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The Effect of Land Surface Temperature on Dengue Hemorrhagic Fever Incidence

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ABSTRACT Land Surface Temperature (LST) can be used to detect the occurrence of climate change. The change in LST can affect disease patterns such as Dengue Hemorrhagic Fever (DHF). The incidence of DHF in Madura from 2010-2019 showed instability and the highest incidence rate occurred in 2015. This study aims to analyze the spatial and temporal effect of LST on the incidence of DHF in Madura. This study contributes to increasing public awareness of environmental protection related to climate change, which can cause DHF. The analysis was carried out spatially and temporally, using multivariate regression (spatial) and Autoregression (temporal) methods with a cubic spline for LST. This study used secondary data from MODIS NASA website and Madura health profile. LST in most sub-region, increased in 2003 and 2015, then which is in line with the incidence of dengue fever in Madura, which also increased around 2015-2016. The R^2 value from the cubic spline test shows that the model used is quite good and has the same performance in all regions of Madura. The Z-value in all regions is negative, which indicates a cold area. The highest Z-value in region 1 is related to Bangkalan Regency which has more incidences of DHF in the highest category. While the lowest Z-value is found in region 3 related to Pamekasan Regency which has never been in the high category. The incidence of DHF based on LST in Madura illustrates that Bangkalan and Sumenep regencies have greater potential than Sampang and Pamekasan regencies.

INDEX TERMS Land Surface Temperature, Dengue Hemorrhagic Fever, Spatial, Temporal

I. INTRODUCTION

Weather is the state of the atmosphere concerning temperature, humidity, wind, precipitation, and so on for several hours to several weeks. It is influenced by the oceans, land surface, and ice sheets, together with the atmosphere, that make up the climate system [1]. The occurrence of climate change is a complex problem faced by the whole world. The impact of these changes affects various important sectors that support life, such as human health, forestry, coastal ecosystems, agriculture, fisheries, and water [2]. One of the indicators used to predict climate change is Land Surface Temperature (LST). LST is the surface temperature that can be measured when the soil surface is in direct contact with the measuring instrument. Thus, LST can also be referred to as the temperature of the soil surface layer [3].

MODIS (Moderate Resolution Imaging Spectroradiometer) is NASA's sensor aboard the Terra and Aqua satellites. The two MODIS satellites use remote sensing technology to observe LST data. MODIS Terra is used for LST observations taken at 10.30-12.00 a.m and p.m, while MODIS Aqua is taken during 01.00-03.00 a.m and p.m [4]. Each time series in long-term remote sensing usually consists of long-term trends, seasonality (systematic movement), and irregular (unsystematic) short-term fluctuations [5]. Thus, LST is a very varied aspect of the earth's surface, both in terms of space and time. Therefore, LST analysis is carried out spatially (space) and temporally (time) [6].

In the analysis of temporal (time series) data, the concept of an Autoregression model (AR) is a model developed by regression based on previous values [7]. AR models are very useful in presenting a process that occurs in time series data and can overcome autocorrelation. Thus, the AR model is suitable for LST data analysis. For spatial data analysis, using multivariate regression can find a trend of change from LST and show a relationship between temperature and time with a 95% confidence interval [8]. In addition, LST data analysis is done using multivariate regression to test each point based on longitude and latitude calculations. Combining Autoregression and multivariate regression models with cubic spline models in LST analysis is compatible with this process because there is an assumption that the seasonal pattern is the same every year and changes in other parameters affect the increase or decrease in LST consistently [9]. The cubic spline model has a function to see seasonal patterns and connect variables by smoothing the curve. Cubic splines need to use knots to get the optimal model.

Dengue Hemorrhagic Fever (DHF) is a disease caused by the dengue virus, which is carried by vectors, namely the Aedes mosquito species, especially the *Aedes aegypti* mosquito [10]. The dynamics of the spread of DHF are influenced by environmental and meteorological factors that peak in the hot-wet period [11]. Increasing temperatures affect viruses, increase the speed at which vectors find food, and extend the season of DHF transmission, which can increase the incidence of DHF [12]. Mapping DHF using a geographic information system is an effective countermeasure for early awareness [13]. LST is one of the climate variables that can be used for geographic information related to disease occurrence.

Based on the 2018 East Java Province climate risk and vulnerability study report, it is projected that in 2030–2040 on Madura Island there will be an increase in the highest average temperature between 0.8^0C-1^0C due to increasing population and changes in land use [14]. In addition, based on data from the East Java Provincial Health Office, the incidence of DHF in Madura from 2010–2019 is still experiencing instability. In 2015, the incidence of DHF in Madura was very high, but after that, it decreased until 2017 and then increased again from 2017 to 2019.

This research aims to analyze the effect of LST on the incidence of DHF on Madura Island through a comparison of LST patterns on Madura Island during the period 2000–2019 with the pattern of DHF incidents in 2010–2019 on Madura Island. So from this research, it can be seen what the relationship is between LST and the incidence of DHF. The contributions of this research are as follows:

1. Provide an overview and information regarding the impact of LST changes that can affect health.
2. Increasing sensitivity in minimizing activities that impact climate change and can cause morbidity.
3. It can be a reference for local governments in preventive efforts in the health sector related to the environment.

II. METHODOLOGY

This study used secondary data from the MODIS NASA website for LST data for the 2000–2019 period in Madura and DHF incident data for 2010–2019 in Madura from the East Java Provincial Health Office. The data is analyzed using the flow of data analysis as shown in Figure 1. The research begins with collecting the data that will be used, namely LST and DHF data. LST data obtained from NASA is daily data from 2000-2019, while DHF data is used from 2010–2019. Then, the LST data is tested using the cubic spline method, which helps see seasonal patterns and connect variables by smoothing. This test obtained LST, which was adjusted for seasonal patterns. Thus, the adjusted LST data were analyzed temporally and spatially using AR and multivariate regression. The results obtained are compared with the DHF data to make conclusions.

The research was conducted on Madura Island. The population in this study was the entire Madura Island from 2000 to 2019, as well as the incidence of DHF in Madura from 2010 to 2019. Meanwhile, the research sample consists of four regions, and each region consists of several sub-regions to avoid spatial correlation. The determination of the four regions is based on the number of districts in Madura.

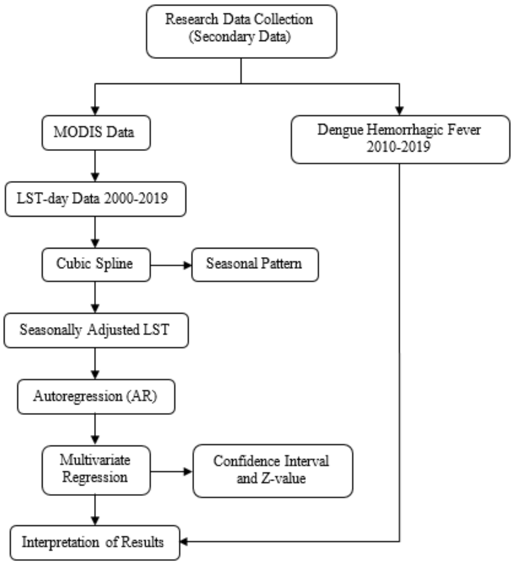

FIGURE 1. Data analysis flow

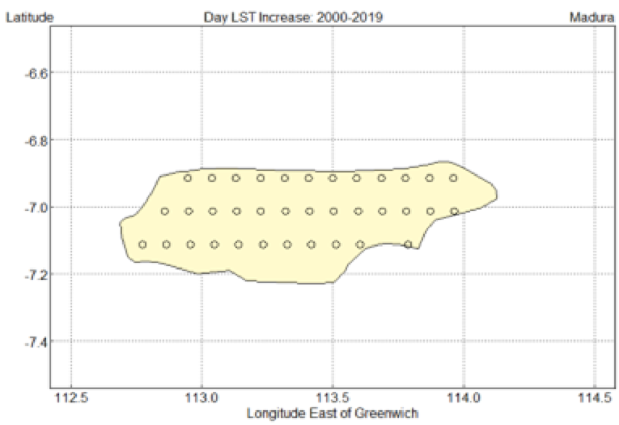

FIGURE 2. Mapping Madura Island with 36 Sub-Regions Based on Longitude and Latitude

Figure 2 shows that Madura Island is divided into four regions with 36 sub-regions. Each region has nine sub-regions to avoid spatial correlations that can affect LST data. Each sub-region has a size of 7 x 7 pixels, or 49 pixels. Thus, each region has a size of 21 x 21 = 441 pixels from nine sub-regions. Sub-regions have a minimum distance of 9 km^2. On Madura Island, it is known that the distance between sideways sub-regions is 10.15 km^2. Meanwhile, the distance between sub-regions up and down is 11.15 km^2. Region 1 represents Bangkalan Regency with sub-regions 1–9, region

2 represents Sampang Regency with 10-18 sub-regions, region 3 represents Pamekasan Regency with sub-regions 19-26 and 28, while region 4 represents Sumenep Regency with sub-regions 27 and 29-36.

A. SEASONAL PATTERN

LST has a characteristic, namely a seasonal pattern. Thus, based on several considerations, it was decided that the most appropriate model to use in this study is the cubic spline, with certain conditions that ensure smooth periodicity and reduce the results that aren't biased in the time series by outliers [9]. Each grid in MODIS includes LST time series data, so a cubic spline can be used for all LST time series data in each grid. For each sub-region, the seasonal variability is believed to be constant, and the pattern is shown by plotting the average value of the response variable for each sub-region every eight days over several years. Seasonal temperature patterns can be found by using the cubic spline function and selecting the right number of knots [15]. The knots are based on location and quantity, which must be chosen correctly as they greatly influence the analysis process. Therefore, this study uses knots 0, 4, and 7 because they can show the highest R^2 values and the lowest p values, so they can produce good models. Knots represent 3 curves, namely knots 0 being linear and knots 4 and 7 as splines.

B. TIME SERIES CORRELATION MODELS

Time series data is synonymous with autocorrelation because there is a tendency for observations in the current time period to relate to or correlate with previous observations [16]. The Autoregression (AR) model is a model used to overcome autocorrelation in time series/temporal data. In addition, AR models can also be used to determine seasonal patterns because time series analysis has two objectives, namely identifying observations and predicting future data.

C. SPATIAL CORRELATION MODEL ADJUSTMENTS

In addition to temporal analysis, this study also carried out the spatial analysis in the form of estimating LST in the sample area with nine sub-regions using a multivariate regression model. Multivariate regression was performed using a first-order Autoregression that was determined, namely AR (1) [17]. The estimates used in the model are multivariate normal maximum likelihood and Ordinary Least Squares (OLS). For the spatial method, Weighted Least Squares (WLS) can be 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 slightly sensitive to large changes in a small part of the observations [9]. A multivariate regression model was used to show the relationship between temperature and time for 19 years with a 95% confidence interval. For most linear regressions, Z is assumed to consist of entries that follow a normal distribution with a mean of zero [18].

III. RESULT

A. DENGUE HEMORRHAGIC FEVER INCIDENCE

An overview of DHF incidence on Madura Island from 2010 to 2019 shows an increase and decrease, as seen in Figure 3. Based on data from the East Java Provincial Health Office, it was shown that the highest incidence of Dengue Hemorrhagic Fever (DHF) on Madura Island occurred in 2015 and 2016, as shown in Figure 3. However, there was a significant decrease in 2017, followed by a slight increase in 2015, 2018, and 2019. Thus, it can be said that the incidence of DHF is experiencing instability.

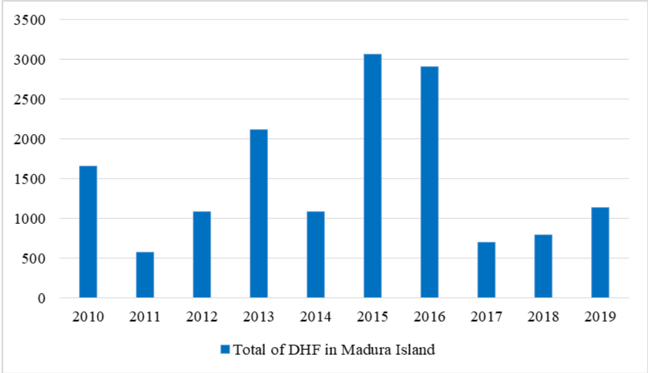

FIGURE 3. Dengue Hemorrhagic Fever Incidence on Madura Island in 2010-2019

TABLE 1
DHF Incidence Rate in Madura Island from 2010 to 2019.

Year	DHF Incidence Rate in Every District of Madura Island			
	Bangkalan	Sampang	Pamekasan	Sumenep
2010	≥55	<55	<55	<55
2011	<54	<54	<54	<54
2012	<53	<53	<53	<53
2013	≥52	≥52	<52	≥52
2014	<51	<51	<51	<51
2015	≥49	≥49	<49	≥49
2016	≥49	≥49	<49	≥49
2017	<49	<49	<49	<49
2018	<49	<49	<49	<49
2019	<49	<49	<49	<49

Table 1 shows the achievement of the DHF incidence rate in each district on Madura Island in 2010–2019, compared to the national target. Districts that are included in the high category are those that have an incidence rate greater than the national target. Based on Table 1, it can be seen that Bangkalan Regency was the district that did not meet the achievement target or was included in the high DHF incidence category in 2010, 2013, 2015, and 2016. Meanwhile, Sampang and Sumenep Regencies did not meet the national target three times, that are in 2013, 2015, and 2016. Pamekasan Regency always met the national target from 2010 to 2019.

B. LAND SURFACE TEMPERATURE MAPPING

Figure 4 is a mapping of the analysis results on LST during 2000-2019. Mapping to describe how LST changes occur in sub-regions and regions on Madura Island. The X-axis in the figure shows the longitude number while the Y-axis shows the latitude number.

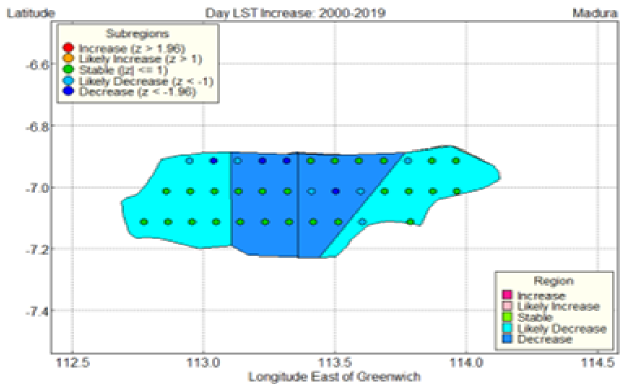

FIGURE 4. LST Change Mapping for Madura Island

Figure 4 shows that most of the sub-regions have not changed and tend to be stable because the circle symbol shows more green. Meanwhile, the other sub-regions experienced a decline consisting of two colors. The light blue color represents the category of possible decrease that occurs in sub-regions 4, 10, 20, 26, 27, and 30, while the dark blue color belongs to the category of decrease that occurs in sub-regions 7, 13, 16, and 23. Furthermore, Figure 4 shows that regions 1 (west) and 4 (east) visualize changes in a light blue color, indicating that they are included in the likely decrease category due to Z -1. In contrast, the colors in regions 2 (central west) and 3 (central east) are dark blue, indicating that the region is in the decrease category due to Z -1.96. Thus, it is assumed that Madura Island has experienced a decrease in LST.

C. SEASONAL PATTERN OF LAND SURFACE TEMPERATURE

The observation of LST seasonal patterns in 36 sub-regions spread across four regions in 2000-2019 is shown in Figure 5. Each panel describes the seasonal pattern in each sub-region. The X-axis shows the 1st to the 365th day, which means one year, while the Y-axis shows the daily LST in ^{0}C.

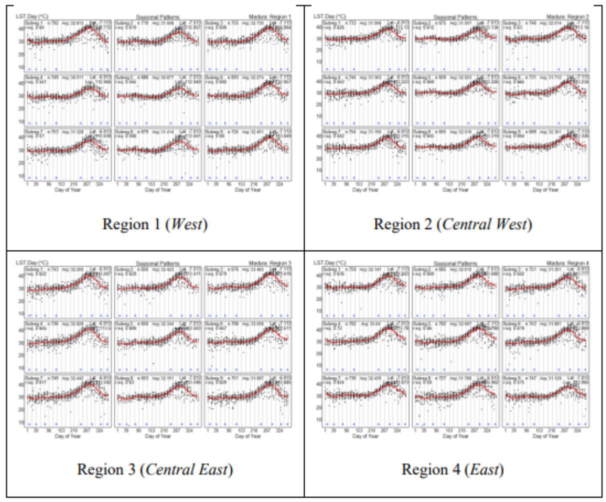

FIGURE 5. LST Seasonal Pattern from Day 1 to 365 in 2010-2019 in Each Region

TABLE 2
R-Square (R2) from Cubic Spline Test in Each Region

Region	Longitude	Latitude	R-Square (R^2)
1	112.772-113.049	-6.913- -7.113	0.541-0.699
2	113.13-113.326	-6.913- -7.113	0.542-0.669
3	113.407-113.592	-6.913- -7.113	0.606-0.679
4	113.603-113.965	-6.913- -7.113	0.575-0.72

According to Figure 5, the four regions of Madura Island have nearly the same pattern of temperature changes and exhibit a seasonal pattern due to an increase at certain times. The increase occurred from the 248th day to the 286th day, which started from the beginning of August to mid-October. The decrease in LST occurred on days 286–343, namely from mid-October to early December. Table 2 shows the value of R^2 from regions 1 to 4. Overall, it is found that the value of R^2 in the cubic spline function of all regions does not show much difference because the value is between 0.541 and 0.72.

D. SPATIAL AND TEMPORAL ANALYSIS OF LAND SURFACE TEMPERATURE

The spatial analysis was carried out using multivariate regression tests and temporal analysis using the Autoregression (AR) test. From the multivariate regression test, Z values and confidence intervals were obtained. The AR model produces a coefficient value.

TABLE 3
Average Temperature, Z-value, and CI in Each Region

Region	Average Temperature	Z-value	Confidence Interval (CI)
1	30.530°C–32.820°C	-1.071	-0.274–0.08
2	< 32.370°C	-1.967	-0.362–0.001
3	32.020°C–33.510°C	-2.244	-0.435–0.029
4	< 33.099^{0}C	-1.564	-0.374–0.042

TABLE 4
Average LST Change (Mean Inc/Dec) in Each Region

Region	Mean Inc/Dec	Koefisien AR (1)	Koefisien AR (2)
1	-0.388-0.094	0.261-0.508	0.173-0.335
2	-0.352 – -0.063	0.259-0.418	0.193-0.367
3	-0.376– -0.116	0.292-0.451	0.175-0.321
4	-0.284– -0.064	0.278-0.4	0.194-0.311

In Table 3, it can be seen the average of temperature, Z value, and confidence interval (CI). In region 1, the average temperature is 30.530°C–32.820°C with a Z-value of -1.071 and a CI value of -0.274–0.08. For region 2, the average temperature is < 32.370 °C with a Z-value of -1.967 and a CI value of -0.362–0.001. Region 3 has the highest average temperature, that is 32.020°C–33.510°C with a Z-value of -2.244 and a CI value of -0.435–0.029. And for region 4, the average temperature is < 33.099^{0}C with a Z-value of -1.564 and a CI value of -0.374–0.042. Thus, it was found that the Z-values in all regions were negative while the CI values in each region were significant, with an average CI being negative. In addition, LST in some sub-regions only increased in 2003 and 2015. Table 4 shows the value of the AR coefficient, which in this study uses the AR model (2). The AR coefficient values (1) and (2) show a value less than 1, while the mean increase/decrease results show a negative value.

IV. DISCUSSION

Dengue Hemorrhagic Fever is caused by the dengue virus, which is carried by the Aedes mosquito vector. The calculation of the incidence of DHF in an area can be done using the Incidence Rate (IR). As a result, the government publishes a national IR target each year to determine the boundaries within which an area is said to have a high incidence of DHF. IR on Madura Island showed instability in the 2010–2019 period. However, Bangkalan Regency is ranked first with the highest IR because, in the 2010–2019 period, there have been 4 IR from DHF, not by the national target or in the high category. Pamekasan Regency is a district in Madura that always meets the national target for 2010–2019. Meanwhile, Sampang and Sumenep Regencies are in second place. Therefore, most districts on Madura Island have the potential to have a high incidence of DHF. This is also in line with Putra and Kurniawan's research (2015) [19] which states that all districts on Madura Island are included in the areas with the highest potential for DHF in East Java.

Changes in LST, both decreasing and increasing, are influenced by several factors originating from humans, such as changes in land use and sustainable infrastructure development [20]. An increase in LST can be an indicator that an island is said to be hot. However, in mapping LST changes on Madura Island, it is estimated that LST has decreased from 2000 to 2019, so the island is not hot. For further tests of the LST estimation results using Autoregression and multivariate regression with cubic splines.

To see seasonal patterns that are characteristic of LST using a cubic spline. The smooth cubic spline function curve is very suitable for the LST time series because it can show patterns and trends [15]. Optimal results in the cubic spline model lie in selecting the number and location of the knots. In this study, 8 knots were used, which is in line with the research of Wongsai, Wongsai and Huete (2017) [9], who said that in the LST fluctuation data, 8 knots were used to get the best results with a suitable and smooth curve. In addition, the selection of knots is 0.4 and 7 because it can produce a good model. Thus, the value of R^2 in the cubic spline function for all regions ranges from 0.541 to 0.72. So, it can be interpreted that the model used is quite good and has the same performance in all regions, which is in line with the research of Ismail et al (2019) [21].

Analysis of time series data with autoregression is very important because it fulfills the assumption of random error, especially when adjusting linear trends with regression, and can show patterns of LST time series data by eliminating seasonal components [9]. This study uses AR (2), with the results of the coefficient values for AR (1) and (2) indicating stationary data because it is less than 1. Meanwhile, the results for the mean increase/decrease, which are negative, indicate that changes in LST from 2000 to 2019 experienced a decline.

Furthermore, a multivariate regression analysis was performed with time series data to show the trend of changes in LST over the 2000–2019 period using a Z-value and a 95% confidence interval (CI). Jaber and Abu-Allaban's study (2020) [22] used a linear regression test for day and night trend cycles and showed 95% CI results to see significant LST changes. In this study, it was found that negative Z-values in all regions meant that there was a decrease and the region was a cooler or colder area because research from Mavrakou et al (2018) [23] said that a negative and small Z-value means the region is cooler. For positive Z-values, cool or cold, and vice versa. The smallest and most negative Z-value is in region 3, while region 1 has the largest Z-value.

The average CI value is also negative, which means that changes in LST lead to a decrease. The upper-level CI value in regions 2 and 3 is negative, while in regions 1 and 4 it is still positive. Therefore, it can be interpreted that the decrease in LST is greater in regions 2 and 3.

LST is included in environmental data via satellite, which can affect human life [24]. LST can also be used to obtain geographic information on disease occurrence. So, the use of LST data can be associated with DHF [25]. Therefore, LST changes can affect the incidence of DHF. Based on the research results, LST in some sub-regions in all regions increased in 2003 and 2005. Then, for the incidence of DHF in 4 districts on Madura Island, there was an increase in the incidence rate around 2015–2016. Thus, it is found that the increase in LST and DHF occurred in the same year, that is 2015. In addition, LST in regions 1 and 4 experienced a slight decrease compared to regions 2 and 3 in the 2000–2019 period. In terms of the DHF incidence rate in 2010–2019 when compared to the national target, Bangkalan Regency was in the high category 4 times, while Sampang and Sumenep Regencies had 3 times, and Pamekasan Regency never had any.

A comparison of the analysis results on LST and DHF incidence rates shows that region 1 experienced a slight decrease in LST, with the highest Z-value associated with Bangkalan District, which has a higher DHF incidence rate in the tall category. Meanwhile, region 3 with the lowest Z value relates to Sumenep District, where the DHF incidence rate has never been in the high category. However, region 3 has the highest average LST temperature, which is < 33.51^{0}C. Therefore, the incidence of DHF in Pamekasan Regency has other factors that have more potential for DHF transmission.

The implication of this research is used as a warning for regions with the same pattern of LST and DHF incidence because it is a high possibility that one of the factors influencing the incidence of DHF in those areas is LST. This study has several limitations. Firstly, the area in the division of the four regions is different from the administrative area of the four districts on Madura Island, where one of region 3 is included in Pamekasan and Sumenep Regencies. Then, comparing the pattern of LST changes with the pattern of DHF events is only visual, where the DHF pattern is carried out using a descriptive method. In addition, this study did not carry out statistical tests related to the influence of LST on the incidence of DHF.

IV. CONCLUSION

This research aims to analyze the effect of LST on the incidence of DHF on Madura Island through a comparison of LST patterns on Madura Island during the period 2000–2019 with the pattern of DHF incidents in 2010–2019 on Madura Island. The results of a comparison of the Land Surface Temperature (LST) pattern with the incidence rate of Dengue Hemorrhagic Fever (DHF) on Madura Island show a similarity, namely an increase in the same year of 2015. In addition, regions with LST that experienced a slight decrease were districts with DHF, which is most often included in the high category as Bangkalan Regency. Therefore, the influence of LST on the incidence of DHF in Madura Island illustrates that Bangkalan and Sumenep Regencies have a more significant potential to experience DHF affected by LST changes compared to Sampang and Pamekasan Regencies. So, the local government needs to be aware of this because based on the 2030–2040 projection, there will be an increase in the highest average temperature on Madura Island. Efforts can be made to reduce population and change land use because these two factors trigger an increase in LST in Madura. For further research, it is necessary to carry out forecasting related to LST with DHF incidence, which is useful for program planning.

REFERENCES

[1] Australian Academy of Science, “The Science of Climate Change: Questions and Answers”, Canberra, 2015.
[2] L. V. Weatherdon *et al*., “Observed and Projected Impacts of Climate Change on Marine Fisheries, Aquaculture, Coastal Tourism, and Human Health: An Update”, *Frontiers in Marine Science*, vol. 3, no. 48, pp. 1–21, 2016, https://doi.org/10.3389/fmars.2016.00048.
[3] D. Jeevalakshmi, S. N. Reddy, and B. Manikiam, “Land Surface Temperature Retrieval From LANDSAT Data Using Emissivity Estimation”, *International Journal of Applied Engineering Research*, vol. 12, no. 20, pp. 9679–9687, 2017.
[4] Y. Z. Yang, W. H. Cai, and J. Yang, “Evaluation of MODIS Land Surface Temperature Data to Estimate Near-Surface Air Temperature in Northeast China”, *Remote Sensing*, vol. 9, no. 5, pp. 1–19, 2017, https://doi.org/10.3390/rs9050410.
[5] C. Kuenzer, S. Dech, and W. Wagner, “Remote Sensing Time Series Revealing Land Surface Dynamics: Status Quo and the Pathway Ahead. In: Remote Sensing Time Series: Revealing Land Surface Dynamics”, Switzerland: *Springer International Publishing*, pp. 1–24, 2015.
[6] N. Luintel *et al*., “Spatial and temporal variation of daytime and nighttime MODIS land surface temperature across Nepal”, *Atmospheric and Oceanic Science Letters*, vol. 12, no. 5, pp. 305–312, 2019, https://doi.org/10.1080/16742834.
[7] A. Pal, P. Prakash, “Practical Time Series Analysis”, Birmingham: *Packt Publishing Ltd*, 2017.
[8] C. Me-Ead, R. McNeil, “Pattern and Trend of Night Land Surface Temperature in Africa”, *Scientific reports*, vol. 9, no. 1, pp. 18302, 2019, http://dx.doi.org/10.1038/s41598-019-54703-z
[9] N. Wongsai, S. Wongsai, and A. R. Huete, “Annual Seasonality Extraction Using the Cubic Spline Function and Decadal Trend in Temporal Daytime MODIS LST Data”, *Remote Sensing*, vol. 9, no. 12, pp. 1–17, 2017.
[10] A. Anyamba, *et.al*., “Global Disease Outbreaks Associated with the 2015–2016 El Niño Event”, *Scientific Reports*, vol. 9, no. 1, 2019.
[11] B. Acharya, C. Cao, and L. Khanal, “Temporal Variations and Associated Remotely Sensed Environmental Variables of Dengue Fever in Chitwan District, Nepal”, *ISPRS International Journal of Geo-Information*, vol. 7, no. 275, pp. 1–14, 2018, https://doi.org/10.3390/ijgi7070275.
[12] A. Woodward, A. Macmillan, “The Environment and Climate Change. In: Oxford Textbook of Global Public Health”, 6th ed. New York : Oxford University Press, Inc, pp. 201–217, 2015.
[13] U. S. Ainnurriza, A. Sudaryanto, “Monitoring of Dengue Hemorrhagic Fever with a Geographic Information System in Sragen Regency”, In: Prosiding Muhammadiyah University Surakarta Nursing National Seminar, Surakarta : Muhammadiyah University Surakarta, pp. 80–85, 2020.

[14] DAI, "Report on Vulnerability and Climate Risk Study of East Java Province", Surabaya, 2018.
[15] I. Sharma, P. Tongkumchum, and A. Ueranantasun, "Modeling of Land Surface Temperature to Determine Temperature Patterns and Detect their Association with Altitude in the Kathmandu Valley of Nepal", *Chiang Mai University Journal of Natural Sciences*, vol. 17, no. 4, pp. 275-288, 2018.
[16] M. S. Paolella, "Linear Models and Time-Series Analysis: Regression, ANOVA, ARMA, and GARCH", 1st ed. Hoboken, NJ: John Wiley & Sons, Inc, 2019
[17] J. C. Fyfe, N. P. Gillett, and D. W. J. Thompson, "Comparing Variability and Trends in Observed and Modelled Global-Mean Surface Temperature", *Geophysical Research Letters*, vol. 37, no. 16, pp. 2–5, 2010, https://doi.org/10.1029/2010GL044255.
[18] X. Zhang *et al*., "Multivariate Regression with Gross Errors on Manifold-valued Data", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 41, no. 2, pp. 444–458, 2017, https://doi.org/10.1109/TPAMI.2017.2776260
[19] F. H. Putra, R. Kurniawan, "Clustering Dengue Hemorrhagic Fever Endemic Disaster Areas in East Java by Fuzzy Geographically Weighted Clustering – Particle Swarm Optimization", *Journal of Statistical Applications and Statistical Computing*, vol. 7, no. 2, pp. 27–38, 2015.
[20] W. Hu, W. Zhou, H. He, "The Effect of Land-Use Intensity on Surface Temperature in the Dongting Lake Area, China". Advances in Meteorology, pp. 1–11, 2015.
[21] N. A. Ismail, W. Z. W. Zin, W. Ibrahim, and L. C. Yeun, "Eight-Day Daytime Land Surface Temperature Pattern over Peninsular Malaysia", *International Journal of Recent Technology and Engineering*, vol. 8, no. 4, pp. 11949–11955, 2019.
[22] S. M. Jaber, M. M. Abu-Allaban, "MODIS-Based Land Surface Temperature for Climate Variability and Change Research: The Tale of a Typical Semi-Arid to Arid Environment", *European Journal of Remote Sensing*, vol. 53, no. 1, pp. 81-90, 2020.
[23] T. Mavrakou, A. Polydoros, C. Cartalis, and M. Santamouris, "Recognition of Thermal Hot and Cold Spots in Urban Areas in Support of Mitigation Plans to Counteract Overheating: Application for Athens", *Climate*, vol. 6, no. 16, pp. 1–12, 2018.
[24] A. Hamza, A.M. Gumi, A.A. Aliero, A.I. Umar, Y. Sarkingobir, and U. Tambari. "Potential of Neem Leaves on Preservation of Selected Elemental Compositions in Two Tomato Cultivars from Sokoto, Nigeria". Journal of Bioresources and Environmental Sciences, vol. 2 no.1, pp. 15-20, 2023. doi:10.14710/jbes.2022.17343.
[25] R. M. Gleiser, "Geoprocessing and Expected Distribution of Diseases (Including Deforestation, Global Warming, and Other Changes)", In: Arthropod-Borne Diseases, Switzerland: *Springer International Publishing*, pp. 577–604, 2017.
[26] R. M. Devi, T. A. E. Prasetya, and D. Indriani, "Spatial and Temporal Analysis of Land Surface", *International Journal of Remote Sensing and Earth Sciences*, vol. 17, no. 1, pp. 45–56, 2020.
[27] V. P. Tresamol, M. A. Antony, K. V. Mini, and J. Siju, "Seroprevalence of Leptospirosis among Cattle in and Around Thrissur District, Kerala", *International Journal of Livestock Research*, vol. 7, no. 3, pp. 45-48, 2017, https://doi.org/10.5455/ijlr.20170124044946.