kelantan, Pahang, and Terengganu. The estimated poverty risk map shows a nearly similar spatial pattern to the Standardised Poverty Rate (SPR) map. This research adds new literature on poverty models in Kelantan, Pahang, and Terengganu for other researchers studying poverty factors in these regions.

1 Introduction

Poverty is a significant issue that has always confounded the advancement of human society. The first sustainable development goal of the United Nations 2030 Agenda for Sustainable Development is eradicating all forms of poverty [1]. The inability to live a life comparable to that of a typical member of society is a definition of poverty. The lack of necessities, such as low education levels, a lack of access to valuable assets such as real estate, and some health

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issues make a living typically tricky [2]. The income-based poverty line income (PLI), which Malaysia now uses to determine the prevalence of poverty, was recently modified in 2019 and will replace the 2005 methodology [3]. According to the country's revised national poverty line income of RM 2,208, more than 400,000 Malaysian households with monthly incomes below this amount were classified as poor in 2019 [4]. Malaysia reduced poverty to 0.4% in 2016, compared to 49.3% in 1970. This demonstrated that Malaysia had successfully reduced poverty to its bare minimum. However, economic growth indexes reveal slight improvement in the poverty level among the poor, indicating the need for inclusivity [5].

Over the past ten years, Peninsular Malaysia has made numerous initiatives to lower poverty levels among its citizens [6]. The East Coast of Malaysia often faces higher poverty rates than other regions. It has been discovered that most people experiencing poverty reside in rural areas in Terengganu, Pahang, and Kelantan [7]. Therefore, this study was conducted to determine the effects of agricultural growth and physical geography on poverty and to examine the level of poverty risk in each district on the East Coast of Malaysia. The study is aligned with the Sustainable Development Goals (SDGs), which are to reduce poverty (SDG 1) and promote sustainable agricultural practices (SDG 2), making it appropriate and relevant for both local and international development agendas.

2 Methods

2.1 Study area and data

In this study, the data on agricultural growth, physical geography, and the demographic characteristics of poor heads of households in each district of Kelantan, Pahang, and Terengganu were obtained from the e-Kasih database from the Ministry of Women, Family, and Community Development and the Department of Statistics Malaysia (DOSM) for the year 2020. The poverty data will be the number of poor households for each district. The independent variables were the socio-demographic characteristics of the poor household head, which comprised the Number of household heads without education, the number of female household heads, the number of government servants of the household heads, agricultural growth, and physical geography for each district.

2.2 Standardised Poverty Rate (SPR)

The Standardized Poverty Rate (SPR) model (1) was used to assess poverty risk. The SPR was calculated using the ratio of observed to predicted poverty cases, which allowed for accurate comparisons of poverty levels across districts with varying household numbers. This method served as a normalization tool to analyse inequality. The formulas used were:

$$SPR_k = \frac{y_k}{E_k}, \tag{1}$$

where E_k is given by,

$$E_k = \frac{\Sigma y_k}{\Sigma p_k} \times p_k, \tag{2}$$

where y_k was the number of poor household heads, p_k was the number of population and E_k in equation (2) was the expected poverty rate for k = 1, …, n districts. An SPR value greater than 1 indicated a high poverty rate, while a value less than 1 indicated a low poverty rate. For instance, an SPR of 1.30 implied a 30% higher poverty risk than expected cases.

2.3 Poisson Generalised Linear Model (GLM)

Model (3) is the Poisson Generalized Linear Model (GLM). The response variable y is measured on a series of counts. This model enabled y to be one of several independent random variables from any exponential family distribution. The model equation was:

$$Y_k \sim f\left(y_k \middle| \mu_{k,}\phi\right) \text{for } k = 1, \dots, n, \tag{3}$$

and the link function $g\ (\mu_k) = \eta_k = x_k{}^T\ \beta$ highlighted the use of covariates $X = (x_1^T, \dots, x_n^T)$ and regression parameters $\beta = (\beta_1, \dots, \beta_p)$ for p was the number of independent variables. Since the dependent variable in this study was count data, the Poisson GLM with a log link function model (4) was employed to ensure non-negative response values, expressed as

$$Y_k \sim Poisson\ (\mu_k) \text{ where } ln(\mu_k) = x_k{}^T\ \beta \text{ for } k = 1, \dots, n,. \tag{4}$$

The residuals from the GLM model were examined for the appearance of spatial autocorrelation using Moran's I, resulting in a value ranging from -1 to 1. Positive values indicated positive spatial autocorrelation, while negative values suggested an inverse autocorrelation. The null hypothesis of no spatial autocorrelation was rejected if the p-value was less than 0.05.

2.4 Poisson log-linear Leroux Conditional Autoregressive (CAR) model

A Bayesian Hierarchical model was utilized to describe the data y_k, incorporating covariate information $(x_{1k}, \dots, x_{pk})$ and a random effect $\emptyset_k$ to represent the unmeasured spatial structure in poverty situations. The random effects $\phi = (\phi_1, \dots, \phi_n)$ were used to simulate any spatial autocorrelation in the data after controlling for covariates. A conditional autoregressive (CAR) prior distribution, a form of the Gaussian Markov random field (GMRF) model, was used to model the random effects. The spatial correlation between the random effects is defined by a binary ($n \times n$) neneighborhoodatrix (W). In this matrix, the element (w_{jk}) is set to one if areas (j) and (k) are considered neighbours, and zero otherwise. If two areas are neighbours, their random effects are correlated. Otherwise, the random effects of non-neighbouring areas are modelled as being conditionally independent, given the remaining elements of (ϕ).

The most common approach is to define areas (j) and (k) as neighbours (i.e., ($w_{jk} = 1$)) if and only if they share a common border, which is denoted as ($j \sim k$).The Poisson log-linear Leroux CAR model (5) was formulated as follows:

$$Y_k \sim Poisson(E_k R_k) \text{ for } k = 1, \dots, n,$$

$$\ln(R_k) = x_k^T \beta + \phi_k, \tag{5}$$

$$\phi_k \mid \phi_{-k} \sim N\left[\frac{\rho \sum_{j=1}^{n} w_{kj\phi k}}{\rho \sum_{j=1}^{n} w_{kj+1-\rho}}, \frac{\tau^2}{\rho \sum_{j=1}^{n} w_{kj+1-\rho}}\right],$$

$$\beta \sim N(\mu_\beta, V_\beta),$$

$$\rho \sim U\ (0,1),$$

$$\tau^2 \sim Inverse - gamma\ (0.001,0.001).$$

In this model R_k estimated the poverty risk in area k. If $R_k = 1$, then $\mathbb{E}(y_k) = E_k$ was the average risk. For instance, if $R_k = 1.5$, it implied 50% more cases than expected. The model estimated the regression parameters β, which quantify the impacts of covariates on poverty risk, with covariates covering demographics, agricultural growth, and physical geography. The level of spatial autocorrelation in the random effects was denoted by ρ, where $\rho = 1$ indicated substantial spatial autocorrelation and $\rho = 0$ indicated independence. The conditional variance of $\phi_k \mid \phi_{-k}$ was denoted by τ^2.

2.8 Spatial mapping using ArcMap

ArcMap software was used for spatial mapping to create poverty distribution maps for Kelantan, Pahang, and Terengganu. The results from the Standardized Poverty Rate (SPR) and estimated poverty risk were used to generate these maps. These poverty maps served as essential tools to determine the distributions of poverty areas.

3 Results

3.1 Exploratory analysis for poverty data

The poverty map, displayed in Fig. 1., categorized districts into four classes: no poverty risk (green), high poverty risk (yellow), and hard-core poverty risk (red). In Kelantan, districts such as Machang, Kota Bharu, and Pasir Mas were green, indicating zero poverty, while others like Tanah Merah, Tumpat, and Gua Musang were yellow, showing high poverty risk. Pahang's map showed mostly green areas, with only Lipis in yellow and Jerantut and Raub in red. In Terengganu, Dungun and Kemaman were green, while Kuala Terengganu and Marang were yellow, and Setiu was red. The Standardised Poverty Rate (SPR) values indicated that three districts in Kelantan, seven in Pahang, and two in Terengganu had zero poverty, whereas several others faced high or hard-core poverty risks.

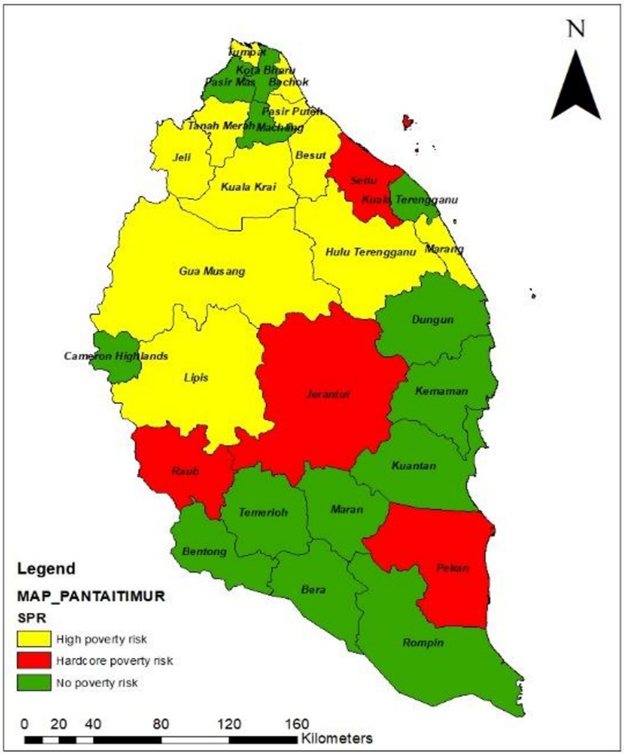

Fig. 1. Poverty risk map.

The poverty risk levels by district were detailed in Table 1, using the Standardised Poverty Rate (SPR) to determine the likelihood of poverty. An SPR value greater than 1.0 indicated a high poverty rate, while values less than 1.0 indicated no poverty. The data revealed that three Kelantan districts, seven Pahang, and two Terengganu had zero poverty with SPR values below 1.0. However, 12 districts faced a high risk of poverty (SPR 1.01–1.5), most of which were located in Kelantan. Additionally, three districts in Pahang and one in Terengganu were at hard-core poverty risk, having SPR values greater than 1.5.

Table 1. SPR value of 28 districts in Kelantan, Pahang, and Terengganu

SPR Value	District
≤ 1.00 (No poverty risk)	Cameron Highlands (Pahang)
	Kemaman (Terengganu)
	Kota Bharu (Kelantan)
	Bentong (Pahang)
	Kuantan (Pahang)
	Rompin (Pahang)
	Temerloh (Pahang)

	Pasir Mas (Kelantan)
	Dungun (Terengganu)
	Machang (Kelantan)
	Maran (Pahang)
	Bera (Pahang)
1.01 – 1.5 (High poverty risk)	Kuala Terengganu (Terengganu)
	Tanah Merah (Kelantan)
	Tumpat (Kelantan)
	Gua Musang (Kelantan)
	Bachok (Kelantan)
	Marang (Terengganu)
	Pasir Puteh (Kelantan)
	Hulu Terengganu (Terengganu)
	Jeli (Kelantan)
	Kuala Krai (Kelantan)
	Besut (Terengganu)
	Lipis (Pahang)
>1.5 (Hardcore poverty risk)	Raub (Pahang)
	Jerantut (Pahang)
	Setiu (Terengganu)
	Pekan (Pahang)

3.2 Poisson Generalised Linear Model (GLM) and Moran's Index (Moran's I)

To measure the existence of spatial autocorrelation, a Poisson log-linear model without any random effects or any spatial structure was fitted to the poverty data. The GLM analysis revealed significant relationships between the number of female heads of households, the number of people without education, the number of government servants, the total land area for cash crops, vegetable crops, and fruit crops, elevation, river density, and slope with the prevalence of poverty in districts. Subsequently, Moran's I was employed to detect spatial autocorrelation in the residuals of the non-spatial model. The significant Moran's I value indicated spatial autocorrelation, leading to the rejection of the null hypothesis and necessitating the use of a spatial model.

3.3 Poisson log-linear Leroux Conditional Autoregressive (CAR) model

Since the existence of a spatial autocorrelation structure of the residuals for the Poisson log-linear model, the data set was modeled using Poisson log-linear Leroux Conditional Autoregressive (CAR) model with a contiguity neighborhood matrix W. The inference value for each model was obtained using 50,000 MCMC samples with burn-in until convergence for the first 10,000 samples, and the remaining samples were thinned by 10 to eliminate autocorrelation, resulting in 4,000 samples.

Table 2 showed the 95% credible intervals for the coefficients of the Poisson log-linear Leroux CAR model, indicating that the number of people without education, number of female household heads, total land area for cash crops and slope significantly influenced the number of poor household heads in each district. The initial model had DIC and p.d values of 340.0173 and 31.6346, respectively. Variables were considered significant if the median, 2.50%, and 97.50% credible intervals had the same sign. Consequently, non-significant factors such as fruit and vegetable crops were excluded, and the model was rerun.

Table 2. Poisson log linear Leroux CAR model

Variables	Median	2.50%	97.50%
Number of people without education	0.0005	0.0005	0.0005
Number of female heads of households	-0.0002	-0.0003	-0.0001
Number of government servant	-0.0032	-0.0128	0.0024
Elevation	0.0123	-0.0453	0.0685
River Density	-0.0189	-0.0609	0.0203
Cash crop	-0.001	-0.0021	-0.0002
Fruits crop	0.0000	-0.0001	0.0000
Vegetable crop	-0.0001	-0.0001	0.0000
Slope	0.3103	0.1871	0.4606
DIC = 340.0173, p.d = 31.6346			

Table 3 Poisson log-linear Leroux CAR new model

Variables	Median	2.50%	97.50%
Number of people without education	0.0006	0.0006	0.0006
Number of female heads of households	-0.0002	-0.0003	-0.0002
Number of government servant	-0.0287	-0.0334	-0.0202
Cash crop	-0.002	-0.0032	-0.0013
Slope	0.161	0.0101	0.3247
DIC = 338.4936, p.d = 30.87256			

The result presented in Table 3 compares the performance of a new model against its predecessor based on DIC (Deviance Information Criterion) and p.d values. The new model achieved a DIC of 338.4936 and a p.d of 30.87256, both lower than those of the previous model, indicating superior model fit. Table 4 provides estimates and 95% credible intervals on the relative risk scale for standard deviations of each covariate based on Table 3, illustrating their impact. Notably, an increase in poorly educated heads of households raised the relative risk of poverty. Conversely, an increase in female-headed households decreased the relative risk of poverty. Furthermore, a 22-person rise in government servants reduced the relative risk by 48%, while a 22-hectare increase in cash crop land decreased it by 25%.

Conversely, a 0.7° slope increased the relative risk by 12%. These findings underscore the multifaceted impacts of demographic and environmental factors on poverty risk.

Table 4 Estimates and 95% credible interval new model for the regression parameters. The results were presented on the relative risk scale for a standard deviation increase in each covariate value.

Variables	Median	2.50%	97.50%
Number of people without education	12.1994	12.19936	12.1994
Number of female heads of households	0.38714	0.2408847	0.38714
Number of government servant	0.52288	0.4702088	0.63358
Cash crop	0.72649	0.5997521	0.81246
Slope	1.12159	1.007224	1.26038

3.4 Spatial mapping

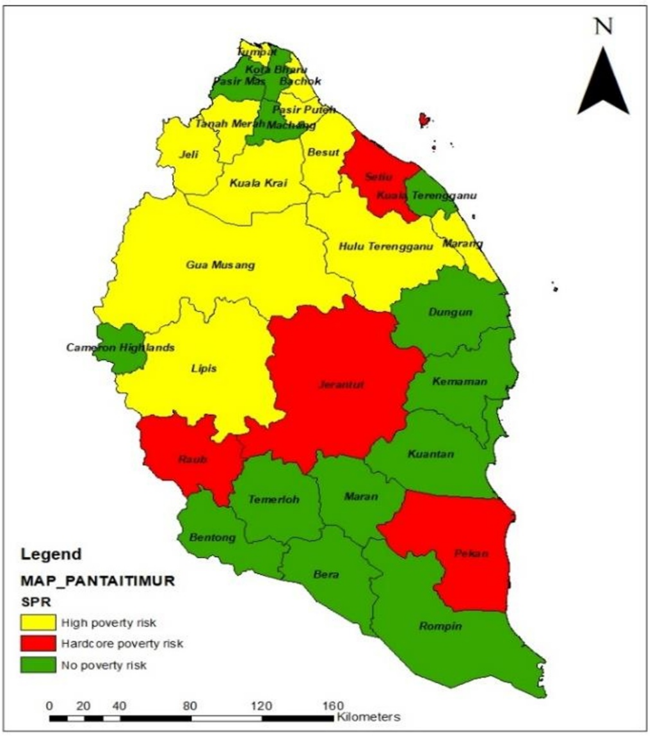

Fig. 2. The Poisson Log Linear Leroux CAR model estimates poverty risks.

The relative risk map from the Poisson log-linear Leroux Conditional Autoregressive model using the same scale as the SPR value was shown in Fig. 2. However, the estimated poverty risk map exhibits a nearly similar spatial pattern to the SPR map, with the highest risk for Setiu, Jerantut, Raub, and Pekan, while in the North, most districts are yellow, which is high poverty risk, and most districts in the South are green which was no poverty risk.

3.5 Determinants of Poverty

According to the findings, several key determinants contribute to poverty on the East Coast. Lack of education among individuals, particularly heads of households, correlates strongly with higher poverty rates. Education not only enhances individual capabilities but also boosts household income and productivity. Additionally, the increasing number of female-headed households plays a significant role in poverty reduction, reflecting their growing participation in economic activities. Government employment offers stability and benefits that mitigate poverty risks, while cash crop cultivation provides crucial income sources in agricultural regions. Conversely, regions with steeper slopes face higher poverty rates due to limited agricultural productivity and infrastructure challenges. The results of this study are in line with [8]. These determinants collectively underscore the complex interplay between education, employment, agricultural practices, and geographical factors in shaping poverty dynamics on the East Coast.

4 Conclusion

The distribution of poverty on the East Coast is quantitatively examined. A poverty risk map has been created, including all 28 districts in Kelantan, Pahang, and Terengganu. The map shows four districts with an SPR value of more than 1.5 at high risk of poverty, namely Raub, Jerantut, Pekan, and Setiu, three of which were in the state of Pahang and the other in Terengganu. These risk differences are caused, in part, by variables. Furthermore, demographic characteristics that significantly influence poverty were effectively identified. Among the eleven features of poor household heads initially examined, three demographic variables were discovered to substantially impact the number of poor household heads in each district, which was the number of female heads of household, the number of people without education, and the number of government servants. Aside from that, the total area of land for crops like cash crops impacts poverty on the East Coast. In addition, the height of the slope was also found to impact poverty on the East Coast.

In conclusion, the East Coast poverty research has established certain crucial issues that affect individuals and communities throughout the area. Several major conclusions have emerged from intensive research and analysis, demonstrating the multidimensional nature of poverty and its influence on various areas of society. After the relative risk map was created, it has been identified that the estimated poverty risk map exhibits a nearly similar spatial pattern to the SPR map, with the highest risk for Setiu, Jerantut, Raub, and Pekan, while in the North, most districts are yellow, which is high poverty risk, and most districts in the South are green which is no poverty risk.

The study concludes that poverty in East Coast Malaysia is influenced by socioeconomic and geographic factors, which require focused government intervention. Lack of education, especially among heads of households, is a major factor in poverty. Educational and vocational programs are proposed in rural areas. Female-headed households are associated with lower poverty, emphasizing the importance of encouraging women's participation in improving the economy through entrepreneurship and microcredit schemes. Employees in the government sector significantly reduce the risk of poverty. This proves the importance of creating stable job opportunities in the public or private sector. Growing cash crops also helps reduce poverty. This can help with increased support to farmers in terms of training, subsidies, and market access. In areas with steep slopes, infrastructure investments in irrigation, terraces, and transportation can reduce agricultural challenges and increase economic returns. Based on the spatial pattern of poverty, districts such as Setiu, Jerantut, Raub, and Pekan need a spatially targeted policy. It is compatible with the socio-economic and geographical context for more effective poverty eradication. The research results highlight the critical need for comprehensive and focused initiatives to effectively eliminate poverty in Malaysia. Policymakers and stakeholders should prioritize programs to improve access to excellent education, health care, and vocational training, particularly in marginalized populations. Furthermore, initiatives that promote equitable economic growth, job creation, and income distribution are critical for long-term poverty reduction.

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