

Spatial determinants of disability prevalence in Myanmar: A district-level spatial regression analysis

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ABSTRACT

Myanmar, a country with a significant number of persons with disability, needs an understanding of the variation in disability prevalence and its determinants for efficient intervention strategies. This study aims to identify geographic patterns and spatial determinants of disability prevalence across Myanmar's districts. This cross-sectional spatial analysis utilized data from Myanmar's 2019 Inter-Censal Survey covering all 80 districts. Getis-Ord G_i^* statistics were employed to discover spatial patterns and identify district-level clusters of disability prevalence. Beyond traditional spatial autocorrelation assessment, we applied comparative spatial regression modeling through Spatial Error Model (SEM) and Spatial Lag Model (SLM) to identify determinants of geographic disparities in disability prevalence. Our analytical framework distinguished between demographic vulnerabilities, technological protective factors, and district-level socioeconomic indicators. Heat mapping revealed substantial geographic variation in disability prevalence across Myanmar (ranging from 4.9 to 24.8 per 100 population). G_i^* statistics identified eight hotspots and ten cold spots ($p < 0.05$), demonstrating non-random distribution of disability prevalence. The optimal SEM ($R^2 = 0.579$) identified child dependency ratio ($\beta = 0.135$, $p < 0.001$) and old dependency ratio ($\beta = 0.665$, $p < 0.001$) as key determinants. Myanmar's disability landscape is characterized by significant district-level disparities. Demographic vulnerabilities, particularly child and elderly dependency ratios, constitute primary drivers of these disparities. These findings provide an evidence-based geographic framework for addressing disability disparities through targeted intervention and resource allocation rather than uniform approaches.

Keywords:

disability disparities, district-level analysis, geographic patterns, Myanmar, spatial regression

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INTRODUCTION

About 1.3 billion people (16%) of the global population are estimated to experience a significant disability, and this number is expected to increase with population aging and the rise of noncommunicable diseases.¹⁻³ According to studies, one in every six people in Asia and Pacific region is estimated to live with disability.⁴ In Myanmar, with a population of roughly 51 million, the 2014 national census estimated that 11.6% of the population were living with disability, equivalent to nearly 6 million people, affecting their everyday activities and societal integration.⁵

Disabilities in Myanmar manifest in diverse ways including physical, sensory, cognitive, and mental health-related challenges.⁶ Rural and remote areas often face higher burdens due to limited access to healthcare facilities, rehabilitation services and educational opportunities while urban centers may have comparatively better infrastructure and service availability.^{5, 7} The allocation and availability of resources and services aimed at supporting individuals with disabilities are also disproportionately distributed which can exacerbate existing social and economic inequalities and limit opportunities for full societal participation.^{1,3} Therefore, intervention strategies for disability including prevention, support, and rehabilitation increasingly require a sophisticated understanding of geographic variation in prevalence and underlying determinants and mechanisms.⁸⁻¹⁰

Disability is shaped by a complex interplay of various factors beyond mere health conditions. These include individual factors, social, and environmental factors.^{11,12} Sociodemographic factors, basic infrastructure, and accessibility to assistive technologies were also found to be associated with disability.¹² Poverty and social exclusion can increase disability risk, while disability often deepens

socioeconomic disadvantages such as lower income, unemployment, and limited access to education and resources, creating a complex, bidirectional relationship that perpetuates disadvantages.¹³ This cycle of disadvantage has been documented in multiple LMIC settings, including Southeast Asia.^{7,14} Structural factors also play a significant role, as persons with disabilities experience stigma, discrimination, and ableism in many aspects of life, with negative consequences for their physical and mental well-being.¹⁵

Geographic Information Systems (GIS) and spatial epidemiological methods have been increasingly applied to analyze health disparities, revealing how geographic location influences disability outcomes through various environmental, socioeconomic, and healthcare access pathways.^{16, 17} Recent studies from diverse contexts have demonstrated that spatial analysis can identify significant clusters of disability prevalence, revealing patterns that may remain hidden in conventional statistical approaches.^{9,16,18} Additionally, spatial regression models have proven particularly valuable for investigating geographic determinants of health outcomes, as they can account for spatial autocorrelation and dependency structures that traditional regression models cannot address.^{19,20} A study conducted in China showed that application of spatial regression revealed heterogeneous effects of study factors such as socio-economic and environmental factors on disability patterns, providing location-specific insights.²¹

Despite the considerable number of people with disabilities in Myanmar, spatial analysis and geographic perspectives have not been widely integrated into policymaking or planning processes. The absence of such insights hinders a comprehensive understanding of the unique challenges faced by people with disabilities in different regions and limits the development of inclusive policies and

targeted interventions. By analyzing disability within its geographical context, policymakers and researchers can gain nuanced insights into the issue and its underlying determinants. Therefore, this study aimed to investigate the determinants of district-level disability prevalence in Myanmar in 2019 using spatial regression analysis.

METHODS

Study area

Myanmar located in Southeast Asia and is administratively divided into 15 regions: 7 states, 7 regions and the union territory of Nay Pyi Taw. These areas are further subdivided into 80 districts which had been served as study areas in this study.²²

Data sources

Datasets for cropland were obtained from the Copernicus Global Land Cover Layers: CGLS-LC100 Collection 3, facilitated by The Copernicus Land Monitoring Service.²³ Disability prevalence and socioeconomic factors such as child dependency ratio, old dependency ratio, media access to television, media access to radio, mobile phone usage, and internet availability and usage were extracted from the Myanmar Intercensal Survey, 2019 covering all 80 districts.²⁴ Disability was defined as the existence of any one out of six functions such as seeing, walking or climbing steps, remembering or concentrating, hearing, self-care and communication. Number of schools and health facilities data were acquired from the Myanmar Information Management Unit.²⁵

Data preparation

After validating and cleaning the dataset for accuracy, we imported the data into Quantum GIS (QGIS) version 3.40 (Open-Source Geospatial Foundation) to

integrate spatial and non-spatial information for mapping disability prevalence and identifying clusters. We then performed detailed spatial analysis using GeoDa, version 1.22 (the Center for Spatial Data Science at the University of Chicago, Illinois, USA).

Complete data for disability prevalence were available for 71 out of Myanmar's 80 districts, with nine districts without reported data in the 2019 Myanmar Intercensal Survey (Danu, Hopan, Kokang, Matman, Maungdaw, Maruk-U, Naga, Pa Laung, and Pa-O Self-Administered Zones). To ensure robustness despite missing data in these nine districts, we first confirmed the stability of our identified spatial patterns by testing our primary analyses with variations in spatial weights specifications, then proceeded with our main analyses using appropriate weight matrices for each analytical approach.

Data analysis

Gi statistics

The Getis-Ord G_i^* statistic was used to find spatial clusters of disability prevalence across Myanmar's districts by comparing the number of cases in each district to those in neighboring districts to provide insights into where targeted public health interventions would have been most effective.²⁶ This method highlights statistically significant hotspots (areas with high case concentrations) and cold spots (areas with low concentrations), indicating whether clusters are higher or lower than would be expected on average.²⁷

Getis-Ord G_i^* statistics were computed using the following formula.

$$G_i^* = \frac{\sum_j w_{ij} \chi_j}{\sum_j \chi_j}$$

Where the weights are determined by w_{ij} , and the normalization is done by dividing by the total sum of X_j values.

The Getis-Ord G_i^* statistic was used to identify statistically significant hot and cold spots of disability prevalence across districts.²⁶ The G_i^* statistic evaluates the degree of spatial clustering by comparing the local sum of values within a specified neighborhood to the expected local sum under spatial randomness.²⁷ It is computed as:

$$G_i^* = \frac{\sum_j w_{ij}x_j - \bar{X}\sum_j w_{ij}}{S\sqrt{\frac{n\sum_j w_{ij}^2 - (\sum_j w_{ij})^2}{n-1}}}$$

where x_j is the value at location j , w_{ij} is the spatial weight between locations i and j , $\bar{X}$ is the global mean, S is the global standard deviation, and n is the number of spatial units. Positive statistically significant G_i^* values indicate hot spots (high-value clusters), whereas negative significant values denote cold spots (low-value clusters). A 3-nearest neighbor spatial weight matrix was used to ensure that each district had a consistent neighborhood structure for hotspot detection.

Local Indicators of Spatial Association (LISA)

Local Moran's I was computed using the equation:

$$I1 = \frac{Z_i}{S_1} * Z_j W_{ij}$$

In this context, " n " represents the number of regions, " Z " denotes each variable's deviation from the mean, " S_1 " is the total of squared deviations, and " W_{ij} " indicates spatial weights between regions i and j .

We assessed spatial autocorrelation using Local Indicators of Spatial Association (LISA), which includes metrics such as Moran's I to identify spatial patterns.²⁸ LISA was used to examine the overall spatial autocorrelation of disability prevalence and related factors. By applying

Moran's I within LISA, we determined whether specific regions formed spatial clusters with similar disability prevalence (e.g., high-high or low-low) or acted as outliers (such as high-low or low-high). Statistical significance was evaluated using 999 permutations, with a p-value threshold of <0.05 .

Local Getis-Ord G_i^* and LISA significance maps were generated using $p < 0.05$ based on 999 permutations. Consistent with standard spatial cluster analysis, no formal multiple comparison correction (e.g., False Discovery Rate, FDR) was applied because cluster detection methods assume spatial dependence rather than independent tests.

Regression analysis

Multivariable analysis was conducted to examine how spatial factors are associated with disability prevalence, while simultaneously accounting for possible confounders to provide a more nuanced understanding of what determines disability. During initial analysis, the p-value and Moran's I statistics were assessed for each variable, and those with a p-value below 0.05 proceeded to the regression phase. The full list of candidate variables included were child dependency ratio, old dependency ratio, media access to radio, mobile phone usage, cropland percentage, number of schools, and number of hospitals. Three types of multivariable models were utilized. The Ordinary Least Squares (OLS) regression estimates the association between disability and several variables, however, this model presumes there is no spatial dependence between observations.²⁹ If significant positive spatial autocorrelation was detected, relying solely on OLS would not be methodologically sound, so Spatial Error Models (SEM) and Spatial Lag Models (SLM) were applied to address this issue in our study.

The Spatial Error Model (SEM) corrects for spatial autocorrelation in the

model's error terms by factoring in spatial dependence, which in turn increases the reliability of the model by ensuring errors do not display spatial clustering.³⁰ By contrast, the Spatial Lag Model (SLM) introduces a spatially lagged dependent variable to represent the impact of disability prevalence in adjacent districts on an area's own prevalence, effectively capturing spillover effects and spatial interactions.³¹ A backward elimination procedure was then applied. All screened variables were entered into the initial OLS model, and at each step the variable with the highest p-value was removed, provided that its removal did not substantially worsen model fit (AIC) or alter key coefficients. After the final OLS model was established, spatial dependence was evaluated using Moran's I of the residuals and the Lagrange Multiplier (LM) family of tests (LMlag, LMerr, robust LMlag, robust LMerr). Both LM tests were significant, but the LMlag statistic showed stronger evidence of spatial dependence, indicating that a spatial lag specification was more appropriate than a spatial error process. Therefore, the Spatial Lag Model (SLM) was selected for final interpretation. Final model selection was based on the significance of the spatial lag parameter (ρ), improved model fit (AIC, BIC, log-likelihood), and the absence of spatial autocorrelation in SLM residuals.

Spatial Weights, Missing Data Handling and Sensitivity Analysis

Weight matrices define spatial relationships between regions and are essential for detecting spatial patterns and dependence.³² This study used a 3-nearest-neighbour (3-NN) weight matrix for the Getis-Ord G_i^* statistic and bivariate Moran's I analysis to ensure that each district had at least three neighbors,

preventing isolated units and producing stable hotspot results. For the spatial regression models, a first-order Queen contiguity matrix was applied. Queen contiguity identifies districts as neighbors if they share a border or vertex and is widely recommended for administrative-area analyses because it reflects realistic geographic, demographic, and administrative interactions.

Disability prevalence data were available for 71 of Myanmar's 80 districts; nine districts (Danu, Hopan, Kokang, Matman, Maungdaw, Maruk-U, Naga, Palaung, and Pa-O Self-Administered Zones) had no reported values. These nine districts were excluded from the primary analysis, and all spatial weight matrices were recalculated based on the remaining 71 districts to ensure consistent and complete model estimation. To assess the robustness of the findings to alternative spatial structures, we conducted a sensitivity analysis using inverse-distance weighting (IDW) in GeoDa. IDW is a deterministic spatial interpolation approach in which the influence of neighboring observations decreases with increasing distance, allowing closer districts to contribute more heavily to the local estimate.³³ Using these distance-based weights, we re-estimated the OLS, Spatial Error Model (SEM), and Spatial Lag Model (SLM) using the same predictor variables. As GeoDa recalculates spatial diagnostics and parameters, whenever the dataset or weight matrix changes, numerical differences between the primary Queen-based models and the sensitivity models were expected. The sensitivity analysis enabled us to evaluate whether the substantive conclusions remained stable under a different conceptualization of spatial dependence.

RESULTS

Distribution of Disability Prevalence Across Myanmar Districts

The heatmap in Figure 1 displays the spatial distribution of disability prevalence across Myanmar districts, using a sequential color gradient from dark purple (lowest prevalence) to bright yellow (highest prevalence). Disability prevalence ranged from 4.9 per 100 population in

Mohnyin district to 24.8 per 100 population in Langkho district, compared to the national prevalence of 12.9 per 100 population. Notable geographic clustering of higher prevalence rates is evident in western border regions, with additional elevated rates observed in select central and northern districts. Eastern and southern regions predominantly exhibited lower prevalence rates relative to the national average (Figure 1).

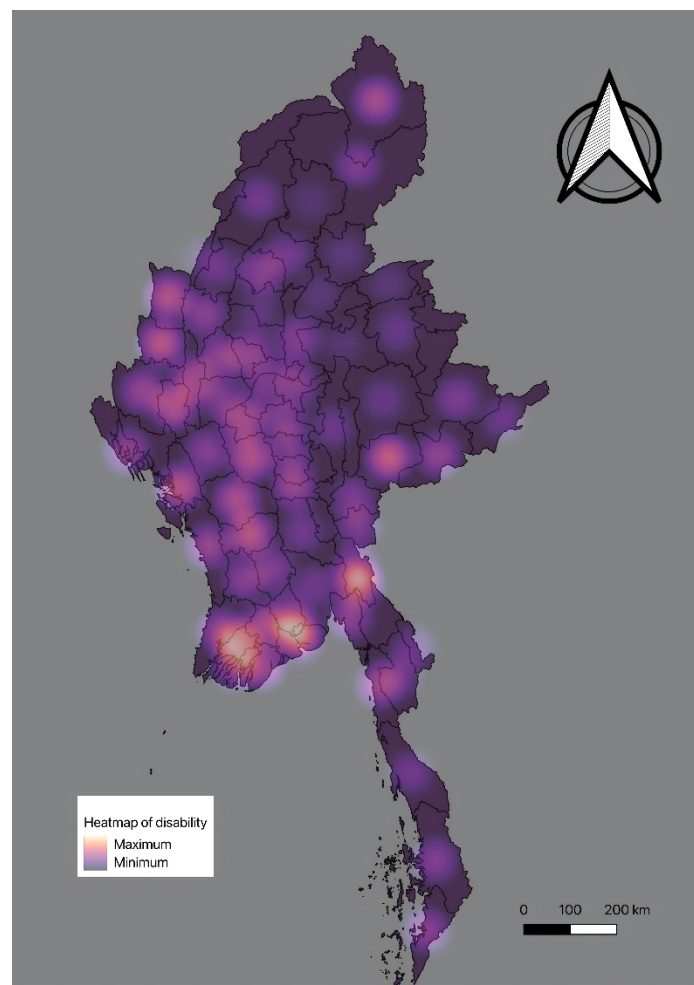


Figure 1. Heatmap of the prevalence of disability in Myanmar

Spatial autocorrelation of disability prevalence using Getis-Ord G_i^* statistics

The Getis-Ord G_i^* spatial clustering analysis identified statistically significant clusters of both high-high (HH) and low-low (LL) disability prevalence patterns across Myanmar districts. Eight

districts demonstrated significant high-high clustering patterns, indicating hot spots where high disability prevalence values cluster spatially with similarly high neighboring values. Conversely, ten districts exhibited significant low-low clustering patterns representing cold spots

of consistently low disability prevalence. The spatial distribution revealed distinct regional patterns where high-high clusters were predominantly located in western and central-western regions, while low-low clusters were primarily concentrated in northern and eastern border areas, confirming statistically significant spatial

clustering that indicates non-random geographic distribution of disability prevalence across Myanmar with clear regional disparities between high-prevalence western areas and low-prevalence northern and eastern regions (Table 1; Figure 2).

Table 1. Gi* cluster of prevalence of disability in Myanmar

Gi* statistics	
HH	LL
Labutta**	Hopang**
Minbu**	Lashio**
Thayet**	Muse**
Hakha*	Taunggyi**
Mrauk-U*	Bhamo*
Patheingyi*	Hkamti*
Pyawbwe*	Kokang Self-Administered Zone*
Thandwe*	Kyaukse*
	Pa Laung Self-Administered Zone*
	Putao*

Note: p -value: 0.05*, p -value: 0.01**, p -value: 0.001***



a. Gi* cluster of cluster map of prevalence of disability

b. Gi* significant map of prevalence of disability

Figure 2. Gi* statistics of prevalence of disability in Myanmar

Bivariate analysis of demographic and social factors with the prevalence of disability

The child dependency ratio exhibited significant spatial autocorrelation with a geographic distribution pattern that

aligned with disability prevalence across Myanmar districts (Moran's $I = 0.137$). Local Indicators of Spatial Association (LISA) analysis revealed five high-high clustering areas where elevated child dependency ratios coincided with increased

disability prevalence, with these districts surrounded by neighboring areas displaying comparable characteristics. Conversely, four low-low clustering patterns were identified in regions characterized by reduced child dependency ratios and lower disability rates, with surrounding districts exhibiting similarly low values. A statistically significant positive spatial clustering pattern was observed between the old dependency ratio and disability prevalence across Myanmar districts (Moran's $I = 0.259$). The LISA analysis revealed geographic concentrations of high-high clusters where districts with elevated elderly dependency ratios coexisted with increased disability rates in seven locations. In contrast, low-low clusters emerged in nine districts characterized by reduced elderly dependency and lower disability prevalence.

Bivariate analysis resulted in Moran's I value of 0.095, suggesting a weak association between media access to television and the prevalence of disability. There was a statistically significant positive spatial correlation between radio access and disability prevalence (Moran's $I = 0.241$).

High-high clusters (hotspots) of both radio access and disability prevalence were detected in Pyapon, Labutta, Pathein, Thayet, Minbu and Thandwe districts. Low-low clusters (cold spots) appeared in Puta-O, Hkamti, the Pa Laung and Kokang Self-Administered Zones, Hopang and Muse districts. In contrast, Mrauk-U and Hakha districts stood out for having low radio access alongside a high prevalence of disability.

The analysis indicated a modest but statistically significant positive spatial autocorrelation between mobile phone usage and disability prevalence (Moran's $I = 0.145$). High-high clusters areas characterized by both high mobile phone usage and high disability prevalence were detected in Pyapon, Thayet, Thandwe, Hakha and Minbu districts. Conversely, low-low cluster regions with both low mobile phone usage and low disability prevalence appeared in Puta-O, Hkamti, the Pa Laung and Kokang Self-Administered Zones, and Hopang district. There was insignificant positive spatial autocorrelation between internet accessibility and disability prevalence (Moran's $I = 0.091$) (Table 2; Figure 3).

Table 2. Bivariate analysis of demographic and social factors with prevalence of disability using LISA

Factors	Moran's I	LISA				p-value
		HH	HL	LH	LL	
Child dependency ratio	0.137	Labutta**	Lashio**	Minbu**	Hopang**	0.05*
		Pathein*	Taunggyi**	Thayet**	Kokang	0.01**
		Pyapon*	Muse**	Mrauk-U*	Self-	0.001***
		Thandwe*	Bhamo*		Administere	
		Hakha*	Hkamti*		d Zone*	
			Put-a-O*		Kyaukse*	
					Pa Laung	
Old dependency ratio	0.259	Minbu**	Kyaukse*	Mrauk-U*	Self-	
		Labutta**			Administere	
		Thayet**			d Zone*	
		Hakha*			Hopang**	0.05*
		Pathein*			Muse**	0.01**
					Taunggyi**	0.001***
					Bhamo*	
					Hkamti*	

Factors	Moran's I	LISA				p-value
		HH	HL	LH	LL	
		Pyapon* Thandwe*			Kokang Self-Administere d Zone* Lashio** Pa Laung Self-Administere d Zone* Putta-O*	
Media access to television	0.095	Minbu**	Lashio**	Labutta**	Hopang**	0.05*
		Thandwe*	Muse**	Thayet**	Hkamti*	0.01**
		Hakha*	Taunggyi**	Mrauk-U*	Kokang	0.001***
			Bhamo*	Pathein*	Self-Administere d Zone* Pa Laung Self-Administere d Zone* Putta-O*	
Media access to radio	0.241	Minbu**	Taunggyi**	Hakha*	Putta-O*	0.05*
		Labutta**	Kyaukse*	Mrauk-U*	Hkamti*	0.01**
		Pathein*	Bhamo*		Pa Laung	0.001***
		Pyapon*			Self-Administere d Zone* Kokang Self-Administere d Zone* Hopang** Muse** Lashio**	
Mobile phone usage	0.145	Thayet**	Kyaukse*	Mrauk-U*	Putta-O*	0.05*
		Minbu**	Taunggyi**	Labutta**	Hkamti*	0.01**
		Thandwe*	Bhamo*	Pathein*	Pa Laung	0.001***
		Hakha*	Muse** Lashio**		Self-Administere d Zone* Kokang Self-Administere d Zone* Hopang**	
Internet usage	0.091	Thayet**	Muse**	Labutta**	Hopang**	0.05*
		Thandwe*	Lashio**	Minbu**	Hkamti*	0.01**
			Taunggyi**	Mrauk-U*	Kokang	0.001***
			Bhamo*	Pathein*	Self-	

Factors	Moran's I	LISA				p-value
		HH	HL	LH	LL	
				Pyapon* Hakha*	Administrere d Zone* Kyaukse* Pa Laung Self- Administrere d Zone* Putta-O*	

Note: HH: High-High, HL: High-Low, LH: Low-High, LL: Low-Low, Significance levels: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

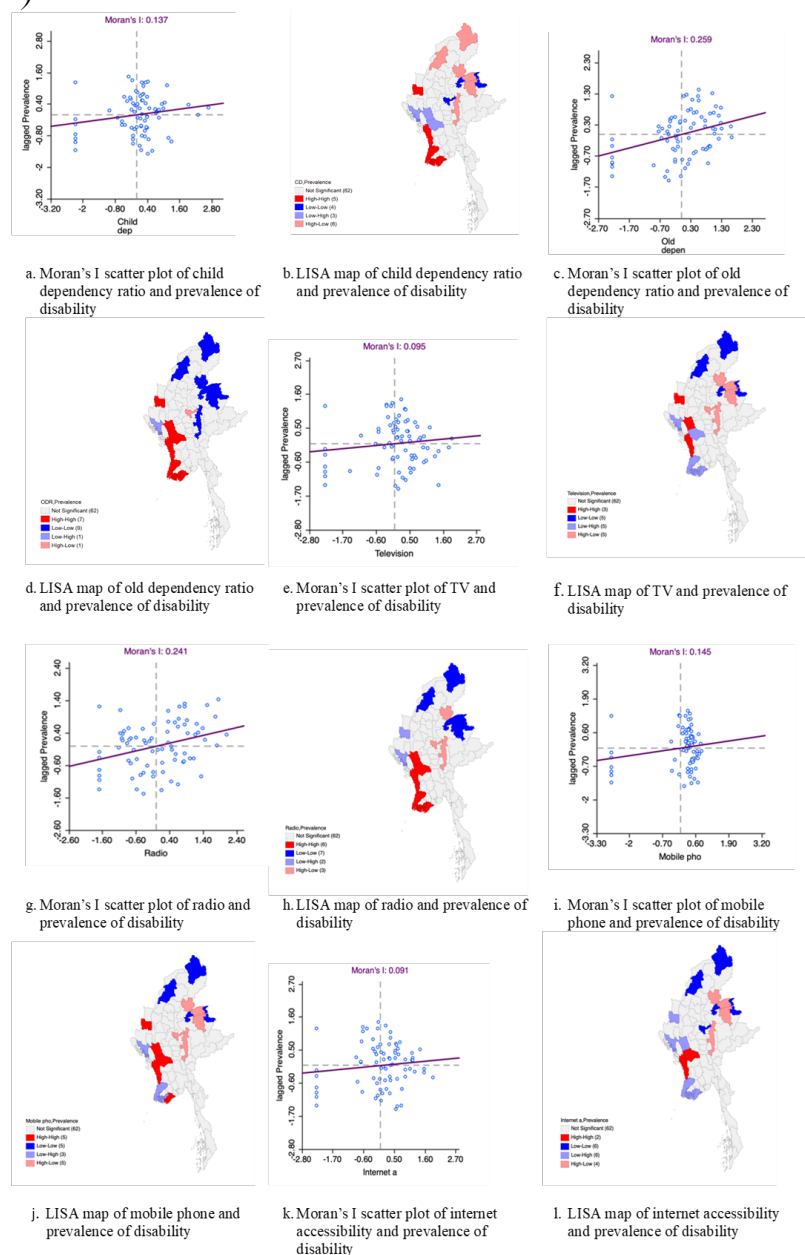


Figure 3. Bivariate analysis of demographic and social factors with prevalence of disability using LISA

Bivariate analysis of environmental and infrastructural factors and prevalence of disability

The bivariate analysis of cropland and disability prevalence revealed a statistically significant positive autocorrelation with a Moran's I value of 0.213. The analysis identified high crop land areas with high disability prevalence (hotspots or High-High clusters) in districts such as Pyapon, Labutta, Pathein, Thayet and Minbu. Additionally, regions with both low crop land area and low disability prevalence (cold spots or Low-Low clusters) were found in Puta-O, Hkamti, Bhamo, Pa Laung Self-Administered Zone, Kokang Self-Administered Zone, Lashio, Hopang, Muse and Taunggyi districts.

The LISA analysis revealed a statistically significant positive autocorrelation between the number of hospitals and disability prevalence with a Moran's I value of 0.214. Hotspot clusters were detected in Pyapon, Pathein, Thayet, Minbu and Mrauk-U districts while cold-spot clusters with a low number of hospitals and disability prevalence were observed in Puta-O, Hkamti, Pa Laung Self-Administered Zone, Kokang Self-Administered Zone, Hopang Bhamo and Lashio districts. In contrast, Labutta, Thandwe and Hakha districts formed low-high clusters, characterized by a low number of hospitals alongside high disability prevalence (Table 3; Figure 4).

Table 3. Bivariate analysis of environmental and infrastructural factors and prevalence of disability using LISA

Factors	Moran's I	LISA				p-value
		HH	HL	LH	LL	
Cropland	0.213	Labutta**	Kyaukse*	Hakha*	Hopang**	0.05*
		Minbu**		Mrauk-U*	Lashio**	0.01**
		Thayet**		Thandwe*	Muse**	0.001***
		Pathein*			Taunggyi**	
		Pyapon*			Hkamti*	
					Kokang Self-Administered Zone*	
					Bhamo*	
					Pa Laung Self-Administered Zone*	
					Puta-O*	
Number of schools	0.242	Minbu*	Sittwe***	Hakha*	Hopang*	0.05*
		Mrauk-U*	Lashio**	Thandwe*		0.01**
		Labutta*				0.001***
		Pathein*				
		Pyapon*				
		Thayet*				
Number of hospitals	0.214	Minbu**	Muse**	Labutta**	Hopang**	0.05*
		Thayet**	Taunggyi**	Hakha*	Lashio**	0.01**
		Pyapon*	Kyaukse*	Thandwe*	Bhamo*	0.001***
		Pathein*			Hkamti*	
		Mrauk-U*				

Factors	Moran's I	LISA				p-value
		HH	HL	LH	LL	
					Kokang Self-Administered Zone*	
					Putao-O*	
					Pa Laung Self-Administered Zone*	

Note: HH: High-High, HL: High-Low, LH: Low-High, LL: Low-Low, Significance levels: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

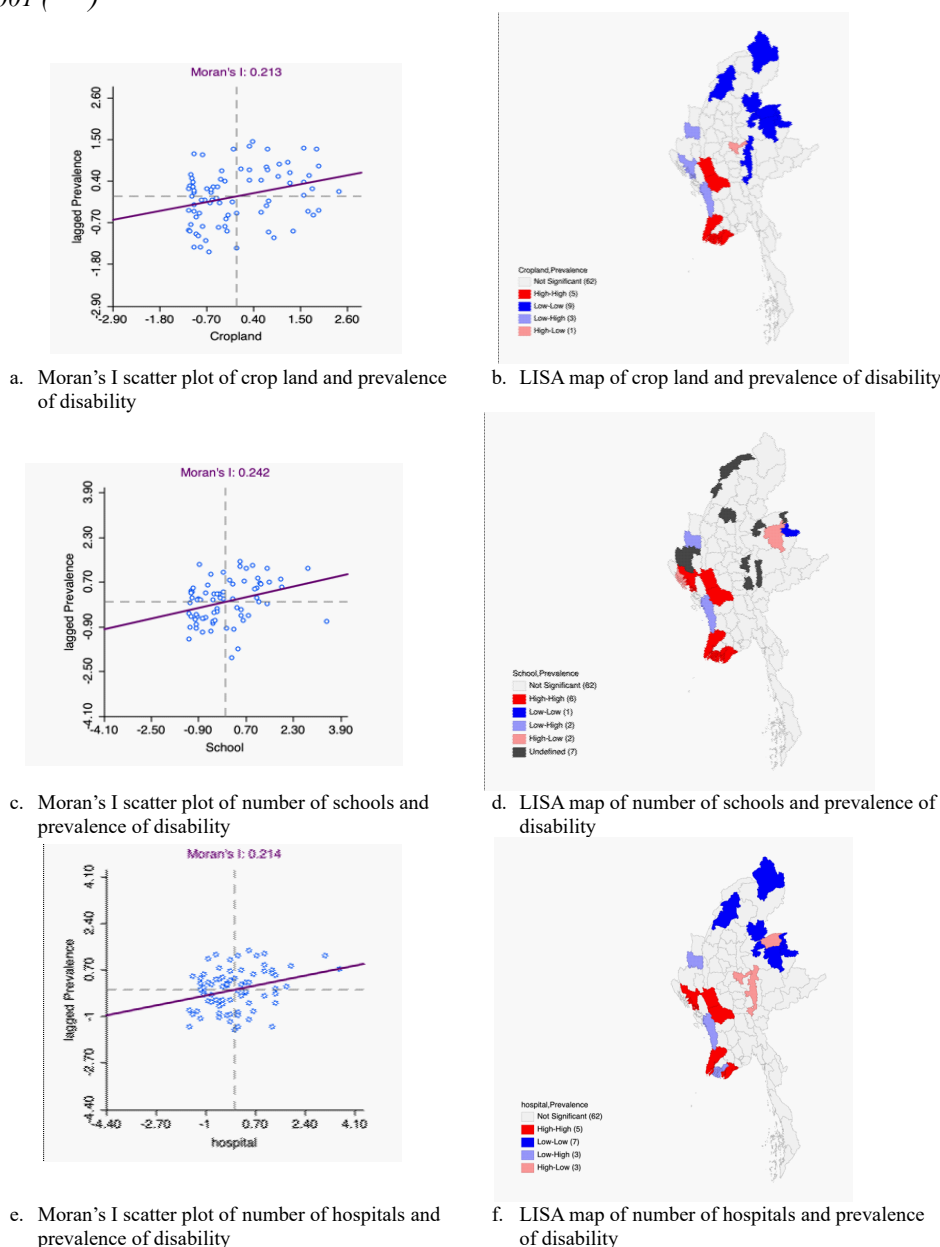


Figure 4. Bivariate analysis of environmental and infrastructural factors and prevalence of disability

Spatial regression analysis of the prevalence of disability in Myanmar at the district level

Child dependency ratio and old dependency ratio remained significant in the final OLS model. Residual diagnostics revealed significant spatial autocorrelation in the OLS residuals, prompting further testing using the Lagrange Multiplier (LM) family of tests. Both LMlag and LMerr statistics were significant; however, LMlag ($p = 0.007$) provided stronger evidence of spatial dependence than LMerr ($p = 0.026$), and the robust LMlag remained significant. These results indicate that a spatial lag process was more appropriate than a spatial error process.

The Queen-contiguity Spatial Lag Model (SLM) provided the best overall fit among the three models examined (AIC = 466.06; BIC = 475.59; log-likelihood = -229.03). Both retained predictors remained positively associated with disability prevalence: child dependency ratio ($\beta = 0.135$, $p < 0.001$) and old dependency ratio ($\beta = 0.665$, $p < 0.001$). The spatial lag parameter was statistically significant (Rho

(ρ) = 0.306, $p = 0.005$), indicating substantive spatial spillover effects, whereby disability prevalence in a district is influenced by conditions in neighboring districts. Although mobile phone usage appeared significant in the exploratory analysis, the association did not persist after updating missing district values, recalculating spatial weights, and applying backward elimination. Mobile phone usage became non-significant in the multivariable model and did not improve model fit; therefore, it was excluded from the final specification (Table 4).

To evaluate whether the final model adequately accounted for spatial dependence, Moran's I was computed for the SLM residuals. The result was very close to zero and statistically non-significant (Moran's I = 0.002, $p = 0.385$), indicating that residual spatial autocorrelation was effectively eliminated. This confirms that the SLM sufficiently captures the spatial structure of the data and that no meaningful spatial clustering remained in the residuals.

Table 4. Spatial regression analysis of prevalence of disability in Myanmar

	OLS	SEM	SLM
Child dependency ratio	0.139 ($p < 0.001$) ***	0.134 ($p < 0.001$) ***	0.135 ($p < 0.001$) ***
Old dependency ratio	0.769 ($p < 0.001$) ***	0.669 ($p < 0.001$) ***	0.665 ($p < 0.001$) ***
Constant	-0.548	0.487	-3.111
ρ	-	-	0.306
λ (varies between 0.1 and 1.0)	-	0.347	-
F-stat (minimum value = 0)	43.191	-	-
R-Squared (coefficient of determination)	0.516	0.579	0.579
Log Likelihood	-232.699	-230.207	-229.031
AIC	471.398	466.414	466.062
BIC	478.544	473.56	475.59
Lagrange Multiplier		4.984 ($p = 0.026$) *	7.336 ($p = 0.007$) **

Sensitivity Analysis

Using inverse-distance weights, the SEM again showed the best performance among the three models (AIC = 463.38; BIC = 472.91, $R^2=0.596$). The same two demographic variables such as child dependency ratio ($\beta = 0.140$, $p < 0.001$) and old dependency ratio ($\beta = 0.619$, $p < 0.001$) remained significant predictors. The spatial lag parameter was also significant ($p = 0.442$, $p < 0.001$), confirming persistent spatial dependence under the alternative weight matrix. Coefficient magnitudes differed modestly between the Queen-based and inverse-distance SEMs, which is expected when the spatial weight matrix changes. Importantly, the core determinants (child and old dependency ratios) remained consistent in direction and significance across both models. Model fit statistics were comparable, and no substantive change in interpretation was observed.

DISCUSSION

Using Getis-Ord G_i^* ,^{9 16 34-38} we identified high-disability clusters in Pyapon, Labutta, Pathein, Thandwe, Minbu, Hakha, and Mrauk-U locations plausibly shaped by environmental hazards such as floods/cyclones with injury and limited rehabilitation,³⁹ entrenched poverty and weak health systems,⁴⁰ and conflict-related trauma (e.g., Mrauk-U).⁴¹ Low-disability “cold spots” (Putao, Hkamti, Bhamo, Lashio, Muse) likely reflect a mix of under-enumeration in remote settings, stigma and language barriers, small denominators, youthful/mobile populations, out-migration of disabled individuals, and more diversified local economies.⁴² Findings aligned with spatial analyses from China⁴³, Iran⁴⁴, India⁴⁵ and the United States⁴⁶ which similarly reported geographically clustered disability patterns driven by demographic ageing and socioeconomic disparities. Studies from Tianjin⁴³, Khuzestan⁴⁴, and US⁴⁶ county-

level analyses have also shown that dependency ratios and age structure are strong predictors of disability burden, reinforcing the consistency of our findings across diverse settings. However, unlike studies in high-income countries where well-developed infrastructure mitigates disability risks, our results suggest that environmental hazards, agricultural occupational risks, and service provision gaps play a greater role in Myanmar.

Spatial overlap with areas of intensive cropland indicates that factors such as pesticide exposure, and labor-intensive agricultural practices likely contribute to higher disability rates, whereas regions with less agricultural activity exhibit lower disability prevalence. An Indian study identified agriculture as one of the most hazardous occupations, exposing workers to a spectrum of risks, including extreme weather, physical injuries, chemical hazards, respiratory conditions, skin diseases, and poisoning.⁴⁷ These risks are exacerbated by limited access to healthcare, insufficient awareness, and inadequate adoption of personal protective equipment.⁴⁸ Therefore, implementing safe agricultural practices and risk mitigation strategies in areas with extensive cropland is essential to reduce disability rates.

Media access showed a positive correlation with disability prevalence, especially for radio. In rural Myanmar, radio's broader reach relative to TV/Internet can raise awareness and care-seeking behavior, inflating observed prevalence through improved case finding.^{49 50} Cold-spot regions with low media access and low recorded disability prevalence likely face a contrasting pattern (limited awareness/reporting). Thus, radio and other accessible channels remain pragmatic levers to strengthen disability awareness, reporting, and service engagement.

Exploratory spatial analysis revealed positive autocorrelation between

mobile phone use and disability prevalence, with high–high clusters (e.g., Pyapon, Thayet, Thandwe) and low–low clusters (e.g., Puta-O, Hkamti). While this might suggest higher disability in mobile-rich areas, the pattern more likely reflects ascertainment and infrastructure effects, as regions with stronger connectivity also tend to have better facilities, higher literacy, and more active surveillance that increase case detection. Consistent with evidence from LMICs, mobile technologies can reduce inequities by improving information access, care navigation, and assistive-technology uptake,⁵¹ whereas Myanmar's limited internet penetration (<50%) and uneven reception^{52 53} likely suppress reporting in low-coverage areas. Studies using spatial exploratory data analysis similarly find local clusters where mobile penetration tracks health outcomes through service access and awareness pathways.⁵⁴ Therefore, these crude clustering reflects better case-finding and reporting of disability cases.

Education (number of schools) and health-facility access (number of hospitals) showed similar dual roles. Regions with greater educational and health facility access (e.g., Mrauk-U, Thayet, Minbu, Labutta, Pathein, Pyapon) recorded higher prevalence, consistent with better case detection while places with low access and low prevalence (e.g., Hopang) likely under-report. Contrasting patterns (e.g., Thandwe, Hakha: high disability with low education access) underscore how inadequate infrastructure and low awareness compound unmet need. This diverges from evidence in China, where greater education and medical access have correlated with lower disability,⁹ suggesting contextual differences in system capacity, socioeconomic structure, and the balance between detection and prevention.

The spatial modelling results from our study revealed that factors such as the

child dependency ratio and old dependency ratio significantly influenced the spatial distribution of disability prevalence in Myanmar. Diagnostic tests identified the Spatial Lag Model as the best-fitting specification for explaining the spatial patterning of disability prevalence. The significant spatial lag parameter ($\rho = 0.306$) suggests that disability levels in one district are influenced by neighboring districts, supporting the presence of substantive rather than residual spatial dependence. The superiority of the SLM was confirmed by both Lagrange Multiplier tests and AIC/log-likelihood criteria. Mobile phone usage was significantly associated with disability prevalence in the preliminary analysis, consistent with the idea that digital access may proxy for socioeconomic status, urbanization, or health service access. However, after applying updated spatial weights and correcting missing data, the association did not remain significant in multivariable modeling and was removed during backward elimination. The loss of significance suggests that the initial association may have been confounded by demographic structure particularly dependency ratios which were more robust predictors in the final model. Future studies incorporating direct socioeconomic indicators (e.g., income, education, urbanicity indices) would help determine whether digital access independently influences disability patterns. Bivariate analysis also revealed districts with higher proportions of older adults clustered with elevated disability prevalence, consistent with the burden of chronic disease and age-related functional decline.⁵⁵ Similarly, districts with high child dependency also exhibited higher disability prevalence, likely linked to congenital conditions, perinatal complications, and socioeconomic vulnerability.⁵⁶

The strong association of both child and old dependency ratios with disability

prevalence reflects plausible demographic mechanisms. Higher old-age dependency indicates larger proportions of older adults who experience age-related functional decline, chronic disease burden, and limited access to long-term care, all of which increase disability burden. Similarly, high child dependency may reflect poorer maternal and child health services, higher rates of perinatal complications, poverty-related nutritional deficiencies, and developmental conditions that contribute to functional limitations. Districts with high dependency ratios may also face constrained household resources, diminishing caregiving capacity and increasing the likelihood of unmet health needs, thereby contributing to higher disability prevalence. Together, these findings suggest that both health system capacity and demographic structures are key determinants of disability distribution, underscoring the need for integrated policies that strengthen healthcare access while addressing the specific needs of ageing populations and children. Policy responses should prioritize disability screening and rehabilitation services in high-burden districts, expand geriatric and maternal-child health programs in areas with high dependency ratios, and address agricultural injury risks through safer farming technologies and pesticide regulation. Strengthening district-level health infrastructure, improving digital connectivity, and integrating disability data into local planning systems would support more equitable service delivery. Community-based rehabilitation and inclusive education programs should be expanded in hotspot areas to mitigate long-term functional limitations.

Although best efforts were made to ensure rigor, some limitations should be acknowledged. First, reliance on secondary district-level data from 2019 limits the temporal relevance of the findings, as subsequent changes in healthcare access and infrastructure are not reflected. Second,

the ecological design restricts inference to populations and may be subject to ecological fallacy. Third, the cross-sectional nature of the analysis precludes causal interpretation, as observed associations may be influenced by reverse causation or unmeasured confounders. Fourth, although nine districts lacked disability data and were excluded, the potential for bias from non-random missingness cannot be fully ruled out, even though we recalculated spatial weight matrices and conducted sensitivity analyses using inverse-distance weighting to assess robustness.

Fifth, while Getis-Ord G_i^* and LISA statistics were used to identify local spatial clusters, no multiple-comparison adjustments (such as False Discovery Rate correction) were applied. As local indicators involve many spatially dependent tests, the absence of correction may increase the likelihood of false-positive clusters. Therefore, hotspot/cold-spot results should be interpreted cautiously, and future studies could incorporate FDR-adjusted local tests for greater statistical rigor. Sixth, disability reporting in Myanmar is likely incomplete, particularly in remote or conflict-affected areas where stigma, enumeration challenges, and limited health services may bias prevalence estimates. Seventh, indicators of healthcare, education, and communication were based on aggregated proxies that did not capture service quality, utilization, or accessibility for persons with disabilities and mobile phone and media access variables did not differentiate between ownership, functionality, or disability-friendly usage, which may have led to overestimation of their potential impact. Finally, although the dataset included 71 districts, the statistical power of spatial regression models may be limited for detecting small effect sizes. While the sample size meets recommended minimum thresholds for spatial autoregressive modeling, larger samples would provide

greater precision and stronger power to detect weaker associations. Therefore, non-significant findings particularly for variables screened during model selection should be interpreted with caution.

RECOMMENDATION

This study identified clear spatial clusters of disability prevalence in Myanmar, with hotspots concentrated in Southwestern and Western districts and lower prevalence in Northern and Northeastern areas. Because the strongest predictors of disability were the old-age and child dependency ratios, followed by cropland exposure and infrastructure constraints, policy actions should prioritize districts with high dependency structures. In these areas, targeted expansion of geriatric care, maternal and child health services, early developmental screening, and rehabilitation capacity is essential. Districts with extensive cropland should additionally receive agricultural safety interventions, including safer farming technologies, pesticide regulation, and injury-prevention training. Implementation of these interventions will require strengthening district-level health infrastructure, deploying mobile rehabilitation teams, improving roads and communication networks, and establishing partnerships with local authorities and disability organizations to ensure feasibility. Resource allocation should follow a spatially targeted approach, directing higher investment to districts with the highest predicted disability burden. To ensure effectiveness, a monitoring and evaluation framework should be established, including district-level tracking of disability prevalence, service utilization, assistive device coverage, and annual reanalysis of hotspot and cold-spot patterns. Digital reporting platforms could further enhance surveillance, particularly in

remote and high-risk regions. Finally, long-term strategies should include strengthening disability data systems, improving district-level surveillance, and conducting longitudinal spatial studies that incorporate socioeconomic and service-quality indicators unavailable in the present dataset. These measures collectively offer a practical, prioritized, and evidence-based approach to reducing spatial disparities in disability across Myanmar.

AUTHORS' CONTRIBUTIONS

ESU: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Software, Visualization, Writing - original draft, Writing - review & editing, Validation and Supervision. WMT: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Visualization, Writing - original draft, Writing - review & editing, Validation and Supervision. KMH: Methodology, Investigation, Data curation, Visualization, Writing - review & editing, and Validation. YYTU: Methodology, Investigation, Data curation, Visualization, Writing - review & editing and Validation.

ETHICAL CONSIDERATIONS

Prior to commencing, this study obtained necessary ethical endorsement from the Research and Ethics Committee (REC) at Yangon's University of Medicine (1), reference 66/UM1, REC, 2023 on 28th February 2024.

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CONFLICTS OF INTEREST

The authors declare that no conflict of interest exists in relation to this study.

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