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Pattern and Trend of Land Surface Temperature Change on New Guinea Island

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ABSTRACT

Global warming will have an impact on nature in many ways, including rising sea levels and an increasing spread of infectious diseases. Land surface temperature is one of the many indicators that can be used to measure climate change on both a local and global scale. This study aims to analyze the change in land surface temperatures on New Guinea Island using a cubic spline method, autoregressive model, and multivariate regression. New Guinea Island was divided into 5 regions each consisting of 9 subregions. The data of each subregion was obtained from the National Aeronautics and Space Administration moderate resolution imaging spectroradiometer database from 2000 to 2019. The average change in temperature was +0.012°C per decade. However, the changes differed by region; significantly decreasing in the northwest at -0.107°C per decade (95% CI: -0.207, -0.007), significantly increasing in the south at 0.201°C per decade (95% CI: 0.069, 0.333), and remaining stable in the centralnorth, southeast and northeast.

Keywords: Cubic spline, global warming, land surface temperature, New Guinea Island

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INTRODUCTION

Climate change, particularly rising temperatures, is one of the important environmental problems facing the world today. Land surface temperature (LST) can provide insights into climatological processes, land surface energy relations and water stability at regional and global scales (Li et al., 2013; Wongsai et al., 2017), including climate change effects. These changes in climate can severely affect human health, the environment, and economic and social development (Marjuki et al., 2016; Mboera et al., 2011; Mishra et al., 2010). Climate change has a significant association with human disease vulnerability (Wu et al., 2016). This is manifested in the slowing down of the long-period decrease in the incidence of undernutrition, which is somewhat linked to extreme climatic events (Wheeler & Braun, 2013). LST is commonly used to assess rising temperatures.

The LST average around the world will continue to increase (Mildrexler et al., 2018). In tropical areas there has been wide variations in the level of increase in average surface temperatures. The variation depends on many factors such as elevation, normalized difference vegetation index (NDVI), and land cover (Alavipanah et al., 2015; Sun et al., 2012). The great variation on land elevation has a significant impact on the LST (Gao et al., 2008).

In South East Asia, a relationship exists between landscape composition and average LST in Jakarta, Bangkok, and Manila, in which green space was found to be cooler by 3^{o}C compared to those of impervious surfaces (Estoque et al., 2017). Some parts of South East Asia such as Indonesia (including Papua province), Malaysia and Papua New Guinea have experienced land use change, mainly for palm oil cultivation (Agus et al., 2013). Indonesia is the region with the highest level of land use change as a result of the development of palm oil farms and agriculture, and this has had a direct impact on LST (Ramdani et al., 2014; Sabajo et al., 2017). Papua New Guinea has also suffered from forest degradation and half of its forests will be damaged by 2021 (Filer et al., 2009).

New Guinea Island is the second biggest island after Greenland (Permana, 2011). The western half of the island forms a part of Indonesia and the eastern half contains the sovereign state of Papua New Guinea. Natural vegetation in this region consists of tropical rain forests in the lowlands and mountains, although there is a savannah area on the southern coast which has a different seasonal climate (Bowler et al., 1976). Annual maximum and minimum temperatures in New Guinea have been increasing in accordance with the global pattern (International Climate Change Adaptation Initiative, 2007). The New Guinea LST variation will affect LST in the surrounding islands, especially those in Indonesian archipelago, Australia, and even the larger Asia continent (Mildrexler et al., 2018). The extreme temperature was one of the factors of significant loss of suitable habitats for plant species in Papua and Papua New Guinea (Robiansyah, 2018).

Several statistical techniques were used to investigate the temperature changes. Cubic splines are widely used for smoothing data, especially data obtained from satellites. Data is fitted using least squares linear regression (Mao et al., 2017; Smith et al., 1974; Wüst et al., 2017). The technique has been used to model the vegetation index in Nepal (Wongsai et al., 2017; Sharma et al., 2018). There are approaches for the best possible selection of those parameters based on procedures to add knots in intervals where the residuals show trends as signaled by autocorrelation or in intervals where the residuals are inadmissibly significant (Wold, 1974). A first-order autoregressive model was used to fit fluxes in humid subtropical monsoon areas (Kumar et al., 2009). Therefore, the objective of this study was to investigate the change in day land surface temperatures on New Guinea Island during 2000 to 2019 using appropriate statistical methods.

MATERIALS AND METHODS

Study Area

The area of this study was New Guinea Island located at 130° to 152° east longitude and -11° to 0° south latitude (Figure 1). The New Guinea super region contains 5 regions with each region consisting of 9 subregions. The first region is located in the northwest and includes subregions 1 to 9 while the last region is located in the southeast and includes subregions 37 to 45. The sample points are located around parallels of latitude 210 pixels widths (190 km) apart. The subregion as the sample point spread with the equal distance, each comprising 49 pixels in a 7×7 array, covering the New Guinea mainland.

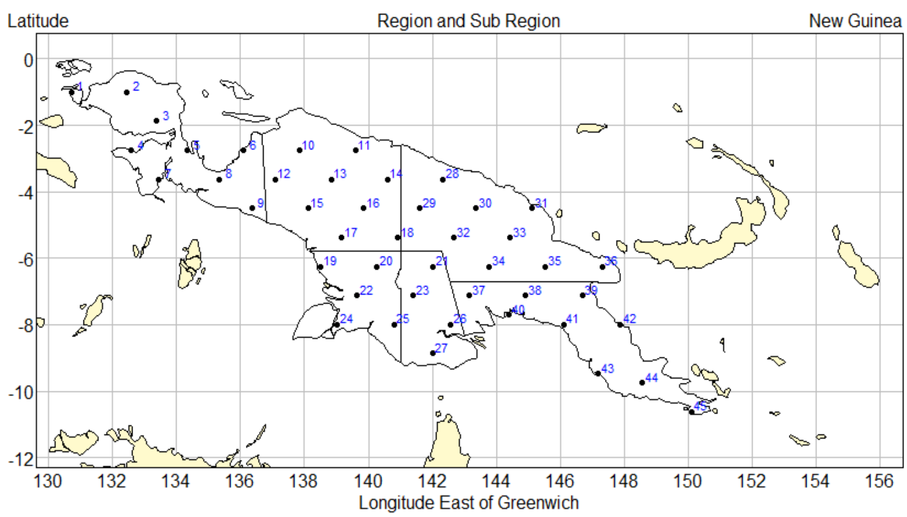

Figure 1. New Guinea Island: area of study

Data

The LST data, which is freely available to download from the MODIS LST (ORNL DAAC, 2018) database, contains average temperatures every 8 days of clear sky for pixels each of area 0.859 km^2. To ensure area equality of all pixels, a sinusoidal projection with tiles of size 10 ×10 latitude degrees was used, with each tile in turn divided into 1200 ×1200 pixels. To avoid missing data, the download was based on the center of the subregion on the island. If there were any missing values, then they were deleted. An unexpected natural disaster (e.g. forest fire, landslide, or tsunami) that may possibly cause a sudden change of data behavior, was excluded. Outliers were kept in the data set to have a comprehensive view of the LST data. The original LST temperature measurements were stored in degrees Kelvin and then converted into degrees Celsius.

The MODIS LST time series data has coverage of global and regular monitoring, include the topography of an area. The Terra (land) satellite will provide the LST data during the daytime and nighttime. The LST data and climate component inland is also influenced by atmospheric and land processes (Luintel et al., 2019; Wan et al., 2015).

MODIS LST data were collected over time with fluctuations due to the season (Wongsai et al., 2017). The seasonal pattern was assumed to be the same for every year and the change in other parameters such as the land cover change that has a direct or indirect effect on the LST data is consistently increasing or decreasing.

Methods

Cubic spline functions are defined as piecewise polynomials of degree r. The joined pieces are called knots. A spline function of degree r is a continuous function with r – 1 continuous derivatives (Wahba, 1990; Wold, 1974). The formula of the cubic spline function is (Equation 1):

$$S\big(t = a + bt + \sum_{k=1}^{p} c_k (t - t_k)_+^3\big) \quad [1]$$

where S is the spline function, t denotes the time in Julian calendar, specified knots are $t_1 < t_2 < ... < t_p$ and $(t - t_k)_+$ is $(t - t_k) > 0$ for $t > x$ and 0 otherwise. The boundary conditions require that $S(t)$ for $t < t_1$ equals $S(t)$ for $t > t_p$. a, b, c_k are the coefficients of the combination between a linear and cubic spline model.

Selecting the position and number of knots for smoothing the spline curve is an important issue. The placement of the knots relies on the LST data in a tropical area with a rainy and dry season (Kohavi, 1995; Lukas et al., 2010; Wongsai et al., 2017). In the different regions of the biosphere, inter-seasonal variation can affect the land surface temperature variation (Singh et al., 2014). Areas that have both dry and rainy seasons will have lower LST during the rainy season (de Jesus & Santana, 2017). In a tropical area, changes in LST may be linked with heatwaves (during April and May) and rainfall (during

June-September) (Gogoi et al., 2019). We used 8 knots and placed 4 knots at the beginning of the year and the remaining 4 knots at the end of the year based on the seasons that are characteristic of tropical regions.

The LST was seasonally adjusted using the Equation 2:

$$Y_a = Y - S_f + \bar{x} \quad [2]$$

where Y_a is a seasonally adjusted time series for LST, Y is an observed data (LST per day) for 18 years, S_f is a vector of spline fitted values that we estimated from the cubic splines and $\bar{x}$ is the average LST per year.

A second order autoregressive model AR(2) was used to fit the LST seasonally adjusted. The model is given by Equation 3:

$$Y_{at} = \alpha_1 Y_{at-1} + \alpha_2 Y_{at-2} + \varepsilon_t \quad [3]$$

where Y_{at} is the seasonally adjusted LST at time t, and Y_{at-1} is the LST at time t-1, t = 1, …, 365 days, α_1 and α_2 are unknown parameters to be estimated and ε_t is the random error with zero mean and finite variance (Chan & Wei, 1987).

A multivariate regression model (Mardia et al., 1979) was then used to analyse the seasonally adjusted LST data. The model is given by Equation 4:

$$\mathrm{Y} = \mathrm{XB} + \mathrm{U} \quad [4]$$

where Y is the outcome matrix of variables with dimension $n \times m$, n is the number of observations, m is the number of subregions, X is a matrix of independent variables $n{\times}q$, q is the number of independent variables, B is a regression parameter matrix with dimension $q{\times}m$ and U is an unobserved random disturbance matrix.

All analyses and graphical displays were carried out using R (R Core Team, 2018).

RESULTS AND DISCUSSION

Region 1 of New Guinea Island was used to represent the results of this study. Figure 2 shows the LST for each day in region 1 of New Guinea Island where Figures 1 and 2 depict the distribution of LST records.

The vertical axis denotes average temperatures on the same day for each of the 18 years. The solid red curves are the fitted natural spline functions with 8 knots denoted by blue crosses. Land surface temperatures showed a moderate seasonal pattern with two summer peaks commonly found in tropical zones.

During the years from 2000-2019 the lowest LST corresponded to day 210 which was during the rainy season and the highest LST corresponded to day 324. The highest average LST was 27.7^{o}C which occurred in subregion 9 of Region 1. The R-squared was 0.31. The lowest R-squared was 0.034 which occurred in the model for subregion 4. The cubic spline with 8 knots was fitted to the LST data and the annual LST data showed a seasonal pattern.

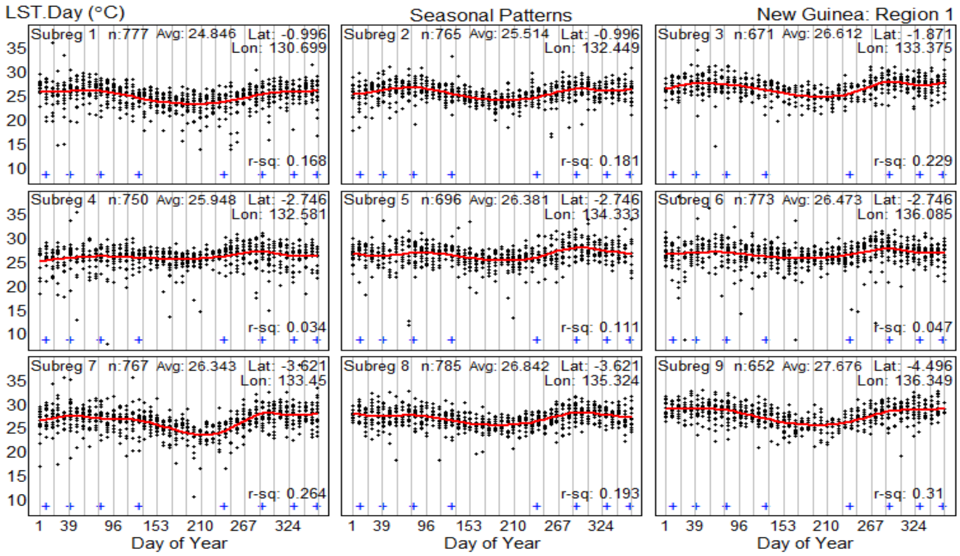

Figure 2. Land surface temperatures in New Guinea Region 1 showing a seasonal pattern

Figure 3 displays the seasonally adjusted LST. The estimated coefficients of a_1 and a_2 were very low, indicating that the time series of daily temperatures are independent.

In Figure 3, the dotted lines in the right panel indicate that LST decreased in subregions 1, 2, 7, and 9, increased in subregions 3, 4, and 8 and remained stable in subregions 5 and 6 over the 18 year period, but p-values for the linear models (zero knots) with two parameters indicate that none of these changes were statistically significant. The thick curves in the right panel show fitted cubic splines with seven knots (with significant p-values for subregions 4, 7 and 9) whereas the dashed lines (cubic splines with zero knots) show the same trends in 18 years for Region 1. The number of knots depends on the LST variation between years. We used 7 knots which divided the data equally into 4-year intervals (assuming that the variation of LST happens every 3 years). In the bottom-right panel of Figure 3, multivariate regression was used to reduce spatial correlation and estimate the mean LST for this region. We found a statistically significant decrease, with a z-value -2.098 and 95% confidence interval (-0.21 - 0.01) °C per decade.

The increases in LST (°C per decade) for each region is shown in Figure 4. The overall mean increase was 0.024°C per decade. There was a wide variation for each region. The mean change in daily land surface temperatures for the northwest, central-north, south, northeast and southeast regions were -0.11°C, 0.002°C, 0.20°C, -0.07°C and 0.03°C, respectively. Only the south and northwest regions had significant changes in day land surface temperatures.

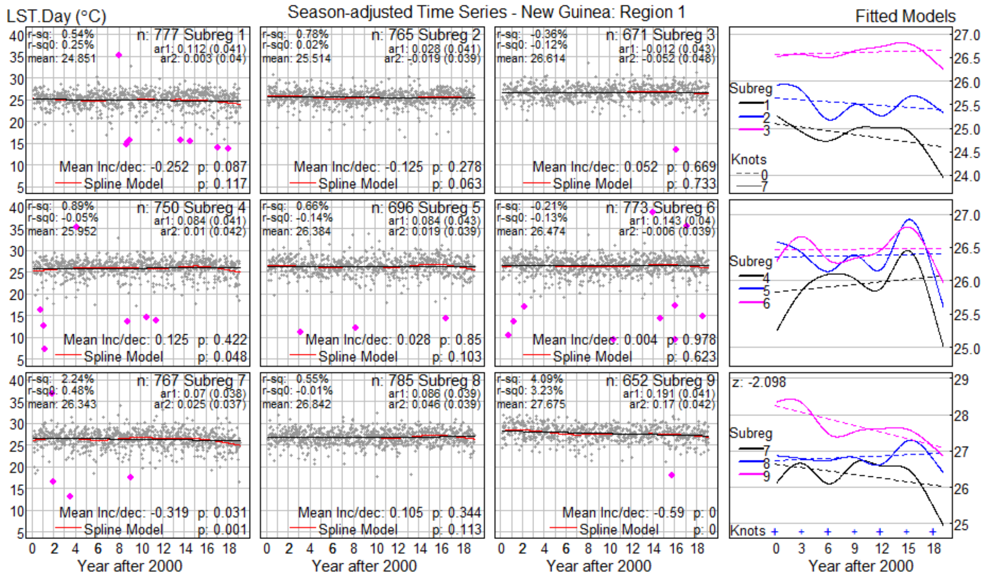

Figure 3. Seasonally adjusted land surface temperatures for New Guinea, Region 1

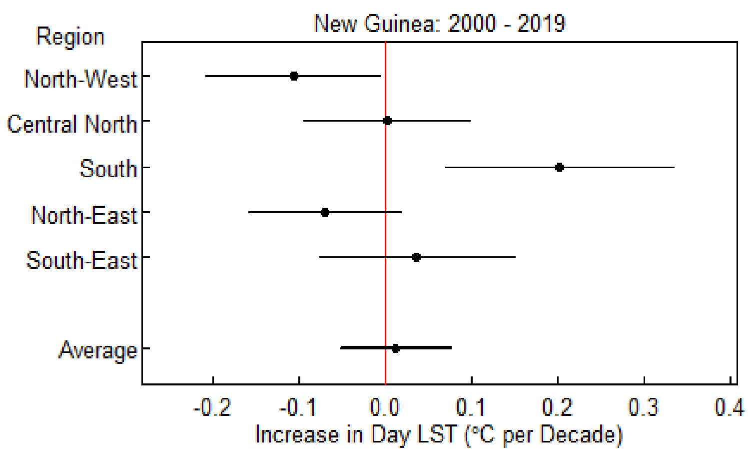

Figure 4. Increase in mean day land surface temperatures with 95% confidence intervals for New Guinea Island

This finding illustrates that the land surface temperatures in New Guinea Island would increase by 0.12°C per decade which was lower than that predicted for Papua New Guinea by the Papua New Guinea National Weather Service (predicted increase in temperatures ranging from 0.4–1.0°C, International Climate Change Adaptation Initiative 2007). The change in land surface temperatures in New Guinea Island was not significant. The islands laying on the equator line tend to have warm temperatures (stable) and the island close to the pole consistently cold and the variation of LST depend on the position of a place on the earth and its elevation (Gillespie, 2014).

Figure 5 shows the results of LST change for the 45 subregions in New Guinea using the multivariate regression model. The probability that temperatures in each of the 5 regions increased, decreased, or remained stable were determined by averaging the LST trends for each subregion. The day LST decreased in the northwest, increase in the south, and is likely to be stable in the central-north and southeast, while it is likely to decrease in the north-east.

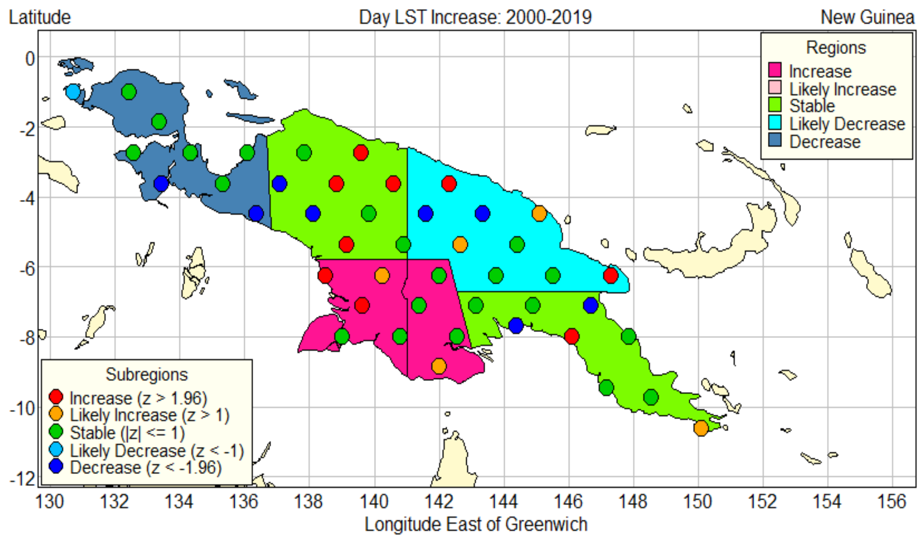

Figure 5. Trends in land surface temperatures (˚C/decade) in New Guinea Island, 2000-2019

The seasonal pattern of the data showed that the highest LST for region 1 occurred between day 267 and day 324. However, the findings indicate that there was a seasonal pattern. Other studies conducted in areas with four seasons showed that the highest LST appeared during summer (Singh et al., 2014). LST has also been shown to be influenced by vegetation, land use/land cover (LULC) and surface solidity (Khandelwal et al., 2018).

Several studies have shown that LULC affects LST temperatures (Odindi et al., 2015; Rasul et al., 2017). The area will experience an increase in temperatures if the land cover is greatly reduced (Parmesan & Hanley, 2015). Green trees or other plants that cover the ground surface can absorb heat as a result of the reflection of sunlight through the evaporation process. The heat on the surface of the trees will metabolize the heat and convert it into other forms of energy therefore reducing the temperature on the land surface. This means that LULC in the form of healthy vegetation tends to not produce an increase in LST (Babalola & Akinsanola, 2016).

Vegetation or healthy plants in an area were affected by LST variation (Rahmad et al., 2019). Two studies reported on the increasing rate of forest conversion in the areas of Papua New Guinea and Papua (Alamgir et al., 2019; Austin et al., 2019). This deforestation is suspected to be the cause of an increase in temperatures in the area. A study found that areas with a low vegetation index will have high LST (Buyadi et al., 2014).

Temperature changes on the island of New Guinea occurred at a minor rate. Research shows that an increase in the temperature of an area can be reduced if the vegetation can be recovered again (Cooper et al., 2017). In other words, if the NDVI is increased in an area that experiences an increase in temperature, it is expected that this will reduce or prevent further increases in LST.

Use of a cubic spline and multivariate regression analysis was suitable for examining the seasonal pattern and variation in the LST for the 5 study regions. Only 2 of the 5 regions showed a significant change in LST. This might due to the number of subregions when compared to the size of New Guinea Island. We included 210 pixels in each grid, which equated to a longitudinal distance of 190 km between each subregion. It has been shown that increasing the sample size can improve the estimation of the true population mean (Storch & Zwiers, 1999; Mehta & Pocock, 2011).

CONCLUSIONS

With the appropriate number and placement of knots, the cubic spline model provided a satisfactory fit to the LST data on New Guinea Island. This study demonstrated a decreased LST in the northwest and south regions. There were variations in the increase of LST, although the increases were not significant. An increase in LST on the Island of New Guinea is an indication of global warming at the regional level. However, further investigations are needed to confirm these findings on a wider scale. Another approach is needed to improve the accuracy of estimation, especially to validate our findings for the same area such as Sumatra and Borneo islands, which are on the equator. The sample size can be increased by increasing the number of regions or subregions. Finally, since New Guinea Island contains many rainforests and mountainous areas, including other variables such as NDVI or land elevation in the analysis may help to improve the model fit.

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