Geospatial Health 2023; volume 18:1203

Spatial pattern and heterogeneity of chronic respiratory diseases and relationship to socio-demographic factors in Thailand in the period 2016 to 2019

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Abstract

Chronic respiratory diseases (CRDs) constitute 4% of the global disease burden and cause 4 million deaths annually. This cross-sectional study used QGIS and GeoDa to explore the spatial pattern and heterogeneity of CRDs morbidity and spatial autocorrelation between socio-demographic factors and CRDs in Thailand from 2016 to 2019. We found an annual, positive, spatial autocorrelation (Moran's I >0.66, p<0.001) showing a strong clustered distribution. The local indicators of spatial association (LISA) identified hotspots mostly in the northern region, while coldspots were mostly seen in the central and north-eastern regions throughout the study period. Of the socio-demographic factors, the density of population, households, vehicles, factories and agricultural areas, correlated with the CRD morbidity rate, with statistically significant negative spatial autocorrelations and coldspots in the north-eastern and central areas (except for agricultural land) and two hotspots between farm household density and CRD in the southern region in 2019. This study identified vulnerable provinces with high risk of CRDs and can guide prioritization of resource allocation and provide target interventions for policy makers.

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Key words: chronic respiratory diseases; northern region; socio-demographic factors; spatial analysis; Thailand.

Conflict of interest: the Authors declare no conflict of interest.

Ethical considerations: the KhonKaen University's Ethics Committee for Human Research accepted this study (Reference no. HE652145).

Availability of data and materials: all data generated or analyzed during this study are included in this published article.

Acknowledgements: the data support of the National Statistics Office of Thailand, Ministry of Digital Economy and Society; allowed for the successful completion of this study and also by a variety of Sectors: Department of Provincial Administation, Ministry of Interior; Department of Agriculture and Office of Agriculture Economic, Ministry of Agriculture and Cooperatives; Ministry of transport; Ministry of industry and Technology, Epidemiology and Community Measures Group Division of non-communicable diseases,Health Data Center, Ministry of Public Health. Accordingly, we would like thank specially for providing us the advanced data to analyze.

Received for publication: 29 March 2023.
Accepted for publication: 1 May 2023.

Geospatial Health 2023; 18:1203
doi:10.4081/gh.2023.1203

Introduction

Chronic respiratory diseases (CRDs) are major health problems. In Thailand, mortality due to CRD is increasing (Laohasiriwong *et al.*, 2018). Its severity has a considerable negative effect on the quality of life for affected people worldwide, contributes 4 % to the global disease burden and causes 4 million annual deaths (Thanaviratananich *et al.*, 2016). It is particularly problematic for people with chronic obstructive pulmonary disease (COPD) commonly resulting in a deadly outcome in this group of people (Labaki & Han, 2020). According to the World Health Organization (WHO), loss of productivity at work and home together with high healthcare costs add significantly to the economic burden for family, community and country (World Health Organization, 2022). Recent data studied studied by the WHO indicate that 92% percent of people living in areas with poor outdoor air quality are at risk for developing CRD (Alvarez-Mendoza *et al.*, 2020).

The risk factors encountered at different phases of peoples' lifetime include smoking, childhood infections, poor nutrition and low body mass index (BMI), indoor air pollution, work-related dust and smoke and airborne pollution in general (Brashier and Kodgule, 2012; Hill *et al.*, 2010; Postma *et al.*, 2015; Zhou *et al.*, 2013). Llongstanding exposure to dangerous elements and particles in the air account for 0.4 million deaths (Bhandari & Sharma, 2012), and work-related CRDs account for 15–20 percent of all cases (Pallasaho *et al.*, 2014). Despite being non-smokers, a larger fraction of farmers developed CRDs compared to people occupied in other activities (Salvi & Barnes, 2009). In the United States, undiagnosed COPD cases are estimated to be as common as diagnosed ones (Pallasaho *et al.*, 2014). Even when properly diagnosed, between one and two thirds do not receive adequate treatment. Even in Singapore, CRDs ranks as the seventh or eight most common cause of hospitalization due to missed diagnosis (Tee, 2013). Geographic information systems (GIS) and computer-aided graphical methods have been used to visualize spatiotemporal occurrences of various diseases, which assists health service planning and public health interventions (Fradelos *et al.*, 2014; Noble *et al.*, 2012; Ramírez-Aldana *et al.*, 2020). Causal disease factors and intervention options have been spatially defined (Anselin *et al.*, 2006; Rankantha *et al.*, 2018).

Only a limited number of studies on CRDs and associated factors have been carried out in Thailand by means of GIS-assisted methodology for the study of spatial distribution pattern of diseases. This study aimed to compare regional heterogeneity and spatial pattern for CRDs and relationship to associated socio-demographic factors for 2016 and 2019 in Thailand.

Materials and Methods

Study area

The area of this research was the whole country of Thailand with a land size of 514,000 km^2 including 77 provinces divided between four administrative areas (north-eastern, northern, central and southern) as seen in Figure 1.

Data sources

Patient data were obtained from individual databases from the universal health insurance and medical welfare for civil servants and their families,that had been analyzed by the Technology, Epidemiology and Community Measures Group Division of non-communicable diseases, Health Data Center, Ministry of Public Health, Thailand. The dataset included the province-by-province population of all 77 provinces; 254,507 in-patients cases for 2016 and 253,159 for 2019. The data on CRDs including bronchitis, emphysema and COPD were based on codes J40-J44 as given by the International Statistical Classification of Diseases and Related Health Problems, 10th Revision classifications (ICD-10) for 2016 and 2019.

Socio-demographic data, consisting of population density, household density, farm household density, percentage of land used for agriculture, number of vehicles and number of factories per km^2, were acquired from the Department of Provincial Administration, Ministry of the Interior, Ministry of Digital Economy and Society (Department of Agriculture Extension), Ministry of Agriculture and Cooperatives, all attained from the Thailand's National Statistical Office (https://statbbi.nso.go.th/staticreport/page/sector/ en/01.aspx).

Data analysis approach

Geospatial methodology offers spatial analytical description, autocorrelation and basic spatial regression to comprehensive modeling based on inferential statistical methods (Anselin *et al.*, 2006).

Thailand's administrative regions' geographic coordinates were obtained from the publicly accessible on DIVA-GIS

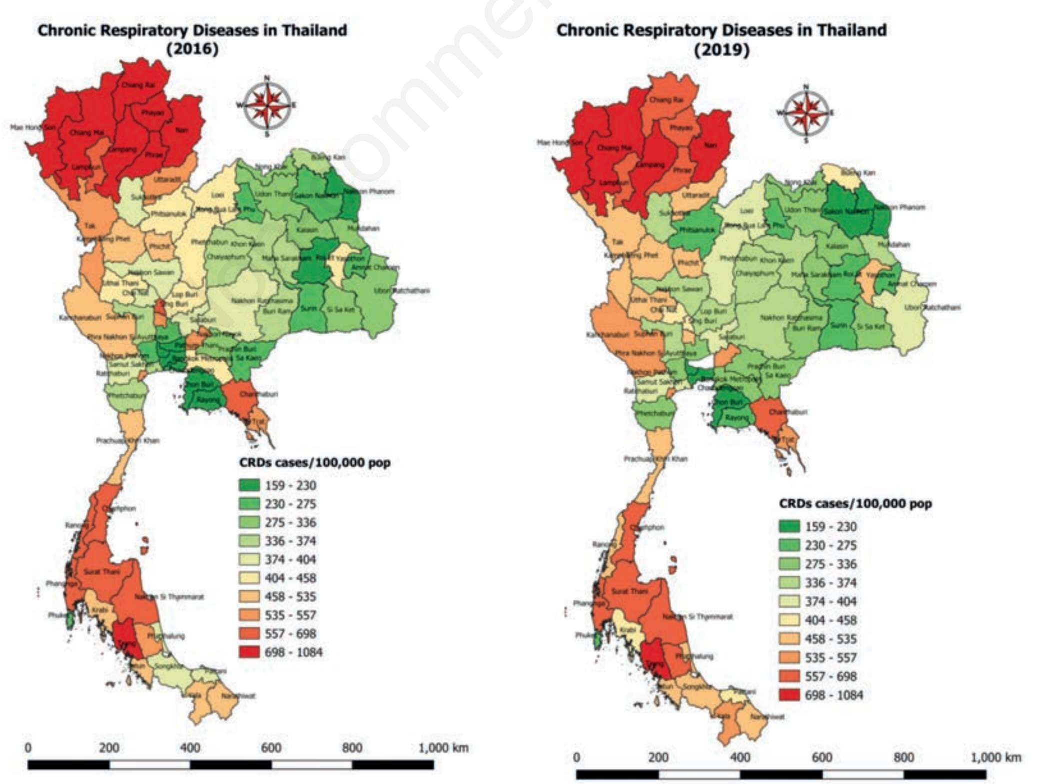

Figure 1. Distribution pattern of chronic respiratory disease morbidity rates per 100,000 population in Thailand 2016 and 2019. The number of CRD cases per province varied from high (in dark red) to low (in dark green).

(http://www.diva-gis.org/gdata). We utilized Quantum GIS (QGIS), GeoDa (https://geodacenter.github.io) and Microsoft Excel 2010 to describe and analyze the province's spatial distribution pattern of the CRD morbidity rate, the variables mentioned above and their spatial autocorrelation. The weight matrix was based on distance exploring the spatial correlations. The global and local test Moran's *I* statistics were applied to study spatial autocorrelation and clustering tendencies. Moran scatterplots with the slope of the regression line were used to display the global tests. Strong positive, spatial autocorrelation is indicated by values near +1, values around 0 designate random spatial ordering, while values close to -1 denote strong, negative spatial autocorrelation.

Moran's *I* is commonly used to determine the level of geographic correlation (Steiniger & Hunter, 2013). This study used 999 permutations to assess the sensitivity of the significant locations to the number of permutations ($p<0.05$). Since 77 observations do not constitute big data, an uncritical application of the false discovery rate (FDR) would not give meaningful results, we selected one of the pre-selected p-values from the list provided by the Significance Filter (*i.e.*, 0.05, 0.01, 0.001). The computation of Moran's *I* is shown in the following mathematical illustration:

$$I = \frac{N \sum i \sum j W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum i \sum j W_{ij} \sum i (x_j - \bar{x})^2} \qquad \text{Eq. 1}$$

where x_i and x_j are the CRD morbidity rates in province *i*, and its neighbour province *j*; N the number of CRDs in-patients cases in these provinces; W_{ij} the spatial weight matrix applied to the comparison between the provinces; and $x_i - \bar{x}$ and $x_j - \bar{x}$ the deviation of x_i and x_j from their means.

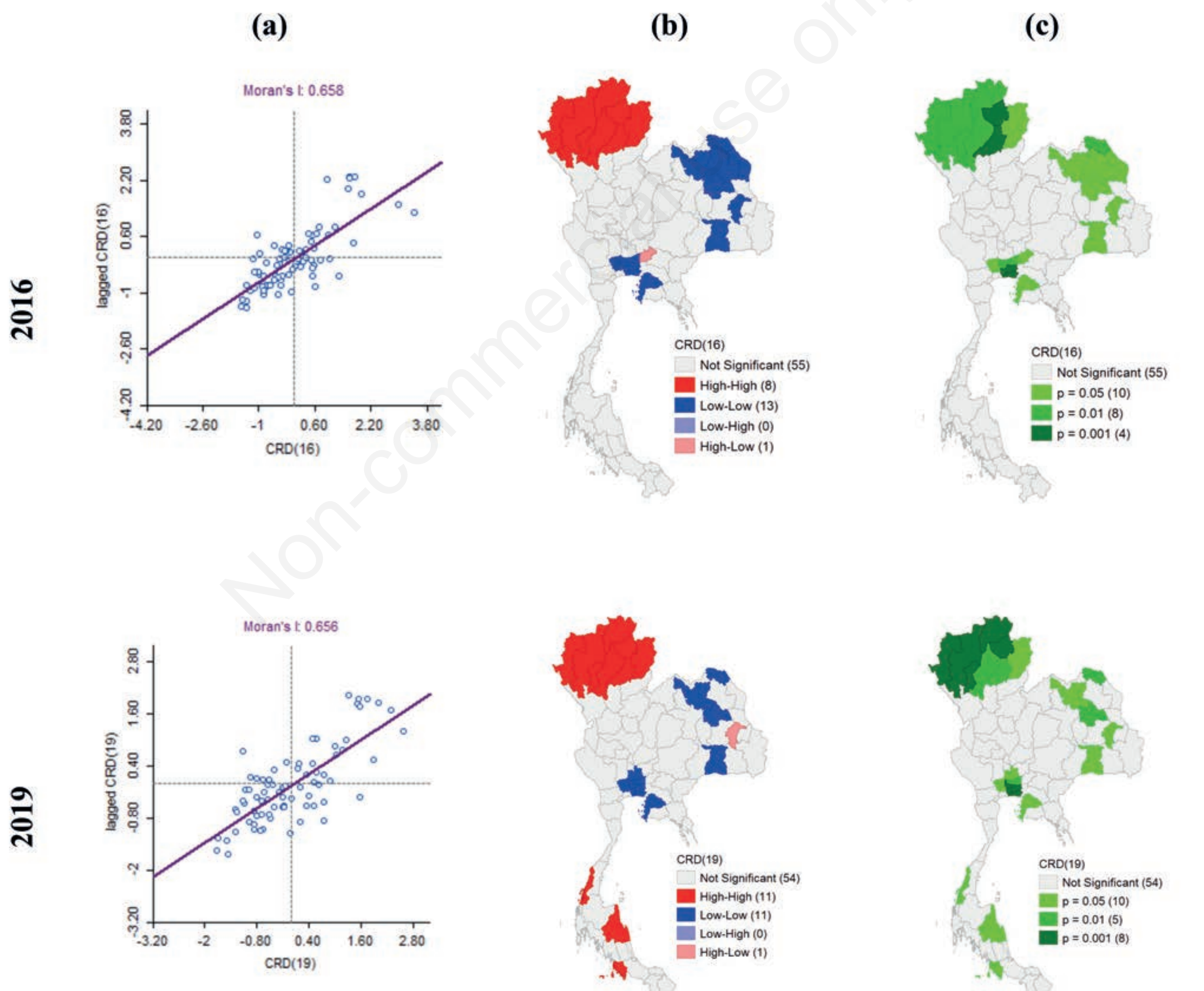

Figure 2. Variation of the chronic respiratory disease morbidity rates per 100,000 population in Thailand between 2016 and 2019. a) Moran's *I* scatterplot matrix; b) LISA cluster (univariate) map; c) LISA significant (univariate) map.

Table 1. Significant, spatial respiratory disease morbidity clusters by province of Thailand in 2016 and 2019.

2016 Moran's *I*	High-High	Low-Low	Low-High	High-Low
0.658	Nan* Lampang** ChiangMai** Phrae*** ChiangRai** Mae Hong Son** Phayao*** Lamphun**	SamutPrakan*** Nonthaburi** Bangkok*** PathumThani** NakhonPathom* SakonNakhon* ChonBuri* Bueng Kan** Kalasin* NakhonPhanom* Surin* UdonThani* Yasothon*		NakhonNayok*
2019 Moran's *I*	**High-High**	**Low-Low**	**Low-High**	**High-Low**
0.656	ChiangMai*** Mae Hong Son*** Nan* Lampang** Phrae** ChiangRai*** Phayao*** Lamphun*** Nakhon Si Thammarat* Ranong* Satun*	Nonthaburi*** SamutPrakan*** PathumThani** Bangkok*** NakhonPathom* ChonBuri* PhraNakhon Si Ayutthaya* Bueng Kan** Kalasin** Surin* UdonThani*		Yasothon*

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

Table 2. Geospatial distribution of the percentage of agricultural land in relation to respiratory disease morbidity in Thailand 2016 and 2019.

2016 Moran's *I*	High-High	Low-Low	Low-High	High-Low
-0.386		Bangkok*** NakhonNayok* SamutPrakan***	Phayao*** Phrae*** Lampang** ChiangMai** Lamphun** ChiangRai** Mae Hong Son** Nan*	Bueng Kan** Kalasin* PathumThani** NakhonPhanom* Nonthaburi** Surin* UdonThani* NakhonPathom* Yasothon* SakonNakhon* ChonBuri*
2019 Moran's *I*	**High-High**	**Low-Low**	**Low-High**	**High-Low**
-0.389		Bangkok*** SamutPrakan***	ChiangMai*** Lamphun*** ChiangRai*** Mae Hong Son*** Lampang** Nan* Phrae** Phayao*** Nakhon Si Thammarat* Ranong* Satun*	Bueng Kan** Kalasin** Surin* UdonThani* Yasothon* NakhonPathom* ChonBuri* Nonthaburi*** PathumThani** PhraNakhon Si Ayutthaya*

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

As Global Moran's I is unable to give a correlation's exact location, Anselin (1995) developed the Local Moran's I or local indicators of spatial association (LISA), whose formula is the following:

$$\frac{(x_i - \bar{x}) \sum jW_{ij}\,(x_j - \bar{x})}{s_i^2} \qquad \text{Eq. 2}$$

where s_i^2 is the spatial weight matrix, *i.e.* $\frac{\sum j(x_j - \bar{x})^2}{(N-1)}$, W_{ij}; and N the number of CRD spatial units.

LISA produced two types of maps: significance maps which represent the locations shown by the Local Moran statistic at the significance $p<0.05$; and cluster maps, which classify the associated locations (Anselin *et al.*, 2010). Cluster maps express four categories: High-High (HH), which means a high CRD morbidity correlated with similar high morbidity in surrounding areas (hotspots), while Low-Low (LL) means a low CRD correlated with similar low morbidity in surrounding areas (coldspots). Moreover, High-Low (HL) or Low-High (LH) clusters signify outliers, *i.e.* those where an area with high CRD morbidity is surrounded by areas with low CRD morbidity, and vice versa.

Results

Spatial distribution pattern of CRDs morbidity rate

The highest morbidity CRD rates (10[th]decile) were seen in the northern region, but the number of affected provinces was reduced from seven in 2016 to four in 2019. In the southern region, only one HH province was found (Trang) and this did not change

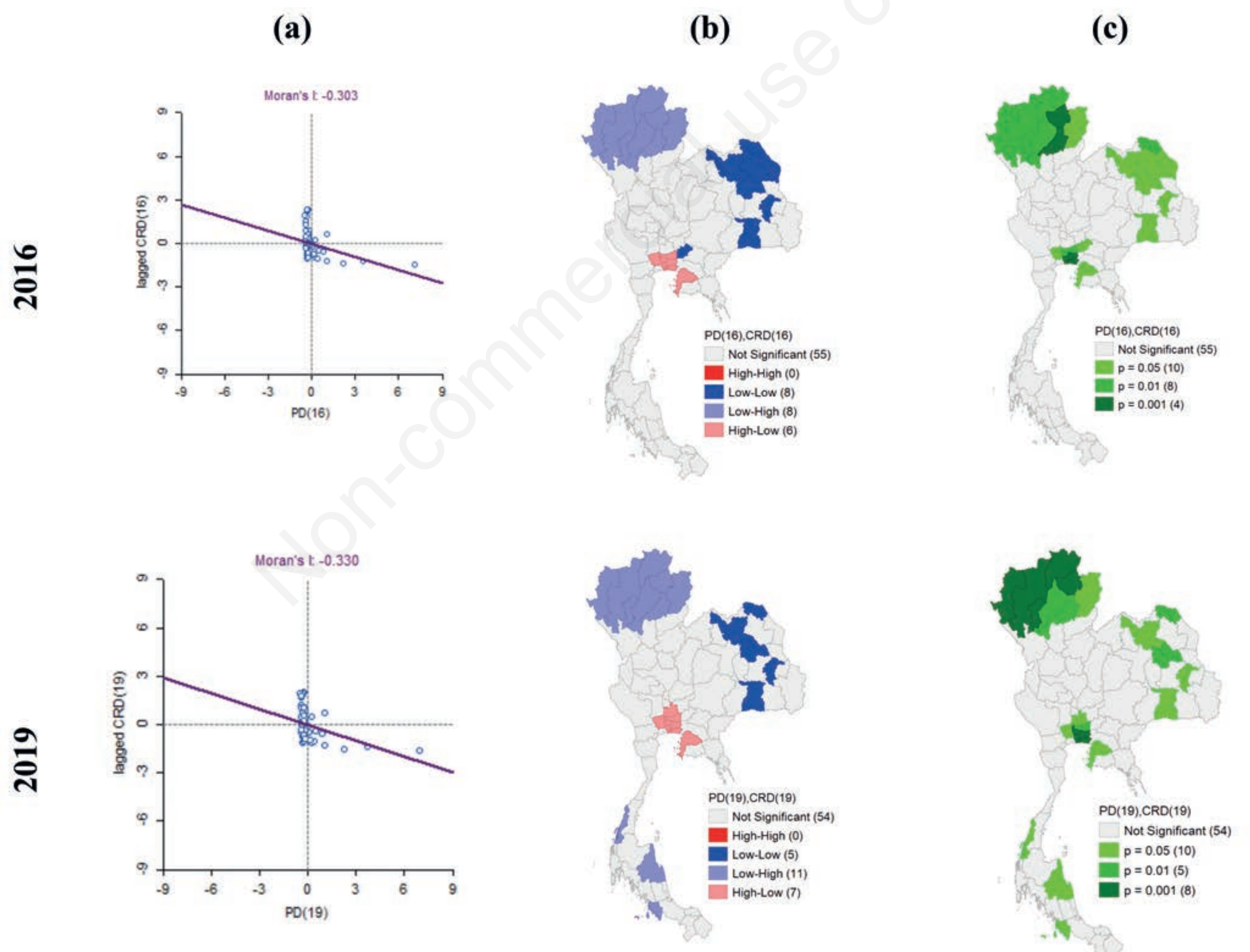

Figure 3. Impact of the population density on the chronic respiratory disease morbidity rates per 100,000 population in Thailand between 2016 and 2019. a) Moran's *I* scatterplot matrix; b) LISA cluster (bivariate) map; c) LISA significant (bivariate) map.

between the two years under investigation. The lowest CRD morbidity rates (1st decile) were seen in the same five provinces of central region and one in the North-eastern region, some minor changes between the provinces occurred between at 2016 and 2019 as can be seen in Figure 1.

The univariate global Moran's *I* of CRD morbidity rate were 0.658 in 2016 and 0.656 in 2019 with a high statistical significance (p=0.001), which showed that pointed towards a situation with strongly clustered CRD characteristics (Table 1). Most were of the HH and LL variety with very few outliers for both years. Although particular provinces with HH and LL cluster had changed somewhat between the years, the number of provinces found to be of the LL kind did not differ strongly, while there was a much higher number of HH clusters in 2019. The provinces were found to be either HH, LL,HL or LH as shown shown in Table 1 and Figure 2.

Socio-demographic factors associated with CRD morbidity

In this study, we considered population density, household density, farm household density, percentage of land used for agriculture, number of vehicles per km^2 and factories per km^2. The bivariate analysis between each variable and the CRDs morbidity rate showed significant negative autocorrelations with regard to population density (Moran's *I*: -0.303, p=0.001 in 2016 and -0.330, p=0.001, respectively, in 2019); and with regard household density (Moran's *I*: -0.294*, p*= 0.001 in 2016 and -0.316, 0.001, respectively, in 2019). LISA identified the same cluster distribution pattern of those two socio-demographic variables and CRD for each year. In 2016, there were eight LL clusters, mostly in the north-eastern region, but only five of these were left in 2019 (Figures 3 and 4).

For farm household density, we found different bivariate results with respect to the CRD morbidity rate. There was a signif-

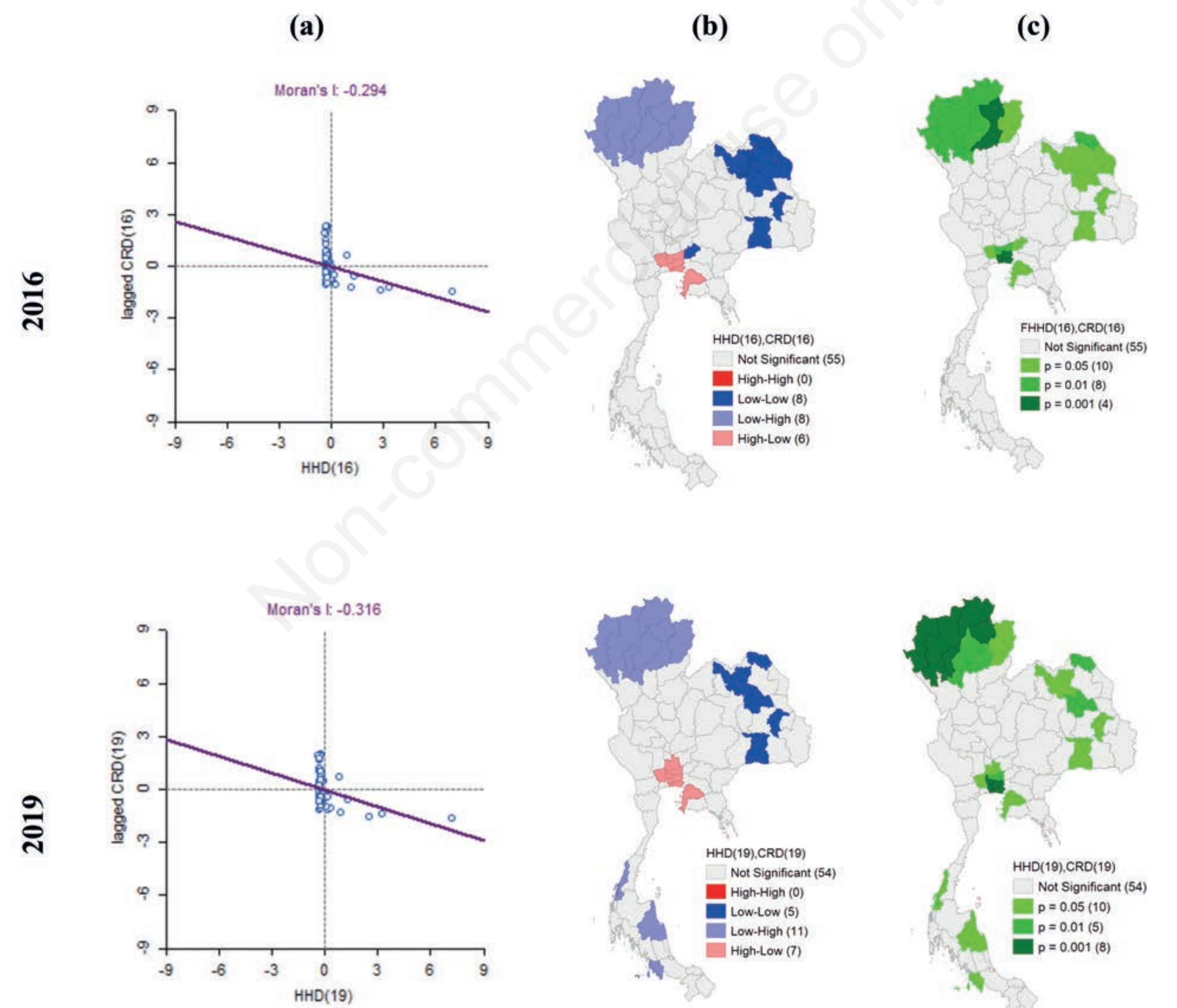

Figure 4. Impact of the household density on the chronic respiratory disease morbidity rates per 100,000 population in Thailand between 2016 and 2019. a) Moran's *I* scatterplot matrix; b) LISA cluster (bivariate) map; c) LISA significant (bivariate) map.

icant, negative, spatial autocorrelation with the value of Moran's *I* in 2016 of -0.249, p= 0.001 and in 2019 of-0.280, p=0.001, respectively, while there were some differences between 2016 and 2919 as can be seen in Figure 5. With regard to the proportion of land used for agriculture, there was a significant, negative, spatial autocorrelation between percentage of cultivated land and the CRD morbidity rate. Moran's *I* was -0.386 in 2016 and -0.389 in 2019 and LISA showed three LL clusters; all of them in the central region in 2016 and two in 2019 (Table 2).

For the bivariate analysis results of spatial autocorrelation between vehicle density and CRD morbidity rate, there were also significant, negative spatial autocorrelation with Moran's *I* = -0.176 in 2016 and = -0.197in 2019 indicating ten LL clusters in 2016 and seven in 2019. With regard to individual provinces, two in the north-eastern region and one in the central region were noted not to occur in 2019 (Table 3).

For the results of bivariate spatial autocorrelation between factory density and CRD morbidity rate, there were significant negative spatial autocorrelation, with Moran's *I* = -0.204 in 2016 and -0.208 in 2019. LISA showed nine LL clusters, mostly in the North-eastern region in 2016, with only six of them left in 2019 (Table 4).

Discussion

The highly clustered spatial distribution of morbidity due to CRD in northern Thailand discovered in our countrywide study is consistent with the findings of Pothirat *et al.* (2015), who described a higher COPD prevalence among a rural community in the North. There are reasons to believe that the reasons behind the problems in this part of the country may be due to an inflammatory environmental issue connected with a move to turn forest land into cornfields, which has led to rapid deforestation in the Thai highlands (Trisurat *et al.*, 2010). The extensive use of fire to prepare and maintain land for agriculture called human-initiated biomass burning (Yin, 2020), has released large amounts of particulate matter into the atmosphere, which has been linked with an increase of respiratory diseases as described by Rujivanarom (2019). The lowered air quality has harmed health, increased hospitalization and led to premature mortality due to CRD (Reddington *et al.*, 2015). Moreover, there are several high mountains in the northern region of Thailand, which could block airflow distribution and results in increased air pollution (Long *et al.*, 2016).

The statistically significant spatial association of CRD morbidity rates between the different provinces of Thailand presented also indicate that several socio-demographic factors are significantly, negatively correlated with the CRDs morbidity rate. For example, this kind of morbidity was found to be lower in the Northeast, where there are also a low population density and fewer households. Among a total of twenty provinces in this region, there were at least five with low CRDs morbidity rate. We aso found an association between a low density and a low number of CRDs with respect to farm households, particularly in the central region. In the Southern region, on the other hand, there is a high density of farm households and we found two CRD hotspots, which support the spatial correlation between the density of farms and higher morbidity of CRD. This was also true for the central region, since a low percentage of agriculture land was also found to be associated with low CRDs morbidity there. This result is consistent with the other studies reporting that the reduction of human-initiated biomass burning would improve both indoor and outdoor air quality (Yin, 2020), whereas open burning of crop straw and agriculture residues is an important source of air pollution (Wang &

Table 3. Impact of geographic distribution of vehicle density on respiratory disease morbidity in Thailand 2016 and 2019.

2016 Moran's *I*	High-High	Low-Low	Low-High	High-Low
-0.176		Samut Prakan*** Bueng Kan** Kalasin* Nakhon Phanom* Sakhon Nakhon* Surin* Udon Thani* Yasothon* Nakhon Nayok* Pathum Thani**	Phrae*** Phayao*** Chiang Rai** Mae Hong Son** Chiang Mai** Lamphun** Nan* Lampang**	Bangkok*** Chon Buri* Nakhon Pathom* Nonthaburi**
2019 Moran's *I*	**High-High**	**Low-Low**	**Low-High**	**High-Low**
-0.197		Bueng Kan** Kalasin** Surin* Udon Thani* Yasothon* Pathum Thani** Samut Prakan***	Chiang Mai*** Lampang** Mae Hong Son*** Phayao*** Chiang Rai*** Lamphun*** Phrae** Nan* Nakhon Si Thammarat* Ranong* Satun*	Bangkok*** Chon Buri* Nonthaburi*** Phra Nakhon Si Ayutthaya* Nakhon Pathom*

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

Zhang, 2008; Zhang *et al.*, 2016). Another study carried out in north-eastern Thailand showed that the use of biomass is the primary or secondary source of fuel for cooking and that higher person-hour density areas led to COPD case clustering (Surendran *et al.*, 2022). CRDs in agriculture workers must thus be recognized as an occupational disease, with high prevalence (Kitjakrancharoensin *et al.*, 2020). By showing a significant spatial autocorrelation between CRD and outdoor burning of biomass, our study confirmed the strong relevance of these results.

Importantly, we identified that areas with low numbers of vehicles and factories per km^2 were associated with the presence of CRD cases, mostly in the north-eastern region for both years investigated. This situation reflects the strong risk of rapid urbanization and industrialization for Thailand and other middle-income countries as they are being faced with air pollution that most probably will make the CRD problem worse. The fact that urban expansion leads to increased automobile usage, and therefore more air pollution, has been shown in a Chinese study (Zhang *et al.,* 2016). Moreover, it has also been shown that residencies near dense industrial areas also run an increased risk of respiratory diseases due to exposure to industrial toxic elements released into the air (Lotfata & Hohl, 2021). In addition, Wang *et al.* (2015) have shown that such situations are also associated with a rise in hospitalizations with acute CRD exacerbation.

The strength of this study is that we could map the whole country with respect to the presence of CRDs and indicate the main risk elements in different geographical parts. However, some limitations were encountered, e.g., we studied CRD clustering by population rather than in individuals. It is essential to also review the interaction between numerous factors at the individual level. Another drawback was the cross-sectional character of the study, which made it unable to establish a definite link at the individual

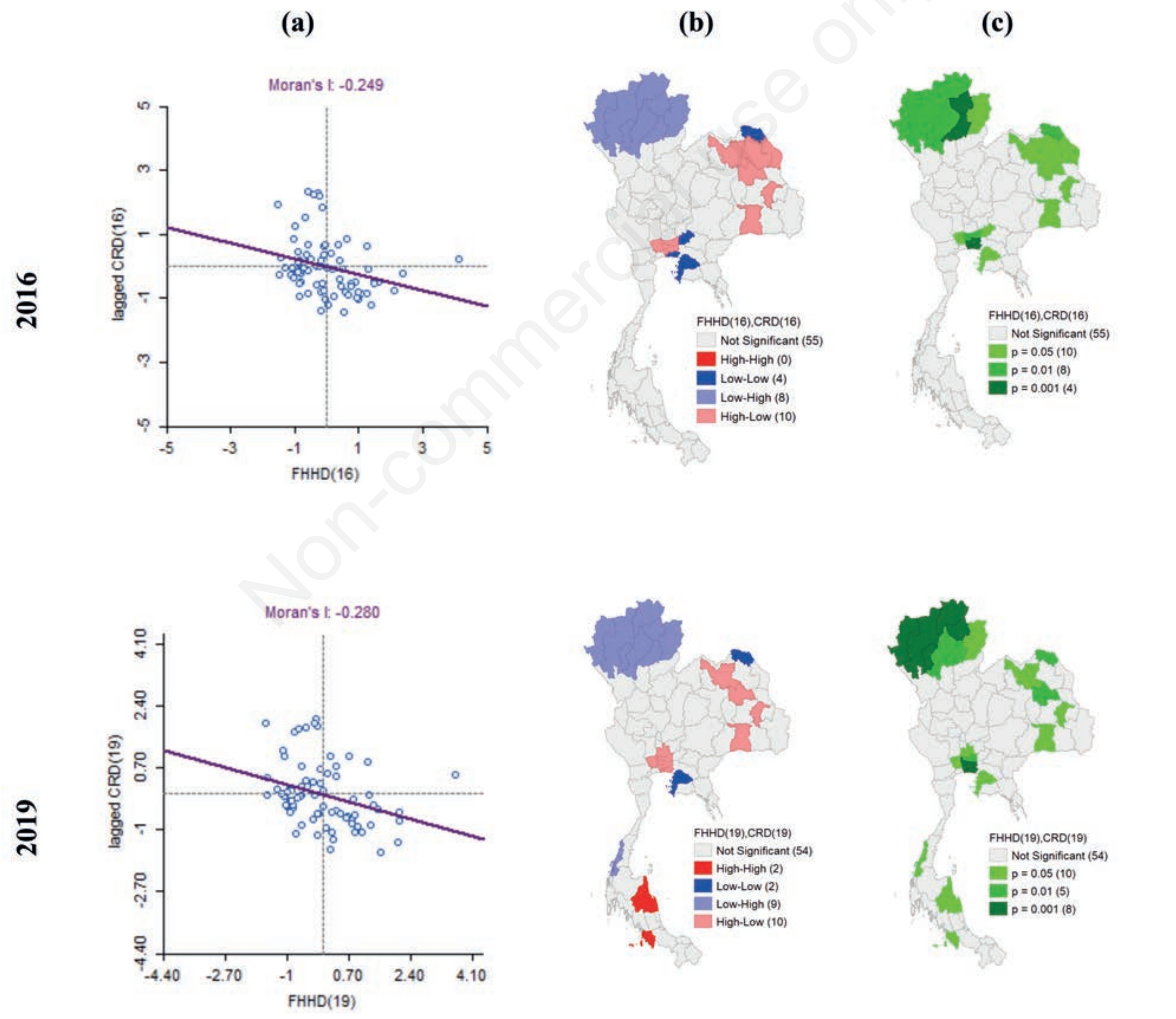

Figure 5. Impact of the farm household density on the chronic respiratory disease morbidity rates per 100,000 population in Thailand between 2016 and 2019. a) Moran's *I* scatterplot matrix; b) LISA cluster (bivariate) map; c) LISA significant (bivariate) map.

Table 4. Geospatial distribution of factory density among patients diagnosed with chronic respiratory diseases in Thailand 2016 and 2019.

2016 Moran's *I*	High-High	Low-Low	Low-High	High-Low
-0.204		Bueng Kan** Kalasin* Nakhon Phanom* Sakon Nakhon* Surin* Udon Thani* Yasothon* Nakhon Nayok* Pathum Thani**	Phrae*** Mae Hong Son** Chiang Mai** Lamphun** Chiang Rai** Lampang** Nan* Phayao***	Bangkok*** Chon Buri* Nakhon Pathom* Nonthaburi** Samut Prakan***
2016 Moran's *I*	**High-High**	**Low-Low**	**Low-High**	**High-Low**
-0.208		Bueng Kan** Kalasin** Surin* Udon Thani* Yasothon* Pathum Thani**	Phayao*** Chiang Rai*** Lamphun*** Chiang Mai*** Mae Hong Son*** Lampang** Nan* Phrae** Nakhon Si Thammarat* Ranong* Satun*	Samut Prakan*** Bangkok*** Nonthaburi*** Chon Buri* Nakhon Pathom* Phra Nakhon Si Ayutthaya*

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

level between variables and the CRD morbidity rates. The final limitation was that this study did not include other widely used risk factors for CRDs.

Conclusions

Vulnerable provinces with high risk of CRDs were identified, especially the northern region of Thailand, which should assist and guide policy makers and healthcare personal to prioritize resource allocations and target interventions. This would contribute to diminish spatially correlated health inequalities and those related to socio-demographic variables. The study has also raised the awareness of CRD risk factors, enhance the identification and management of CRDs in Thailand as a whole and lead to long-term lowering of the prevalence, morbidity and mortality associated with CRDs. Preventive and therapeutic programmess should be adopted in the all communities at risk.

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