Spatial associations between chronic kidney disease and socio-economic factors in Thailand

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Abstract

Chronic kidney disease (CKD) is a persistent, progressive condition characterized by gradual decline of kidney functions leading to a range of health issues. This research used recent data from the Ministry of Public Health in Thailand and applied spatial regression and local indicators of spatial association (LISA) to examine the spatial associations with night-time light, Internet access and the local number of health personnel per population. Univariate Moran's *I* scatter plot for CKD in Thailand's provinces revealed a significant positive spatial autocorrelation with a value of 0.393. High-High (HH) CKD clusters were found to be predominantly located in the North, with Low-Low (LL) ones in the South. The LISA analysis identified one HH and one LL with regard to Internet access, 15 HH and five LL clusters related to night-time light and eight HH and five LL clusters associated with the number of health personnel in the area. Spatial regression unveiled significant and meaningful connections between various factors and CKD in Thailand. Night-time light displayed a positive association with CKD in both the spatial error model (SEM) and the spatial lag model (SLM), with coefficients of 3.356 and 2.999, respectively. Conversely, Internet access exhibited corresponding negative CKD associations with a SEM coefficient of -0.035 and a SLM one of -0.039. Similarly, the health staff/population ratio also demonstrated negative associations with SEM and SLM, with coefficients of -0.033 and -0.068, respectively. SEM emerged as the most suitable spatial regression model with 54.8% according to R^2. Also, the Akaike information criterion (AIC) test indicated a better performance for this model, resulting in 697.148 and 698.198 for SEM and SLM, respectively. These findings emphasize the complex interconnection between factors contributing to the prevalence of CKD in Thailand and suggest that socio-economic and health service factors are significant contributing factors. Addressing this issue will necessitate concentrated efforts to enhance access to health services, especially in urban areas experiencing rapid economic growth.

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Introduction

Chronic kidney disease (CKD) is a progressive condition that affects more than 10% of the general population worldwide, amounting to an absolute number of 800 million individuals (Kovesdy, 2022). The disease is more prevalent in older individuals, women, racial minorities and people with co-morbidities and is related to low birth weight, history of diabetes, history of kidney diseases and history of chemotherapy (Ghelichi-Ghojogh *et al*., 2022). It represents an especially large burden in low- and middle-income countries, which are the least equipped to deal with its consequences. CKD has emerged as one of the leading causes of mortality worldwide, and is one of a small number of non-communicable diseases showing an increase in associated deaths over the past two decades (Kovesdy, 2022).

Cardiovascular disease (CVD) does not lead to CKD; the situation is the opposite, *i.e.* most patients with moderate to advanced CKD will prematurely die with CVD as the main cause of death (Vallianou *et al*., 2019). Of note, the cardiovascular risk increases with 33.3% to 37.1% in patients with mild to moderate CKD, while 39.9% of patients with moderate to severe CKD die from CVD compared to 21.7% to 26.0% of the general population (Noels & Jankowski, 2023), while co-morbidities, such as atrial fibrillation (30.5%), CVD (25.0%), diabetes mellitus (17.1%) and hypertension (14.8%) are common (Radford *et al*., 2019). According to data from rural areas in Northeast Thailand, the prevalence of CKD was 26.8%, with hypertension, diabetes mellitus and renal stones as the major underlying diseases - still only 3.5% of study participants in this study were aware of having CKD (Cha'on *et al*., 2020). Increased age, male gender, unemployment, smoking, underweight, anaemia, hyperuricemia and leukocytosis are other significantly associated factors (Cha'on *et al*., 2022). In addition, low income is closely associated with both prevalence and progression of CKD, while low education relates positively only with prevalence according to Zeng *et al.* (2018).

Geographic factors may also contribute to CKD. For example, global burdens of disease (GBD) reports have shed light on the disproportionate nature of the burden imparted by CKD-associated death in different regions of the world, with Latin America, the Caribbean region, East and Southeast Asia, Oceania, North Africa and the Middle East being especially affected (Ke *et al.*, 2022). Among high-income nations, CKD was among the top 10 causes of death in Singapore, Greece and Israel - especially noteworthy reports considering that they did not include deaths indirectly caused by CKD, *e.g.*, acute kidney injury or various cardiovascular causes, which can be caused or potentiated by CKD (Kovesdy, 2022). In 2022, the total number of CKD patients in Thailand was 1,007,251 according to data from the Health Data Center (HDC) database of the Ministry of Public Health (MoPH). Furthermore, the trend from 2018-2021 indicated an increase in the end stage of CKD patients in the population, rising from 5.7 % to 5.9%. In 2022, the total number of CKD patients in Thailand was 1,007,251. Furthermore, the trend from 2018-2021 indicated an increase in the end stage of CKD patients in the population, rising from 5.7 % to 8.6% (Tsai *et al.*, 2023). Although it is clear that geographic and environmental factors play a role in CKD, there is still insufficient research on the geo-epidemiological and spatial relationships of socio-economic factors among CKD in Thailand. This study aimed to investigate potential relationships with emphasis on urbanization, Internet access and the local number of health personnel per population (HPP) with the intension of providing useful information for the development of public health service and preventive interventions.

Materials and Methods

Study area

This research focused on Thailand, a Southeast Asian nation with a landmass spanning 513,120 km^2 and a population of approximately 71.6 million individuals (Thailand Board of Investement, 2022). It shares its borders with Myanmar and Laos to the North, Laos and Cambodia to the East, Malaysia to the South and is bounded by the Andaman Sea and Myanmar to the West. Thailand's landscape is rich and varied, featuring mountains, hills, plains and an extensive coastline that runs along the Gulf of Thailand (1,875 km) and the Andaman Sea (740 km). In addition, there are roughly 400 islands, primarily situated in the Andaman Sea. The geographical coordinates of the country lie within latitudes 20°28'N - 5°36'S and longitudes 105°38'E - 97°22'W.

Data sources

We employed secondary data from the MoPH's HDC for the year 2022. The primary outcome variable of interest was the incidence of CKD per 10,000 population in the country's 77 provinces sourced from the Health Archives of MoPH. The diagnosis codes utilized to identify CKD cases were N18.3 for stage 3 (moderate) and N18.4 for stage 4 (severe) of the disease as given by the International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD-10).

The independent variables of Internet access and HPP were derived from a survey report of the National Statistical Office. As a measure of urbanization, the study incorporated index values of night-time light (NTL) obtained via Google Earth Engine platform (http://earthengine.google.com) from the American Suomi national polar-orbiting partnership (SNPP) (https://eospso.nasa.gov/missions/suomi-national-polar-orbiting partnership) with special reference to the visible infrared imaging radiometer suite (VIIRS) onboard this satellite (https://ncc.nesdis.noaa.gov/VIIRS/).

Statistical approach

The GeoDa program (http://geodacenter.github.io/) was employed for the analysis of spatial autocorrelation and for conducting spatial regression pertaining to the socio-economic factors and CKD mortality in Thailand. To visually depict spatial correlation, Moran's scatter plot was utilized, which sets the spatially lagged variable on the x-axis against the y-coordinates of the original independent variables. This spatial correlation was quantified using Moran's *I* statistic (Griffith, 1983; Anselin, 2022). The value computed using this equation indicates the correlation between Xi and its geographical neighbours. The limitation is that it cannot identify the exact location of the correlation. Accordingly, Anselin (1995) developed a local version of Moran's *I* called local indicators of spatial association (LISA), which was utilized to determine the local spatial autocorrelation patterns of the variables in this study. We used LISA significance maps and classified locations according to association type (LISA cluster maps) setting the significance level at $p<0.05$, with the degree of significance reflected in increasingly darker shades of green. The selection of the spatial-weight matrix is one of the key factors contributing to the outcome of LISA computation; thus, its specification was carefully formulated in the present study for the 32 full-border provinces and the 23 coastal ones, including the island province of Phuket. Since the spatial weight matrix, using the adjacent boundaries as criterion, did not apply nationwide, we also used a distance-based spatial weight matrix with a radius of 111.25 km that was automatically calculated by the GeoDA software. This value is the minimum distance ensuring a non-zero spatial weight matrix. Cluster maps were produced to show the presence and localization of areas with particularly high or low CKD presence. Briefly, areas with high CKD levels surrounded by other areas with similarly high levels are high-high (HH) clusters or hotspots (shown dark red in the figures shown), while areas with low CKD levels surrounded by areas with low levels are low-low (LL) clusters or coldspots (shown dark blue in the resulting figures). High level areas surrounded by low level ones (HL) are shown in light red in the resulting figures and low level areas surrounded by high level ones (LH) are shown light blue in the figures. Moran's *I* is basically a presentation of autocorrelation, where both HH and LL are positive outcomes, while HL and LH are negative.

Three regression models: i) ordinary least squares (OLS); ii) the spatial lag model (SLM); and iii) the spatial error model (SEM) were used to analyse the potential associations among socio-demographic factors and CKD. OLS regression is limited by the fact that it assumes that the autocorrelation between dependent and explanatory variables is uniform in space and does not consider spatial autocorrelation, which is often viewed as an outright violation of the principle of independence of observations in classical regression. SLM and SEM, on the other hand, capture the spatial dimension: in the former, the dependent variable is affected by the dependent variable in the neighbouring space, whereas spatial influence arises only through error terms in the latter (Viton, 2010). We used the maximum likelihood method to compare the outcomes of the three regression models with respect to the potential

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impact of the variables on CKD rates as suggested by Elhorst (2010) and Lee and Yu (2015). Distance-based weights were selected as spatial weights in the regression models (Pacheco & Tyrrell, 2002). The spatial autocorrelation of the incidence of CKD was detected by Local Moran's *I*. When a significant spatial dependence was identified, SEM and SLM were performed. The (robust) Lagrange multiplier (LM) test statistic was used for determining which of the two models would be suitable (Anselin, 2001). In outcomes where both models had statistically significant LM values, the model with the lower value was selected. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used to find the model with the best fit, i.e. showing the lowest AIC and BIC values (Akaike, 1981).

Results

Local spatial patterns

In 2022, the CKD rate was 82.47 cases per 10,000 population in Thailand, with tremendous variations observed among different provinces (Ministry of Public Health, 2023). Singburi Province in central Thailand, near Bangkok had the highest rate at 182.5 cases per 10,000 population, while Bangkok itself, with 21.1 cases per 10,000 population, had the lowest. The provinces with the highest CKD rates (133.7-182.5) were grouped by decile and found to include the provinces of Ang Thong, Singburi, Chainat, Lampang, Phayao, Nakhon Sawan, Kamphaeng Phet, Sukhothai and Phang Nga (Figure 1).

The spatial pattern technique indicated that the clusters of CKD patients occurred in central and northern areas of the country. In addition, significant low-rate clusters were noted in Bangkok and central regions. The univariate Moran's *I* scatter plot for CKD patients in 2022 showed a positive spatial autocorrelation, with a value of 0.393 at the p=0.05 significance level, which indicates a degree of clustering. Hotspots were noted in the provinces of Udon Thani, Nan, Phayao, Lampang, Phrae, Sukhothai, Uttaradit, Phitsanulok Kamphaeng Phet, Phichit, Nakhon Sawan, Lopburi, Singburi, Chainat and Suphanburi, while coldspots were seen in in Pattani, Yala, Narathiwat, Songkhla, Samut, Sakhon, Bangkok and Nonthaburi (Table 1 and Figure 2).

LISA analysis of factors associated with CKD

The results showed a significant correlation between NTL, Internet access and HPP on the one hand and CKD on the other, a fact suggesting that areas with high socio-economic levels can be used to define the spatial extent of progression of CKD patients. The results indicated a positive spatial autocorrelation at the p <0.05 level of significance, with Moran's *I* giving 0.396, -0.197 and 0.148 for NTL, Internet access and HPP, respectively. The identified hotspots were located in the provinces of Udon Thani, Nan, Phayao, Lampang, Phrae, Sukhothai, Uttaradit, Phitsanulok Kamphaeng, Phet, Phichit, Nakhon Sawan, Lopburi, Singburi, Chainat and Suphanburi, while coldspots were seen in Pattani, Yala, Narathiwat, Songkhla Samut, Sakhon, Bangkok and Nonthaburi (Table 1 and Figures 3-5).

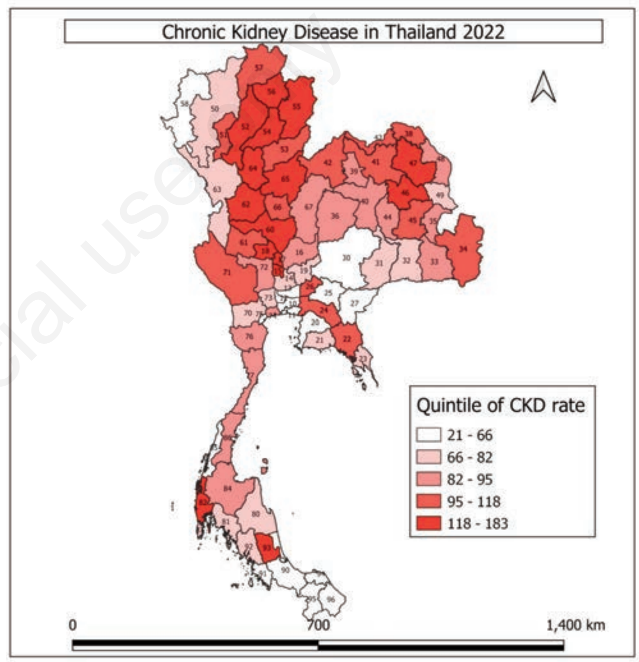

Figure 1. Distribution of chronic kidney disease in 2022.

Table 1. Geographical distribution of chronic kidney disease by province in Thailand in 2022.

Global Moran's *I*	Local indicators of spatial association (LISA)			
0.393	HH	HL	LL	LH
	Udon Thani*	Ubon Ratchathani*	Pattani** Yala** Narathiwat* Songkhla*	Tak*
	Nan*	Chachoengsao**	Samut Sakhon* Bangkok** Nonthaburi**	
	Phayao* Lampang*	Phatthalung*		
	Phrae**			
	Sukhothai*			
	Uttaradit** Phitsanulok**			
	Kamphaeng Phet*			
	Phichit*			
	Nakhon Sawan** Lopburi* Singburi**			
	Chainat** Suphanburi*			

*p=0.05; **p=0.01; ***p=0.001.

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Night-time light

Moran's *I* indicated a spatial correlation between the distribution pattern of NTL in the same direction as the CKD pattern ($p<0.05$). Bivariate LISA indicated areas positive correlation (HH cluster) of high NTL and CKD values (Moran's *I*=0.396) with similar prevalence in the 15 surrounding the provinces of Chiang Rai, Phayao, Lampang, Phrae, Nan, Sukhothai, Uttaradit, Phitsanulok, Kamphaeng Phet, Phichit, Phetchabun, Nakhon Sawan, Chai Nat, Singburi, Lopburi. However, there were also a LL cluster with low NTL and CKD values in a province with five surrounding ones in Surat Thani, Pattani, Yala, Bangkok and Nonthaburi provinces (Figure 3).

Internet access

Moran's *I* indicated significant statistical association patterns of an independent factor and CKD (*p*-value <0.05). The pattern of Internet access was distributed in the same direction as that of the CKD pattern. The outcomes of the bivariate LISA revealed a statistically significant positive correlation between Internet access and CKD (Moran's *I*=-0.197). LISA indicated areas with a high value of Internet access and high prevalence of CKD in Nakhon Phanom and in one of the surrounding provinces (Chachoengsao). In contrast, LISA analysis showed a low value of Internet access and CKD with a low value in another close province (Figure 4).

Healthcare personnel/population ratio

Moran's *I* indicated significant statistical association patterns of an independent factor and CKD ($p<0.05$). LISA revealed a statistically significant spatial correlation between the distribution pattern of good access to health personnel and a high number of CKD patients (Moran's *I* = 0.148). LISA indicated areas with high prevalence rates of HPP and CKD with high values in the surrounding eight provinces in Phitsanulok, *i.e.* Nong Khai, Udon Thani, Bueng Kan, Sakon Nakhon, Khon Kaen, Roi Et and Sisaket. In contrast, LISA analysis showed clusters of a province with a low level of HPP and CKD with correspondingly low values in the surrounding five provinces of Pathum Thani, Nakhon Pathom, Samut Sakhon, Samut Prakan and Rayong (Figure 5).

Spatial regression analysis

OLS regression, particularly the spatial modelling results by SEM and SLM, indicated a likelihood of CKD being associated with NTL, Internet access and HPP. The SLM models explained approximately 54.4% of the CKD distribution (R^2 = 0.544), while the SEM result outperformed that result (54.8% with R^2 = 0.548) to some extent. The AIC and BIC tests mirrored that outcome for SEM and SLM with AIC values of 697.148 versus 698.198, respectively, and corresponding BIC values of 718.125 and 721.506 (Table 2).

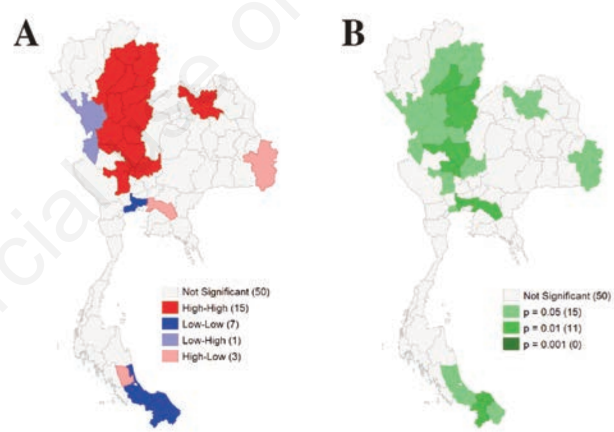

Figure 2. Univariate LISA cluster and significance maps of chronic kidney disease by province in 2022. **A**) cluster map; **B**) significance map.

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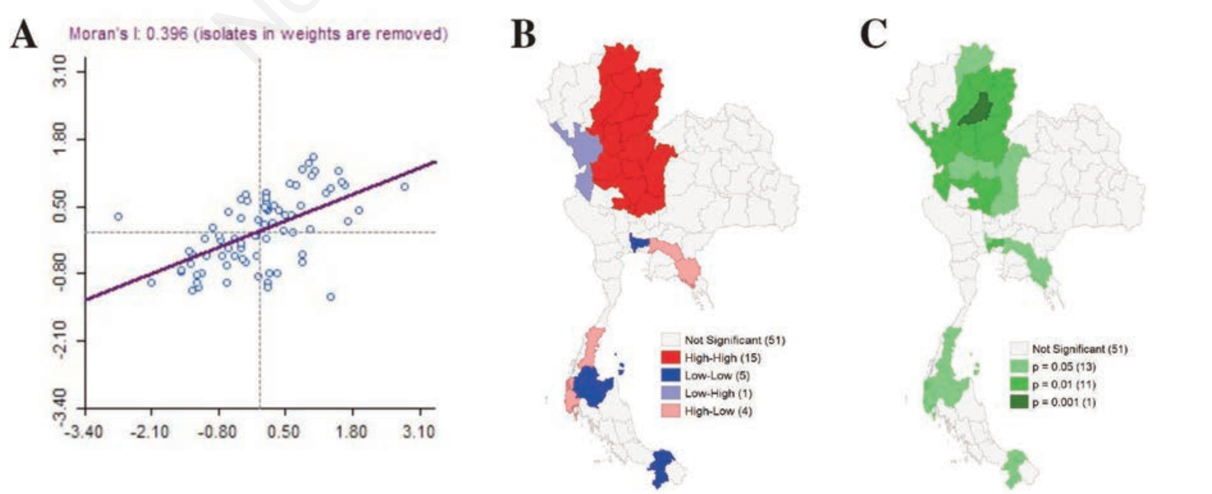

Figure 3. Bivariate Moran's *I* scatter plot and LISA results with regard to night-time light and chronic kidney disease in 2022. **A**) Moran's *I* scatter plot; **B**) cluster map, **C**) significance map.

Discussion

Our spatial analysis has quantified the distribution of CKD patients in Thailand, highlighting the clustering of patients with high CKD rates in central and northern regions and low-rate clusters in areas surrounding Bangkok. The relation of CKD with low socioeconomic status observed in this study is in line with associations to both development and progression of CKD previously noted by Bello *et al.* (2008). Factors such as race, gender, age and family history have been studied in other countries. For instance, being of African American decent, older age, low birth weight and family history of kidney disease are considered to be strong risk factors for CKD (Kazancioğlu, 2013). Moreover, smoking, obesity, hypertension, and diabetes mellitus can also lead to kidney disease. An uncontrolled diabetic and/or hypertensive patient can easily and quickly progress to the end-stage (Muleta *et al.*, 2017). Exposure to heavy metals, excessive alcohol consumption, smoking, and the use of analgesic medications also constitute risks (Kazancioğlu, 2013). Although highly important, these aspects were not investigated by us as we turned our attention to other potentially equally important variables. For example, the average intensity of light significantly influences host-pathogen interactions, with physiological effects disrupting biorhythms, potentially causing metabolic and immune dysfunctions (Kernbach *et al*., 2018). Our study showed that NTL, a factor also shown to be a valuable tool for forecasting economic growth and assessing people's well-being, did play a role in CKD clustering in Thailand. Obtaining an optimal night-time sleep duration and better sleep quality might reduce the risk of CKD (Sun *et al*., 2021). However, even if these authors showed that poor sleep quality was associated with increased risk of CKD in middle-aged and older Chinese, this link needs further study.

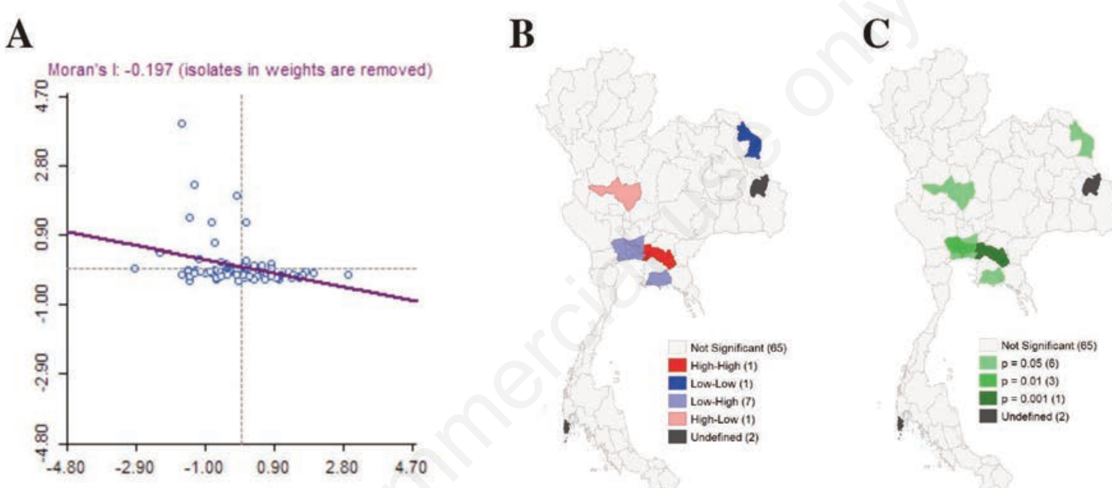

Figure 4. Bivariate Moran's *I* scatter plot and LISA results with regard to Internet access and chronic kidney disease in 2022. **A**) Moran's *I* scatter plot; **B**) Cluster map, **C**) Significance map.

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Table 2. Regression analysis between socio-economic factors and CKD in Thailand, 2022.

Independent variable	OLS (Standard Error)	SEM (Standard Error)	SLM (Standard Error)
Night-time light (NTL)	3.731 (0.762) ***	3.356 (0.777)***	2.999 (0.756) ***
Internet access	-0.034 (0.017)*	-0.035 (0.015)*	-0.039 (0.015)*
Healthcare/population ratio	-0.066 (0.035)*	-0.067 (0.033)*	-0.068 (0.032)*
Constant	78.803 68.902	91.262 64.599	73.657 62.982
ρ		0.292	
λ			0.261
R^2	0.517	0.548	0.544
Log likelihood	-341.009	-339.574	-339.099
AIC	700.018	697.148	698.198
BIC	720.995	718.125	721.506

*OLS, ordinary least squares; SLM, spatial lag model; SEM, spatial error model; Constant, regression model intercept (the expected mean value of Y when all X=0); ρ, rho, the SEM lag coefficient; λ, lambda, the SLM lag coefficient; AIC, Akaike information criterion; BIC, Bayesian information criterion; *p =0.05; **p =0.01; ***p =0.001.*

We chose Internet access as one of our study variables since it not only reflects a high socio-economic level but also allows patients to learn more about their condition, treatment options and lifestyle changes to manage their disease effectively. We found a spatial correlation between the distribution pattern of Internet access and that of the CKD. Access to information thus seems to benefit those who might have difficulty traveling to healthcare facilities or live in remote areas with limited access to medical specialists. This is also consistent with a study on CKD and mobile phone ownership that is high across age, education and socioeconomic status (Bonner et al., 2018). Simple one-way SMS messages are likely to reach and be read by everybody, including those with CKD and should therefore be useful for short, simple reminders to support self-management. Younger people, particularly with earlier stages of kidney disease, would benefit from this kind of more complex health strategies that focus on primary prevention or to improve adherence with treatment (Bonner *et al.*, 2018).

The reason for the focus on access to healthcare is due to its central position with respect to prevention, early detection, management and overall care. The expertise of the personnel at health facilities and their support significantly influence the outcome and quality of life for individuals living with CKD. We identified potentially modifiable barriers and facilitators to optimize management of CKD in primary care, foremost in relation to gaps in health care coordination, patient-physician communication and provider knowledge. Moving forward, collaborative team-based care models using multifaceted strategies for structured CKD management, risk stratification to prioritize nephrology referrals using validated instrument, coupled with CKD training for all primary care physicians need urgent attention. Concerted efforts with regard to implementation and evaluation are likely to improve outcomes of patients with CKD and reduce the CKD burden (Ramakrishnan *et al.*, 2022). Healthcare resource utilization and costs associated with CKD impose a substantial burden on the healthcare system, particularly in the more advanced stages of CKD. New interventions delaying the progression of CKD to kidney failure may not only prolong patients' lives but they would also provide significant resources and cost savings for healthcare providers (Pollock *et al.*, 2022). It is essential for the public sector to play an active role in promoting preventive measures and guidelines to combat CKD. This can be achieved through a cohesive integration of various working procedures, actively involving the community and all sectors and implementing effective policies that address population-level CKD risks. The government should utilize appropriate mechanisms or tools to facilitate prevention strategies. Creating conducive surroundings that support healthy living can significantly contribute to reducing CKD incidence and its related complications. Embracing cutting-edge technologies can enhance disease prevention and management. It includes also the utilization of spatial analysis techniques, open data, and open-source software packages in public health planning, not limited to CKD but extended to other diseases as well. By taking these measures and adopting a proactive approach, the public sector can indeed play a pivotal role in combating CKD, improving overall health outcomes, thereby fostering a healthier and more informed society.

Conclusions

Significant positive associations between socio-economic factors and CKD prevalence in the Thai population has been unveiled shedding light on previously overlooked CKD risks, such as those related to NTL, Internet access and healthcare accessibility. These findings hold crucial implications for healthcare allocation and targeted CKD interventions. Further research on underlying factors of the geographic CKD disparity is imperative. Our findings underscore the importance of social determinants of health and improving healthcare, particularly for vulnerable groups. More extensive research is necessary to fully comprehend the mechanisms driving these associations and to tailor interventions for reducing CKD prevalence in Thailand.

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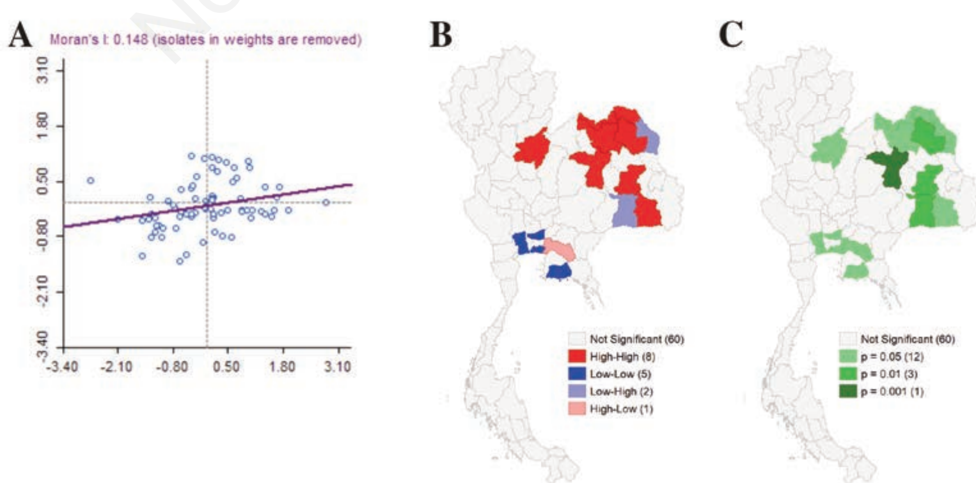

Figure 5. Bivariate Moran's *I* and LISA results with regard healthcare/population ratio and chronic kidney disease in 2022. **A**) Moran's *I* scatter plot; **B**) cluster map, **C**) significance map.

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