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SPATIAL DISTRIBUTION PATTERNS OF HOTSPOT AND RELATIONSHIP BETWEEN HOTSPOT AND VEGETATION INDICES IN CHIANG MAI PROVINCE, THAILAND

Abstract: This work focused on Chiang Mai Province, Thailand, had 2 targets which were 1) to analyse spatial distribution patterns of hotspot and 2) to analyse a relationship between hotspot and vegetation indices in the area. The hotspots data of 2016 – 2020 which had a significant level > 70% were gathered from MODIS satellite images, was provided by Fire Information for Resource Management System (FIRMS). An analyse method was performed by Nearest Neighbour Index (NNI) with Moran' s I to present spatial distribution patterns and density of hotspot. Analysis of Getis – Ord Gi* statistic was for identify heat of hotspot comparing with surrounding area. Moreover, vegetation indices values (Normalized Difference Vegetation Index: NDVI, Soil Adjustment Vegetation Index: SAVI and Normalized Difference Water Index: NDWI) was examined by satellite images of the same period from Landsat 8 OLI to analyse a relationship between hotspot and each vegetation index. The results illustrated that there were different number of hotspots over 5 studying years, especially in 2016 which had the most hotspot. The spatial distribution of hotspot patterns was classified as clustered type (Getis – Ord Gi* statistic with Z-Score > 1.96) with different hotspot density in each year. The area which had high heat was found in upper and west area with medium to high hotspots density. The hotspot and NDVI had relationship in contrast by a correlation coefficient value at -.887 (r = -.887) with a significant level at .05. However, SAVI and NDWI had no relationship with hotspot.

Key words: spatial distribution patterns, hotspot, Getis – Ord Gi*, vegetation indices, Chiang Mai Province

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Introduction

Biomass Open Burning (BOB) emissions such as agricultural burning, open burning and bushfire were increasing over year in Mainland Southeast Asia (MSEA) especially in Cambodia, Myanmar, Laos, and Thailand (Yadav et al., 2017; Vongruang and Pimonsree, 2020). As a consequence of Biomass burning, the level of PM 2.5, PM10 and Smog in MSEA including of Thailand risen (Bhardwaj et al., 2016; Shi et al., 2014; Shi and Yamaguchi, 2014). Open burning in Thailand was concentrated prominently in Northern part of Thailand from the beginning of 2021, caused by weeds burning, wild foraging, crop preparation (Chang et al., 2013; Gadde et al., 2009; North Dakota Department of Health Division of Air Quality, 2015; Sirimongkonlertkun, 2014). Open burning leaded PM2.5, PM10, CO, NO_2, SO_2, and O_3 increasing, forced health problem such as chronic obstructive pulmonary disease (COPD), asthma, pulmonary disease, lung cancer, cardiovascular and respiratory diseases (Jiang et al., 2016; Manisalidis et al., 2020; Mueller et al., 2020; Ramakreshnan et al., 2018; Ruchiwit et al.,2022; Sweileh et al., 2018). These health problems occurred in many countries including Northern of Thailand which had these problems prominently (Thongtip et al., 2022). Rotjanabumrung et al. (2023) founded that people who lived and associated with longer exposure duration to pollution in open burning area, visited the hospital to consult about cardiovascular and respiratory diseases.

Forest Fire Control Division, The Department of National Park, Wildlife and Plant Conservation (DNP) of Thailand (2021) explained about Geographic Information Systems (GIS) and Remote Sensing (RS) technology contributed to hotspot investigation using thermal sensor which was installed in Earth Observation Satellite. Moreover, these technologies were associated to examine wildfire by hotspot investigation (Akyürek, 2023) using weather satellite such as NOAA12 and NOAA18 (Advanced Very High-Resolution Radiometer: AVHRR) (Tian et al, 2013), Terra and Aqua weather satellite (Moderate Resolution Imaging Spectroradiometer: MODIS) (Sirin and Medvedeva, 2022). However, hotspots which were illustrated in form of map, did not always cause forest fires due to these spots only referred to abnormal heat on land. Hotspot maps which were published in public website, were not validated that points has wildfire occurring or only false alarm points. These irresolate points leaded uncertain data commutations. Therefore, DNP brought hotspot data from Terra and Aqua Earth Observation Satellite (MODIS) to analyse forest fire area in conservation areas and outside with curtain incident date then the data were cooperated with ground survey and sent to related agencies to assess the situation and forest fire prevention planning. Preventive measures for PM2.5 are to increase more moisture in the air by watering, to provide more masks, and to prepare more clean room in the area. Moreover, if hotspots are found, fire extinguishing is quick required (Chiang Mai Governor Office, 2023).

Chiang Mai Province is located in upper-northern region of Thailand, faced to PM2.5, PM10, Smog every year (Jeensorn et al., 2018) caused by wildfire and biomass open burning. Moreover, many hotspots were always detected in this province especially in 2023, there were 300 hotspots founding in one day which was increasing from other year. Chiang Mai Provincial Administrative Organization select suspect hotspots which always appeared then evaluate expected hotspots per district to predict and finding any wildfire protection methods (Thai Public Broadcasting Service, 2023).

Geographic Information System: GIS and Remote Sensing: RS were used to analyze spatial distribution and phenomena changing. Valjarević et al. (2018) used GIS numerical and RS technology, cooperated with topographic map to analyse forest area changing, trees density and number of trees with RGB-NDVI analysis. Moreover, Kadušić et al. (2021) brought GIS to analyse industrial plant spatial distribution pattern using Kernel Density Estimation: KDE and finding a relationship between spatial distribution and spatial characteristics. Furthermore, Jansenburg and Staufer – Steinnocher (2004) cited in Kadušić et al. (2021) reported that Dual KDE was used to study a spatial changing in time series of food trade market in Australia.

This work focused on 1) to analyse spatial distribution patterns of hotspot in Chiang Mai Province, Thailand. The hotspots which had confidence at >70%, were extracted from weather satellite (Moderate Resolution Imaging Spectroradiometer: MODIS) of Chiang Mai province in 2020 from Fire Information for Resource Management System (FIRMS). Then, 2) to analyse relationship between hotspot and vegetation Indices in Chiang Mai Province, Thailand. Landsat 8 OLI (which had 9 bands with resolution at 30 meter, except with resolution at 15 meter in panchromatic band) was used to analyse Vegetation Indices (Normalized Difference Vegetation Index: NDVI, Soil Adjustment Vegetation Index: SAVI and Normalized Difference Water Index: NDWI) and investigated relationship between Hotspot and each vegetation Index. The result can support all decision about hotspot tracking and reduction for sustainable forest management including wildfire protection and pollution decreasing in the area.

Study Area

Chiang Mai province is about 20,107.057 km^2, located in upper-northern region of Thailand at about 160 N 990 E. The top area connects to Shan State, Myanmar (separated by The Daen Lao Range). The right side is close to Chiang Rai, Lampang, and Lamphun Province. The left side is next to Mae Hong Son Province. The bottom area connects to Tak province. The dominant topography is the large mountain range with various forest types locating in north to south direction, classified as 80% of the total area. Flood plains and foothill slopes are found between the ranges. The highest peak is at Doi Inthanon with the height approximately at 2,565 meters from mean sea level (msl.). (Provincial Labour Office Chiangmai, n.d.). The dominant land use type is forest area (68.22%), following by field crops (7.31%), urban area (5.85%), rice field (4.55%), and others (6.91%) (Ministry of agriculture and cooperatives, 2023). Low humidity, high temperature, Wind directions, and type of forest encourages hotspot and wildfire occurrence especially in December to April (Akkaak, 2000; Thanadolmethaphorn et al., 2019). Chiang Mai province is classified as Tropical savanna climate or tropical wet and dry climate (Aw) (Phumkokrux, 2021) which had dry period around January to April. Highest temperature always founded in March to April (Phumkokrux and Rukveratham, 2020; Phumkokrux et al., 2022) with the mean monthly temperature and total precipitation are about 25.4 ^{o}C and 1,100-1,200 mm./year under southwest monsoon in May to October and northeast monsoon in November to February. The lowest relative humidity (RH) and precipitation are founded in January to March with RH average about 63% and monthly precipitation at 12.1 - 46.8 mm (Chiang Mai Meteorological Station, 2023). The study area as presented in figure 1.

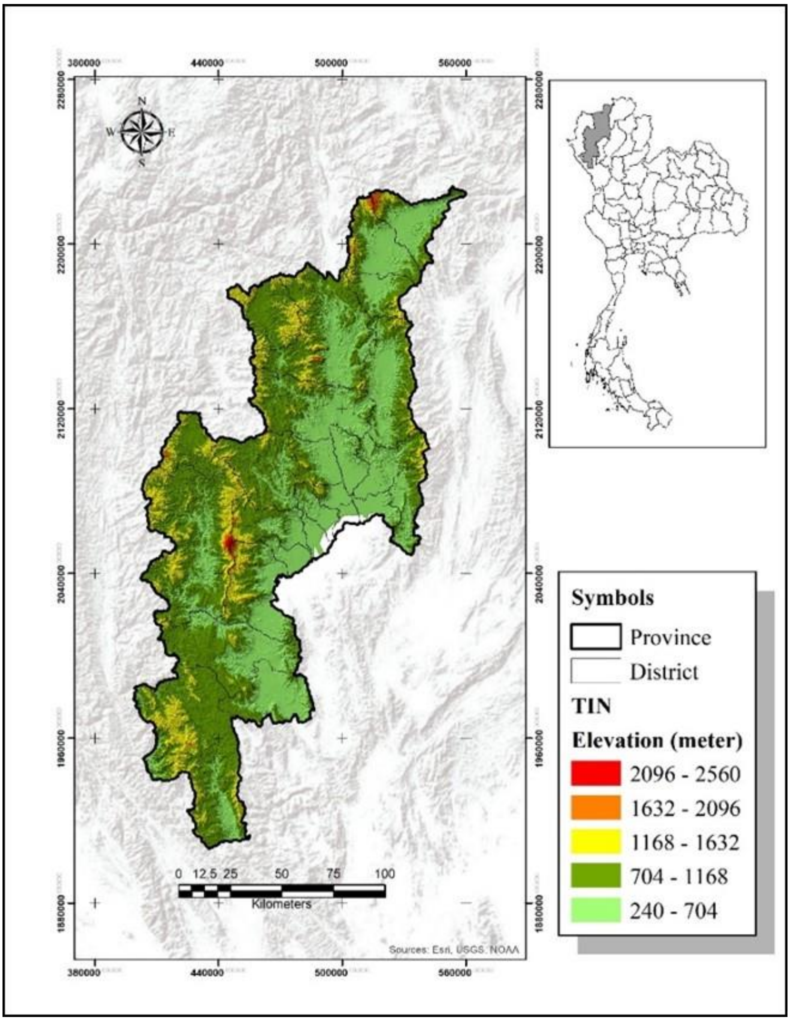

Fig. 1. Study area Chiang Mai province, Thailand (Base map: Esri, USGS, NOAA, Garmin, NPS)

Data and Methods

Hotspot's data in Chiang Mai province of 2016 - 2020 (5 years) were extracted from weather satellite (Moderate Resolution Imaging Spectroradiometer: MODIS), which were operated by Fire Information for Resource Management System (FIRMS), accessed by https://www.earthdata.nasa.gov/learn/find-data/near-real-time/firms. All selected-hotspots for analysis needed to have confidence level at >70% then set geographic coordinates for each point by GIS. Spatial distribution patterns of hotspots were managed by 1) Nearest Neighbour Analysis: NNA method using Nearest Neighbour Index: NNI. Random type was classified by NNI value at equal to 1 whereas clustered type was reminded by NNI value at below 1; however, dispersed type was in contrast. The positive value and Spatial autocorrelation which has the values between -1 to 1, was calculated by Moran's I statistic focusing brightness of hotspots point. Moreover, NNI and Moran's I statistic consider by Z score value. The patterns can be classified as in the table 1.

Table 1. Hotspot Patterns Classification (Moran, 1948; Scott and Janikas, 2009)

Spatial Distribution Pattern	NNI Value	Z-score of NNI	Moran' I Value	Z-score of Moran's I
Dispersed patterns	> 1	1.65 – 1.96 (p=0.10)	Close to -1	< -2.58 (p=0.01)
		1.96 – 2.58 (p=0.05)		-2.58 to – 1.96 (p=0.05)
		> 2.58 (p=0.01)		-1.96 to -1.65 (p=0.10)
Random patterns	= 1	-1.65 to 1.65	Close to 0	-1.65 to 1.65
Clustered patterns	< 1	< -2.58 (p=0.01)	Close to 1	1.65 – 1.96 (p=0.10)
		-2.58 to – 1.96 (p=0.05)		1.96 – 2.58 (p=0.05)
		-1.96 to -1.65 (p=0.10)		> 2.58 (p=0.01)

Hotspot density per unit area was examined by Kernel Density Estimation: KDE. Moreover, Getis – Ord Gi* was used to analyse hotspot and coldspot which had Gi* 's confidence level at 90, 95, and 99. Hotspot and Coldspot data were illustrated in a form of spatial distribution map cooperated with GIS programme.

Furthermore, three vegetation indices which were 1) Normalized Difference Vegetation Index (NDVI) as eq. (1) (Kriegler et al., 1969), Soil Adjustment Vegetation Index (SAVI) as eq. (2) (Huete, 1988), and Normalized Difference Water Index (NDWI) as eq. (3) (McFeeters, 1996) were extracted from Landsat 8 (OLI) weather satellite image covering Chiang Mai Province of 2016 – 2020 period. The selected-images were in January, April, and November in each year of 2016 – 2020, which was the lowest clouds period (the clouds covered <20% of the sky). The last process, relationship between hotspot and each vegetation index in the period of 2016 – 2020 was evaluated by Pearson product moment correlation coefficient.

$$\text{Normalized Difference Vegetation Index (NDVI)} = \frac{\text{NIR-Red}}{\text{NIR+Red}} \quad (1)$$

$$\text{Soil Adjustment Vegetation Index (SAVI)} = \frac{\text{NIR-Red}}{\text{NIR + Red + L}}(1+L) \quad (2)$$

$$\text{Normalized Difference Water Index (NDWI)} = \frac{\text{NIR - SWIR}}{\text{NIR + SWIR}} \quad (3)$$

Notes: L refers to a soil brightness correction factor, determined as 0.5 to accommodate most land cover types. Red, NIR, and SWIR refers to the spectral reflectance measurements acquired in the red (visible), near-infrared, and short-wave infrared.

Results and Discussion

Spatial Distribution Patterns of Hotspot in 2016-2020

There were different number of hotspots in each year over 2016-2020 about 214-856 hotspots. The highest and lowest hotspot points with a confidence level more than 70% was found in 2016 at 856 hotspot points and in 2018 at 214 hotspot points. Statistic Information and Spatial Distribution Pattern of Hotspots in 2016 – 2020 was illustrated in figure 2, figure 3, and table 2 that all NNI and Moran's I value were between 0.490-0.550 and 0.128-0.454. Moreover, NNI Z score < -2.58 and Moran's I z score > 2.58. These values classified the results as Clustered Pattern.

Tab. 2. Statistic Information and Spatial Distribution Pattern of Hotspot in 2016 – 2020

Year	No. of Hotspot with a confidence level > 70%	NNI	Z-score of NNI	Moran's I	Z-score of Moran's I	Pattern
2016	856	0.55 (p = 0.000)	-25.166	0.192 (p = 0.000)	6.454	Clustered
2017	303	0.490 (p = 0.000)	-16.965	0.216 (p = 0.000)	7.151	Clustered
2018	214	0.491 (p = 0.000)	-14.24	0.454 (p = 0.000)	9.428	Clustered
2019	540	0.531 (p = 0.000)	-20.818	0.202 (p = 0.000)	7.916	Clustered
2020	818	0.502 (p = 0.000)	-27.248	0.128 (p = 0.000)	8.059	Clustered

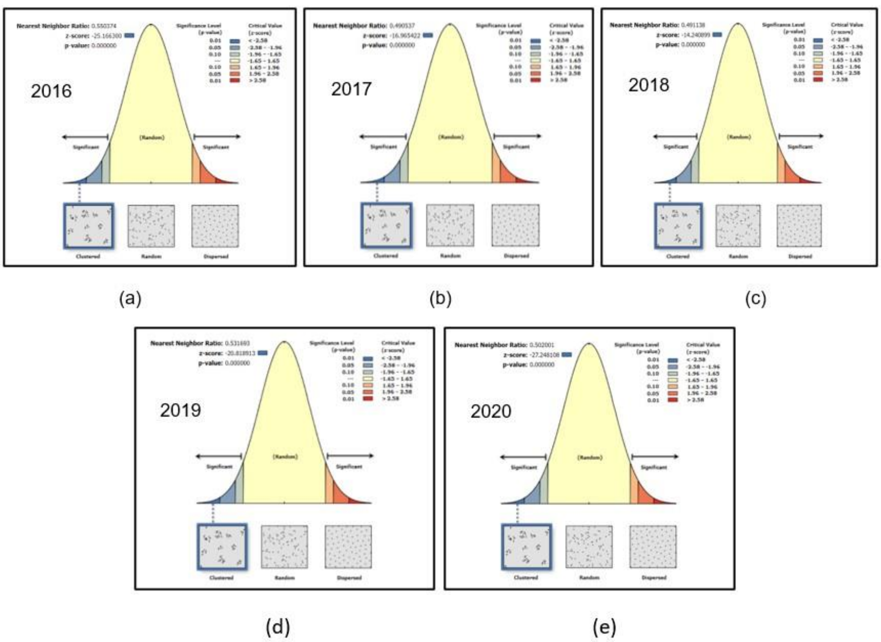

Fig. 2. (a)-(e) Nearest Neighbour Index (NNI) of hotspot, Thailand of 2016 – 2020

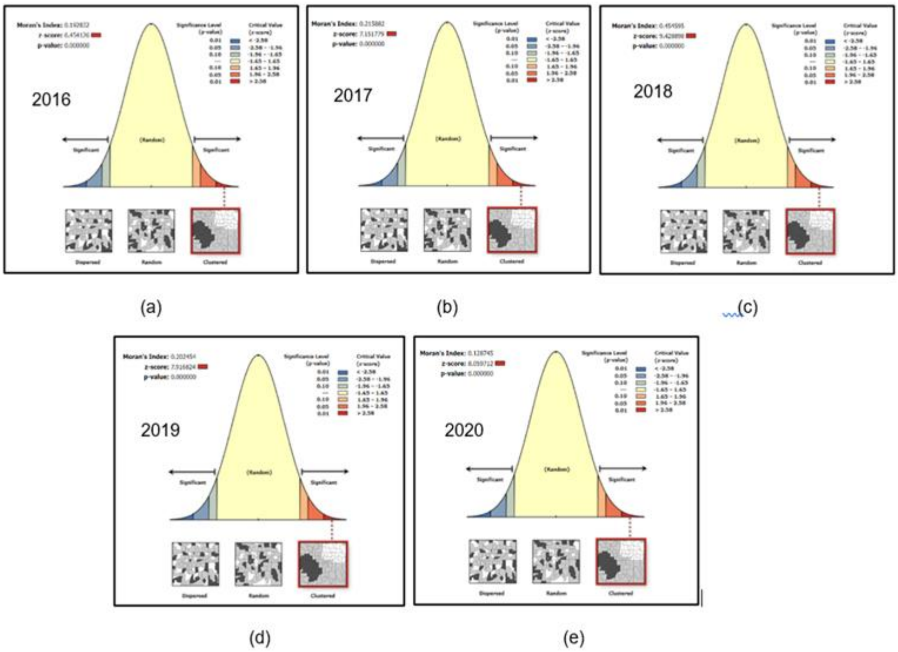

Fig. 3. (a)-(e) Maran's I Analysis of hotspot, Thailand of 2016 – 2020

Density of Hotspots in Chiang Mai Province between 2016-2020 in a form of maps were performed by Kernel density estimation, were illustrated in figure 4 (a) – (e) whereas Green, Yellow, and Red referred to density levels as Low, Moderate, and High respectively. The results indicated that the most hotspots were found in 2016 and 2020. Moreover, high hotspots density were appeared in forest area especially at the upper area and the left side of Chiang Mai province. Hotspots and Coldspots of 2016-2020 were analysed by Getis Ord Gi* with Gi* 's confidence level at 90, 95, and 99 then the results were overlayed with density map to analyse relationship between the area which had high hotspots and heat concentration comparing to surrounding area, cooperated with hotspots density in the area from figure 4 (a)-(e) as presented in figure 5 (a)-(e). Hotspots were shown in red scale (dark red to light red referred to hotspot with confidence level at 99, 95, and 90 respectively) whereas coldspots (the area which had low hotspots with lower heat comparing to surrounding area) were illustrated in blue tone (dark blue to light blue referred to coldspot with confidence level at 99, 95, and 90 respectively). The final results illustrated that the hotspots area had Z-Score over 1.96 (95% of confidence). From figure 5 (a)-(e) were according to figure 4 (a)-(e) that the hotspots (95% and 99 % of confidence) related with moderate to high density were appeared especially around the left side of area which were forest area. Moreover, there were hotspots with high density around the upper side of area (Chai Prakan and Fang District) in 2018-2020 which had land use activities as forest and field crops type. Therefore, all government agencies and concerned sectors needs to monitor wildfire closely especially in the dominant area.

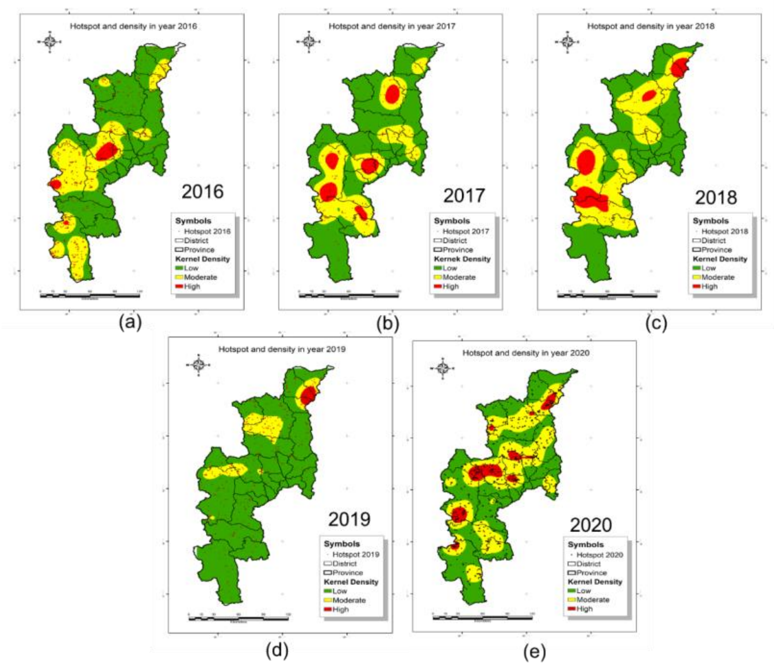

Fig. 4. (a)-(e) Kernel Density Estimation of hotspots in Chiang Mai province, Thailand between 2016 – 2020

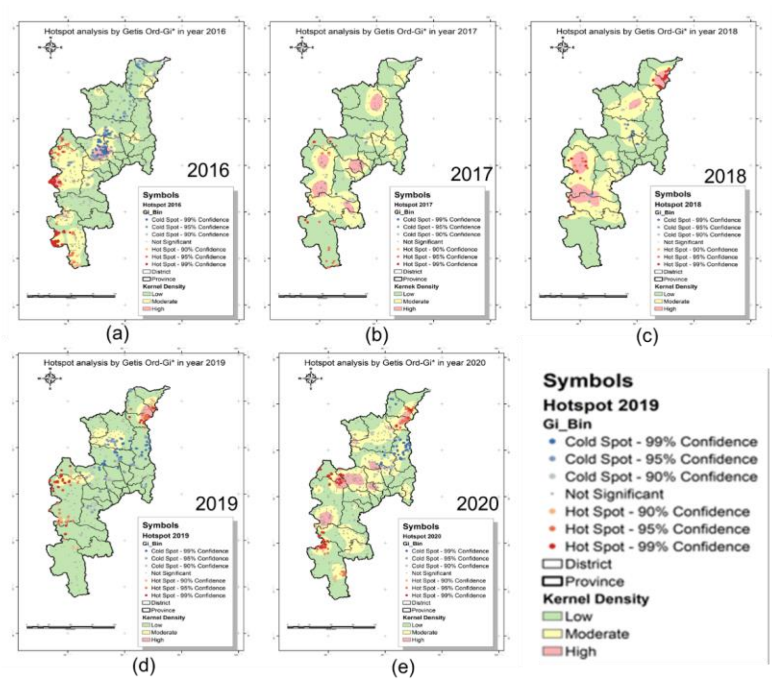

Fig. 5 (a)-(e) Hotspots and Coldspots analysis with Gi 's confidence level at 90, 95, and 99, overlayed with density map between 2016 – 2020*

Analysis of Vegetation Indices by Remotely sensed data

Vegetation indices analysis such as NDVI, SAVI, and NDWI were performed by Landsat 8 OLI with 30 cm. resolution. satellite images of 2016-2020 which were operated by United States Geological Survey: USGS, cooperated with GIS technology. The satellite images of January, April, and November in clear sky period covering Chiang Mai Province were selected about 3 scenes per month. Mosaic images of each month were performed then vegetation indices were analysed and calculated by GIS programme. Vegetation indices values defined by selected-month of 2016-2020 periods was presented in table 3.

Green bar chart of NDVI values in Chaing Mai Province was illustrated in Fig. 6 (a), defined by month. The values were in a range of 0.135-0.399. In January 2018 had the highest NDVI value at 0.399 following by in April 2018, November 2019, and April 2019 at 0.390, 0.316, and 0.314 respectively. However, the lowest NDVI value was found at 0.135 in January 2016 due to high temperature fluctuations affecting to vegetative activity in this period (Ghebrezgabher et al., 2020; Muradyan et al., 2019).

SAVI values in Chaing Mai Province were presented in yellow bar chart form as illustrated in Fig. 6 (b). The values also defined by selected-month of 2016-2020. The values of over study's period were not different from each month much with a range of 0.403-0.525. The highest values found at 0.525 and 0.523 in November 2020 and 2016 respectively. In contrast, the lowest values found at 0.403 in January 2017.

NDWI values in Chaing Mai Province of each selected-month in all study's period were illustrated in blue bar chart form, presented in figure 6 (c). The highest value was found at 0.175 in November 2019, following by in January and April of 2018 at 0.469 and 0.450 respectively. However, there were the lowest values founding in April and November of 2016 at 0.090 and 0.060 respectively due to abnormal temperature in 2016 which was higher from based value about +2 degree Celsius (Thailand Meteorological Department, 2017) leading soil humidity were low (Berg and Sheffield, 2018).

Tab. 3 Number of Hotspot and Vegetation Indices Values, defined by selected-month of 2016-2020 Periods

Year	Month	No. of Hotspot	NDVI	SAVI	NDWI
2020	Jan	42	0.250	0.445	0.120
	Apr	218	0.211	0.476	0.090
	Nov	0	0.260	0.525	0.060
	Annual	Total: 818	Mean: 0.240	Mean: 0.495	Mean: 0.090
2019	Jan	7	0.292	0.489	0.137
	Apr	135	0.314	0.499	0.097
	Nov	1	0.316	0.498	0.175
	Annual	Total: 540	Mean: 0.307	Mean: 0.495	Mean: 0.136
2018	Jan	11	0.399	0.469	0.170
	Apr	74	0.390	0.450	0.150
	Annual	Total: 214	Mean: 0.394	Mean: 0.460	Mean: 0.160
2017	Jan	8	0.269	0.403	0.092
	Mar	155	0.311	0.442	0.083
	Annual	Total: 303	Mean: 0.290	Mean: 0.423	Mean: 0.089
2016	Jan	55	0.135	0.489	0.110
	Apr	457	0.205	0.460	0.006
	Nov	0	0.290	0.523	0.010
	Annual	Total: 856	Mean: 0.210	Mean: 0.490	Mean: 0.070

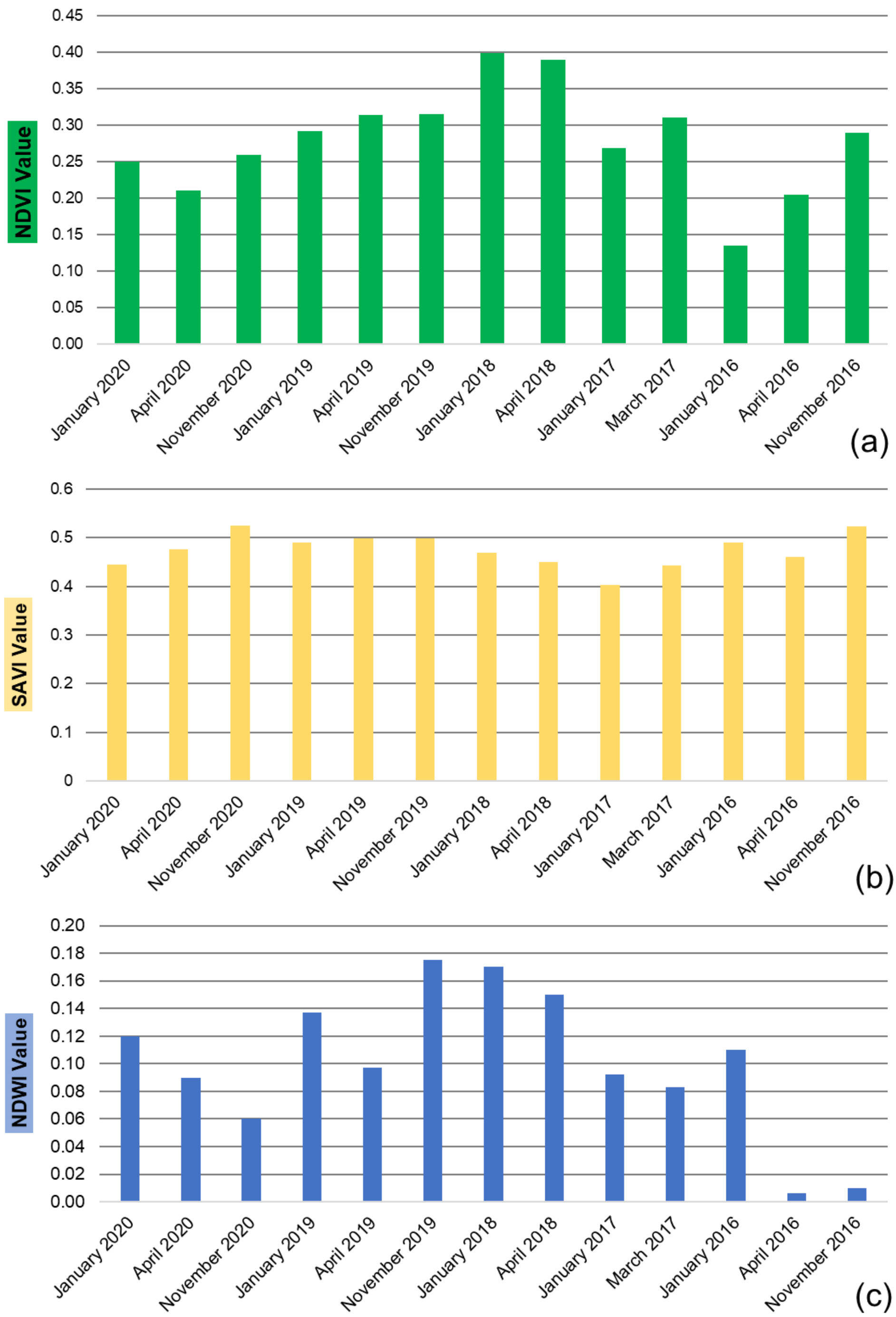

Fig. 6. Bar Chart of (a) NDVI Values, (b) SAVI Values, and (c) NDWI Values, defined by selected-month in each year.

Relationship between Hotspots and Vegetation Indices

Relationship between hotspot and each vegetation index was calculated by Pearson Correlation Coefficient. The results as illustrated in table 4. indicated that the hotspots point over 2016 – 2020 which had a confidence level more than 70%, had a relationship to NDVI in contrast way. The hotspot points increased while NDVI value declined due to an increasing of high temperature in the area, with Pearson Correlation Coefficient value at -0.887 and a significant level at .05 (r = -0.887). In 2016, the abnormal temperature which was higher than based value leaded the highest of hotspot points and the lowest of NDVI value were appeared especially in urban land use area, whereas NDVI value was high in forest and agricultural land use area. However, SAVI, and NDWI in the same period had no relationship to number of hotspots.

Tab. 4. Relationship Between Hotspot and Each Vegetation Index of 2016 – 2020, performed by Pearson Product Moment Correlation Coefficient.

		Hotspot	NDVI	SAVI	NDWI
Hotspot	Pearson Correlation	1	-.887*	.698	-.676
	Sig. (2 – tailed)		.045	.190	.211
	N	5	5	5	5
NDVI	Pearson Correlation	-.887*	1	-.333	.928*
	Sig. (2 – tailed)	.045		.584	.023
	N	5	5	5	5
SAVI	Pearson Correlation	.698	-.333	1	.026
	Sig. (2 – tailed)	.190	.584		.967
	N	5	5	5	5
NDWI	Pearson Correlation	-.676	.928*	.026	1
	Sig. (2 – tailed)	.211	.023	.967	
	N	5	5	5	5

* Correlation is significant at the .05 level. (2-tailed)

Conclusion

Hotspot which had a confidence level > 70% in Chiang Mai Province, Thailand of 2016-2020 were extracted from weather satellite (MODIS), operated by Fire Information for Resource Management System (FIRMS). There were different of number of hotspot points in each year. The highest amount was found in April 2016 at 457 points, following by April 2020, March 2017, April 2019, and April 2018 at 218, 155, 135, and 74 points. In April 2016, there was a report by Thailand Meteorological Department (2017) that abnormal temperature was appeared covering the area due to low pressure patch covered the most upper area of Thailand, cooperated with south wind direction moved covering Thailand. This situation leaded air temperature of the upper area of Thailand rising in hot and very hot range through the month, brought mean monthly temperature higher than based-value about +2 degrees Celsius thus the highest of hotspots was found than other year. This situation was according to a work of Pumnoun and Iamchuen (2020) that the number of hotspots was rising while air temperature was increasing also. Moreover, the highest points of each year always found in April due to this month always has the highest temperature because of the sun is perpendicular to Thailand leading air temperature rising then hit the peak of the year (Phumkokrux and Rukveratham, 2020; Phumkokrux, 2021; Phumkokrux, 2023).

Spatial distribution pattern of hotspots in Chiang Mai Province, Thailand over 2016 – 2020 was classified as clustered type. This result was agreeable to a study of Plaengsungnoen et al. (2019) that hotspots pattern in the same time of Phayao Province, Thailand which has topography characters similar to Chiang Mai Province, was clustered type. Moreover, the results also were according to GISTDA (2018) that the most hotspots were found at Conservation and National Forest in northern region of Thailand.

Getis – Ord Gi* was used to analyse hotspot and coldspot with Gi* 's confidence level at 90, 95, and 99. Hotspot of 95% and 99% of confidence were found in the area which had high heat was found in upper and west area with medium to high hotspots density. The hotspot and NDVI had the relationship with contrast. The result agreeable to Reddy et al. (2019) Unnikrishnan and Reddy et al (2019) and Xu et al. (2022) that number of hotspots increased while NDVI values decreased with a significant level at .05, however; it did not have any relation to SAVI and NDWI. Hotspots were captured by infrared wave and heat from fire, could easily find in forest area which lack of moisture area leading the temperature increased. However, the author recommended that data more than 5 years past and other vegetation indies were needed to analyse hotspots and its pattern in next step to execute more accurate and better clear results. Moreover, the hotspot could be predicted by the results from NDVI equation with simple linear regression analysis. The results can support all decision about hotspot tracking and reduction for sustainable forest management including wildfire protection and pollution decreasing in the area.

Approval of Documents Related to Study Protocol: The Human Subject Research Ethics Sub-Committee of Ramkhamhaeng University, Thailand, has approved this study. Study Code: RU-HRE 65/0058, Approval Date: 24 March 2022 and Expiry Date: 23 March 2023.

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