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ORIGINAL ARTICLE

Health vulnerability and adaptation of community in the repetitive haze area: Phayao Province, Northern Thailand case study

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ABSTRACT

This was a cross-sectional study to examine health vulnerability and adaptation of community in the repetitive smog area and transboundary haze effect: Phayao Province. According to the findings, the majority of people were male (61.86%), with a high-level of 35.70%, a low-risk level of 34.10%, and a medium risk level of 30.20%, in that order. According to the findings of this study, income was shown to be positively correlated with quality of life (r=0.136), body mass index (BMI) (r=0.116), risk level (r=0.213), adaptive capability (r=0.364), and vulnerability (r=0.364), all significant at $p<0.05$. Furthermore, multi-variable analysis to determine the predictive factors affecting groups with a tendency to be health vulnerable found that sensitivity affecting health vulnerability was adjusted OR: 7.61, B: 2.09 (S.E.: 0.03), Wald: 90.10 ($p<0.01$). To minimize vulnerability to the repeated haze area in the next decades, adaptation activities and a more conscious effect and sensitivity of the health sector are critically needed. The health vulnerability assessment of smog communities adaption suggestions were included in local public health risk planning and monitoring.

Key words:
health vulnerability; adaptive capacity; haze area; Northern Thailand

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INTRODUCTION

Climate change's health implications include rising temperatures, horrible atmospheric conditions, droughts, floods, wildfires, and emerging and recurring disease outbreaks that might have an impact on human health and well-being[1]. Consequently, the impact of climate change and air pollution on human health is an international concern. There is now strong evidence that air pollution from particulate matter is one of the most significant drivers of death and public health burden worldwide, as well as a risk factor for heart disease (Cardiovascular diseases, CVD).[2] Hystad et al. (2020)[3] performed research on the relationship between microparticles and heart disease in 21 low-, middle-, and high-income countries, involving 157,436 persons from 747 adult populations. It was discovered that exposure to atmospheric $PM_{2.5}$ concentrations increased the risk of heart disease in those aged 35 to 70. While a study of long-term exposure to $PM_{2.5}$ in China discovered that all concentrations of 10 g/m^3 increased the incidence of heart disease 1.25-fold (95% CI, 1.22-1.28) and the risk of fatalities from disease 1.16-fold (95% CI, 1.12-1.21).[4]

In 2014, a study by Guo et al.[5] found that the impact of air pollution was related to death in Thailand. The upper northern provinces, namely Chiang Mai and Lampang, and especially PM_{10}, were significantly associated with respiratory mortality. Furthermore, a 2017 study by Pinichka et al.[6] found that the burden of illness from $PM_{2.5}$ air pollution in Thailand for lung cancer and heart disease was 16.8% and 14.6%, respectively. As per a study, exposure to dust pollution PM_{10}, $PM_{2.5}$, CO, O_3, and NO_2 was associated with the number of daily outpatients in Thai hospitals between 2014 and 2017. In March, PM_{10} levels were high, and when combined with biomass incineration, the incidence rate of daily PM_{10} exposure resulted in a 1.020-fold increase in outpatient admissions in the lower respiratory tract and CBVD groups.[7]

Furthermore, issues of health vulnerability are required for integrating three components: hazard exposure, hazard sensitivity, and hazard adaptive capability.[8-10] To lead to a model of planning and adapting to live as safely as possible, fewer risk mitigation measures are required by attempting to achieve a balance of risk and ability to adapt for the effect of minimizing fragility.[11] If a community lacks sufficient capacity to adapt to smog, it becomes more susceptible to health issues, making them more vulnerable. Therefore, it is essential to prioritize efforts to enhance the adaptation capabilities of the agricultural community to mitigate the impact on health and the environment. The health burden arising from air pollution is a cause for concern at both national and global levels, as it presents a complex challenge to address on a spatial scale.[5] All of these contribute to sources of emissions into the atmosphere, both quantitatively and chemically. Especially in places without the technology to prevent and control pollution caused by tribal activities in the open (open burning), such as agricultural areas, sanitary and engineering uncontrolled incineration of waste in landfills. A study by Vongruang and Pimonsree[12] revealed that biomass burning in Southeast Asian countries played a crucial role in the expansion of PM_{10} between 2011 and 2019. The majority of land use patterns in northern Thailand are agricultural. Whenever combined with the mountainous terrain, it results in less diffusion and dilution of day mist, increasing the risk of exposure to dust particles smaller than 2.5 and 10 microns ($PM_{2.5}$ and PM_{10}), which can have adverse health and environmental consequences. The pattern and intensity of health consequences are determined by demographic and social features, as well as individual susceptibility to disease.[2]

In the meantime, there are very few studies evaluating community health vulnerabilities due to environmental problems in Thailand. Furthermore, the smog problem is constantly worsening. This is because it is an area in northern Thailand that suffers from smog pollution from January to May each year. As a result, it is a noteworthy national problem that must be studied and addressed urgently to lessen the impact on people's health and the environment at both the local and regional levels, to examine health risks and community concerns about pollution. The purpose of this research is to study the health vulnerability and adaptation of communities in the repetitive haze area: Phayao Province, Northern Thailand case study. Since it is an area that suffers from haze pollution in the northern part of Thailand from January to May every year. Therefore, it is an important problem at the national level that should be studied and measured to reduce the impact on people's health and the environment urgently, both locally and regionally. The information obtained will be crucial to public health officials in applying the study results to local public health risk planning and monitoring. This will enable them to effectively handle and adapt to the smog situations while minimizing risks to health.

METHODS

Study Area

Pong District is located in Phayao Province, 90 kilometers from the Phayao Provincial Office and 800 kilometers from Bangkok. The landscape is highly mountainous. It is a community study of five communities in Pong District, Phayao Province, as shown in Figure 1.

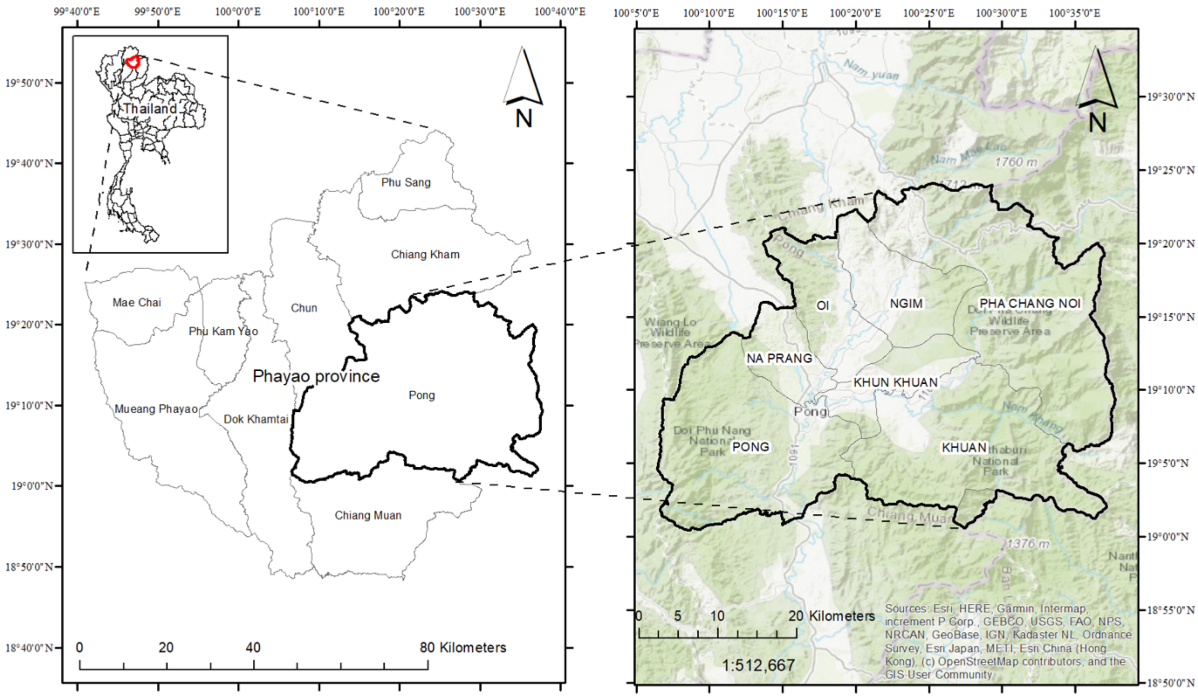


Figure 1 Map of location study area

Study Design and Participants

This is cross-sectional descriptive-analytical research. The study's population was participants who lived in Pong District, Phayao Province. People living in five villages in Pong district, Phayao Province, a total of 4120 people, with the criteria for selection 1) People over 18 years old, 2)

Reside in the Pong District area for more than 1 year and, 3) Consent to participate in the research process. For those who have a physical or psychiatric disease that is an obstacle to answering the research questions, withdrawing subjects from the research are as follows: 1) In the event that the volunteer does not wish to continue or has problems and cannot continue 2) Any physical or psychiatric disease that made it difficult to answer the research questions would be excluded from this study. The sample size was calculated using the following Equation (1)[13-15] for estimating the proportion of the population:

$$n = \frac{Np(1-p)z^2_{1-\frac{\alpha}{2}}}{d^2(N-1)+p(1-p)z^2_{1-\frac{\alpha}{2}}} \quad (1)$$

Substitute the p value in the formula using the ratio of the prevalence of vulnerable groups in the haze case study to vulnerability and social impact at the household level, p = 0.48.[16] The sample size was 451 people.

Tools and Data Collection

The data collection tool used was an individual questionnaire. The questionnaire focused on community adaptation model to cope with climate change and health vulnerability: a case study in a haze-prone area in Pong District, Phayao Province. The item objective congruence (IOC) of the health vulnerability assessment of the smog community (HVSM) questionnaire, which was 0.86 in this study, was assessed by three experts in the environmental and public health fields. The question was examined subsequently on thirty subjects who were similar to the participants in the area study in a pilot study. Furthermore, for each tool, the Cronbach's alpha coefficient is as follows:

Part 1 General information questionnaire (Personal information) 35 items.

Part 2 The measurement form:

2.1 World Health Organization Quality of Life Scale, (WHOQOL - BREF - THAI): 26 items[17] are divided into four dimensions: physical health (seven items), psychological health (six items), social relationships (three items), and environment (eight items) with Cronbach's alpha coefficient = 0.84. The following response options were available on a 5-point Likert scale: 1, not at all; 2, not much; 3, moderately; 4, a lot; and 5, entirely. Three items have negative wording (numbers 2, 9, and 11). The total scores may be broken into three categories: 1) poor quality of life, 2) moderate quality of life (17-26), and 3) good quality of life (27-35).

2.2 Thai Mental Health Indicator Version 2007, (TMHI-15): 15 items[18] developed by The Department of Mental Health, Ministry of Public Health with Cronbach's alpha coefficient = 0.93. The purpose was to assess Thai people's mental health. The response alternatives were on a 4-point Likert scale: 1, not at all; 2, not much; 3, a great deal; and 4, completely. Three negatively worded items (numbers 3, 4, and 5) were included. The total scores are divided into 3 groups: 1) better than average mental health (51-60), 2) average mental health (44-50), and 3) below average mental health (< 43).

2.3 The State-Trait Anxiety Inventory (STAI): 34 items developed by Charles D. Spielberger in 1980.[19] The aim was to assess anxiety broadly in research and therapeutic practice with Cronbach's alpha coefficient = 0.92. The response options were on a 4-point Likert scale: 1, never; 2, sometimes; 3, a frequency; and 4, almost always. There are nine negatively worded items (numbers 1, 3, 6, 7, 10, 13, 14, 16, and 19). The overall score could be b divided into 5 groups: 1, not at all (<20), 2) mild anxiety (41-60), 3) moderate anxiety (61-70), 4) high anxiety (61-70), and 5) very high anxiety (61-70).

2.4 Health Vulnerability Assessment of Smog Communities (HVSM) 32 items, divided into three dimensions: exposure (six items), sensitivity (twelve items), and adaptive capacity (fourteen items), using the model of Ebi and Kovats[20] and Nelson and Crimp[21] with Cronbach's alpha coefficient = 0.80, as shown in Equation 2. On a 4-point Likert scale, the response options were: 0 (not at all), 1, low, 2, moderate, and 5, high.

$$\text{Vulnerability} = \frac{\text{Risk}}{\text{Adaptive Capacity}} \qquad (2)$$

$$\text{Where Risk} = \text{Sensitivity} \times \text{Exposure}$$

Statistical Analysis

For this study, the data analysis involved the use of the SPSS software package to conduct descriptive statistics and correlation analysis. Descriptive statistics, such as frequency, percentage, mean, and standard deviation, were employed to analyze general personal information. In addition, inferential statistics including the Pearson correlation coefficient, Chi-square test, Fisher exact test, and simple correlation coefficient (r) at a 95% confidence interval were utilized to examine the predicted factors. These statistical techniques were applied to analyze the data and draw inferences from the findings. The statistics were used to analyze multiple logistic regression using the Backward Stepwise (Wald) method to bring the variables into the equation. The behavioral level variables, health care behaviors, and mental health were adjusted to bivariate data, and the variables were assigned as high-risk and normal levels. The level of statistical significance was set at p-value<0.05 and the results were displayed with the Adjusted Odds ratio value, with statistical significance set at p<0.05.[22]

Ethical Considerations

The study was approved by the University of Phayao Human Ethics Committee, Thailand. Project reference number: UP-HEC 1.2/019/65 was the ethical clearance certificate (May 17, 2022).

RESULTS

General Information

Table 1 shows the demographic information of the respondents. The results of this study revealed that the subjects were male 279 (61.86) and female 172 (38.14). The participants' age average was 57.46 (SD: 13.56), mostly aged between 40-59 years, 60.75%. The average BMI was 23.15 (SD: 3.90) and the body mass index exceeded the standard ≥ 23.00 (high), 48.34%, marital status was 76.50%, most of them graduated in secondary school level, 61.86% were engaged in agriculture, 61.20% had an average income of 3748.56 (SD: 4705.18) baht, most of them had less than 5000 baht, the majority of participants did not drink alcohol and were non-smokers, with 57.20% and 73.90% , respectively. 82.26% and the sample group stated that 55.65% had underlying disease and most of them had moderate pressure level, 71.40%.

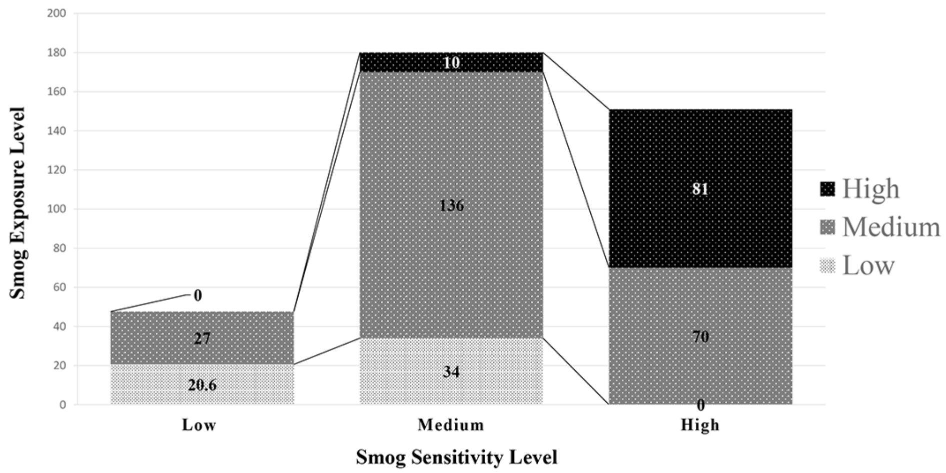
Table 1 Demographic characteristics of the study respondents (n = 451).

Demographic characteristics	**No. (%)**
Gender	
Female	172 (38.14)
Male	279 (61.86)
Age (years old)	
20-39	48 (10.64)
40-59	274 (60.75)
≥ 65	129 (28.60)
Average: 57.46±13.56	
Median: 59.00, Min: 21; Max: 95	
Body mass index (BMI)	
< 18.50 (Low)	35 (7.76)
18.50-22.99 (Average)	198 (43.90)
≥ 23.00 (High)	218 (48.34)
Average: 23.15±3.90	
Median: 22.86, Min:8.89; Max: 42.46	
Status	
Single	38 (8.43)
Married	345 (76.50)
Divorced	58 (12.86)
Separated	10 (2.22)
Education level	
No study	1 (0.22)
Primary school level	69 (15.30)
Secondary school level	279 (61.86)
High school	35 (7.76)
Diploma degree	38 (8.43)
Bachelor’s degree	14 (3.10)
Above bachelor’s degree	15 (3.33)
Income (THB)	
< 5000	371 (82.26)
5001-10,000	61 (13.53)
> 10,000	19 (4.21)
Average: 3748.56±4705.18	
Median: 2,500, Min: 0; Max: 50,000	
Occupation	
Farmer	276 (61.20)
General employee	76 (16.85)
Commerce	32 (7.10)
Government servant	3 (0.67)
Other	64 (14.19)

Demographic characteristics	No. (%)
Alcohol consumption	
Yes	193 (42.80)
No	258 (57.20)
Smoking	
No	333 (73.84)
Had smoked	71 (15.74)
Smoked < 1 item/week	39 (8.65)
Smoked 1 item/week	5 (1.10)
Smoked > 1 item/week	3 (0.67)
Underlying	
Yes	251 (55.65)
No	200 (44.35)
Blood pressure	
Low	52 (11.50)
Medium	322 (71.40)
High	77 (17.10)

The ratio of smog exposure to smog sensitivity

Figure 2 is a consideration of the decision matrix for determining a household's smog risk level. The results showed that most of the samples had a high-risk level of 35.70%, followed by a low-risk level of 34.10% and a medium-risk level of 30.20%, respectively. Furthermore, when considering the characteristics of the relationship between the level of risk and adaptative capacity, it was discovered that the R^2 score was 0.1943, implying that as the risk level score increases, the adaptative capacity will increase in a positive direction. This is displayed in Figure 3.



Smog exposure	Smog sensitivity level		
	Low	**Medium**	**High**
Low	Low: 93 (20.60)	Low: 27 (6.00	Medium: 0 (0.00
Medium	Low: 34 (7.50)	Medium: 136 (30.20)	High: 10 (2.20)
High	Medium: 0 (0.00	High: 70 (15.50)	High: 81 (18.00)

Note: The interpretation score. Exposure : Low[a] (1-6) Medium (7-12) High[b] (13-18), Sensitivity : Low[a] (1-12) Medium (13-24) High[b] (25-36), Adaptive capacity : Low[a] (1-14) Medium (25-28) High[b] (29-42)
[a]None of respondent had scores of 0, [b]Maximum scores are 18, 36, and 42, respectively.

Figure 2 Decision matrix for determining a household's smog risk level (n = 451)

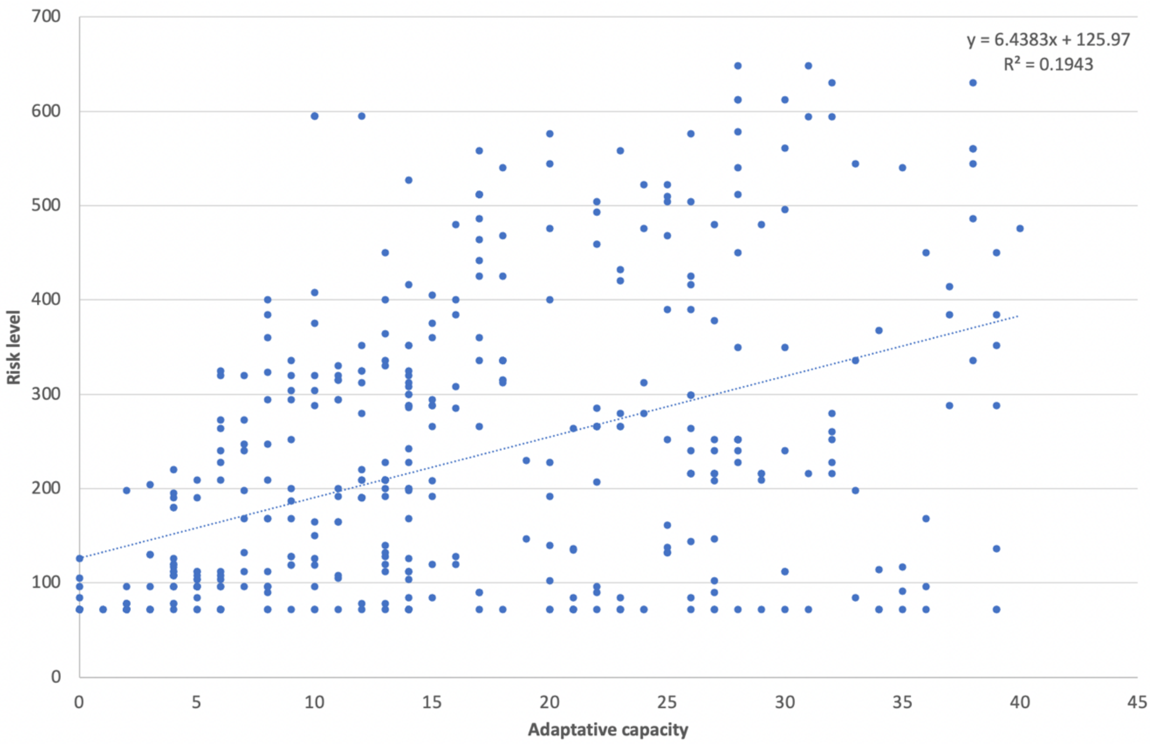


Figure 3 Scatter plot correlation of risk level and adaptive capacity in household's smog area

The study examined the factors contributing to vulnerability in three areas affected by haze: exposure, sensitivity, and adaptive capacity. The results indicated that exposure and sensitivity scores were at a moderate level, accounting for 39.90% and 51.70% respectively. On the other hand, adaptive capacity was found to be low at 54.80%. However, in terms of distribution, the majority of the areas fell into the low vulnerability category (58.55%), followed by a moderate level (38.10%) and a small percentage categorized as high vulnerability (3.35%) as shown in Table 2. Although the overall vulnerability level was low, it is worth noting that a considerable proportion of the population still fell into the moderate vulnerability group.

Table 2 Level of individual's health vulnerability to smog, No. (%).

Components related to smog	Total score level assessment (n = 451)		
	Low, n (%)	**Medium, n (%)**	**High, n (%)**
Exposure	120 (26.60)	180 (39.90)	151 (33.50)
Sensitivity	127 (28.20)	233 (51.70)	91 (20.10)
Adaptive capacity	247 (54.80)	147 (32.60)	57 (12.60)
Health vulnerability	264 (58.55)	172 (38.10)	15 (3.35)

Social Components Associated with both the Community in the Repetitive Smog Area and the Factor's Health Vulnerability

In addition, we considered social components related to community in the repetitive smog area and used the data to study their relationships. Income was positively correlated with quality of life (r=0.136) and body mass index (BMI) (0.116) at $p<0.05$ significance. It was found that the risk level adaptive capacity and vulnerability were significantly correlated with quality of life ($p<0.05$) at r=0.213, r=0.364, and r=0.364, respectively. The level of risk correlated with adaptive capacity (r=0.463), vulnerability (r=0.819), and mental health (r=0.159) and was statistically significant at $p<0.05$. Meanwhile, adaptive capacity was correlated with vulnerability (r=0.872), vulnerability was correlated with mental health (r=0.152), and mental health was significantly correlated with anxiety (r=0.127) at $p<0.05$, as shown in Table 3. In addition, the results of bivariate study factors such as smoking, sleep hour, sensitivity, exposure, and adaptive capacity were found to be correlated with health vulnerability (Table 4). Multi-variable analysis to determine the predictive factors affecting groups with a tendency to be health vulnerable found that sensitivity significantly affected health vulnerability at the Adjusted OR: 7.606 (95%CI, 5.003-11.564) with statistically at p-value < 0.001 (Table 5).

Table 3 Social components related to the community in the repetitive smog area.

Factor	Age	Income	Quality of life	Risk level	Adaptive capacity	Vulnerability	Mental health	Anxiety	BMI
Age	1.000								
Income	-0.3596*	1.000							
Quality of life	-0.1310*	0.1355*	1.000						
Risk level	-0.0742	-0.1249*	0.2125*	1.000					
Adaptive capacity	0.078	-0.0696	0.3644*	0.4631*	1.000				
Vulnerability	0.014	-0.1213*	0.3638*	0.8190*	0.8724*	1.000			
Mental health	-0.0657	-0.1695*	-0.0104	0.1585*	0.0927	0.1520*	1.000		
Anxiety	-0.1464*	0.029	-0.1156*	0.069	-0.0855	-0.0112	0.1266*	1.000	
BMI	-0.2048*	0.1160*	0.024	-0.0209	-0.0129	-0.0231	0.0331	0.0645	1.000

*$p < 0.05$.

Table 4 Factors related to health vulnerability among participants living in repetitive smog-prone areas, Pong District, Phayao Province.

Factor	Health vulnerability		Crude OR (95% CI)	χ^2	*p*-value
	Low	High			
Gender					
Male	102 (22.60)	70 (15.50)	1.052	0.067	0.796
Female	162 (35.90)	117 (25.90)	(0.715-1.548)		
Age (year old)					
< 60	136 (30.20)	104 (23.10)	0.848	0.739	0.390
≥ 60	128 (28.40)	83 (18.40)	(0.582-1.235)		
BMI					
< 18.50	22 (4.90)	13 (2.90)	NA	0.297	0.862
18.50-22.99	116 (25.70)	84 (18.60)			
≥ 23.00	126 (27.90)	90 (20.00)			
Status					
Single	26 (5.80)	12 (2.70)	NA	1.773	0.412
Married	200 (44.30)	145 (32.20)			
Divorced/separated	38 (8.40)	30 (6.70)			
Occupation					
Farmer	158 (35.00)	118 (26.20)	NA	3.271	0.352
Employee	44 (9.80)	35 (7.80)			
Own business	18 (4.00)	14 (3.10)			
Other (unemployment)	44 (9.80)	20 (4.40)			
Education level					
None	39 (8.60)	31 (6.90)	NA	4.259	0.372
Primary school	172 (38.10)	107 (23.70)			
Secondary school	37 (8.20)	36 (8.00)			
Diploma	9 (2.00)	5 (1.10)			
Above bachelor	7 (1.60)	8 (1.80)			
Income (THB)					
< 5,000	216 (47.90)	155 (34.40)	NA	-	0.629[(1)]
5,001-10,000	37 (8.20)	24 (5.30)			
> 10,000	11 (2.40)	8 (1.80)			
Alcohol consumption					
Yes	114 (25.30)	79 (17.50)	0.961	0.043	0.836
No	150 (33.30)	108 (23.90)	(0.659-1.401)		
Smoking					
No	201 (44.60)	132 (29.30)	NA	-	0.036[*,(1)]
Had smoked	43 (9.50)	28 (6.20)			
Smoked < 1 item/week	15 (3.30)	24 (5.30)			
Smoked 1 item/week	3 (0.70)	0 (0.00)			
Smoked > 1 item/week	2 (0.40)	3 (0.70)			

Factor	Health vulnerability		Crude OR (95% CI)	χ^2	*p*-value
	Low	High			
Underlying					
Yes	148 (32.80)	103 (22.80)	0.962	0.039	0.848
No	116 (25.70)	84 (18.60)	(0.659-1.406)		
Blood pressure					
Low	29 (6.40)	23 (5.10)	NA	0.306	0.585
Medium	191 (42.4)	131 (29.00)			
High	44 (9.80)	33 (7.30)			
Sleep hour (hrs.)					
< 8	80 (17.70)	85 (18.80)	NA	9.320	0.009*
8	62 (13.70)	125 (27.70)			
≥ 8	45 (10.00)	54 (12.00)			
Sleep pill experienced					
Yes	34 (7.50)	27 (6.00)	0.876	0.228	0.676
No	230 (51.00)	160 (35.50)	(0.508-1.509)		
Quality of life					
Medium	165 (36.60)	111 (24.60)	1.141	0.455	0.500
High	99 (22.00)	76 (16.90)	(0.777-1.675)		
Sensitivity					
Low	127 (28.20)	0 (0.00)	NA	45.105	0.001**
Medium	112 (24.80)	121 (26.80)			
High	25 (5.50)	66 (14.60)			
Exposure					
Low	120 (26.60)	0 (0.00)	NA	120.529	0.001**
Medium	88 (19.50)	92 (20.40			
High	56 (12.40)	95 (21.10)			
Adaptive capacity					
Low	107 (23.70)	140 (31.00)	NA	69.394	0.001**
Medium	100 (22.20)	47 (10.40)			
High	57 (12.60)	0 (0.00)			
Mental health					
Normal	165 (36.60)	111 (24.60)	1.141	0.455	0.500
Abnormal	99 (22.00)	76 (16.90)	(0.777-1.675)		
Anxiety					
No	7 (1.60)	2 (0.40)	NA	2.296	0.317
Medium	249 (55.20)	176 (39.00)			
High	8 (1.80)	9 (2.00)			

*$p < 0.05$; **$p < 0.01$; (1): Fisher exact test; NA: None available.

Table 5 Multi-variable analysis to determine the predictive factors affecting groups with a tendency to be health vulnerable in the sample using Binary Logistic Regression Analysis (Backward Stepwise (Wald).

Variable	B	S.E.	Wald	*p*-value	Adjusted OR	95% CI Adjusted OR	
						Lower	Upper
Sensitivity	2.029	.214	90.104	0.001**	7.606	5.003	11.564
Constant	-4.367	.446	95.830	0.001	0.013		

$^{*}p<0.05$, $^{**}p<0.01$, Nagelkerke R Square = 36.20%.
Chi-Square = 31.71 df= 1, (Hosmer and Lemeshow Test) and Overall Percentage = 66.60% (Classification Table).

DISCUSSION

Though most research shows health vulnerabilities to climate change, evidence on community-level consequences is lacking. Smog, on the contrary, is a concern at community, local, national, and ASEAN levels, and it can have an effect on health from short-term as well as long-term exposure. For instance, our research focuses on studying and assessing the health, vulnerability, and adaptation of a community in a repetitive haze area: Phayao Province, Northern Thailand, as a case study. Our study's findings indicated a high-risk level, followed by a low-risk level and a medium-risk level. However, our study discovered that health vulnerability was low (58.55%), whilst health vulnerability was moderate (38.10%), which implies that while exposure, sensitivity, and evaluation outcomes are moderate, adaptation is low. As it turns out, low adaptation to the conditions at hand is likely to increase population exposure and health problems. Reduced exposure would lead to decreased health vulnerability knowing that adaptation was an important determinant of well-being in society and a living environment.[23] Thus, reducing exposure would lead to lower health vulnerability. Adaptation is seen as an important social and ecological feature.[24] Therefore, reducing exposure would result in lower health vulnerability.

Furthermore, Mikhun and Leknoi[16] explained that the severity of the transboundary haze pollution problem across the Association of Southeast Asian Nations (ASEAN) region is due to globalization and the expansion of contract farming as a result of rising neoliberal policies across the region, particularly in northern Thailand, which has affected transboundary haze pollution from both Laos and Myanmar. Maize monocultures have also exacerbated the smog pollution problem. These actions are in response to the desire for economic growth and food security, and burning wasteland is one of the cheapest and most rapid ways to facilitate rapid production.[16] As ascribed to the complexities of the socioeconomic background and land usage, combating haze is a difficult problem. However, assessments of health vulnerability and adaptability are being performed at various scales that assist in adaptation planning.[25]

One intriguing finding from this study was the correlation between increased risk levels and lower income. The researchers observed that when individuals face the risk of air pollution, they tend to adapt by limiting their exposure to outdoor air, which can make it challenging for them to carry out work-related activities. This suggests that individuals with lower incomes may face additional difficulties and limitations in their daily lives due to the impact of air pollution. As a consequence, income decreased[26,27], and it was observed that adaptive capacity was positively associated with quality of life, leading the researchers to infer that the faster the patients' level of adaptation to pollution, the higher their quality of life.[28-30] Simultaneously, it was discovered that anxiety contributes to a poorer degree of quality of life, as the researcher claimed, even though the components of quality of life do not focus primarily on physical issues but also incorporate mental, social, and environmental factors. Having said that, all of these factors are linked. That is, being easily nervous is related to a negative mental state. As a result, the number of individuals who are unable to live a quality life has grown, along with the number of people who are unable to live a quality life.[31,32] The researcher also identified a connection between age and anxiety, noting that individuals who are susceptible to anxiety tend to experience an accelerated onset of depression symptoms. Furthermore, anxiety has been found to weaken the immune system, increasing the likelihood of infections, cancer, hypertension, cardiovascular disease, diabetes, and other ailments. Consequently, these factors contribute to a shorter life expectancy for individuals affected by anxiety.[33-35] Furthermore, body mass index was found to be correlated, indicating that the researchers determined that an increase in BMI was associated with a higher risk of developing several diseases, such as high blood pressure, heart disease, and diabetes, all of which are associated with a reduced life expectancy.[36,37] Therefore, areas with recurring haze problems, even in a short period of time, may affect health in the long term in the future, relevant agencies should have standards and policies for health protection to reduce health risks that will continue to increase. Despite the moderate level of health vulnerability found in the study, it is important for relevant agencies to prioritize and promote activities that raise awareness about the impact (sensitivity) of living in smog-affected areas and enhance adaptive skills. By doing so, it is possible to mitigate further risks and reduce health vulnerabilities. This proactive approach can have positive outcomes, including improved income and overall quality of life for individuals residing in these areas, by addressing the identified problems and implementing preventive measures.

CONCLUSION

The examination of health vulnerability and adaptability has undergone advancements across various disciplines and research traditions. In this study, we employed a model that assessed exposure, sensitivity, risk, and vulnerability, along with their associations with social factors. The findings revealed that the sample group residing in the haze-affected Pong area exhibited a moderate level of exposure, a high level of sensitivity, and a high-risk level of 35.70%. Additionally, there was a low level of risk observed in 34.10% of the group, while a medium risk level was identified in 30.20% of the participants. Moreover, the level of adaptation was found to be poor, resulting in a health vulnerability rate of 58.50%. This was followed by a moderate vulnerability level of 38.10%, and a high vulnerability level of 3.30%, respectively. In addition, income was positively correlated with quality of life (r=0.135), and adaptive capacity and vulnerability risk levels had a significant correlation with the quality of life ($p<0.05$) at r=0.21, r=0.364, and r=0.364, correspondingly. The level of risk was statistically significant when associated with adaptive capability (r=0.463), vulnerability (r=0.819), and mental health (r=0.159). Furthermore, sensitivity impacting health vulnerability was adjusted OR: 7.61, B: 2.09 (S.E., 0.03), and Wald: 90.10 ($p<0.01$) in multivariable analysis to determine the predictive factors affecting groups with a tendency to be health vulnerable.

RECOMMENDATIONS

Our grasp of governance and decision-making on the one hand and system resilience on the other, as well as the implications for effective adaptation techniques in a constantly changing environment, will be improved by current and future study, and future issues are as follows:

1. The various smog problems in each area may not be comparable: what social and environmental adaptation goals have the appropriate authorities established?

2. Which factors are crucial for adaptation in haze-affected areas? And exactly how will it affect personal security, society, and the environment?

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