Unveiling the Impact of Physical Geography on Poverty: A Comprehensive Analysis for Sustainable Development

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Abstract. This study examines the effects of physical geography, demographic characteristics of household heads, and poverty, with a specific focus on the number of poor household heads within districts of Terengganu. Through the utilization of a Poisson log-linear modeling approach, the research investigates the effects of physical geography and demographic factors, on the number of poor household heads for each of the sub-districts. The central concern of this research revolves around the need to comprehend the underlying reasons for differing poverty rates among sub-districts in Terengganu. To carry out the analysis, a Poisson log-linear modeling is employed for the data, leveraging SPSS and Rstudio for statistical analysis. This method enabled us to thoroughly assess how physical geography factors (including terrain and accessibility) and demographic characteristics of household heads (including age, education level, and employment status) influence poverty rates. To determine the distribution of spatial poverty, ArcMap is used to visualize the Standardised Poverty Ratio. The results of the study show that 31 sub-districts were identified as not being at risk of poverty and another 31 were labeled as having a high poverty rate. Furthermore, the Poisson regression analysis yielded several important insights into the factors influencing poverty rates. Specifically, it is found that a higher average age is associated with a decrease in poverty. Conversely, an increase in non-formal education levels, lower elevations, steeper slopes, and higher river density are linked to an increase in poverty. These findings have significant implications for policy formulation and targeted interventions in Terengganu, providing valuable guidance for addressing poverty-related challenges. The mapping of high-risk poverty areas offers crucial information for spatially targeted interventions, facilitating the implementation of more efficient poverty reduction measures. Furthermore, research findings enhance the understanding of the intricate dynamics between physical geography, demographic characteristics, and household poverty. By identifying the significant factors impacting poverty, this study provides valuable insights for developing targeted poverty alleviation strategies and formulating evidence-based policies. In conclusion, this study serves to inform policymakers, researchers, and practitioners about the multifaceted relationships between physical geography, demographic characteristics, and household poverty. By recognizing the critical role played by these factors, stakeholders can devise comprehensive approaches tailored to specific contexts, effectively addressing poverty, promoting inclusive growth, and improving the well-being of vulnerable populations.

1 Introduction

Poverty significantly impacts society, affecting the quality of life and the economy [1]. It plays a crucial role in shaping various aspects of human existence, such as access to necessities, education, healthcare, and opportunities for social and economic progress. Countries across the globe have been combating this poverty issue for a long time [2]. Poverty is a condition where people cannot fulfill their basic needs due to a lack of resources [3]. Various factors can influence poverty incidence, varying according to region. Previously, researchers had conducted studies on poverty's determinants. Multiple factors can affect poverty, such as demographic variables, human capital attributes, capital of social, bothersome life circumstances, and neighborhood-level characteristics [4].

By 2030, all countries worldwide are expected to achieve the 17 Sustainable Development Goals (SDGs) successfully. The primary focus of the SDGs is to eradicate poverty in all its forms. Poverty has been a pressing concern that has worried numerous individuals due to its threats to the country. In addition to striving for the SDGs, Malaysia has also aimed to attain developed country status by 2020. Extensive efforts have been made as alternative approaches to accomplish this objective. However, poverty is a significant obstacle hindering the realization of this goal [5]. Kelantan is one of the poorest states on the east coast of Malaysia, followed by Terengganu and Pahang. Since a study on poverty in Kelantan has been conducted by [6], this study focuses on poverty in Terengganu. Currently, there is limited knowledge regarding how poverty is distributed and the factors contributing to this issue in all sub-districts of Terengganu. Consequently, this study examined the level of poverty risk and identified the socio-demographic and environmental factors affecting poverty.

2 Methods

The demographic characteristics are the number of the average age of poor heads of household, and the number of non-formal education level poor heads of family. At the same time, the environmental factors are topography and water resources. A method called the standardized poverty rate (SPR) was used to understand the level of poverty risk in Terengganu. This allowed researchers to measure and compare poverty rates across different sub-districts. The results were then visualized on a map using a Geographic Information System (GIS) software called ArcMap. By mapping the poverty rates, it became possible to identify areas in Terengganu with higher poverty levels. Poisson Log-linear regression analysis was employed to determine the factors contributing to poverty. This statistical technique helped identify the variables that had a significant impact on poverty levels in Terengganu. By understanding these factors, policymakers and stakeholders can effectively develop targeted interventions and strategies to combat poverty.

2.1 Study Area & Data.

The area of this study is Terengganu, located in eastern Peninsular Malaysia. Bordering to the northwest is Kelantan, to the southwest is Pahang, and to the east is the South China Sea. Pulau Perhentian, Pulau Kapas, and Pulau Redang are some of the state's outlying islands. The total area of Terengganu is 13,035 km2 (5,033 square miles), divided into 7 sub-districts, involving 74 sub-districts was covered in this study. This study used secondary data on socio-demographic characteristics of the poor household head, namely the average age of poor heads of household and the number of non-education level poor heads of household in each district while for the environmental factors were topography and water resources. For elevation, have 4 classes, class 1 stands for 0-150 meters, class 2 is 0-300 meters, class 3 is 0-1000 meters, and class 4 is 0-1509 meters. Slope also has 4 classes: class 1 stands for 0-5 meters, class 2 is 0-15 meters, class 3 is 0-20 meters, and class 4 is 0->25 meters. Meanwhile, water resources are a range of river density have 3 classes, class 1 stands for 0-3.7 m/ha, class 2 is 0-14.6 m/ha, and class 3 is 0-18.3 m/ha. These variables were the independent variables of this study. Meanwhile, the dependent variable in this study was the number of poor heads of household. Data was obtained from the e-Kasih database, maintained by the Ministry of Women, Family, and Community Development, and census data from the Department of Statistics (DOS).

2.2 Standardized Poverty Rate (SPR).

A standardized poverty rate (SPR) was utilized to assess the poverty risk level in Terengganu. The assumption that a high total number of households leads to a significant number of poor households across all sub-districts may not accurately reflect the situation. To analyze the disparities and account for this discrepancy, the SPR was employed as a normalization method, as mentioned in references [8, 9]. The SPR values were calculated for each of the 74 sub-districts using the formula $SPR_j = y_j / E_j$, where $E_j = \Sigma y_j / \Sigma P_j \times P_j$. Here, SPR represents the standardized poverty rate. The variable Y_j, for $j = 1, \dots, n$, denotes the number of poor household heads in district j. P_j signifies the total number of households residing in district j, and E_j represents the expected rate of poverty for district j. An SPR value exceeding 1 means a poverty risk area. For instance, if the SPR value is 1.20, it indicates an occurrence of 20% more poverty cases than initially expected.

2.3 Spatial Mapping Using ArcMap.

Using ArcMap software, the Standardized Poverty Ratio (SPR) values were then used to create a poverty distribution map of Terengganu. This map serves as a valuable tool to identify areas with a higher poverty risk. Using different colours on the map showcases varying levels of poverty risk across the region. This spatial representation of poverty in sub-districts of Terengganu plays a crucial role in guiding poverty reduction strategies and policymaking [8].

2.4 Poisson Generalized Linear Model (GLM).

The relationship between the dependent and independent variables was modelled using a Poisson Generalized Linear Model (GLM) with a log link function using Rstudio-software. The log link function's purpose was to ensure that the predicted count of poor heads of households remains non-negative, which is crucial when dealing with count data. The formulation of the Poisson GLM can be represented as $\log(\mu) = \beta 0 + \beta 1$Average Age of Poor Heads + $\beta 2$Number of Non-Education Level Poor Heads + $\beta 3$Topography + $\beta 4$Water Resources. Where μ represents the mean (expected count) of poor heads of households in each district, $\beta 0$ until $\beta 4$ are regression coefficients that quantify the impact of the respective independent variables on the log-transformed mean.

3 Results

3.1 Spatial Poverty Map.

After computing the SPR values, a poverty map was generated using ArcMap, as illustrated in Fig. 1. The map depicts four distinct risk classes, each represented by a specific colour: green signifies areas with no poverty risk, light green indicates regions with high poverty risk, orange represents moderate-high poverty risk areas, and red marks locations with hardcore poverty risk.

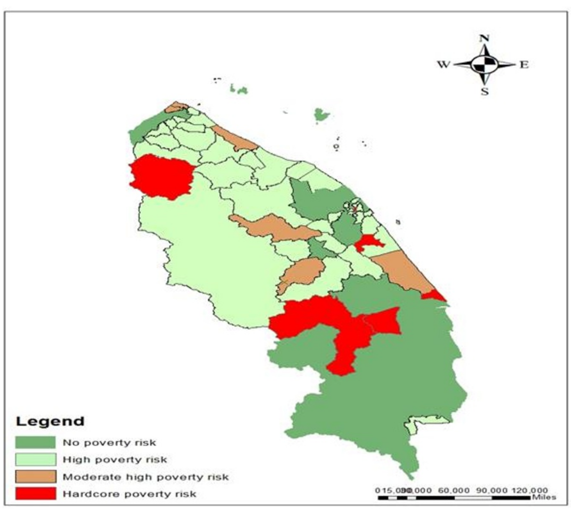

Fig. 1. Poverty Risk Map For Sub-Districts in Terengganu.

Table 1 displays the level of poverty risk for each sub-district. Firstly, 31 sub-districts are not at risk of poverty. The sub-district are Hulu Jabur, Bandi, Teluk Kalung, Batu Buruk, Rasau, Pasir Semut, Binjai, Sura, Bukit Payung, Kerteh, Belara, Cukai, Kijal, Paka, Kubang Parit, Bandar Kuala Terengganu, Alur Limbat, Tebak, Kuala Berang, Hulu Cukai, Kuala Dungun, Kemasik, Kepong, Losong, Kuala Nerus, Pelagat, Bukit Puteri, Jerangau, Kampong Raja, Manir, and Kuala Ibai. Then, there are 31 sub-districts classified as having a high poverty rate. The sub-district are Tasek, Chendering, Serada, Rusila, Bukit Kenak, Paloh, Bukit Besar, Pengadang Buluh, Tanggul, Lubok Kawah, Keluang, Hulu Setiu, Chalok, Jenagur, Atas Tol, Pulau Kerengga, Jabi, Cabang Tiga, Hulu Nerus, Kubang Bemban, Guntung, Pasir Akar, Kerandang, Tembila, Kuala Telemong, Hulu Berang, Tenang, Gelugor/Rengas, Penghulu Diman, Banggul, and Merang. After that, six sub-districts were identified as having a moderately high poverty risk: Kuala Besut, Pengkalan Nangka, Hulu Telemong, Tersat, Pantai, and Merchang. Lastly, six sub-districts, Hulu Besut, Jerong, Gelugur Raja, Besol, Abang, and Jengai, have SPR levels greater than 3.0 for the hardcore poverty risks. Jengai in Dungun is the sub-district in Terengganu with the highest poverty risk, with an SPR value of 10.54.

Table 1. The list of sub-districts by SPR level.

SPR Value	Sub-Districts	
≤ 1.00 (No poverty risk)	1. Hulu Jabur	11. Belara
	2. Bandi	12. Cukai
	3. Teluk Kalung	13. Kijal
	4. Batu Buruk	14. Paka
	5. Rasau	15. Kubang Parit
	6. Pasir Semut	16. Bandar Kuala Terengganu
	7. Binjai	17. Alur Limbat
	8. Sura	18. Tebak
	9. Bukit Payung	19. Kuala Berang
	10. Kerteh	20. Hulu Cukai
	21. Kuala Dungun	26. Pelagat
	22. Kemasik	27. Bukit Puteri
	23. Kepong	28. Jerangau
	24. Losong	29. Kampong Raja
	25. Kuala Nerus	30. Manir
		31. Kuala Ibai
1.01 – 2.00(High poverty risk)	1. Tasek	11. Keluang
	2. Chendering	12. Hulu Setiu
	3. Serada	13. Chalok
	4. Rusila	14. Jenagur
	5. Bukit Kenak	15. Atas Tol
	6. Paloh	16. Pulau Kerengga
	7. Bukit Besar	17. Jabi
	8. Pengadang Buluh	18. Cabang Tiga
	9. Tanggul	19. Hulu Nerus
	10. Lubok Kawah	20. Kubang Bemban
	21. Guntung	26. Hulu Berang
	22. Pasir Akar	27. Tenang
	23. Kerandang	28. Gelugor/Rengas
	24. Tembila	29. Penghulu Diman
	25. Kuala Telemong	30. Banggul
		31. Merang

2.01 – 3.00(Moderate high poverty risk)	1. Kuala Besut	4. Tersat
	2. Pengkalan Nangka	5. Pantai
	3. Hulu Telemong	6. Merchang
> 3.00(Hardcore poverty)	1. Hulu Besut	4. Besol
	2. Jerong	5. Abang
	3. Gelugur Raja	6. Jengai

3.2 Poisson Generalized Linear Model (GLM).

The significant value in the Tests of Model Effects Table 2 shows the statistical significance of each independent variable. Therefore, all the independent variables are included in the model significance, within which the significance is less than *0.05.*

Table 2. Tests of Model Effects

Source	**Wald Chi-Square**	**df**	**Significant**
Range of Elevation	143.427	3	0.000
Range of Slope	290.024	3	0.000
Range of River Density (m/ha)	193.339	2	0.000
Average Age	5.985	1	0.014
Number of Non-Formal Education Level	2216.686	1	0.000

3.2.1 Parameter Estimates.

Table 3 presents the results of the Poisson regression analysis, including coefficient estimates (β) and their corresponding exponentiated values (Exp(β)), as well as robust standard errors, p-values, and 95% confidence intervals for each variable. The coefficients indicate each variable's impact on the logarithm of the count of poor heads of households. The findings provide insights into the expected changes in poverty rates associated with one-unit increases in the respective predictors. Concerning elevation, the poverty rate for the range of elevation=2 (0-300 meters) is 1.034 times higher than that for the reference group, range of elevation=4 (0-1509 meters). Conversely, the poverty rate for the range of elevation=1 (0-150 meters) is 0.868 times lower than the poverty rate for the reference group, and the poverty rate for the range of elevation=3 (0-1000 meters) is 1.213 times higher. Regarding slope, the poverty rate for the range of slope=1.00 (0-5 meters) is 1.473 times higher than the poverty rate for the reference group, range of slope=4.00 (0->25 meters). Similarly, the poverty rate for the range of slope=2.00 (0-15 meters) is 1.723 times higher, and the poverty rate for the range of slope=3.00 (0-20 meters) is 1.230 times higher than the poverty rate for the reference group. Furthermore, for river density, the poverty rate for the range of river density=1.00 (0-3.7 meters/ha) is 1.281 times higher than the poverty rate for the reference group, range of river density=3.00 (0-18.3 meters/ha). Likewise, the poverty rate for the range of river density=2.00 (0-14.6 meters/ha) is 1.233 times higher. Additionally, the coefficient estimate for average age is 0.991, indicating that a one-unit increase in the average age is associated with a 0.9% expected decrease in the log count of the number of poor heads of household. Conversely, the coefficient for the number of non-formal education levels is 1.007, implying a 0.7% expected increase in poverty with every one-unit increase in non-formal education levels.

Table 3. Parameter Estimates

Parameter	**β**	**Significant**	**Exp(β)**	**Lower**	**Upper**
(Range of Elevation=1)	-0.142	0.001	0.868	0.800	0.941
(Range of Elevation=2)	0.033	0.355	1.034	0.964	1.109
(Range of Elevation=3)	0.0193	0.000	1.213	1.147	1.284
(Range of Elevation=4)	0	.	1	.	.
(Range of Slope=1.00)	0.388	0.000	1.473	1.351	1.607
(Range of Slope=2.00)	0.544	0.000	1.723	1.591	1.866
(Range of Slope=3.00)	0.207	0.000	1.230	1.156	1.309
(Range of Slope=4.00)	0	.	1	.	.
(Range of River Density=1.00)	0.248	0.000	1.281	1.229	1.336
(Range of River Density=2.00)	0.210	0.000	1.233	1.194	1.274
(Range of River Density=3.00)	0	.	1	.	.
Average Age	-0.009	0.014	0.991	0.984	0.998
Number of Non-Formal Education Level	0.077	0.000	1.007	1.007	1.007

4 Conclusion

In conclusion, the results of the Poisson regression analysis presented provide valuable insights into the factors influencing poverty rates in the studied region. The statistical significance of all independent variables, as evidenced by the p-values below 0.05 in the Tests of Model Effects, underscores their relevance in explaining variations in the dependent variable—the count of poor heads of households. The findings reveal the individual impacts of specific socio-demographic and geographic variables on poverty rates. Average age exhibits a negative association, with a coefficient of 0.991, implying that a one-unit increase in average age results in a 0.9% expected decrease in the log count of poor heads of households. A family led by a young household head has a better chance of escaping poverty since young people actively work and have the energy to accomplish things that will improve their lives. Families led by the elderly, are more likely to fall into poverty. On the other hand, the number of non-formal education levels displays a positive relationship with poverty rates, with a coefficient of 1.007. Consequently, there is a 0.7% expected increase in poverty for every one-unit increase in non-formal education levels. Literacy and education are important markers of quality of life in and of themselves and critical factors of poor people's capacity to take advantage of income-generating possibilities.

Furthermore, the analysis examines the impact of geographic variables on poverty rates relative to their respective reference groups. Elevation, slope, and river density are considered, providing valuable insights into their effects. The findings reveal varying magnitudes of influence on poverty rates across different elevation ranges, slope categories, and river densities. For instance, specific elevation ranges show higher and lower poverty rates than the reference group. Likewise, different slope categories and river densities display varying degrees of impact on poverty rates.

Given these results, policymakers and stakeholders should consider the multifaceted nature of poverty determinants. Addressing poverty effectively necessitates targeted interventions that account for socio-demographic and geographic complexities. The identified variables should be considered when formulating policies and strategies for poverty reduction and sustainable development in the studied region. Further research and data analysis may provide deeper insights into the underlying mechanisms and potential interactions among these factors, aiding in more comprehensively designing evidence-based interventions to combat poverty.

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