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Statistical Modeling of Impacts El Niño Southern Oscillations (ENSO) on Land Surface Temperature in Small Medium Size City: Case Study Kuching Sarawak

Ricky Anak Kemarau[1*], Oliver Valentine Eboy[1]

[1]Geography Program, Faculty of Social Science and Humanities,
Universiti Malaysia Sabah, Jalan UMS, 88400 Kota Kinabalu Sabah, MALAYSIA

*Corresponding Author

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Abstract: El Niño Southern Oscillation (ENSO) can affect the daily temperature and the amount of rainfall and extreme weather such as floods and droughts. For that reason, scientists need to understand the process of developing ENSO and develop statistical models to predict the impact of ENSO to land surface temperature. The remote sensing data provide spatial information that allows analyzing the influence of ENSO on land surface temperature spatial patterns. This study examines the ability of remote sensing data to study and develop model statistical for predicting the ENSO effect on land surface temperature spatial patterns. Remote sensing data needs to go through a pre-process and digital Number conversion to Land Surface Temperature (LST). To ensure accurate remote sensing information, the calibration process is carried out using temperature records from the Meteorological Malaysia Department (MMD). The next step is to conduct a correlation analysis between LST and Oceanic Niño Index (ONI). The final step is to use linear regression in building a statistical model forecasting the influence of ENSO on temperature and LST. The result found that changes in ONI values influence the value of LST and temperature. Improving knowledge and understanding of ENSO can provide ideas and strategies in reducing and adapting to the impact of ENSO on human beings.

Keywords: ENSO, LST, ONI, Modeling

1. Introduction

The El Niño - Southern Oscillation (ENSO) phenomenon poses a major threat such as creating a higher-than-normal amount of rainfall resulting in major floods and severe hot, dry, and prolonged weather such as in 1997/1998 and 2015/2016 [1], [2]. This witnessed a severe forest fire in Borneo that caused haze and the highest temperature increase in the history of El Niño in 2016 [3]. Existing studies use data from MMD such as the relationship between ENSO and temperature [1],[4],[5]. However, Tan *et al*., [6] stated that still a deficiency of studies in the study for the effect of ENSO on temperature, especially in urban zones. In addition, most studies in Malaysia [6],[7] analysis at the influence of ENSO on climatological and meteorological data. Due to the expansion in data, hardware, and techniques such as remote sensing. It leads to the emergence of in-depth learning and the provision of spatial information [8]. This opens up new opportunities to explore the effectiveness of remote sensing data to study the impact of ENSO using a statistical model to predict the influence of ENSO on climate and meteorological conditions in particular. In both developing and tropical countries, the use of remote sensing technology in predicting the effects of ENSO on temperature and LST is still lacking [9]. In addition, the results of previous studies show that the effects of El Niño vary as the Malaysian area is affected by the monsoon season, Indian Ocean Dipole (IOD), and Madden Julian Oscillation (MJO) by using meteorological data and with scale region. The findings of Kemarau and Eboy [10] and Tan *et al*., [6] using temperature from MMD found that temperature effects are greatly influenced by urbanization activities. This

*Corresponding author: ricky.geo2005@gmail.com

indicates the need for in-depth studies especially the use of big data remote sensing in researching the effects of ENSO and predicting the effects of ENSO on the temperature in a local size namely in Kuching city, Sarawak.

2. Methodology and Dataset

Figure 1 shows the flow chart steps required to achieve the objective study.

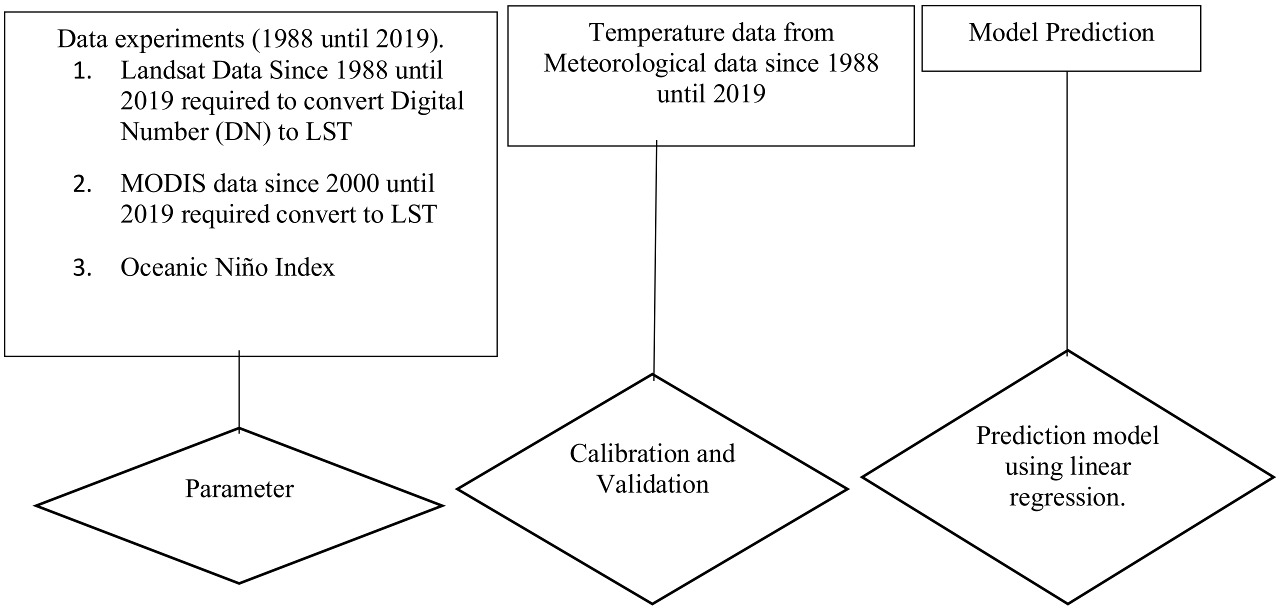

Fig. 1 - The figure shows the framework for achieving the objectives of the study

The first step is to pre-process the Landsat and MODIS satellite data. After that, the data was converted from digital numbers to LST. After that, the Landsat data was calibrated with mean daily temperature data from MMD, and Data MODIS was calibrated with mean monthly data from MMD. To calibrate the value LST satellite data of MODIS and Landsat, the value of LST pixels is equal to the temperature coordinate taken by MMD. Once the MODIS and Landsat LST data were calibrated with temperature data from MMD, modeling of the effect of ENSO which is represented by ONI will be carried out on mean monthly LST for MODIS data, daily mean LST for Landsat, and mean monthly and mean daily temperature from MMD.

2.1 Temperature from MMD

This study uses temperature data average mean monthly and mean daily temperature from the Malaysian Meteorological Department (MMD). Table 1 shows the detailed data utilized in achieving the objective of this study.

Table 1 - Detailed information about the location data was collected from 1988 until 2019

Coordinate	From sea Level (Meter)	Unit	Duration
Latitude 01 ˚ 29 North Longitude 20 ˚ 20 East	21.7 meter	˚ C	1988 until 2019

2.2 Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper (ETM), and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

This study uses Landsat satellite generation data namely Landsat TM, ETM, and OLI TIRS. The data used is a thermal wave and is restricted to data with no cloud and haze coverage because the thermal data not being able to penetrate the cloud cover. The study used the data from the year 1988 until 2019.

2.3 Moderate Resolution Imaging Spectroradiometer (MODIS)

In addition to Landsat satellites, this study also uses MODIS satellite data through MOD11B1 products from Terra sensors. The MODIS data was limited use from the year 2000 until 2019 because the MODIS data has been used since 2000. After all, MODIS services only started in 2000.

2.4 Oceanic Niño Index (ONI)

ONI is an ENSO indicator that many researchers have considered in the study identifying the occurrences and examining the strength of El Niño and La Niña. This ONI index is indicative of the growth and strength of El Niño and La Niña in the Pacific Ocean. Table 2 shows the category strength of ENSO [10]. The data of ONI able to access at the National Oceanic and Atmospheric Administration (NOAA) at the website https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php.

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Table 2 - Classification of ENSO events

Value of ONI	Category of strength
ONI ≥ 2.0	Very strong El Niño
1.5 to 1.9	Strong El Niño
1.0 to 1.4	Moderate El Niño
0.5 to 0.9	Weak El Niño
-0.5 to 0.5	Neutral
ONI ≥ -2.0	Very strong La Niña
-1.5 to -1.9	Strong La Niña
-1.0 to -1.4	Moderate La Niña
-0.5 to -0.9	Weak La Niña

Source: Kemarau & Eboy [10]

2.5 Area of Study

Figure 2 refers to the Kuching area as classified as a Köppen-Geiger climate as a Tropical Rainforest. Kemarau & Eboy [10] report a normal daily temperature of 23 ˚C in the early morning to 32 ˚C for the day. Tangang *et al.,* [7] and Kemarau & Eboy [10] stated that weather in Kuching is affected by Madden Julian Oscillation (MJO), ENSO, and Indian Ocean Dipole (IOD). In addition, to its geographical position, it undergoes two seasons. The first season is the Northeast Monsoon which often occurs in November, December, and January. The northwest monsoon ranges from May to September, which is a relatively dry period during the active monsoon month [10], [7]. The monsoons are in April and October. The selection of Kuching city as areas studies because Mahmud discovered during El Nino 1997/1998 the total amount of rainfall decreased from 25 to 30 % in the study areas. Besides that Kuching city, has the highest population in Sarawak with a total population of 700 450. The finding of this research is vital to improve knowledge influence of ENSO to land surface temperature in urban areas.

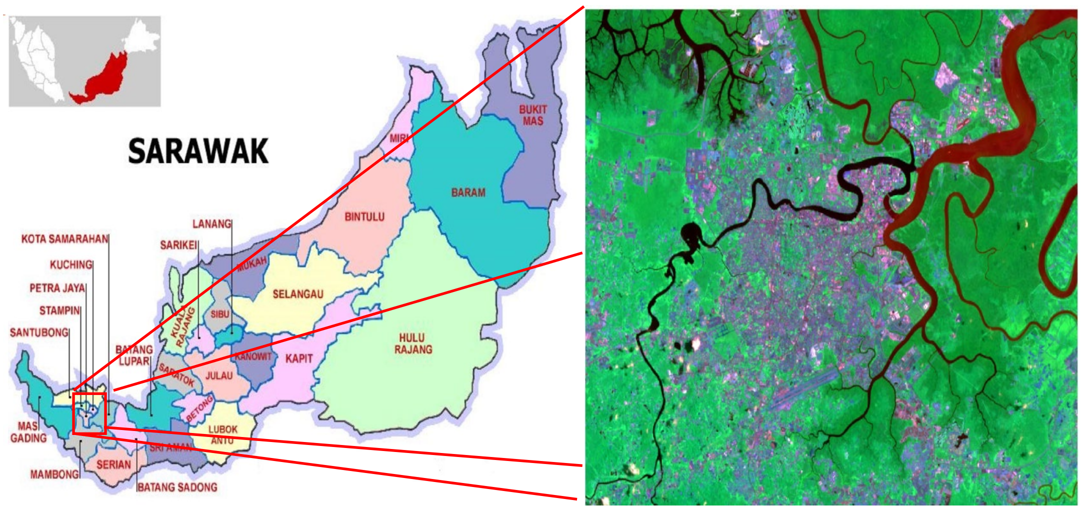


Fig. 2 - Location of Study.

3. Result and Discussion

Based on figure 3, it was found that there is also a positive connection between temperature from daily mean temperature from MMD and daily mean LST from Landsat. Besides that, the same result correlated between mean monthly from MMD and mean monthly LST from MODIS satellites. The correlation between daily mean LST from Landsat shows that the value of the correlation coefficient is 0.97 compared to monthly mean LST from the MODIS satellite which is 0.90. The correlation between temperature from mean daily temperature MMD with a daily mean of LST from Landsat and mean monthly MODIS aims to measure the truth of mean monthly LST value from MODIS and daily mean of LST from Landsat satellites. Based on the correlation value (Figure 3) carries the meaning of the truth of the measurement value of the daily mean of LST from Landsat was 97 % truth or similar to the daily mean temperature from MMD. Besides that, monthly mean LST from MODIS found 90% similarity with mean monthly temperature from MMD. In another word, the value of LST from MODIS and Landsat data can observe the outcome of ENSO on temperature because has a similarity of more than 90%. To comprehend the risks and improve the facility to forecast unusual weather numerous statistics are used in detecting the ONI relationship with rainfall and temperature [11; 12]. This study applied direct regression because can deliver an evaluation of the response of climate variable quantity on a huge measure including ONI [10].

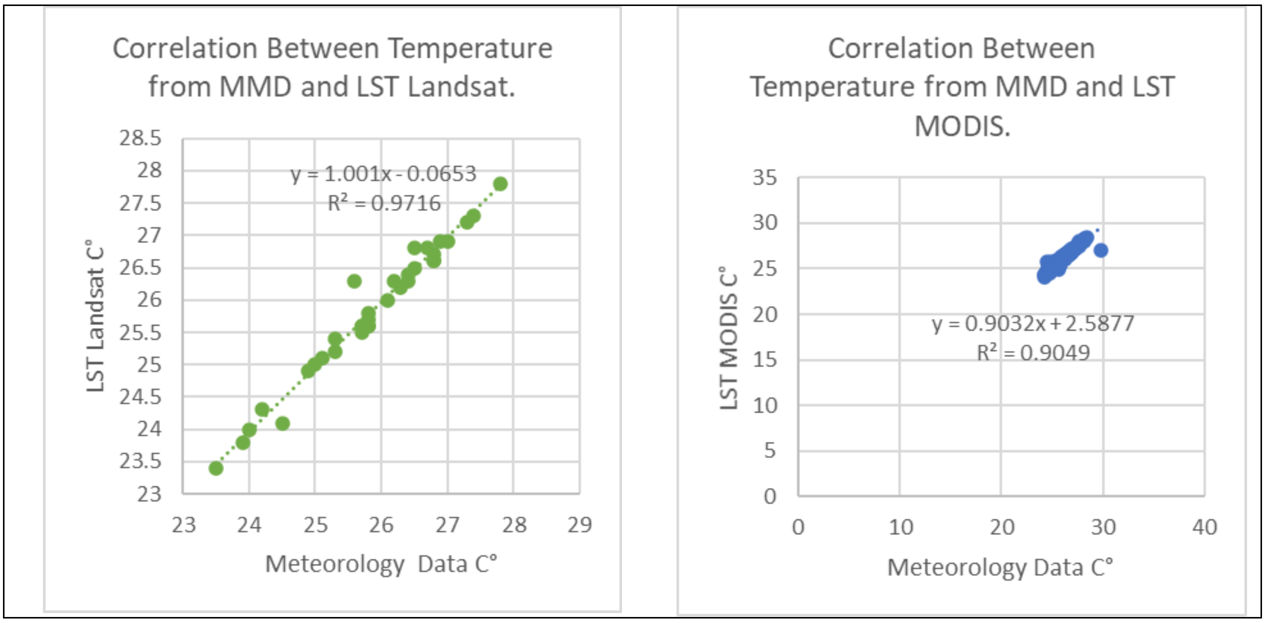


Fig. 3 - The correlation graph between LST from MODIS and Landsat satellites with temperature from MMD

Figure 3 shows the correlation graph between ONI and the monthly mean of LST from MODIS and the daily mean of LST from Landsat satellites. Based on the graph, it was found that there was a positive relationship between LST from Landsat and MODIS satellites with ONI. The correlation between LST from MODIS shows that the value of the correlation coefficient is 0.73 compared to the LST from the Landsat satellite which is 0.71. A positive correlation relationship is shown to mean that if the ONI rate rises it will increase the LST temperature of both satellites. If the positive ONI value exceeds 0.5 it is classified as El Niño which causes hotter and drier weather than neutral and during La Nina. Whereas if ONI exceeds negative 0.5 it is classified as La Niña. The occurrence of La Niña often causes higher rainfall than usual. This explains the temperature drop if the ONI value rainfall important factor causes low ambient temperatures.

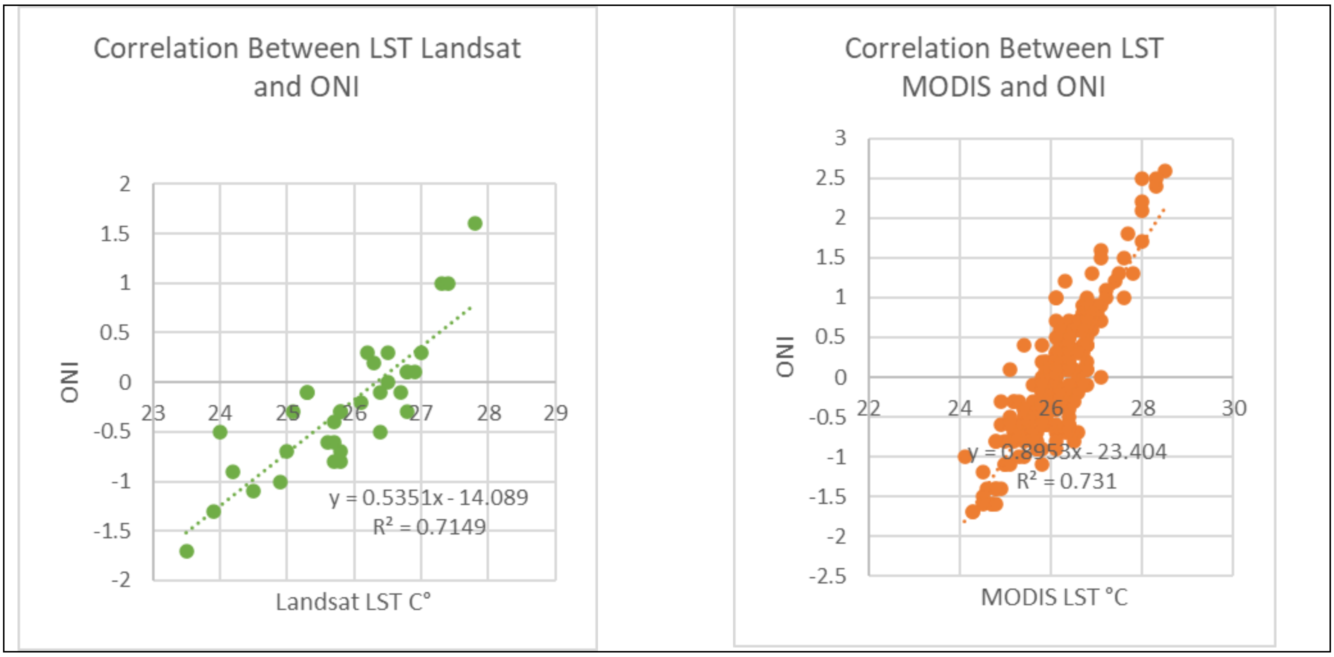


Fig. 4 - The correlation graph between ONI and LST from MODIS and Landsat

Table 3 illustrates the outcomes of single regression in forecasting the consequence of ONI on four independent parameters and demonstrations a strong result on dependent parameters (ONI). The highest R ^{2} rate is the average monthly temperature from MMD which is 0.730. The second is the daily temperature from MMD with R^2 0.710, the third mean monthly of LST from MODIS satellite which is 0.683 and followed by the fourth daily mean of LST from Based on the R^2 value shows a positive connection between ONI with average, daily temperature, and LST from MODIS and Landsat satellites.

Table 3 - The outcomes of single factor regression based on the effect of ONI on four independent parameters

Independent variability (Y)	Model Predicter Impact ONI (X)	R^2	P - Regression Coefficient Value
Mean Monthly temperature (MMD)	Y = 0.817*(X)+26.148	0.73	0.000
LST from MODIS	Y = 0.632*(X)+26.08	0.68	0.000
LST from Landsat	Y = 1.139*(X)+26.610	0.57	0.000
Daily Mean from MMD	Y = 0.715*(X)+26.19	0.71	0.000

Table 3 shows a single regression formula for understanding the effect of ONI on four independent parameters to predict the effect of ENSO occurrence on air temperature and surface temperature. Based on table 3, it is found that the highest adjusted value of R ^{2} is the normal monthly air temperature from the Malaysian Meteorological Department, which is 0.73, the second daily mean temperature from MMD which with 0.71 R^2 and followed by the third is the land surface temperature monthly average from MODIS data with R ^{2} 0.68 and finally, daily mean land surface temperature from Landsat satellite which is 0.57.

The mean monthly mean temperature from MMD discovered a high value of R^2 linear regression because the highest total of data was applied to determine and predict the effect value ONI on temperature and follow the daily mean temperature with 0.71 R^2. The monthly average temperature parameter shows that the value of the adjusted coefficient R^2 is the highest at 0.75. This is because the data from is the most in this study which is 386 data compared to MODIS data which is 238 and then Landsat satellite 53 data. The total data plays a significant role in determining the adjusted R^2. However, the adjusted R^2 for MODIS satellite surface temperatures is 0.68 and 0.55 but this regression model is reliable and applicable because it exceeds 0.50 or 50% (Min et al., 2013). This means that 50% of variables such as air temperature, the surface temperature of MODIS, and Landsat satellites can explain the relationship of these parameters between ONI. Table 3 demonstrates that the regression model understands the dependent variables' fit. These demonstrate the statistical importance of the regression model run. Here, $p < 0.0005$, which is less than 0.05, designates that, in general, the regression model statistically comprehends the outcome variable (i.e., it is appropriate for the data). The table reports by what method well the regression equations fit the data (i.e., understanding the dependent variables) and is displayed below. The statistical significance of each independent variable tests whether the non-standard (or standard) coefficient is equal to 0 (zero) in the population freeing each of these coefficients, $H_0 = Ɓ = 0$ versus Ha: $Ɓ \neq 0$ is carried out. If $P < 0.05$, the coefficient is statistically significant to 0 (zero). In this event, the assessment demonstrates an ONI index of a P-value of 0.000. That describes the ONI variable as significant for this model.

Based on the adjusted value of R^2 shows a positive relationship between ONI with monthly, daily average temperature, and surface temperature from MODIS and Landsat satellites. Things clearly explain that the ONI rate improvement results in the value enhancement of the above parameters i.e. the average monthly air temperature and surface temperature from MODIS and Landsat satellites. The subsequent formula describes the outcome of ONI on independent parameters. For illustration, to predict the effect of ENSO on the monthly average air temperature must follow the forecast formula below the matter clearly explains that the ONI value increase causes the four-parameter value increase i.e., average temperature, daily, and LST from MODIS and Landsat satellites. The resulting model clarifies the impact of ONI on independent parameters. For illustration, for the average monthly temperature from MMD which is the prediction formulation as follows:

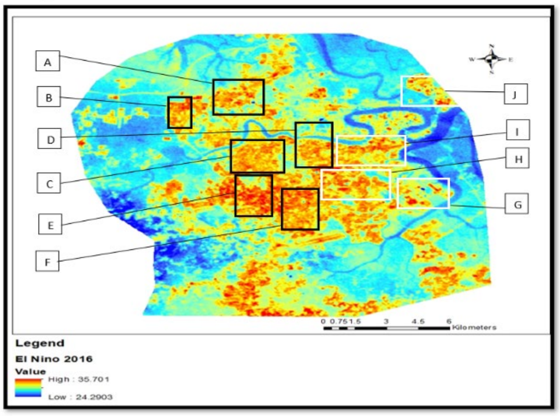
$$Y\ (\text{Monthly Mean from MMD}) = 0.817*(\text{ONI Value}) + 26.148$$

If the ONI rate is 1 then the monthly temperature value of MMD is 26.965 degrees Celsius. The second example is to use a model to predict LST from the Landsat satellite where the ONI value is negative 0.7.

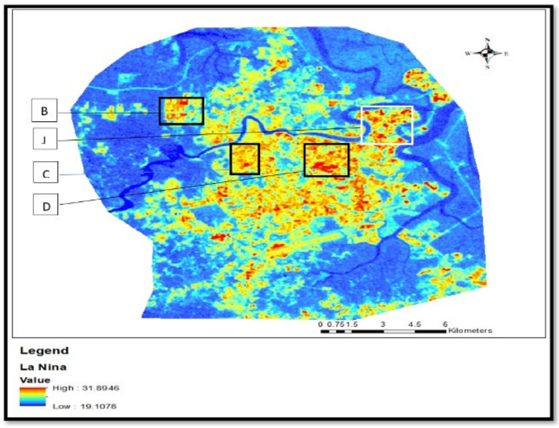
$$Y\ (\text{LST from Landsat}) = 1.139*(\text{ONI Value}) + 26.61$$

And the answer to the effect of the negative value of 0.7 ONI on temperature is 25.81 degrees Celsius.

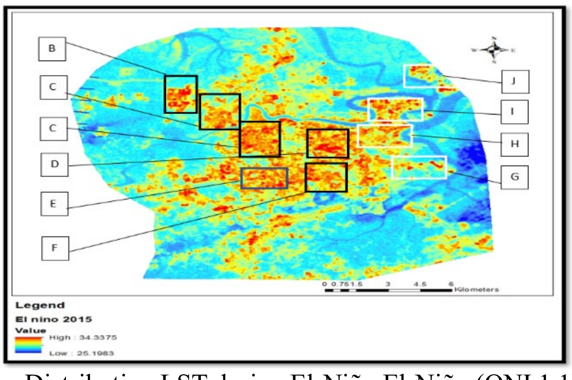
Based on the diagram above shows the highest and lowest temperature values in different study areas. The highest and lowest temperature values differ due to the ONI value. For illustration, if the rate of ONI is 2 then the highest temperature is 33 degrees Celsius compared to the negative ONI value of -1 which is 30 degrees Celsius. In addition to the hot-colored temperature distribution of yellow to red is scattered more than the LST forecast temperature map during the negative ONI value of 1. The regression findings of this research paper were discovered to be related to the correlation results achieved by Chen *et al*., [13] and Jeong *et al*., [14] where the study found a correlation coefficient using observation data in predicting the ENSO index found the coefficient value of 0.6 and upward. Further details on the spatial pattern change for each ENSO event will be discussed further in the next paragraph.



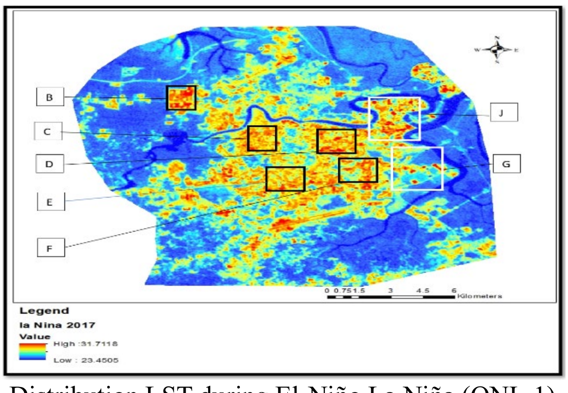
Distribution LST during El-Niño (ONI 1)



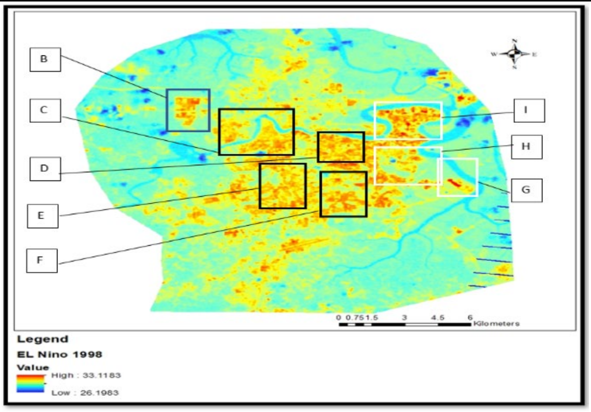
Distribution LST during El-Niño La Niña (ONI -1)



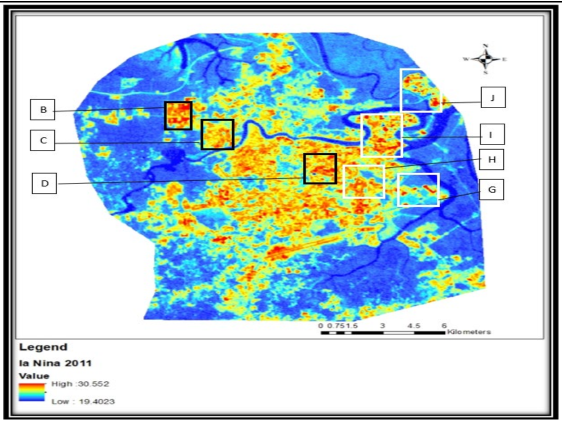
Distribution LST during El-Niño El-Niño (ONI 1.1)



Distribution LST during El-Niño La Niña (ONI -1)



Distribution LST during El-Niño El-Niño (ONI 1)



Distribution LST during El-Niño La Niña (ONI -1.1)

Fig. 5 - Surface temperature distribution for Landsat for the duration of La Niña and El-Niño

Figure 5 shows that figure on right was during El Niño and on the left was during La Niña. Daily observations from near the time of the surface temperature distribution pattern in Kuching Capital changes for each event of La Niña and El-Niño. ONI values play an important role in determining the pattern of temperature distribution and hot spot zones. Figure 5 maps the surface temperature during El-Niño Meanwhile, the time of the La Niña event can be observed in the study area of the city of Kuching, Sarawak looking at the temperature map of the bluish color distribution which represents the lower temperature during the La-Niña event. For clearer knowledge, it is possible to observe the hotspots in the Kuching town area, Sarawak through the representation of the zones to see the hot zone areas more El-Niño events for the duration of the La Niña event. Examples of the time of the El-Niño event are almost the entire zone (B, C, D, E, F, G, H, I, and J) of the time having a temperature of 30°C residents in the City of Kuching all through the La event Niña as in figure 5.13 For illustration in figure 5.11 in the El Niño incident indicated the hot spot zone B, C, D, E and F (Urban area) and G, H and I for the Industrial area which has 8 hot time zones during the event La Niña which has 7 zones B, C, D, G, H, I and J. The growth in the area is described directly using figure 4 which estimates the area during the heat of 30°C temperature in La Niña and El Niño events. Next, to facilitate the application of understanding the effect of ENSO on temperature distribution using the RS technique in Kuching, Sarawak. This study analyzes the effect of ENSO on the temperature distribution using statistical data required maximum, minimum, and temperature values of satellite RS data during the La Niña and El Niño events. Table 4 shows the information on maximum, minimum, and mean statistical values during the La Niña and El Nino events in Kuching City. This difference in temperature, maximum and minimum values is based on Landsat satellite RS data which has no cloud coverage, and ONI value is negative per 1 event during La Niña and positive 1 is El Niño event in Kuching City, Sarawak. The next paragraph will detail in-depth, the differences in maximum, minimum, and distance statistical data for Landsat satellite data during the La Niña and El Niño events in the study area.

Table 4 - The information on maximum, minimum, and mean statistical values in the La Niña and El Nino incidents

Date	ONI Value	LST Value (°C)	Date	ONI Value	LST Value (°C)	Difference (°C)
24 October 2018	-1 (La Niña)	Maximum (31.39) Minimum (19.10) Mean (24.8)	6 July 2016	1 (El-Niño)	Maximum (35.90) Minimum (24.29) Mean (26.90)	Maximum (4.51) Minimum (5.29) Mean (2.10)
21 August 2018	-1 (La Niña)	Maximum (31.71) Minimum (23.45) Mean (24.2)	28 July 2015	1.1 (El-Niño)	Maximum (34.33) Minimum (25.19) Mean (26.72)	Maximum (2.62) Minimum (2.74) Mean (2.52)
9 November 2011	-1.1 (La Niña)	Maximum (30.55) Minimum (19.42)	3 April 1998	1 (El-Niño)	Maximum (33.31) Minimum (26.19)	Maximum (2.76) Minimum (6.77)

	Mean (24.91)		Mean (27.81)	Mean (2.9)

Table 4 illustrates the data values for each ONI value difference for the optional information of each value which is an additional 1 value of -1 and there is no cloud coverage in the study area. The values of maximum, minimum, and mean statistical values were higher in El-Niño associated with La Niña. For illustration, where the rate of ONI was 1.1 in April 1998 and the rate of mean LST was 27.81 ° C compared to La Niña's existing ONI value of -1.1 in November 2011 where the value is 24.91 ° C. This rate numerical LST pattern is the same for the data taken in July 2015 where the ONI value is 1.1 which denotes El Nino where the value is different such as 2.52 ° C compared to the occurrence of La Niñ0 incident the ONI value is -1 where the temperature value is 24.2 ° C. The maximum and minimum LST values for are El-Niño 35.90 ° C and 24.29 ° C correspondingly which is higher at the time of La Niña occurrence the maximum value is 31.39 ° C and the minimum value is 19.10 ° C which is the ONI value during El-Niño 1 in July 2016 and La Niña in October 2017. The LST values vary from 2.10 ° C to 2.90 ° C. The difference between the maximum of 2.32 ° C to 4.51 ° C and the last minimum value is between 2.74 ° C to 6.77 ° C.

A La Niña event will cause a drop in temperature due to an increase in the amount of rainfall during La Niña. This is supported by Drosdowsky [21] also accepted by Kemarau and Eboy [1] which supports the increase in rainfall during the La Niña event lowering the temperature in the vicinity of Kuching City, Sarawak. On the other hand, during El Niño events causing drought due to a lack of rainfall amount than normal will cause temperatures to rise [21]. The amount of rainfall is small during El Niño because of its ability to shorten the monsoon season [22; 23]. In addition, Freychet et al. [24] also found that the highest meteorological temperatures were recorded during the peak of El Niño in 2015 which was during the day and night compared to during the neutral ONI event.

The rise in temperature during the occurrence of El Niño is because of the influence of El Niño to increase the temperature globally [15;16]. The result of this research is supported by the research by Song *et al*., [17] and Yu *et al.,* [18] whose results also found the influence of local climate cannot impact the warming by El Niño when it is dominant and at maturity. This clarifies the results of this research. Based on table 4 it is found that the average temperature was 27.8 ° C and 26.9 ° C during the 1997/ 1998 El Niño and during the 24 ° C La Niña incident in November 2011 and September 2010. There was a temperature difference of 2 to 3 ° C between ONI events. In contrast to the findings of the study of Moura *et al*., [19] who conducted a study in the Amazon where there is a temperature difference of 7.5 to 8 degrees Celsius between the two occurrences of El Niño and La Niña. The high difference compared to the study area is due to the landform factor where the study area in the lowland area compared to the study area Moura *et al.*, [19] are close to Andes mountains. However, the findings of this study are almost the same as the findings of a study by Moskov and Smirnov [20] who made a study of temperature changes between the occurrence of El Niño and La Niña from 1870 to 2014 in areas on the same continent.

4. Conclusion

This study explored remote sensing expertise in predicting the effect of ENSO on temperature and LST using a combination of low- and high-resolution data from 1988 to 2019. This study found that remote sensing data technology can predict the effect of ENSO through linear regression statistical methods. The remote sensing data is calibrated with temperature data from the MMD. The outcomes of the study discovered that the change of ONI which is the ONI index and often used in ENSO studies causes changes in LST value and daily or monthly temperature. Things clearly show that ENSO incidents have an impact on climate and weather in the study area despite being influenced by the monsoon, IOD, or MJO factors. Besides, this work can be used as proof of concept by studying the effects and interactions of ENSO on temperature and LST. ONI works as an ENSO incident forecasting agent. The use of remote sensing technology can provide spatial information that has the potential to improve forecasts' continuous spatial and physical shape.

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