

Ground-Level Ozone Pollution in Upper Northern, Thailand : An ArcGIS-Based Approach

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Abstract

Ground-level ozone in the air we breathe even relatively low levels can cause health effects. Thus, it is important to analyze the spatial-temporal ozone concentrations. The IDW interpolation technique by ArcMap 10.5® software was used to simulate and access ground-level ozone data in areas where without ambient air quality monitoring stations in 8 provinces (Chiang Rai, Chiang Mai, Phrae, Nan, Phayao, Lampang, Lamphun, and Mae Hong Son) during the year 2017 – 2019. The ground-level ozone input data were obtained from the pollution control department, Thailand. The Mean Error (ME) and Root Mean Squared Error (RMSE) were used to find the most suitable power for IDW interpolation. The IDW interpolation with power 3 was represented the best condition. IDW interpolation of monthly maximum 1-hour reveal that orange and red were found as the major of AQI colors in all 8 provinces. Orange was found in every province, while red was only distributed in Chiang Rai and some areas in Chiang Mai during ozone crisis (February to June). For monthly maximum 8-hour, AQI ratings were ranging from green to purple, and most areas were faced with ozone pollution in the red to the purple. Nevertheless, July to January was rarely reached a high level of ozone. Additionally, the IDW interpolation map of Chiang Mai in May 2017 was chosen for discussion as an example to converted data from 2D - spatiotemporal interpolation map to the number of sub-districts in which ozone AQI levels were got to the unhealthy zone.

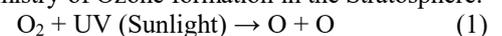
Keywords: Ground-Level Ozone, ArcGIS, Spatial Interpolation, Inverse Distance Weighted.

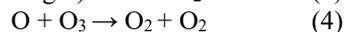
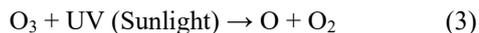
1.Introduction

Ozone (O₃), a gas composed of three atoms of oxygen, is one of the six common air pollutants indicated in the Clean Air Act, and its level in ambient air needs to be decreased based on health criteria (US. EPA, 2021). Ozone can be "good" or "bad" for the environment and human health depending on where it is found in the atmosphere (US. EPA, 2021). Good ozone or Stratospheric ozone, which can protect living things from ultraviolet radiation from the sun, is found in the

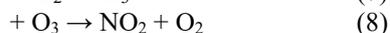
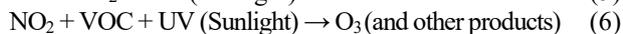
Stratosphere (US. EPA., 2021a). Eq.1 – Eq.4 illustrates the ozone formation in the Stratosphere. Ozone forms readily as incoming ultraviolet (UV) radiation can readily destroy two oxygen atoms of an oxygen molecular into atomic oxygen (a single atom) (National Aeronautics and Space Administration, 2003). Afterward, atomic oxygen can combine with an oxygen molecule to form ozone. Moreover, sunlight can readily split ozone into an oxygen molecule and an individual oxygen atom which is ready to form a new molecule of ozone again. Bad ozone or tropospheric ozone, found in ground-level where humans live, is found in the Troposphere (US. EPA., 2021a). Ground-level Ozone is a destructive air pollutant, because of its effects on a variety of health problems and the environment (US. EPA., 2021a). People with asthma, children, older adults are at greatest risk from breathing air containing ozone especially children because their lungs are still developing (US. EPA., 2021b). Moreover, ground-level ozone in high amounts can cause serious health issues, such as chronic lung disorders like bronchitis and cancer (Stockholm Environment Institute, 2021). In the troposphere near the Earth's surface, ozone is formed by two origins. Eq.5 – Eq.8 illustrates the ozone formation in the Troposphere. Firstly, ozone forms through the splitting of molecules by sunlight as it does in the stratosphere (National Aeronautics and Space Administration, 2003). Secondly, ozone is formed by chemical reactions between oxides of nitrogen (NO_x) and volatile organic compounds (VOC) emitted by the burning of fossil fuels, cars, power plants, industrial boilers, refineries, chemical plants, and other sources, as well as some natural sources react in the presence of sunlight (US. EPA, 2021). Burning fossil fuels is also the main driver of climate change. Climate change is a rise in global and local temperatures. Climate change causes temperatures to climb, more ozone pollution is formed because the warmer the air, the faster the chemical reaction that creates ozone (State of Global Air, 2020). Moreover, ozone is also a greenhouse gas and is now 30–70% higher than 100 years ago (State of Global Air, 2020).

Chemistry of Ozone formation in the Stratosphere:





Chemistry of Ozone formation in the Troposphere:



Thailand has seen ground-level ozone exceeding the Thailand National Ambient Air Quality Standard (TNAAQs) value of 1-hour and 8-hour as 100 and 70 parts per billion (ppb) (Table 1) countrywide over the last 10 years especially during the summer season (Pollution Control Department, 2020). It is normal to detect a higher level of ground-level ozone during the summer as high temperatures and sunlight are the catalysts for an increase in the ground-level ozone (Asian Institute of Technology, 2020; US. EPA, 2021). Thailand has an average temperature of about 30°C with a tropical climate (Viroat Srisurapanon & Chana Wanichapun, 2019). Northern Thailand faces high levels of particulate matter (PM_{2.5} and PM₁₀), VOCs, and ground-level ozone from January to April for more than 10 years, which is the dry season, when wildfires are common and agricultural burning takes place (Pollution Control Department, 2020; Stockholm Environment Institute, 2021). Furthermore, topography and weather conditions like solar radiation, rain, temperature, wind speed, and air pressure play an important role in determining the concentration of pollutants (Stockholm Environment Institute, 2021). For example, on March 10, 2020, at the Chiang Mai provincial government center monitoring station has been observed the level of the maximum 8-hour average value of ozone was as high as 86 ppb, reaching a maximum value at 117 ppb, thus exceeding the TNAAQs (70 ppb) up to 1.67 times (Asian Institute of Technology, 2020; Pollution Control Department, 2020). Ekbordin Winijkul, an Asian Institute of Technology atmospheric scientist whose work focuses on PM 2.5 and other air pollution, has suggested people in northern Thailand should avoid outdoor activities during the summer daytime for reducing high risks or health problems (Asian Institute of Technology, 2020).

Currently, only 14 ambient air quality monitoring stations (AAQMS) in 8 provinces (758 sub-district) across upper northern Thailand can monitor, record, and report ground-level ozone (Pollution Control Department, 2021) as illustrated in Figure 1(a) and 1(b) and Table 2. It should be noted that AAQMS does not cover all areas. The ozone concentration was measured in part per billion (ppb). AAQMS have typically been installed in urban areas where population density is high or industrial areas (Beelen et al., 2009; Bell, 2006). GIS is a computer-based tool for mapping and analyzing the geographic phenomenon that exists and occurs on earth (Mishra et al., 2015). GIS is not only innovative and important

component of many projects for public health and epidemiology studies but also plays a vital role in the planning of air quality management (Mishra et al., 2015). GIS has been used to identify risks of exposure to air pollutants at the community level (Hammond et al., 2011; Rytönen, 2004). For example, mortality rates from toxic air pollutants were calculated using the number of people exposed to pollution at the census area unit level (Mishra et al., 2015). Interpolation technique in GIS is an optional technique to predict the value of attributes at non sites from measurements made at point locations within the same area (Sajjadi et al., 2017) by specifying search distance, closest points, power setting, and barriers (Bartier & Keller, 1996; GISGeography, 2021; Gong et al., 2014; Pinichka et al., 2017a; Rojas-Avellaneda, 2007; Weber & England, 1992). Evaluations of interpolation techniques have been determined across environmental disciplines (Simpson & Wu, 2014) such as rainfall (Jeffrey et al., 2001; Willmott et al., 1985), wind velocity (Jarvis & Stuart, 2001), air temperatures (Jarvis & Stuart, 2001), evapotranspiration studies (Willmott, 1982), air pollution exposure (Mishra et al., 2015; Sajjadi et al., 2017), and others. However, evaluations of interpolation involving ozone data is rarely studied and never has a study such as this occurred in the in the upper northern, Thailand.

Therefore, this study has two goals. First, we would like to use a mathematical model via IDW interpolation technique by ArcMap 10.5® software to simulate and access ground-level ozone data in areas where without AAQMS in 8 provinces in upper Northern, Thailand (Chiang Rai, Chiang Mai, Phrae, Nan, Phayao, Lampang, Lamphun, and Mae Hong Son) during the year 2017 – 2019. Second, we converted the IDW interpolation data (2D - Spatiotemporal Interpolation map) to the number of sub-districts in which ozone AQI levels were got to the unhealthy zone.

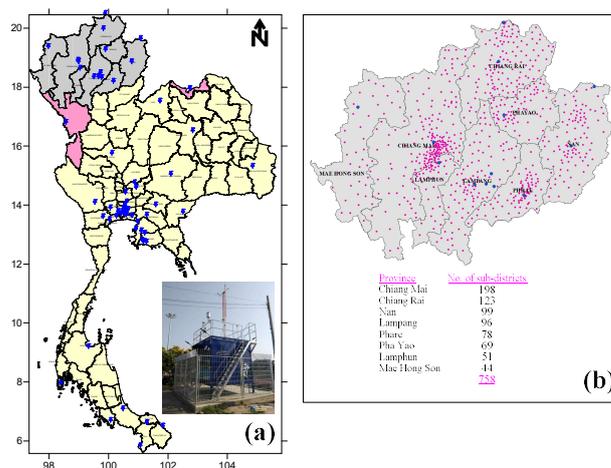


Figure 1 (a) Ambient air quality monitoring stations in Thailand (blue markers), (b) 758 sub-districts (pink markers) in 8 provinces

Table 1 National Ambient Air Quality Standard (NAAQS) for Ozone

Parameter		Value
Thailand	1-hour	100 ppb (200 µg/m ³)
	8-hour	70 ppb (140 µg/m ³)
EPA	1-hour	120 ppb (235 µg/m ³)
	8-hour	70 ppb (140 µg/m ³)
		O ₃ 1 ppb = 2.00 µg/m ³

2. METHODOLOGY

2.1 Study Area and Input Data

Figure 1(a) shows the positions of 14 AAQMS and study areas in 8 provinces in the north of Thailand. These stations are operated under the supervision of the division of air quality and noise management bureau, pollution control department, Thailand. Measurement of ozone according to the standard method by ultraviolet light metering (Pollution Control Department, 2022). The coordinate longitude and latitude were used for specifying the location of each monitoring station (Table 2). The ground-level zone input data were the monthly averages maximum of 1-hour and 8-hour during 2017–2019 (Table S1 – S6 and Figure S1 – S2 in supporting information (SI)). Moreover, we also use the data from 2 monitoring stations outside the main study area (Tak and Nong Khai province) (Pink area in Figure 1(a)) to obtain more reliable results in the southern part of Mae Hong Son, Chiang Mai, Lamphun, Lampang, Phrae, and in the eastern part of Nan where have no AAQMS. Forasmuch, the IDW interpolation technique is based on the proximity of neighboring stations to the target station (Wuthiwongyothin et al., 2021).

Table 2 Description of ambient air quality monitoring stations (Pollution Control Department, 2021)

No.	Station	ID	Lat.	Long.
1	Chiang Rai	57T	19.90921	99.82334
2	Chiang Rai	73T	20.42738	99.88371
3	Chiang Mai	36T	18.84075	98.96974
4	Chiang Mai	41T	18.79090	98.98813
5	Nan	67T	18.78880	100.77640
6	Nan	75T	19.57592	101.08158
7	Pha Yao	70T	19.20027	99.89285
8	Phare	69T	18.12886	100.16240
9	Mae Hong Son	58T	19.30462	97.97161
10	Lampang	37T	18.27823	99.50649
11	Lampang	38T	18.25074	99.76399
12	Lampang	39T	18.41963	99.72650
13	Lampang	40T	18.28278	99.65912
14	Lamphun	68T	18.56734	99.03862
15	Tak	76T	16.73445	98.56696
16	Nong Khai	82T	17.87790	102.72861

2.2 Colored Bar of the Ground-level Ozone Risk Map

Risk map colors use color-coded criteria from Air Quality Index (AQI) of the United State. Because Thailand has a benchmark of only 8-hour, but not for 1-hour (Figure 2). The meaning of AQI colors has been described in Figure 3. The AQI uses colors, numbers, and

words to tell people about the air quality (AirNow, 2022). The AQI is divided into six categories. Each category corresponds to a different level of health concern. Each category also has a specific color. The color makes it easy for people to quickly determine whether air quality is reaching unhealthy levels in their communities (AirNow, 2021). AQI is a color rating that runs from 0 to 500. The higher the AQI value, the greater the level of air pollution and the greater the health concern. For example, an AQI value of 50 or below represents good air quality, while an AQI value over 300 represents hazardous air quality (AirNow, 2021).

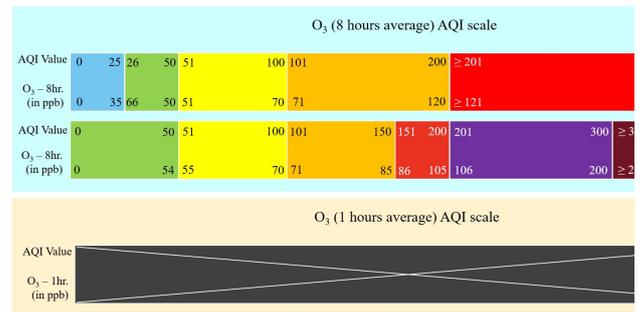


Figure 2 AQI ratings of Thailand and the US

Daily AQI	Color	Levels of Concern	Values of Index	Description of Air Quality
Green	Green	Good	0 to 50	Air quality is satisfactory, and air pollution poses little or no risk.
Yellow	Yellow	Moderate	51 to 100	Air quality is acceptable. However, there may be a risk for some people, particularly those who are unusually sensitive to air pollution.
Orange	Orange	Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is less likely to be affected.
Red	Red	Unhealthy	151 to 200	Some members of the general public may experience health effects; members of sensitive groups may experience more serious health effects.
Purple	Purple	Very Unhealthy	201 to 300	Health alert: The risk of health effects is increased for everyone.
Maroon	Maroon	Hazardous	301 and higher	Health warning of emergency conditions: everyone is more likely to be affected.

Figure 3 AQI ratings and Description of US (AirNow, 2021)

2.3 The Evaluation Method for the Accuracy of Spatial Interpolation

The error statistics used in this paper are: Mean Error (ME) and Root Mean Squared Error (RMSE). ME is used for determining the degree of bias in the estimates often referred to as the bias. Since positive and negative estimates counteract each other, the resultant ME tends to be lower than the actual error prompting caution in its use as an indicator of accuracy (Maduako et al., 2017). RMSE provides a measure of the error size, but it is sensitive to outliers as it places a lot of weight on large errors (Maduako et al., 2017). They are defined as follows in Eq.9 – Eq.10 (Royal Irrigation Department, 2018):

$$ME = \frac{1}{n} \sum_{i=1}^n (x_i - x) \quad (9)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - x)^2} \quad (10)$$

Where n is the number of observations, x_i is the observed value at location x_i , and x is the interpolated value at location x_i (Maduako et al., 2017; Qiao et al., 2018; Royal Irrigation Department, 2018).

2.4 ArcGIS: Spatial Interpolation Using Inverse Distance Weighting (IDW)

The study involved integrating data from in-situ measurements (AAQMS) of ozone concentration into digital map layers to determine the spatial variations. The coordinate longitude and latitude tool helped identify various households in which the data were obtained and processed in excel format for use in GIS software (ESRI, ArcMap 10.5®).

In this study, the generation of spatial objects and their attributes, geospatial analysis (IDW) technique was performed to calculate the value of each cell at locations without AAQMS. IDW interpolation is easy to apply, less time consuming, and requires inexpensive computation than more complicated methods (Wuthiwongyothin et al., 2021). IDW interpolation is one of the best ways to estimate unknown values by specifying search distance, closest points, power setting, and barriers (GISGeography, 2021; Kravchenko & Bullock, 1999; Li et al., 2016; Robichaud & Ménard, 2014) and largely used for creating continuous data when data are collected at discrete locations in a GIS (Akkala et al., 2010). IDW interpolation assuming closer values are more related than further values with its function (GISGeography, 2021). For example, the red points have known concentration values, the other points will be interpolated (Figure 4). Accordingly, if you need to measure the purple point, you can set up your interpolation so that it takes a fixed or variable number of points. Therefore, it uses a fixed number of points of 3 and uses the three closest points. The main factor affecting the accuracy of IDW is the value of the power parameter (Isaaks, 1989). The general formula of the IDW interpolation method is defined as follow in Eg.11 (Eldrandaly & Abu-Zaid, 2015; GISGeography, 2021; Li et al., 2016):

$$Z_p = \frac{\sum_{i=1}^n \left(\frac{Z_i}{d_i^p} \right)}{\sum_{i=1}^n \left(\frac{1}{d_i^p} \right)} \quad (11)$$

Where Z_p is the interpolated value at the unknown (or unsampled) location (x, y) , n is the number of nearest known points surrounding (x, y) , Z_i are the observed values at the nearest known points of (x_i, y_i) , d_i are the distances between each (x_i, y_i) and (x, y) , p is the specified power which controls the degree of local

influence (Eldrandaly & Abu-Zaid, 2015; GISGeography, 2021; Li et al., 2016).

An important considerations that were required prior to the use of IDW interpolation was the power value (Munyati & Sinthumule, 2021). The power parameter can be chosen based on error measurement (e.g., Mean Error (ME) and Root Mean Squared Error (RMSE)), resulting in optimal IDW (Isaaks, 1989). The most reasonable IDW interpolation results are obtained using power parameter values from 0.5 to 3 (Munyati & Sinthumule, 2021). Please note that the method is suitable to evaluate for events that already happened (Li et al., 2016).

2.5 Linking Ozone to Community Level

As is evident from Figure 1(b), the study areas in 8 provinces consist of a total of 758 sub-districts, spread over an area of 85,852.40 square kilometers (Energy Policy and Planning office, 2022). In this section, the IDW interpolation data were converted to the number of sub-districts where at risk of exposure to ground-level ozone. The shapefile data of 758 sub-districts was used to identify the location of the each 758 sub-district obtained from Chontanat Suwan (2022) (Chontanat Suwan, 2022) (pink markers in Figure 1(b)). The shapefile is a geospatial data format for use in geographic information system (GIS) software (United States Census Bureau, 2022). Moreover, we also analyze the population with unhealthy ozone exposure. The current population of 8 provinces in the upper northern is 5,874,503 (Table S7) as of December 31, 2021, based on the Bureau of Registration Administration (BORA), Thailand data (Bureau of Registration Administration, 2021). We assumed the proportions of population located within each grid to have been exposed to the same pollutant concentrations in the grid cells (Pinichka et al., 2017b).

3. RESULTS AND DISCUSSION

3.1 The Accuracy of IDW Spatial Distribution Method

The significant of this section is to find the most suitable power for IDW interpolation. Table 3 illustrates the level of bias in estimation for IDW interpolation with power 1 to 3 ($p=1$ to $p=3$). The lower value of ME and RMSE for each interpolation method indicates the optimality of that method (Sajjadi et al., 2017). The results revealed that power 3 ($p=3$) provided better performance than the power 1 ($p=1$). Through the comparison of power 1 to power 3, we had known that the level of bias in estimation is lowest for power 3 ($p=3$) and highest for power 1 ($p=1$) as indicated by the respective ME and RMSE. A negative result indicates that the prediction has been achieved with a value that is lower than the actual value (Royal Irrigation Department, 2018). On the other hand, A positive result indicates that the prediction has been achieved with a value that is higher than the actual value (Royal Irrigation Department, 2018). The results were the same as in previous studies of Munyati

et al (2021), higher power value puts more weightage on the nearest data points, means that nearby data will have

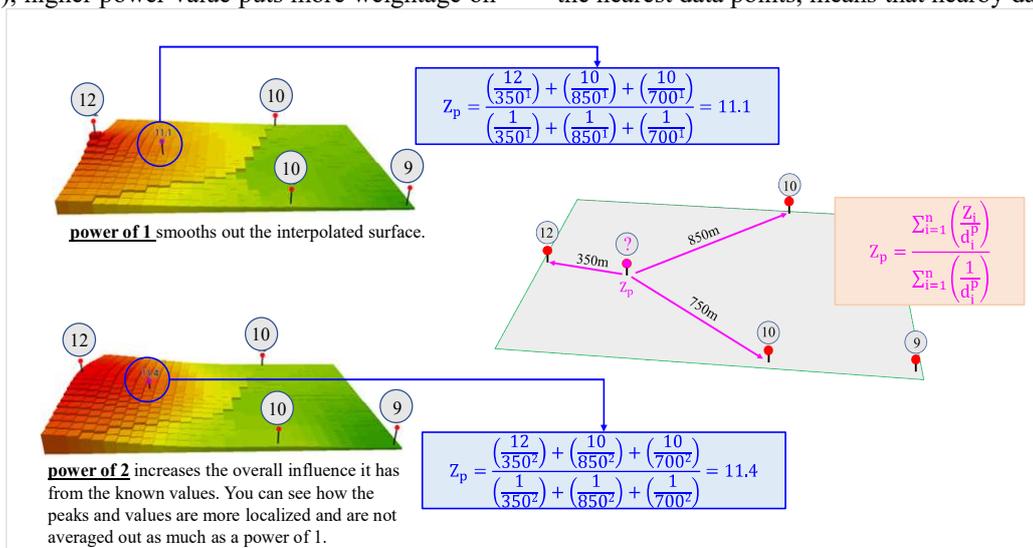


Figure 4 Inverse Distance Weighting (IDW) Interpolation (GISGeography, 2021)

the most influence (Munyati & Sinthumule, 2021). Therefore, IDW with Power 3 ($p=3$) was utilized in this study to generate all maps of ground-level ozone interpolation in section 3.2.

Table 3 The level of bias in estimation for IDW interpolation with power 1 to 3

Data Set	IDW- Power 1		IDW- Power 2		IDW- Power 3	
	Min. (ppb)	Max. (ppb)	Min. (ppb)	Max. (ppb)	Min. (ppb)	Max. (ppb)
1 Actual: Xi	77	112	77	112	77	112
Predicted: X	77.8269	110.7949	77.0037	111.9733	77.0000	111.9993
2 Actual: Xi	60	129	60	129	60	129
Predicted: X	61.1308	128.1412	60.0042	128.9982	60.0000	129.0000
3 Actual: Xi	69	97	69	97	69	97
Predicted: X	69.9159	96.5726	69.0056	96.9977	69.0000	97.0000
n	3	3	3	3	3	3
ME	-0.9579	0.8304	-0.0045	0.0103	0.0000	0.0002
RMSE	1.6591	1.4384	0.0078	0.0178	0.0000	0.0004

3.2 IDW Interpolation

The using of mathematical model via IDW interpolation technique by ArcMap 10.5® software to simulate and access ground-level ozone data in areas where without AAQMS in 8 provinces in upper Northern, Thailand during the year 2017 – 2019 is the first goal of this paper. Figure 5 and Figure 6 show the generated maps of the monthly maximum of 1-hour and 8-hour during 2017–2019 predicted using IDW interpolation technique of the study area in 8 provinces.

3.2.1 Monthly Maximum 1-hour Average Value of Ozone

As can be seen from Figure 5, the data reveal that orange (unhealthy for sensitive groups; 125 - 164 ppb) and red (unhealthy; 165 - 204 ppb) were found as the major of AQI colors in all 8 provinces. Anywise, ozone was never seen the AQI get to purple and maroon. It can be observed that every province was faced with orange zone, but the red zone was only distributed in Chiang Rai and some areas in Chiang Mai. February to June (summer season) shows more unhealthy zones than other months since temperature is one of the elements

which impacts ozone production, increased temperature also means increased ozone (State of Global Air, 2020; US. EPA, 2021). The temperature profile of 8 provinces was shown in Figure S3 in SI (Weather Spark, 2022). Nevertheless, July to January was rarely reached a high level of ozone.

3.2.2 Monthly Maximum 8-hour Average Value of Ozone

In this section, IDW interpolation map of monthly maximum 8-hour average value of ozone will be discussed. The AQI ratings of ozone were ranging from green (good: 0 to 50 ppb), yellow (moderate: 51 to 100 ppb), orange (unhealthy for sensitive groups; 101 - 150 ppb), red (unhealthy; 151 to 200 ppb), and purple (very unhealthy; 201 to 300 ppb), respectively (Figure 6). February to May, almost all areas were faced with ozone pollution in the red to the purple zone over the period of 3 years, like in case of the monthly maximum 1-hour average in section 3.2.1. From the data, during the ozone crisis, people living in Chiang Mai, Lampang, Phare and Mae Hong Son were significantly more health risks from ozone exposure than other provinces due to the AQI get to purple color. Nevertheless, July to January was found relatively high correlation of yellow and green, while the orange zone was found slightly.

In summary, it is apparent that the green zone was found only in 2017 (June to September), the yellow zone was encountered for 4-month in 2017, 7-month in 2018, and 3-month in 2018, the orange zone was suffered for 2-month in 2017 and 2018 and 5-month in 2018, the red zone was detected for 2-month in 2017 and 2018, and 4-month in 2018, and the purple zone was discovered for 2-month in 2017 and 1-month in 2019, respectively.

3.3 Linking Ozone to Community Level

The second goal of this paper is to convert the IDW data (2D - Spatiotemporal Interpolation map) from section 3.2 to the number of sub-districts in which ozone AQI levels were got to the unhealthy zone. However, the data conversion must be converted on a case by case. Thus, the total cases are 576 cases (288 cases for 1-hour and 288 cases for 8-hour (3-year x 12-month x 8-province = 288 cases)). Therefore, this study cannot present the calculations for the entire of 576 cases. Consequently, at this article, Chiang Mai in May 2017 was chosen to debate as an example.

3.3.1 Monthly Maximum 1-hour Average Value of Ozone

In May 2017, 12 sub-districts of Chiang Mai province including 1) Mae Ai, 2) Ron Mae Sao, 3) Son Ton Mue, 4) Wiang, 5) Mon Pin, 6) Mae Ngon, 7) Sansai, 8) Mae Kha, 9) Pong Nam, 10) Pong Tam, 11) Si Dong Yen, and 12) Mae Thalop, respectively (accounting for 7.48% of Chiang Mai's population (133,873 people)) were got in orange zone (unhealthy for sensitive groups). Furthermore, 3 sub-districts including 1) Tha Ton, 2) Mae Na Wang, and 3) Ban Luang (accounting for 1.99% of Chiang Mai's population (35,569 people)) were got in red zone (unhealthy). The details were presented in Figure 7 and Table 4.

3.3.2 Monthly Maximum 8-hour Average Value of Ozone

In May 2017, 15 sub-districts of Chiang Mai province including 1) Pong Nam Ron, 2) Mon Pin, 3) Wiang, 4) San Sai, 5) Mae Kha, 6) Mae Ngon, 7) San Ton Mue, 8) Ban Luang, 9) Mae Ai, 10) Nong Bua, 11) Mae Thalop, 12) Si Dong Yen, 13) San Sai, 14) Pa Nai, and 15) Pa Tum, respectively (accounting for 9.66% of Chiang Mai's population (172,837 people)) were got in orange zone. In addition, 2 sub-districts including Tha Ton and Mae Na Wang (accounting for 1.55% of Chiang Mai's population (27,806 people)) were got in red zone (unhealthy). The details were demonstrated in Figure 8 and Table 5.

4. CONCLUSION

The mathematical model via IDW interpolation technique by ArcMap 10.5® software can used as an alternative method to simulate and access ground-level ozone data in areas were without AAQMS. This technique has been used in other research to forecast alert pollutant levels, assessment of relationships between air pollutant exposure and health outcomes, alternative for epidemiological analyses at the individual-level on the health effects for locations without authentic data (Jung et al., 2016; Mishra et al., 2015), for example. The IDW interpolation with Power 3 ($p=3$) was represented the best condition of this study via Mean Error (ME) and Root Mean Square Error (RMSE) equations.

The ground-level ozone concentrations in 8 provinces in upper Northern, Thailand (Chiang Rai, Chiang Mai, Phare, Nan, Phayao, Lampang, Lamphun, and Mae Hong Son) during the year 2017 – 2019 were usually high in the summer (February to June) because temperature is one of the elements which impacts ozone production (State of Global Air, 2020; US. EPA, 2014, 2021), while July to January was found at a safe level for both 1-hour and 8-hour. The highest AQI ratings of monthly maximum 1-hour average value of ozone was red (unhealthy; 165 - 204 ppb), while 8-hour average value of ozone was purple (very unhealthy; 201 to 300 ppb). From the data, during the ozone crisis, people should spend more time indoors than outdoors to avoid the health effect from ozone, especially those who are sensitive (US. EPA, 2014). This is because ozone levels are higher outdoors, and physical activity causes faster and deeper breathing, drawing more ozone into the body (US. EPA., 2014).

Lastly, on behalf of the researcher, I sincerely hope that the authorities or government agencies should not ignore the ground-level ozone pollution. Additionally, I hope this article will be helpful for stakeholders or sensitive groups can utilize this information for initial assessment of relationships between ground-level ozone exposure and health outcomes, provide useful basic information for authorities to improve strategy formulation to choose appropriate locations for future AAQMS in Thailand, respectively.

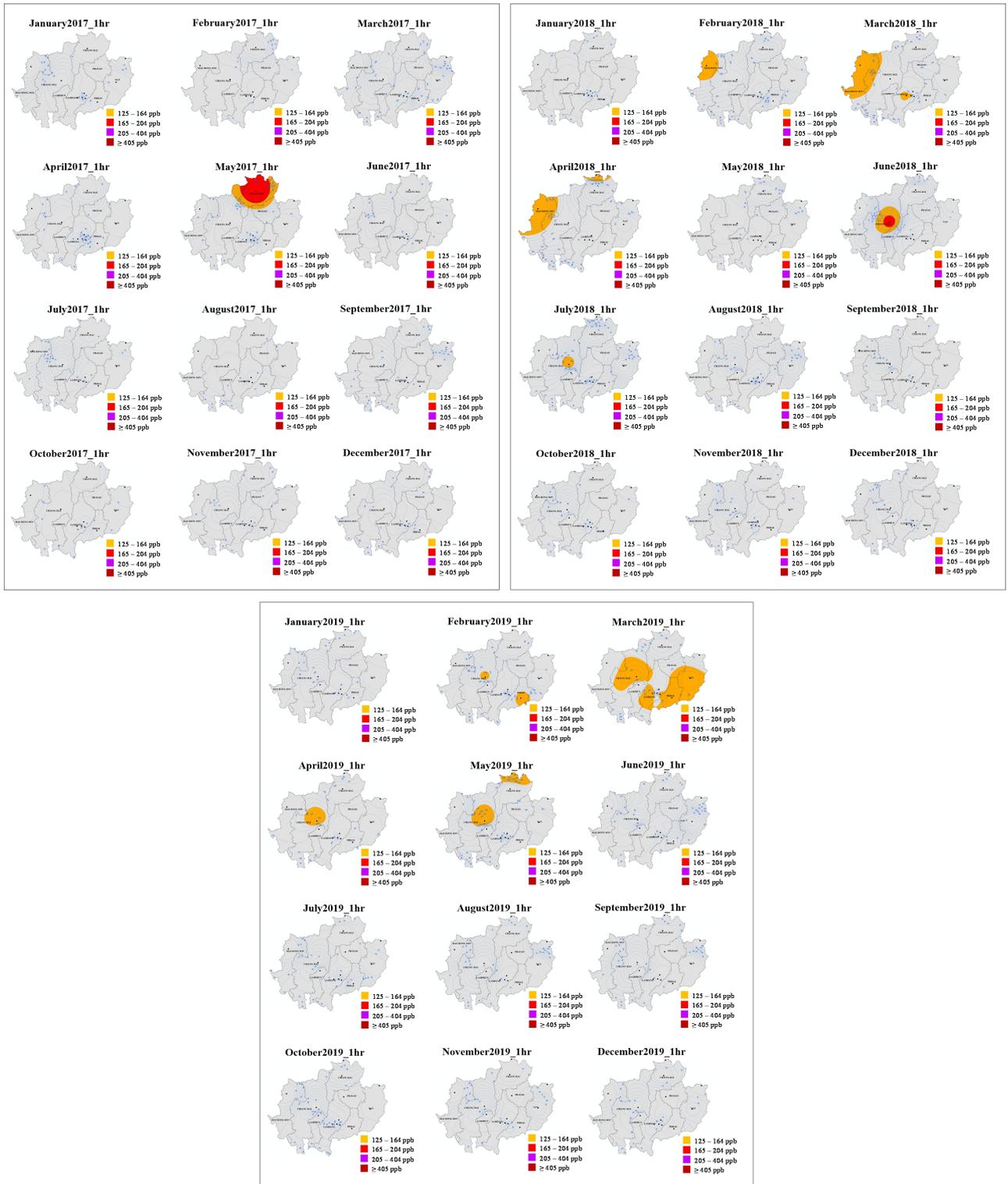


Figure 5 IDW interpolation map of monthly maximum 1-hour average value of ozone in 2017 – 2019

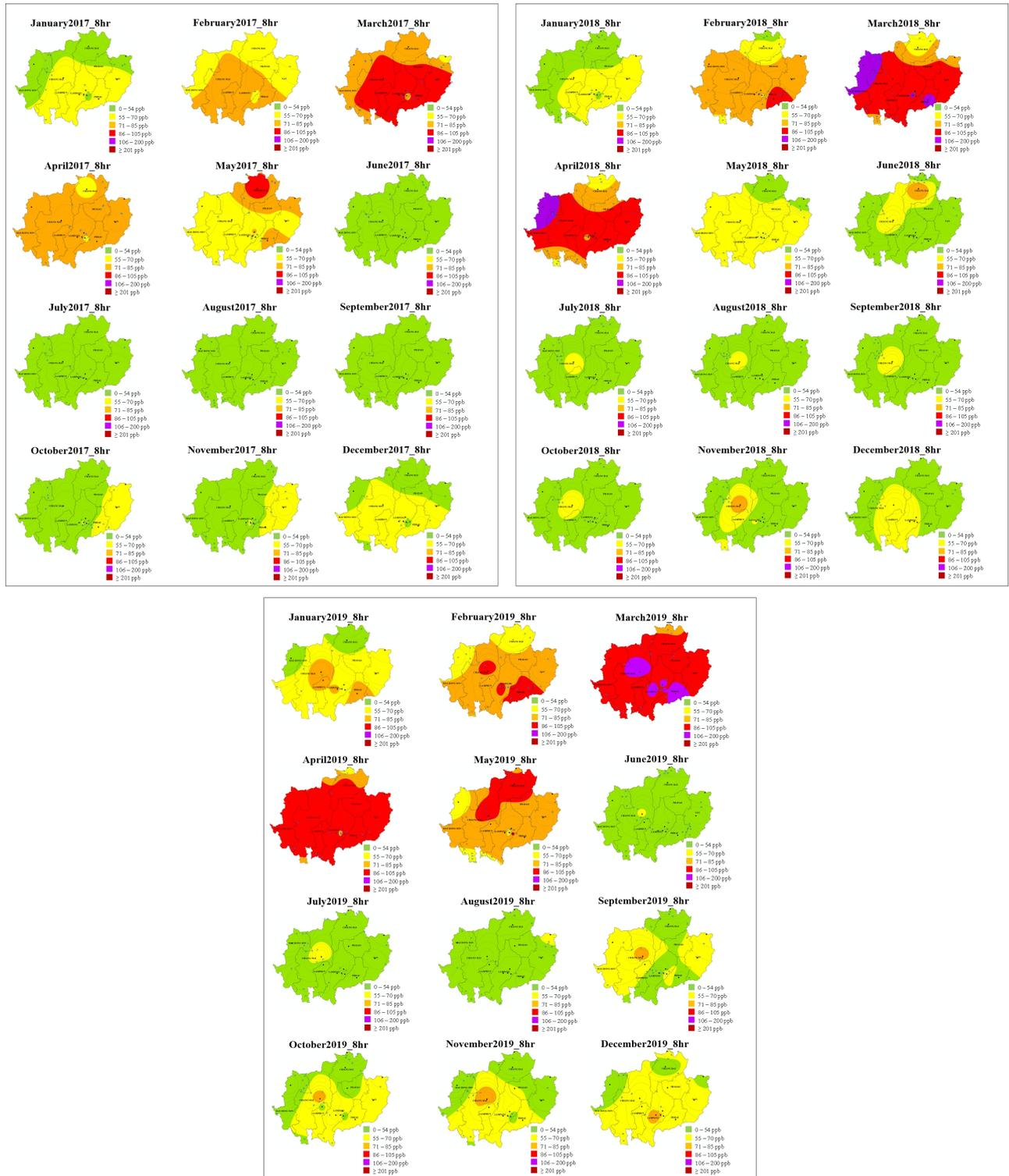


Figure 6 IDW interpolation map of monthly maximum 8-hour average value of ozone in 2017 – 2019

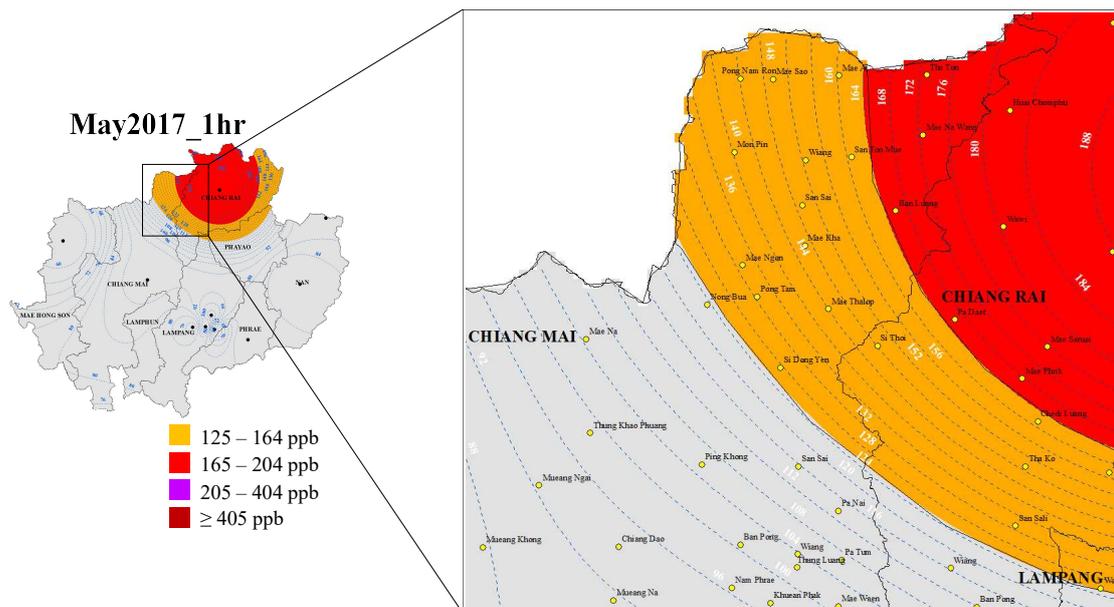


Figure 7 Map of sub-district where exposure to maximum 1-hour average of ozone in orange zone and red zone in Chiang Mai in May 2017

Table 4 The number of population exposure to monthly maximum 1-hour average of ozone in orange zone (unhealthy for sensitive groups) and red zone (unhealthy) in Chiang Mai in May 2017

No.	Sub-district Name	Population (Orange Zone)		
		Male (people)	Female (people)	Total (people)
1	Mae Ai, Mai Ai District	1,834	1,721	3,555
2	Ron Mae Sao, Mai Ai District	6,185	6,301	12,486
3	San Ton Mue, Mai Ai District	7,686	7,522	15,208
4	Wiang, Fang District	9,809	9,808	19,617
5	Mon Pin, Fang District	10,389	10,632	21,021
6	Mae Ngon, Fang District	8,545	8,504	17,049
7	Sansai, Fang District	5,341	5,754	11,095
8	Mae Kha, Fang District	3,710	3,887	7,597
9	Pong Nam, Fang District	3,130	3,156	6,286
10	Pong Tam, Chai Prakan District	52	24	76
11	Si Dong Yen, Chai Prakan District	6,020	5,891	11,911
12	Mae Thalop, Chai Prakan District	3,980	3,992	7,972
Total		66,681	67,192	<u>133,873</u>
No.	Sub-district Name	Population (Red Zone)		
		Male (people)	Female (people)	Total (people)
1	Tha Ton Sub-district, Mai Ai District	3,032	3,196	6,228
2	Mae Na Wang Sub-district, Mai Ai District	10,780	10,798	21,578
3	Ban Luang Sub-district, Mai Ai District	3,898	3,865	7,763
Total		17,710	17,859	<u>35,569</u>

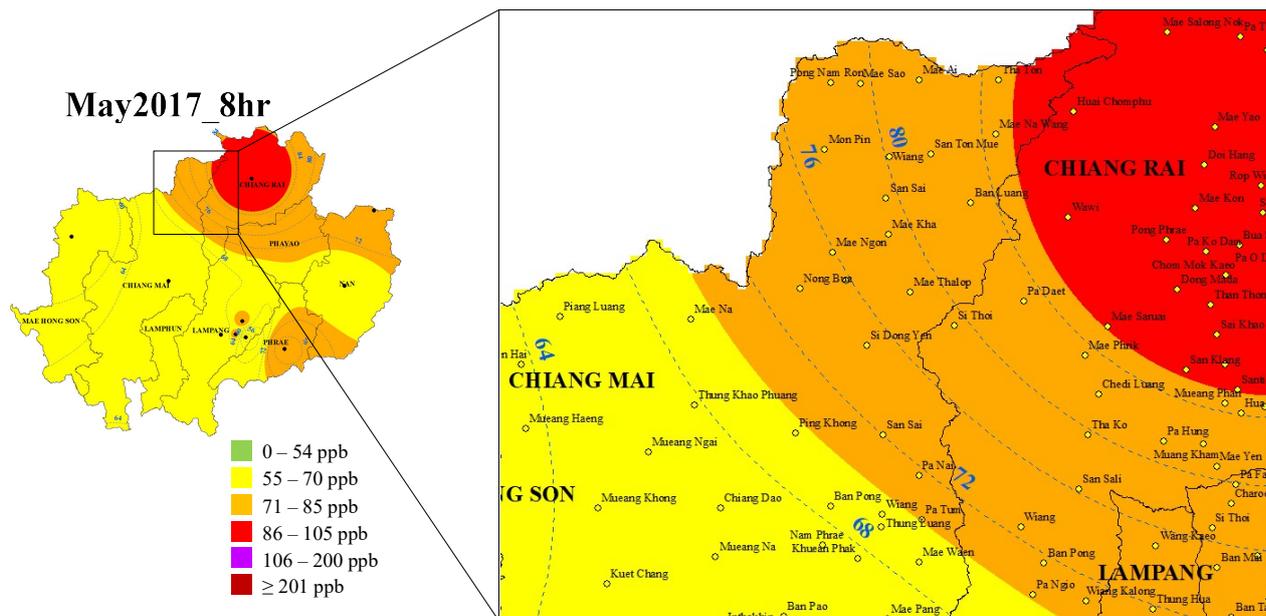


Figure 8 Map of sub-district where exposure to monthly maximum 8-hour average of ozone in orange zone and red zone in Chiang Mai in May 2017

Table 5 The number of population exposure to monthly maximum 8-hour average of ozone in orange zone (unhealthy for sensitive groups) in Chiang Mai in May 2017

No.	Sub-district Name	Population (Orange Zone)		
		Male (people)	Female (people)	Total (people)
1	Pong Nam Ron, Fang District	3,130	3,156	6,286
2	Mon Pin, Fang District	10,389	10,632	21,021
3	Wiang, Fang District	9,809	9,808	19,617
4	San Sai, Fang District	5,341	5,754	11,095
5	Mae Kha, Fang District	3,710	3,887	7,597
6	Mae Ngon, Fang District	8,545	8,504	17,049
7	San Ton Mue, Mai Ai District	7,686	7,522	15,208
8	Ban Luang, Mai Ai District	3,898	3,865	7,763
9	Mae Ai, Mai Ai District	1,834	1,721	3,555
10	Nong Buat, Chai Prakan District	7,571	7,798	15,369
11	Mae Thalop, Chai Prakan District	3,980	3,992	7,972
12	Si Dong Yen, Chai Prakan District	6,020	5,891	11,911
13	San Sai, Phrao District	3,101	3,200	6,301
14	Pa Nai, Phrao District	2,218	2,191	4,409
15	Pa Tum, Phrao District	2,537	2,661	5,198
	Total	85,954	86,883	172,837
No.	Sub-district Name	Population (Red Zone)		
		Male (people)	Female (people)	Total (people)
1	Tha Ton, Mai Ai District	3,032	3,196	6,228
2	Mae Na Wang, Mai Ai District	10,780	10,798	21,578
	Total	13,812	13,994	27,806

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