SPATIAL AND TEMPORAL ANALYSIS OF LAND SURFACE TEMPERATURE CHANGE ON NEW BRITAIN ISLAND

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Abstract. Land Surface Temperature (LST) is a parameter to estimate the temperature of the Earth's surface and to detect climate change. Papua New Guinea is a tropical country with rainforests, the greatest proportion of which are located on the island of New Britain. Hectares of rainforests have been logged and deforested because of infrastructure construction. This study aims to investigate the change in land surface temperatures on the island from 2000 to 2019. The temperature data were taken from National Aeronautics and Space Administration (NASA) Terra satellites and were analysed using two statistical models: spatial and temporal. The spatial model used multivariate regression, while the temporal one used autoregression (AR). In this study, a cubic spline fitted curve was employed because this has the advantage of being smoother and providing good visuals. The results show that almost all the sub-regions of New Britain have experienced a significant increase in land surface temperature, with a Z value of 7.97 and a confidence interval (CI) of 0.264 – 0.437. The study only investigated land surface temperature change on New Britain Island using spatial and temporal analysis, so further analysis is needed which takes into account other variables such as vegetation and land cover, or which establishes correlations with other variables such as human health.

Keywords: *Land Surface Temperature, New Britain Island, Climate change, Cubic Spline*

1   INTRODUCTION

The systematic changes in the long-term state of the atmosphere which have been taking place for decades or longer is known as climate change (Public Health Institute, 2016). The statistical description of weather and the related conditions of oceans, land surfaces and ice sheets constitute climate in the broadest sense (Australian Academy of Science, 2015). Climate change is a complex problem that is occurring in around the world. It impacts on various sectors, such as agriculture, forestry, coastal ecosystems, human health,

fisheries and water (Weatherdon, Magnan, Rogers, Sumaila, & Cheung, 2016). When it lowers water quality and quantity, for example, this will result in more water-borne and vector-borne disease. It will also increase the potential for crop failure because agriculture requires 90% of available water for irrigation purposes in many countries (Ahmed, Scholz, Al-Faraj, & Niaz, 2016).

Papua New Guinea (PNG) is a country with many tropical rainforests, which are mostly found on New Britain Island (Bryan & Shearman, 2015). PNG is prone to a variety of natural hazards,

such as cyclones, floods and droughts. Some of these are expected to increase in frequency, magnitude and intensity due to climate change (International Organization for Migration, 2015). An indicator used to predict climate change is Land Surface Temperature (LST). According to a study by Samanta (2009), high land surface temperatures have been found in Morobe Province on Papua New Guinea Island. Oyoshi, Akatsuka, Takeuchi, & Sobue (2014) state that the LST on the island of Papua New Guinea in 2007 was more stable than in Indonesia and Thailand, whereas Australia experienced temperature changes in a short period of time. One of the causes of significant LST changes is the sudden transformation of land use and land cover pattern as the result of rapid urban growth (Choudhury, Das, & Das, 2019).

LST data were obtained from thermal radiation emitted by MODIS (Moderate Resolution Imaging Spectroradiometer), which observes land surfaces at instant viewing angles (Wan & Li, 2010). MODIS is a NASA sensor aboard the Terra and Aqua satellites. Terra MODIS retrieves data at 10:30-12:00 a.m. and p.m. (daytime/nighttime) local time, while Aqua MODIS captures images from 01:00 to 03:00 a.m. and p.m. (daytime/nighttime) (Yang, Cai, & Yang, 2017). LST is a highly variable aspect of the Earth's surface, in both space and time. It analysed with the data spatially and temporally due to the fact that space is spatial and time is temporal (Luintel, Ma, Ma, Wang, & Subba, 2019).

In time series, the concept of autoregressive models refers to ones that are developed by regressing on previous values (Pal & Prakash, 2017). Many processes which are observed through time exhibit autocorrelation, which can be described by using the best autoregressive process (Paolella, 2019). The LST data correlated between time and space are analysed with multivariate regression. In such analysis, the relationships between independent and dependent variables are predicted in order to analyse the effects of the former on the latter (Mansouri, Feizi, Jafari Rad, & Arian, 2018). Land surface temperature is analysed using multivariate regression to examine each point based on latitude and longitude. The cubic spline model is compatible with this process because there is an assumption that seasonal patterns are the same every year, as well as the fact that changes in other parameters such as land cover change have a direct or indirect effect on consistently increasing or decreasing LST (Wongsai, Wongsai, & Huete, 2017). The best cubic spline model is determined by the location and point of the knot. In this study, the cubic spline used 0-knot, 4-knot, and 7-knot. The study aims to investigate LST changes on New Britain Island from 2000 to 2019 using autoregression (AR) and multivariate regression with a cubic spline.

2   MATERIALS AND METHODOLOGY

This study employs secondary data from the NASA MODIS (Moderate Resolution Imaging Spectroradiometer) website. The research focuses on the LST of New Britain Island from 2000 to 2019. A flowchart of the study data analysis is shown in Figure 2-1.
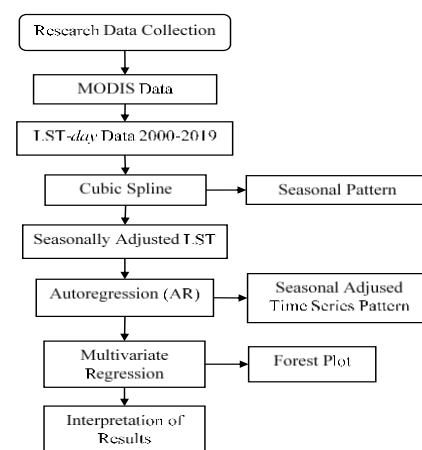

Figure 2-1: Data analysis flowchart

2.1 Location and Data

The study area was on New Britain Island, which is part of Papua New Guinea (PNG). The island was formed from volcanic activity, which makes it the most productive region for the development of geothermal energy resources in Papua New Guinea (PNG) (Lahan, Verave, & Irarue, 2015). Identification of geothermal resources can be made by using remote sensing with LST values (Tampubolon, Abdullah, San, & Yanti, 2016). Geographically, the island of New Britain is located from 148°17'56.20" E to 153° 7'31.50" E, and 6°17'55.88" S to 2°19'57.57" S. It is located to the east of the main island of Papua New Guinea and its size is around 36,520 km². It is the second largest island of Papua New Guinea. Its tropical climate is divided into humid and rainy seasons. The rainy season occurs from May to October, with the average peak of the rainy seasons occurs from July to September. Climate transition occurs in April and November.
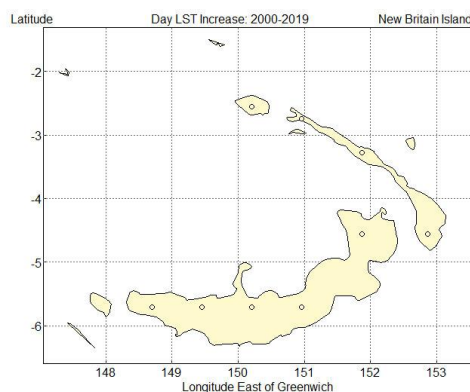

Figure 2-2: Map of New Britain Island with nine sub-region locations (circles) based on longitude and latitude.

Figure 2-2 shows the sample of LST data in relation to sub-regions; these data from the nine sub-regions are referred to as sampling points. Nine such regions were used as sample points to avoid spatial correlation. The sub-region samples were expected to be unbiased

and able to represent the population of the whole islands. The island consists of nine sub-regions with point locations based on calculated longitude and latitude. Spatial correlations can occur between sub-regions and must be avoided; therefore, the data were collected minimum of 3 x 3 km² area, but the measurements were made with 7 x 7 km² area. The Terra satellites of NASA take pictures based on pixels. A pixel represents 1 x 1 km² and each sub-region comprises 49 pixels. In the time series, there were 907 observations of each sub-region (February 2000 to November 2019, which covered precisely 19 years of observational data.

2.2 Data Source

The New Britain Island LST data from 2000 to 2019 were obtained free of charge from satellite records. The data were recorded in the Earth Observing System Data and Information System (EOSDIS) and observed every 8 days. LST uses remote sensing technology to observe changes in temperature data. The data are managed by Oak Ridge National Laboratory (ORNL) and are available on the MODIS website.

MODIS is run by NASA, and provides Land Surface Temperature and Emissivity (LST&E) data. The LST data were obtained from the MODIS website https://modis.ornl.gov. The initial stage to obtain the data is to sign in using a personal account. The user then needs to determine the longitude and latitude of the point from which the data will be taken. These are available on Google Earth and can be calculated using tools on the MODLAND website https://landweb.modaps.eosdis.nasa.gov/cgi-bin/developer/tilemap.cgi to find vertical tiles, horizontal tiles, lines, and samples. The distance between sub-regions must be the same for the calculations based on lines and samples.

MODIS has many variables, each of which has a code for observation purposes. Land Surface Temperature and Emissivity (LST&E) have the code MOD11A2, this provides daytime LST data with observations every 8 days for 19 years. MODIS LST data are a geometrically-corrected product with special utility programs (Busygin & Garkusha, 2013). MODIS Terra data are produced with a generalised split-window LST algorithm that is used to minimise the influence of the atmosphere on surface temperature. The data from longitude and latitude points input by selecting the MOD11A2 code are sent via email in CSV format. Data analysis can be made using the point data. The spatial resolution of the LST data used for each region was a 1 km x 1 km grid (Sharma, Tongkumchum, & Ueranantasun, 2018).

2.3 Statistical Methods
2.3.1 Seasonal Pattern

The curve used to smooth periodicity was a spline. A cubic spline function is a piecewise cubic polynomial with continuous second derivatives and is smoothest among all the functions in the sense that it has a minimal integrated squared second derivative, so it is fitted using linear least squares regression (Me-Ead & McNeil, 2019). LST has the characteristics of seasonal patterns; in light of several considerations it was decided that the most appropriate model for use in the study was the cubic spline, with certain boundary conditions that ensured smooth periodicity and reduced the unbiased results in time series by outliers (Wongsai et al., 2017). Each grid in MODIS includes LST time-series data, so the cubic spline could be used for all the LST time-series in each grid (Sharma et al., 2018). The ability to handle any amount of missing data is one of the advantages of using the cubic spline function (Me-Ead & McNeil, 2019).

Therefore, the model for the function (Wongsai et al., 2017) is:

$$s(t) = a + bt + \sum_{k=1}^{p} c_k[(t-t_k)_+^3 - d(t-t_{p-2})_+^3 + e(t-t_{p-1})_+^3 - f(t-t_p)_+^3] \quad (2\text{-}1)$$

For each sub-region, seasonal variability is believed to be constant, and the pattern shown by plotting the average response variable value for each sub-region every eight days at several years. Seasonal temperature patterns have been found by the use of the cubic spline function by selecting the right number of knots (Sharma et al., 2018). Such knots are based on the location and number, which must be chosen correctly because this is an important process. More knots would result in a smoother covariance surface, but more parameters would need to be estimated (Wongsai et al., 2017). This study used 0, 4, and 7 knots because these showed the highest r-squared value and the lowest p-value. The knots were represented by three curves, with 0 knot being linear, and 4 and 7 knots being the spline.

2.3.2 Time Series Correlation Models

There are two possible approaches to seasonal series: one is to decompose the series into a trend, a seasonal component and residual, and the other is to apply non-seasonal methods to the residual component (Venables & Ripley, 2002). Statistical tests related to the time series method include the autoregressive (AR) test. Analysis of autoregression can predict future values that may affect past values. Therefore, the AR model is the best for describing the value of the event. The autoregressive model is a stochastic model that is very useful to represent occurring series (Box, Jenkins, & Reinsel, 2015).

Autoregressive models are used to predict model curves according to the

correlation of the time series (Venables & Ripley, 2002). Autoregression can determine seasonal patterns because times series analysis has two goals: to identify the observation and to forecast future data. The effect of lagged values can cause problems such as autocorrelation. Many processes that are observed through time exhibit autocorrelation, or the tendency for the observation in the current time period to be related, or correlated, to previous observations, usually in the very recent past (Paolella, 2019). If in the first-order there is obvious autocorrelation, then it is likely that there will be autocorrelation in the second-order autoregression (Montgomery, Jennings, & Kulahci, 2015).

2.3.3 Adjusting for Spatial Correlation Models

The other statistical test is multivariate regression. Spatial analysis such as LST estimation in the sample region with nine sub-regions employed a multivariate regression model. Multivariate regression is a natural extension of multiple regression because both methods aim to explain possible linear relationships between certain input and output variables. Each output variable can be affected by exactly the same set of inputs (Izenman, 2013). Multivariate regression is performed using prescribed first-order autoregression, AR(1), a model for noise ε(t) (Fyfe, Gillett, & Thompson, 2010). The estimation used in the model is the multivariate normal maximum likelihood and ordinary least squares (OLS). The equation of multivariate regression (Leufen & Schädler, 2019) is:

$$y_j = \sum_i \beta_{ij}.x_i + \epsilon_j \qquad (2\text{-}2)$$

For the spatial method, weighted least squares (WLS) was added to the statistical test, because such a regression method can be used when the OLS assumption of constant error variation is violated and is less sensitive to big changes in small parts of the observations (Wongsai et al., 2017).

Within the regression model used heteroscedasticity (non-variance) exists, so WLS can be used to resolve this (Kantar, 2016). In addition, WLS is used when the variance is non-constant (Tharmalingam & Vijayakumar, 2019). A multivariate regression model was developed to show the relationship between temperature and time over the 19 years, with a 95% confidence interval. For most linear regression, Z is considered to consist of entries following a normal distribution with zero mean (Zhang, Shi, Sun, & Cheng, 2017).

3 RESULTS AND DISCUSSION

Land Surface Temperature (LST) is a variable that can indicate climate change because it can affect the Earth's ecosystems, such as glaciers, ice sheets, and vegetation. Climate change is an alteration in climate patterns over a long period of time and may be due to a combination of natural and human causes (Australian Academy of Science, 2015). LST changes occur slowly over time because many other associated aspects also change, such us environmental or ecosystem conditions. Temperature variations were observed in nine sub-regions on New Britain Island during the period 2000 to 2019. To ascertain the temperature changes in each sub-region, LST observations were made every 8 days during the period 2000 to 2019 through the MODIS Terra satellite. The research is related to LST using spatially and temporally correlated data analysis and seasonal LST patterns

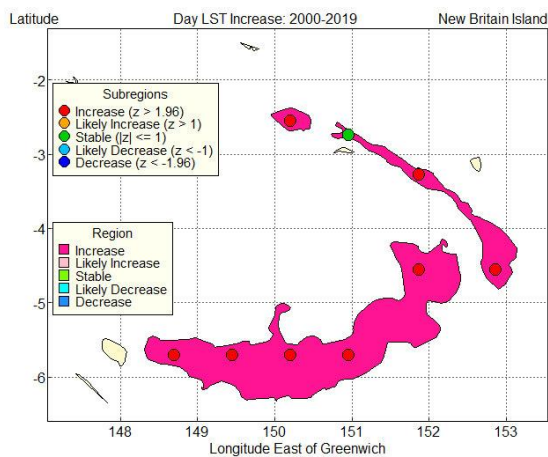were analysed using a cubic spline (Wongsai et al., 2017).

Figure 3-1: Spatial analysis of LST day changes on New Britain Island based on observations from 2000 to 2019

Figure 3-1 illustrates the LST changes in nine sub-regions (shown by circles) and one region on New Britain Island. Sub-region 1 is located in the top left-hand corner, while sub-region 9 is located in the bottom left-hand corner of the map. The location of the sub-regions is from top left to the right, and then from bottom right to the left. In the LST, there were increased temperatures in the regions between 2000 and 2019. The eight sub-regions which experienced an increase are indicated by a red circle, while the one which remained stable is indicated by a green circle. Specific results for each sub-region can be seen in the table 3-1. A red circle shows an increase in LST because the Z value is

higher than 1.96, while the green circle represents stable LST because the Z value is lower than 1. There was not only an increase in land surface temperatures, but also in surface air and sea surface temperatures on Papua New Guinea Island. During the period 1950-2009, it is known that there were warming trends in surface air temperatures, whereas the sea surface temperature rose gradually since 1950 (CSIRO & Australian Bureau of Meteorology, 2011).

Table 3-1 shows that the LST-day increased from 2000 to 2019 in the sub-regions based on longitude and latitude. The region on New Britain Island experienced LST changes with a Z value of 7.97. The highest LST change was in sub-region 9, with a value of mean inc/dec of 0.56 °C and a p-value 0.003, while the lowest LST change was in sub-region 2, with a value of mean inc/dec of 0.118 °C and a p-value of 0.433. Sub-region 9 is located in the west of New Britain Province. Changes to warmer LST conditions are associated with rising concentrations of greenhouse gases and deforestation. It has been shown that the road construction planning that has occurred in the east and west of New Britain has put lowland forests at risk, meaning they will release substantial carbon into the atmosphere and set the stage for future emissions (Alamgir et al., 2019). Land use and land cover on New Britain Island is analysed in a study by Lamo et al. (2018).

Table 3-1: Mean of LST change in the nine sub-regions of New Britain Island

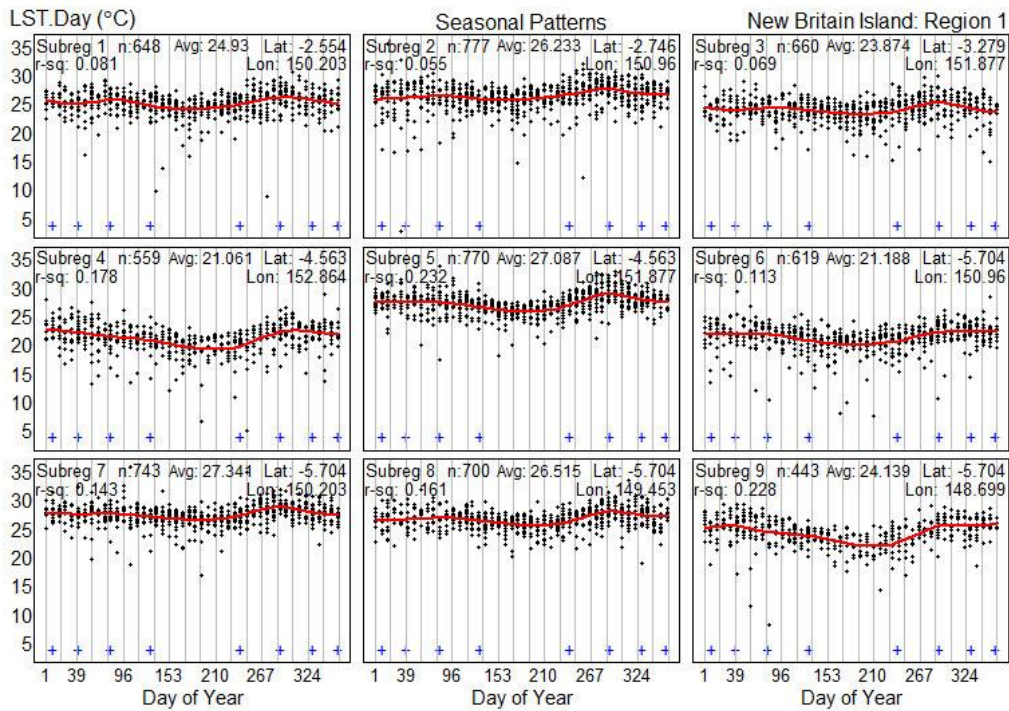| Sub-region	Longitude	Latitude	Mean Inc/Dec	P
1	150.203	-2.554	0.354°C	0.017
2	150.96	-2.746	0.118°C	0.433
3	151.877	-3.279	0.353°C	0.013
4	152.864	-4.563	0.414°C	0.02
5	151.877	-4.563	0.299°C	0.006
6	150.96	-5.704	0.323°C	0.046
7	150.203	-5.704	0.449°C	0
8	149.453	-5.704	0.339°C	0.003
9	148.699	-5.704	0.56°C	0.003

Figure 3-2: Seasonal pattern of Land Surface Temperature (LST) day with cubic spline function in the nine sub-regions of New Britain Island from day 1 to 365

Figure 3-2 represents the LST-day seasonal patterns in New Britain Island observed from 2000 to 2019. There were 19 points for each day as observations took place for 19 years. Each panel shows a sub-region, so there are nine panels with eight knots with a positive shape (+) on each panel. A smooth spline curve in the form of a red line is derived from the cubic spline model to produce an r-square of between 0.05 to 0.23. In sub-regions 1, 2, 3, 5, 7 and 8, there was an increase of LST in October to November (days 286-305). On the other hand, in sub-regions 4, 6, and 9 there was an increase from October to December (days 286-363), with stability at the end of the period. With regard to the seasonal pattern, there was also a decrease in LST on approximately days 172-210 because those days in June to July correspond to the rainy season. This season has a cooling effect on LST because the land is usually covered with vegetation (Khandelwal, Goyal, Kaul, & Mathew,

2018). This shows that seasonal patterns do not occur very often in the sub-regions of New Britain Island. The statistical results with R^2 ranged from 5% - 23%, with an average of around 10%.

Figure 3-3 shows the season-adjusted time series for LST-day on New Britain Island. Three kinds of spline curve were employed, consisting of knots 0, 4, and 7. The fitted models present the seasonal pattern curve in the nine sub-regions, with thick lines for 4-knot, thin lines for 7-knot, and dotted lines for 0-knot. Acceleration is shown from 4-knot, while the 7-year cycle is shown from 7-knot. In some of the sub-regions there are 7-year cycles. From the observations during the 19 years period, it can be seen that the LST of New Britain increased around by 0.12 °C - 0.56 °C, with the lowest CI value of 0.264 and the highest of 0.437. The CI (confidence interval) value was significant because the lower and upper values did not exceed 1.
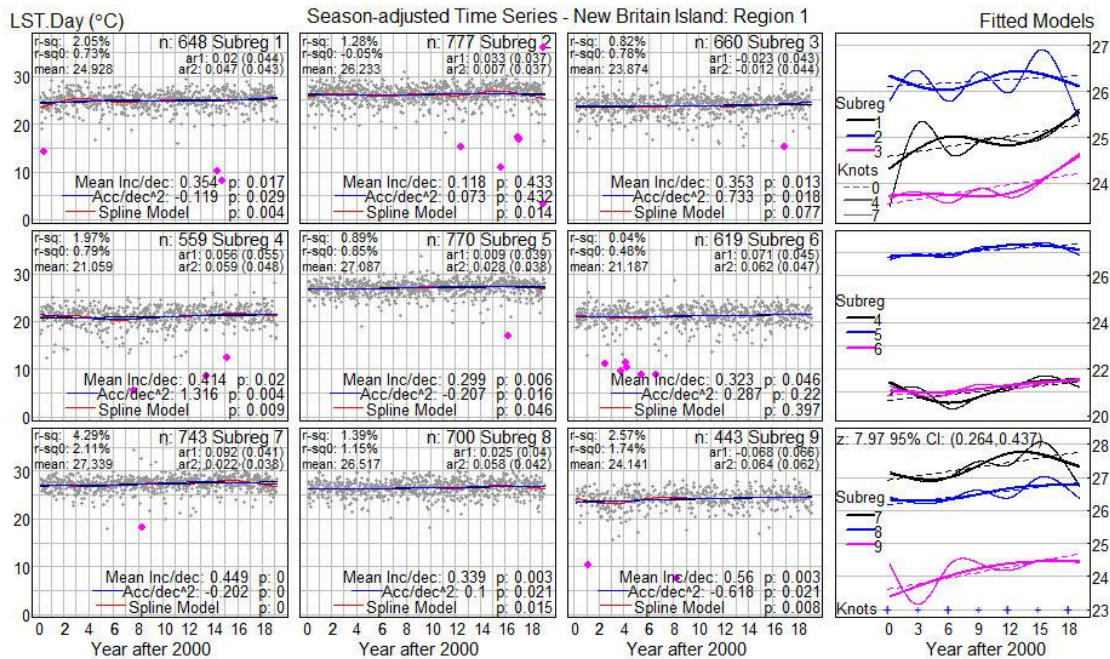
Figure 3-3: Season-adjusted time series of LST-Day in the nine sub-regions of New Britain Island for the period 2000-2019

In addition, Figure 3-3 shows a few outliers in the LST data, depicted by pink dots. These indicate that the LST observations took place when the sky was clear. In addition, sometimes the observations were not optimal because of heavy clouds in the rainy season. Autoregression was used to handle autocorrelation with a model of the p order. Autoregression was conducted in each sub-region in order 2, with observations for 19 years, so it can be called AR(2).

In the cubic spline function, it is given that the end of any year is followed by the beginning of the next year (Suwanwong & Kongchouy, 2016). Seasonal curves are the result of the function of the cubic spline, which produces temperature patterns and trends. The cubic spline function is excellent for observing the adjusted r-squared values for the assumption that the optimal knots and appropriate model (Wongsai et al., 2017). In this study, there were eight knots on different days. The change in LST occurred on the island of New Britain. The observations used a multivariate regression test with a cubic

spline of 95% significance, assuming that in great measure of the sub-region in New Britain showed a significant increase in LST.

The Z value result indicates that pixels with high or low LST values are spatially clustered, even though they were measured to be statistically significant. In the case of a statistically significant positive Z value, as well as a greater Z value, they were included in the higher value cluster (hot spot), whereas the lower value cluster (cold spot) included those with a statistically significant negative Z value and a smaller Z value (Mavrakou, Polydoros, Cartalis, & Santamouris, 2018). In this study, the result of the Z value was positive, with a value of 7.97, meaning it is high.

The increase in LST on the island can be an indicator of climate change because it is part of frequent weather change (Ayuningtyas, 2015). LST changes because it is influenced by urbanisation land use and land cover change (such as forest degradation and deforestation) (Fu & Weng, 2016). The island of New Britain has a sizeable amount of rainforest, but it suffered the highest extent of

deforestation and logging from 2002 to 2014 (Bryan & Shearman, 2015). The location of the greatest deforestation is near sub-regions 5 and 7.

The greater levels of human activities which do not pay due care to the environment can cause global warming, especially because of the reduced areas of rainforest or green open space. Warming could occur on the island of New Britain because of increased LST. In addition, the increase in LST can be used as an indicator of heat islands, which are one of the causes of LST becoming warmer. Heat islands can impact on heatwaves, which affect the quality of life and the environment. LST is one of the climatic variables that can be an indicator of drought disasters; droughts can therefore be predicted from geographical conditions (Karnieli et al., 2010).

In the study of Korada, Sekac, Jana, & Pal (2018) related to drought in Papua New Guinea with reference to the LST and Normalized Difference Vegetation Index (NDVI), it was found that there was a risk zone, especially in the Western Highlands province. Based on that study, LST indicates drought from radiation levels. When radiation is high, there is little water content at the surface of the soil. Drought occurs because the temperature is too high, causing the water in the soil to evaporate. Drought can cause hunger and death because water is a source of life. If drought occurs, the community may not have sufficient food supplies because agriculture is experiencing crop failure.

4   CONCLUSION

The island of New Britain has many tropical rainforests, but it is also experiencing much logging and deforestation. This problem has an impact on climate change, which can result in natural disasters such as droughts. New Britain Island consists of one region with nine sub-regions, which comprised the observation area for the LST study. In eight of the nine sub-regions, LST had increased. The greatest change related to sub-region 9, with an average rise of 0.56°C, while sub-region 2 experienced LST stability.

The method used for the temporal analysis was autoregression (AR). The 19 year time series showed that the increase in temperature was around $0.12°C$ - $0.56°C$. Therefore, the results clearly indicate that the Island of New Britain is becoming warmer. For the spatial analysis, the study used the multivariate regression method based on the spline curve. The cubic spline was used to observe seasonal patterns in LST-day. Spatial and temporal analyses are very suitable for observing patterns in Land Surface Temperature.

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AUTHOR CONTRIBUTIONS

Spatial and Temporal Analysis Of Land Surface Temperature Change On New Britain Island. Lead Author: Rafika Minati Devi, Co-Author: Tofan Agung, Diah Indriani. Author contributions are as follows:

1. Rafika Minati Devi: collect data, analyse data and write manuscripts.
2. Tofan Agung: help command r software, help determine longitude and skyude/coordinate, help write manuscript.
3. Diah Indriani: help write manuscript.

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