Pertanika J. Sci. & Technol. 32 (6): 2723 - 2735 (2024)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Variation and Forecasting of Land Surface Temperature in Malaysia

Munawar Munawar[1]*, Rhysa McNeil[2,3], Rohana Jani[4], Edwar M Nur[5] and Don McNeil[2]

[1]*Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Aceh 23111, Indonesia*
[2]*Faculty of Science and Technology, Prince of Songkla University, Pattani Campus, Pattani, 94000, Thailand*
[3]*Centre of Excellence in Mathematics, Commission on Higher Education (CHE), Ministry of Education, Ratchathewi, 10400 Bangkok, Thailand*
[4]*Department of Decision Science, Faculty of Business and Economics, Universiti Malaya, 50603 UM, Kuala Lumpur, Malaysia*
[5]*Faculty of Economics, Universitas Abulyatama, Aceh Besar 23372, Aceh, Indonesia*

ABSTRACT

Long-term variations in temperature and weather patterns provide evidence that the planet is experiencing global warming. The detrimental consequences of global warming on the ecosystem have affected people, plants, and animals. The rising Land Surface Temperature (LST) in a region has become a crucial indicator for determining specific climate change policies. Malaysia is divided into Peninsular Malaysia and Sabah Sarawak, located on Borneo Island, comprising four super-regions and 36 sub-regions. The distance between sub-regions, measured in latitudes and longitudes, is 150 pixels (equivalent to 95 kilometres), covering the entire country. This study uses data from NASA's Terra satellites' Moderate Resolution Imaging Spectroradiometers (MODIS) covering 2000–2022. Eight, four, and three knots were deployed on the cubic spline equation to analyse cyclical data, variation, and the LST forecast from 2022 to 2030. The global mean rise in LST variation per decade is 0.445°C, with a significance level of 5%, from a confidence interval of [0.377, 0.507]°C. The average predicted fluctuation in LST indicates a significant rise of 0.383°C per decade. Malaysia has not shown a significant decrease in LST acceleration at the 0.05 significance level, and a *p*-value of 0.06 suggests that LST variation is still increasing. Compared to the Sabah Sarawak group, which experiences LST deceleration, most Peninsular Malaysia group experiences LST acceleration.

Keywords: Cubic spline, forecasting, LST increase, Malaysia, NASA MODIS

ARTICLE INFO

Article history:
Received: 24 December 2023
Accepted: 10 June 2024
Published: 25 October 2024

DOI: https://doi.org/10.47836/pjst.32.6.16

E-mail addresses:
munawar@usk.ac.id (Munawar Munawar)
rhysa.m@psu.ac.th (Rhysa McNeil)
Rohanaj@um.edu.my (Rohana Jani)
edwar_ekm@abulyatama.ac.id (Edwar M Nur)
don.mcneil@mq.edu.au (Don McNeil)
* Corresponding author

ISSN: 0128-7680
e-ISSN: 2231-8526

INTRODUCTION

The world is undergoing climate change due to human activities, including industrial operations that utilise gas, coal, and oil for transportation and other purposes. It is evidenced by long-term temperature and weather patterns shifts, impacting the greenhouse effect by trapping solar heat and increasing temperature and precipitation variability (Mikhaylov et al., 2020). The mean global surface temperature rose by 0.3 to 0.6°C during the 20th century; this increase is unlikely to have occurred naturally (Bruce et al., 1996; Metz et al., 2001). People, plants, and animals have all been impacted by the negative environmental effects of global warming (Mall et al., 2021). The rate of economic growth worldwide may be affected by climate change, and certain species may become more susceptible to extinction.

These events will have quite different relative effects in the developed and developing worlds. Climate events serve as the foundation for strategic decisions made by government agencies regarding regional and national economies (Chinowsky et al., 2011; Tol, 2018). In poor nations, agriculture is the industry most recognised to be negatively impacted economically by climate change due to its size and sensitivity (Mendelsohn, 2009). A region's increasing Land Surface Temperature (LST) becomes a significant signal for choosing particular climate change policies as a climate science variable (Fox et al., 2019).

Malaysia is one of the Southeast Asian nations dealing with LST problems because of its expansionist aspirations. Malaysia's average LST increased between 1990 and 2015, ranging from 25.39°C to 32.74°C, as a result of deforestation's impact on LST (Himayah et al., 2019; Jaafar et al., 2020). Malaysia's LST is assumed to have increased variation between 2000–2022, which aligns with the acceleration of LST and LST forecasting from 2023–2030. The Malaysian peninsula and the island of Borneo together comprise the country of Malaysia, which is part of Southeast Asia (SEA). Like other Southeast Asian nations, Malaysia's economy primarily depends on agriculture, fisheries, and industry. According to Murad et al. (2010), the rate of agricultural extension and the climate change score do not exhibit a positive correlation. Malaysia's temperature may impact neighbouring South China Sea nations, including Indonesia, the Philippines, Singapore, and Thailand.

This study used NASA MODIS Web data from 2000 to 2022, along with Eight, four, and three knots deployed on the cubic spline equation, respectively, to analyse the cyclical pattern, variation, and forecast of LST from 2022 to 2030. Unlike previous studies from Munawar et al. (2022, 2023), they examined the cyclical pattern and variance of LST on the main island using the cubic spline function with eight and seven knots. After eliminating the annual seasonality and deploying the cubic spline equation, any long-term trends in LST are identified by analysing the residual data. The LST variation depends on the annual season in an area; a typical tropical area only has two main seasons: dry and wet. The dry season will increase the LST and vice versa. Mapping the LST condition in a region requires not only LST fluctuation but also LST acceleration and forecasting.

MATERIALS AND METHODS

Study Area

Malaysia is situated between L 5.5, 20.5N Latitudes and 97.5, 105.5 Longitudes, as shown in Figure 1. The Malaysian peninsula shares boundaries with Singapore to the south, Thailand to the north, and Sumatra Island in Indonesia to the west. East Malaysia is a country on the island of Borneo. The South China Sea borders it to the north, the Philippines to the west, and Indonesia to the east.

Figure 1 depicts all the super-regions and sub-regions of Malaysia. In Peninsular Malaysia, super-regions A and B represent the west and central-west super-regions, respectively (AB group). Super-region C denotes the central-east super-region, and D represents the east super-region on Sabah Sarawak of Borneo Island (CD group). This results in four super-regions and 36 sub-regions that encompass the entire island.

Sub-regions were created with centres placed at latitudes and longitudes 150 pixels apart, equivalent to 95 kilometres. The 36 sub-regions systematically resulted from the 150-pixel distance between sub-regions from northern Malaysia to eastern Malaysia, covering the whole country. 150-pixel distance minimises the spatial correlation between sub-regions, and the distance results in the representative data rather than using the bigger pixel. Subsequently, super-regions A and B were combined into the Peninsular Malaysia (AB group), and super-regions C and D were grouped into the Sabah Sarawak (CD group).

Data

This investigation utilised the online NASA MODIS Terra Satellite database, which provides LST data during daytime and nighttime, covering the entire globe. The information includes mean temperatures recorded every eight days for an area of 0.859 km², assuming

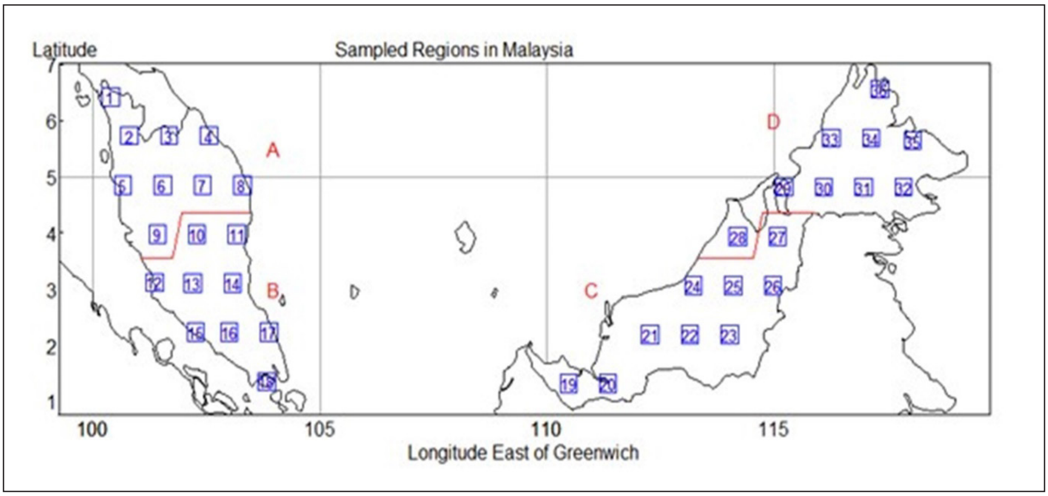

Figure 1. Malaysia area of study

clear skies (Phan et al., 2018; ORNL DAAC, 2018; Wan, 2008). A sinusoidal computation was carried out using tiles with dimensions of 10 × 10 latitude degrees divided into 1,200 × 1,200 pixels each to ensure uniformity across all pixels in the dataset. The downloaded LST data was processed at the island's sub-regional centre to minimise data loss, and any missing values were excluded from the analysis. If the sky was not clear, the satellite could not provide LST data for the target sub-region pixel; thus, such pixels were considered missing values. Natural disasters that could lead to unforeseen changes in data behaviour were not accounted for. All outliers were retained in the dataset to preserve the integrity of the LST data. Before analysis, temperature data originally stored in Kelvin were converted to Celsius.

Methods

The standard cubic spline and linear model was employed and was defined as Equation 1 (Alberg et al., 1967):

$$y = a + bx + \sum_{k=1}^{p-3} c_k S_k(x) \qquad [1]$$

where a, b, c_1, c_2, ..., c_{p-3} are the constants for the linear function. A cubic spline is a segmented cubic function used to interpolate data points while ensuring smooth transitions between these points. The cubic spline model can also manage the seasonal pattern from time series data.

The cubic spline model can be expanded as in Equation 2 (Wongsai et al., 2017):

$$S_k(x) = (x - x_k)_+^3 - \frac{(x_p - x_k)(x_{p-1} - x_k)}{d_3 d_2}(x - x_{p-2})_+^3 + \frac{(x_p - x_k)(x_{p-2} - x_k)}{d_1 d_2}(x - x_{p-1})_+^3 - \frac{(x_{p-2} - x_k)(x_{p-1} - x_k)}{d_3 d_1}(x - x_p)_+^3 \qquad [2]$$

Three limits' circumstances apply for $d_1 = x_p - x_{p-1}$, $d_2 = x_{p-1} - x_{p-2}$ with $x_+ = max(x,0)$, and also $d_3 = x_p - x_{p-2}$.

The seasonally modified LST model was fitted with a second-order AR(2) model. The model's basis is as stated in Equation 3 (Venables & Ripley, 2002):

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

It is necessary to approximate the unknown parameters α_1 and α_2, and the random error with zero average and defined variance is represented by ε_t, where t = 1, ..., 365 days. At t-1, Y_{at-1} is the time of LST, and at t time, Y_{at} is the time of LST that has been seasonally corrected. R was used for all analyses and visual displays (Team, 2018).

RESULTS AND DISCUSSION

Figure 2 manifests the seasonal trend of LST, which corresponds to super-region A from Peninsular Malaysia (AB group) in Malaysia. Similar graphs were used to investigate the seasonal tendencies of the other super-regions.

The average temperature for each of the 22 years corresponds to the same day, as indicated by Figure 2, displaying 46 stacks of data (966 points if none are missing). Solid red curves and blue crosses depict the eight knots fitted natural spline functions. Eight knots were distributed, four at the beginning and four at the end of the year, to anticipate the increase of LST at the start and the decrease of LST at the end of the year. With one summer peak in March and a low LST seasonal pattern in October, the super-region A curves show a modest seasonal trend. The first day (in January) of the year, during the wet cycle, had the lowest LST between 2000 and 2022, and the ninth month (day 267) had the greatest LST. The extreme area sub-region 4 has the highest average day LST, measuring in at 31.176°C.

The cyclically adjusted time series in Figure 3 were analysed for the Malaysian super-region A from the Peninsular Malaysia (AB group). The cyclical trends of the other super-regions were examined, and a figure related to this one was deployed.

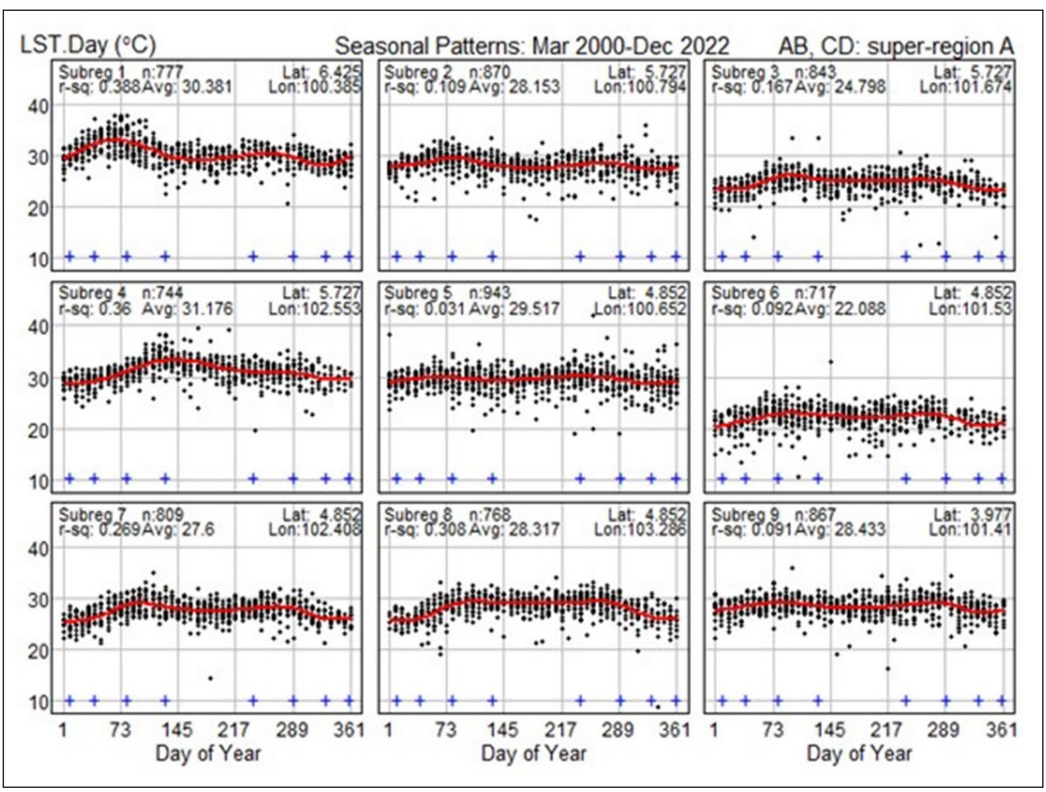

Figure 2. Super-region A LST seasonal pattern

The mean-corrected data was subtracted from the fitted seasonal trends to acquire the seasonally modified temperatures in Figure 3's panels. The daily LST time series were independent, as indicated by the moderately high estimated coefficients of the AR(1) first-order auto-regressive model. The second-order auto-regressive model, stationary at AR(2), had a lower coefficient than AR(1).

The left panels of Figure 3 use black curves to show the LST development over 22 years in all sub-regions, whereas the right panels use dotted lines with different scales. The linear models or zero knots with two parameters have *p*-values that indicate most sub-regions showed a statistically significant rise in LST, except sub-region 4.

The cubic spline's four knots, which correspond to sub-regions 7, 8, and 9, have *p*-values for each knot that indicates statistical significance for the LST rising acceleration. The three knots of the cubic spline revealed sub-regions 1, 2, 4, 5, 7, 8, and 9, and the *p*-values for these three knots show that sub-regions had statistically significant LST forecasting. In the right panel of Figure 3, the fitted cubic splines with four knots for 2000–2022. The tropical area's four knots are sufficient to forecast the variation of LST because the tropical area has two seasons: dry and wet. The knots were distributed two at the beginning and two at the end of the period 2000–2022; with four knots, the model became a polynomial model with three orders.

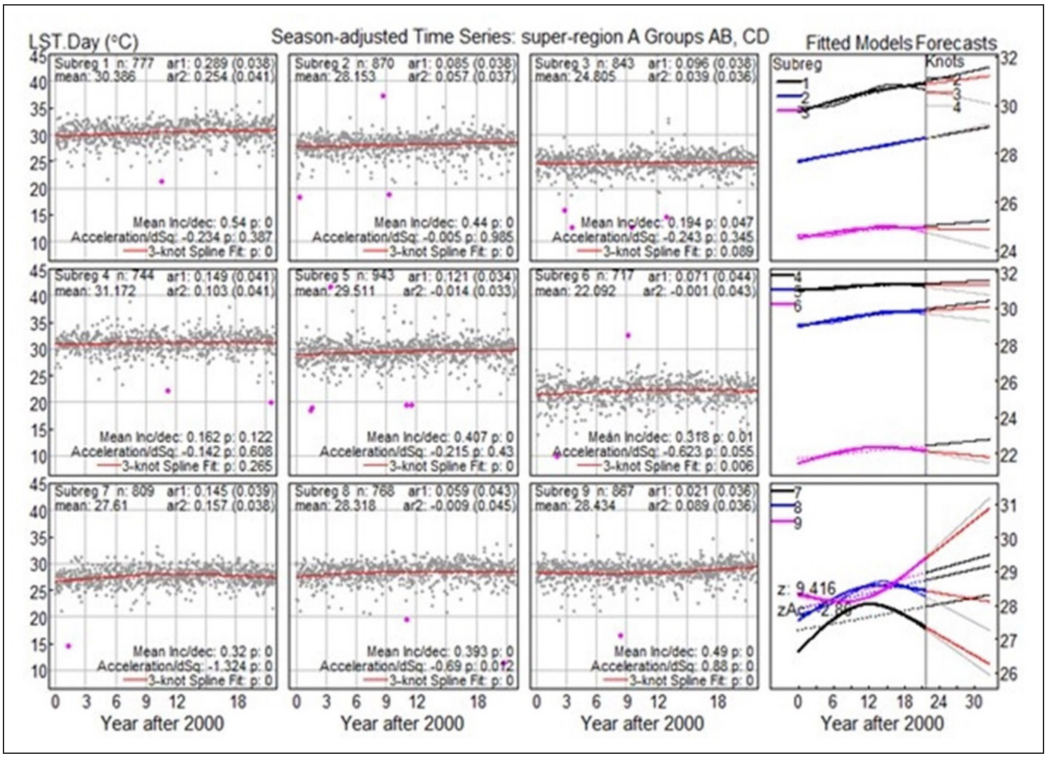

Figure 3. Super-region A seasonal adjusted and forecasting of LST

Three knots for the years 2023–2030 are displayed as solid curves for every sub-region with significant *p*-values. The model becomes a quadratic model to examine the acceleration of LST variation for the 2023–2030 period. The knots are placed at the period's beginning, middle, and end. Figure 3 in the bottom-right panel displays statistically significant *z*-values of 9.416 for the average daily LST rise and 2.860 for the acceleration. A z-value is considered statistically significant if it is an absolute value of 1.96 or above at a 95% confidence level.

Based on sub-region latitude, Figure 4 depicts the expected variations in LST for all sub-regions in Malaysia. There are only two sub-regions where LST declines occur; LST rises differ per sub-region. The red line represents the overall average increase in LST predicted for the next ten years, expected to be 0.381°C for the Peninsular Malaysia (AB group) and 0.387°C for the Sabah Sarawak (CD group). The blue line shows the average annual rise in LST for both the AB and CD groups, which is 0.464°C and 0.285°C, respectively, over ten years.

The LST change at a 5% confidence level and the LST change forecasts for the Peninsular Malaysia (AB) and Sabah Sarawak (CD) groups are shown in Figure 5. The overall mean of the LST predicted change rise is 0.383°C every ten years, with a 95% confidence interval of [0.377, 0.507]°C and a *z*-value of 15.278. However, the overall mean of the LST difference increase is 0.445°C every ten years. These values are accurate, with an LST prediction variance increase of 0.480°C per decade for the AB group, an LST variation increase of 0.302°C, a *z*-value of 14.262, a 95% confidence interval of [0.222, 0.381]°C. With a *z*-value of 8.555 and a 95% confidence interval of [0.180, 0.328]°C, the LST variance increase for the CD group is 0.254°C when compared to the AB group with an increase of LST.

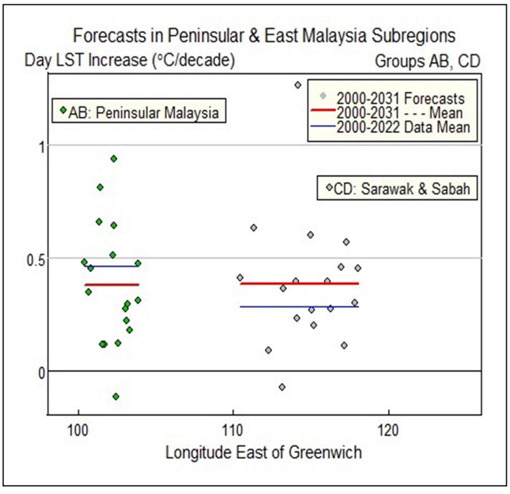

Figure 4. LST forecast increase (°C/decade) and location

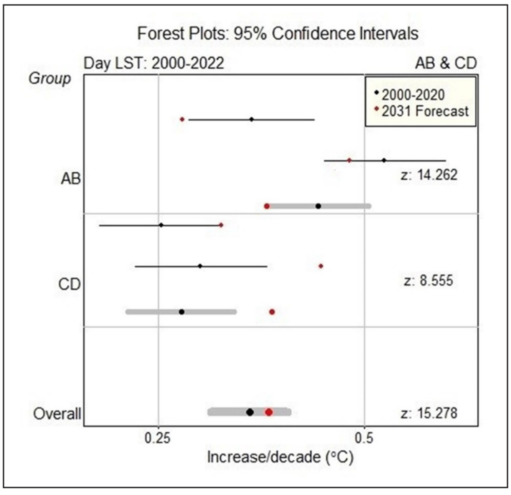

Figure 5. 95% confidence interval of LST variation

Figure 6 presents a 95% confidence interval LST acceleration/decade^2(^{o}C). The overall average acceleration of LST is 0.027^{o}C per decade, and the 95% confidence interval is [-0.193,0.199] with a z-value of 0.429. The Peninsular Malaysia (AB) group has a deceleration of LST -0.238^{o}C per decade, and the 95% confidence interval is [-0.336, -0.108] with a z-value -2.931. The Sabah Sarawak (CD) group has a z-value of 3.440 and an acceleration of LST 0.291^{o}C per ten years with a 95% confidence interval of [0.125, 0.458].

Figure 7 shows the acceleration of Malaysia's LST from 2000 to 2022 in the Peninsular Malaysia (AB) and Sabah Sarawak (CD) groups. Malaysia experiences no significant decrease in the acceleration of LST at a 0.05 significance level, with a p-value of 0.06. In contrast, the CD group exhibits LST deceleration, whereas most AB groups demonstrate LST acceleration.

Super-region A's seasonal pattern of LST data shows a modest seasonal pattern with low LST values all year round and a single summer peak in March. Seasonal trends and changes in LST for the Peninsular Malaysia (AB) and Sabah Sarawak (CD) super-regions were investigated using a cubic spline approach. The results of the investigation showed that daily LST increased significantly in both super-regions, AB and CD. Furthermore, the estimate shows that LST will increase dramatically between 2021 and 2031. Several investigations conducted in Malaysia have documented an increase in temperature in December (Ismail et al., 2019). A comparable study of regions with four distinct seasons indicates that summertime LST peaks from June to September in a year, as reported by Khorchani et al. (2018) and Singh et al. (2014).

Our findings presented that Malaysia's mean LST increased by 0.445°C every decade, equivalent to 4°C over ten years. Tangang et al. (2012) estimated an increase of 3-5°C per century, which is higher than this trend. The average annual rise in LST variation is

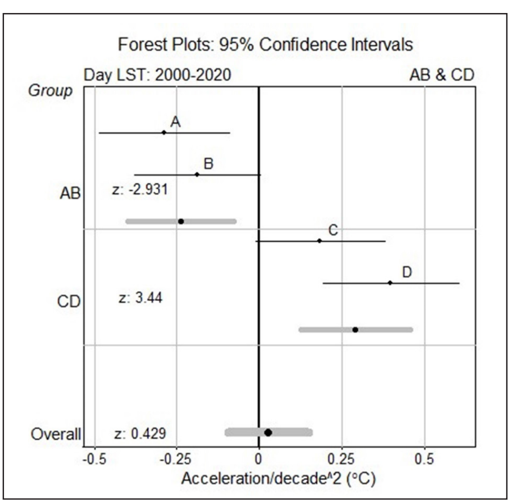

Figure 6. 95% confidence interval LST acceleration/decade^2(^{o}C)

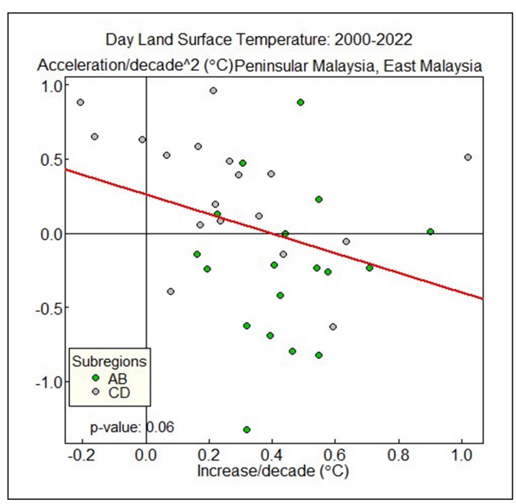

Figure 7. LST acceleration 2000–2022

0.383°C. We discovered that Malaysia exhibits a sizable variation in LST. Wolff et al. (2018) suggest that the increase in LST variance could be attributed to land use changes and deforestation. Eight knots for the cubic spline can model the seasonal pattern, and four can forecast the LST variation over a decade. Although the overall average acceleration of LST is 0.027°C per decade with no significant LST acceleration, the LST variation in Malaysia continues to increase in the next decade.

Variations in land surface temperatures can be determined by the type of land cover, especially vegetation (Buyadi et al., 2014). Dense vegetation in an area can act as a filter or absorbent material to prevent the surface temperature from rising. According to Babalola and Akinsanola (2016), green vegetation has the capacity to absorb solar radiation and use it for photosynthesis. Research has found that changes in the island's vegetation were a reliable predictor of temperature increases in Malaysia (Evans, 2018). Deforestation in the area was considered the cause of the rising temperatures. Additional research (Ferreira & Duarte, 2019) has demonstrated a significant inverse relationship between the Normalised Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). Malaysia's vegetation index shows that LST temperatures have risen (Suherman et al., 2014).

According to Prevedello et al. (2019), differences in land cover—such as those conducted by reforestation or deforestation—ultimately influence the temperature in each place. Previous studies have connected land cover change and land use to LST (Majumder et al., 2020; Odindi et al., 2015; Rasul et al., 2017). According to Parmesan and Hanley (2015), the temperature will rise if a region's land cover decreases. A study carried out in Malaysia found a correlation between rising temperatures and a notable decline in freshwater fish species and functional richness (Wilkinson et al., 2018). A study from Malaysia also demonstrates that built-up regions have the warmest climates, while locations with the coldest climates are those near forests and mangroves (Sheikhi & Kanniah, 2018).

CONCLUSION

The LST in Malaysia exhibited variation and was predicted between 2023 and 2030 using the cubic spline model. The proper quantity and arrangement of knots were established to provide a smoother equation. The cyclical pattern in the cubic spline equation was demonstrated to be adequately captured by eight knots; four knots were utilised to evaluate the variation acceleration in LST (2020–2022), and three knots were employed to predict the variation in LST over a 2023–2030 period. The study discovered that the mean daily LST had increased statistically significantly in Malaysia's Peninsular (AB) and Sabah Sarawak (CD) super-regions. It is anticipated that between 2023 and 2030, the LST variation in these areas will rise, with no discernible slowdown in its acceleration.

While forests persist on the Malaysian peninsula, the rise in LST is predominantly driven by urban expansion spurred by development. According to Kamal et al. (2019), the increase in LST across Peninsular Malaysia is primarily influenced by the heat exposure index, particularly evident in northern and urban locales. In contrast, the Sabah Sarawak region, boasting extensive tropical areas and the elevated Kinabalu Mountain, experiences a surge in LST attributed to El Niño Southern Oscillations, as discovered in Kuching Sarawak by Anak (2022).

One evidence of regional warming has occurred in Malaysia, which is characterised by increased LST. However, additional research is needed to more comprehensively validate the conclusions of this study. Other strategies, such as including larger islands farther from the equator, like China and America, are required to enhance estimation accuracy. Most large islands have mountains (LE), NDVI, a variety of land use/land cover, economic development/urbanisation, industrial activities, natural disasters and climate changes/meteorological factors (e.g., air temperature) as additional factors that could be considered in future LST research. In addition to the variables influencing LST, it is crucial in future research to compare the variation in LST data obtained from MODIS Terra and Aqua satellites.

The constraints inherent in projecting future LST trends must be considered, considering the implications of hindcast results from LST data spanning 2000 to 2022 for forthcoming research. Enhancing hindcast simulations entails fulfilling various prerequisites, including ample data availability, rigorous process refinement, and precise depiction of key climate change indicators, as de Hauteclocque et al. (2023) emphasised.

ACKNOWLEDGEMENTS

The authors express their highest appreciation to the following: Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Aceh, Indonesia; Department of Mathematics and Computer Science, Faculty of Science and Technology, Prince of Songkla University, Pattani, Thailand; Department of Decision Science, Faculty of Business and Economics, Universiti Malaya, Kuala Lumpur, Malaysia; and Faculty of Economics,Universitas Abulyatama, Aceh Besar, Aceh, Indonesia, for all the invaluable assistance received by the authors so far.

REFERENCES

Alberg, J. H., Nilson, E. N., & Walsh, J. L. (1967). *The theory of splines and their applications*. Academic.

Anak, R. (2022). Statistical modeling of impacts El Niño Southern Oscillations (ENSO) on land surface temperature in small medium size city: Case study Kuching Sarawak. *Journal of Sustainable Natural Resources, 3*(1), 14-22.

Babalola, O. S., & Akinsanola, A. A. (2016). Change detection in land surface temperature and land use land cover over Lagos Metropolis, Nigeria. *Journal of Remote Sensing & GIS*, *5*(3), 1-7.

Bruce, J. P., Lee, H., & Haites, E. F. (1996). *Climate change 1995*. Contribution of Working Group III to the Second Assessment Report of the Intergovernmental Panel on Climate Change (No. 574.5222 C639co 1995). Cambridge University Press.

Buyadi, S. N. A., Mohd, W. M. N. W., & Misni, A. (2014). Impact of vegetation growth on urban surface temperature distribution. In *IOP Conference Series: Earth and Environmental Science* (Vol. 18, No. 1, p. 012104). IOP Publishing. https://doi.org/10.1088/1755-1315/18/1/012104

Chinowsky, P., Hayles, C., Schweikert, A., Strzepek, N., Strzepek, K., & Schlosser, C. A. (2011). Climate change: comparative impact on developing and developed countries. *The Engineering Project Organization Journal*, 1(1), 67-80. https://doi.org/10.1080/21573727.2010.549608

de Hauteclocque, G., Maretic, N. V., & Derbanne, Q. (2023). Hindcast based global wave statistics. *Applied Ocean Research, 130*, Article 103438.

Evans, M. (2018, April 25). Forest loss leads to local climate change effect in Borneo. *ThinkLandscape.* https://thinklandscape.globallandscapesforum.org/27161/forest-loss-leads-to-local-climate-change-effect-in-borneo/

Ferreira, L. S., & Duarte, D. H. S. (2019). Exploring the relationship between urban form, land surface temperature and vegetation indices in a subtropical megacity. *Urban Climate, 27*, 105-123. https://doi.org/10.1016/j.uclim.2018.11.002

Fox, M., Zuidema, C., Bauman, B., Burke, T., & Sheehan, M. (2019). Integrating public health into climate change policy and planning: state of practice update. *International journal of environmental research and public health, 16*(18), Article 3232. https://doi.org/10.3390/ijerph16183232

Himayah, S., Ismail, A., Ridwana, R., Arrasyid, R., Affriani, A. R., & Ihsan, M. (2019). Correlation between land surface temperature and vegetation greenness using multi-temporal images. In *IOP Conference Series: Earth and Environmental Science* (Vol. 286, No. 1, p. 012043). IOP Publishing. https://doi.org/10.1088/1755-1315/286/1/012043

Ismail, N. A., Zin, W. Z. W., Ibrahim, W., & Yeun, L. C. (2019). Eight-day daytime land surface temperature pattern over Peninsular Malaysia. *International Journal of Recent Technology and Engineering, 8*(4), 11949-11955. https://doi.org/10.35940/ijrte.D9911.118419

Jaafar, W. S. W. M., Maulud, K. N. A., Kamarulzaman, A. M. M., Raihan, A., Sah, S. M., Ahmad, A., Saad, S. N. M., Azmi, A. T. M., Syukri, N. K. A. J., & Khan, W. R. (2020). The influence of deforestation on land surface temperature - A case study of Perak and Kedah, Malaysia. *Forests, 11*(6), Article 670. https://doi.org/10.3390/f11060670

Kamal, N. I. A., Ash'aari, Z. H., & Abdullah, A. M. (2019). Spatio-temporal variability of heat exposure in Peninsular Malaysia using land surface temperature. *Disaster Advances, 12*(12), 1-9.

Khorchani, M., Martin-Hernandez, N., Vicente-Serrano, S. M., Azorin-Molina, C., Garcia, M., Domínguez-Duran, M. A., Reig, F., Peña-Gallardo, M., & Domínguez-Castro, F. (2018). Average annual and seasonal land surface temperature, Spanish Peninsular. *Journal of Maps, 14*(2), 465-475. https://doi.org/10.1080/17445647.2018.1500316

Majumder, A., Kingra, P. K., Setia, R., Singh, S. P., & Pateriya, B. (2020). Influence of land use/land cover changes on surface temperature and its effect on crop yield in different agro-climatic regions of Indian Punjab. *Geocarto International, 35*(6), 663-686. https://doi.org/10.1080/10106049.2018.1520927

Mall, R. K., Chaturvedi, M., Singh, N., Bhatla, R., Singh, R. S., Gupta, A., & Niyogi, D. (2021). Evidence of asymmetric change in diurnal temperature range in recent decades over different agro-climatic zones of India. *International Journal of Climatology, 41*(4), 2597-2610. https://doi.org/10.1002/joc.6978

Mendelsohn, R. (2009). The impact of climate change on agriculture in developing countries. *Journal of Natural Resources Policy Research, 1*(1), 5-19. https://doi.org/10.1080/19390450802495882

Metz, B., Davidson, O., Swart, R., & Pan, J. (Eds.). (2001). *Climate change 2001: Mitigation: Contribution of Working Group III to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Mikhaylov, A., Moiseev, N., Aleshin, K., & Burkhardt, T. (2020). Global climate change and greenhouse effect. *Entrepreneurship and Sustainability Issues, 7*(4), Article 2897. http://doi.org/10.9770/jesi.2020.7.4(21)

Munawar, M., Prasetya, T. A. E., McNeil, R., & Jani, R. (2022). Statistical modeling for land surface temperature in Borneo island from 2000 to 2019. *Theoretical and Applied Climatology*,*147*, 1627–1634. https://doi.org/10.1007/s00704-021-03891-8

Munawar, M., Prasetya, T. A. E., McNeil, R., Jani, R., & Buya, S. (2023). Spatio and temporal analysis of indonesia land surface temperature variation during 2001–2020. *Journal of the Indian Society of Remote Sensing, 51*, 1393–1407. https://doi.org/10.1007/s12524-023-01713-0

Murad, W., Molla, R. I., Mokhtar, M., & Raquib, A. (2010). Climate change and agricultural growth: an examination of the link in Malaysia. *International Journal of Climate Change Strategies and Management, 2*(4), 403-417. https://doi.org/10.1108/17568691011089927

Odindi, J. O., Bangamwabo, V., & Mutanga, O. (2015). Assessing the value of urban green spaces in mitigating multi-seasonal urban heat using MODIS land surface temperature (LST) and landsat 8 data. *International Journal of Environmental Research, 9*(1), 9-18. https://doi.org/10.22059/ijer.2015.868

ORNL DAAC. (2018). *MODIS and VIIRS Land Products Global Subsetting and Visualization Tool*. Oak Ridge National Laboratory Distributed Active Archive Center. https://doi.org/10.3334/ornldaac/1379

Parmesan, C., & Hanley, M. E. (2015). Plants and climate change: Complexities and surprises. *Annals of Botany, 116*(6), 849-864. https://doi.org/10.1093/aob/mcv169

Phan, T. N., Kappas, M., & Tran, T. P. (2018). Land surface temperature variation due to changes in elevation in northwest Vietnam. *Climate, 6*(2), Article 28. https://doi.org/10.3390/cli6020028

Prevedello, J. A., Winck, G. R., Weber, M. M., Nichols, E., & Sinervo, B. (2019). Impacts of forestation and deforestation on local temperature across the globe. *PloS one, 14*(3), Article e0213368. https://doi.org/10.1371/journal.pone.0213368

Rasul, A., Balzter, H., Smith, C., Remedios, J., Adamu, B., Sobrino, J. A., Srivanit, M., & Weng, Q. (2017). A review on remote sensing of urban heat and cool islands. *Land, 6*(2), Article 38. https://doi.org/10.3390/land6020038

Sheikhi, A., & Kanniah, K. D. (2018). Impact of land cover change on urban surface temperature in Iskandar Malaysia. *Chemical Engineering Transactions, 63*, 25-30. https://doi.org/10.3303/CET1863005

Singh, R. B., Grover, A., & Zhan, J. (2014). Inter-seasonal variations of surface temperature in the urbanized environment of Delhi using landsat thermal data. *Energies, 7*(3), 1811–1828. https://doi.org/10.3390/en7031811

Suherman, A., Rahman, M. Z. A., & Busu, I. (2014). Albedo and land surface temperature shift in hydrocarbon seepage potential area, case study in Miri Sarawak Malaysia. In *IOP Conference Series: Earth and Environmental Science* (Vol. 18, No. 1, p. 012148). IOP Publishing. https://doi.org/10.1088/1755-1315/18/1/012148

Tangang, F. T., Juneng, L., Salimun, E., Sei, K. M., Le, L. J., & Muhamad, H. (2012). Climate change and variability over Malaysia: Gaps in science and research information. *Sains Malaysiana, 41*(11), 1355–1366.

Team, R. C. (2018). *A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.r-project.org/

Tol, R. S. (2018). The economic impacts of climate change. *Review of Environmental Economics and Policy, 2*(1), 4-25.

Venables, W. N., & Ripley, B. D. (2002). *Modern applied statistics with S*. Springer.

Wan, Z. (2008). New refinements and validation of the MODIS land-surface temperature/emissivity products. *Remote sensing of Environment, 112*(1), 59-74. https://doi.org/10.1016/j.rse.2006.06.026

Wilkinson, C. L., Yeo, D. C., Tan, H. H., Fikri, A. H., & Ewers, R. M. (2018). Land-use change is associated with a significant loss of freshwater fish species and functional richness in Sabah, Malaysia. *Biological Conservation, 222*, 164-171. https://doi.org/10.1016/j.biocon.2018.04.004

Wolff, N. H., Masuda, Y. J., Meijaard, E., Wells, J. A., & Game, E. T. (2018). Impacts of tropical deforestation on local temperature and human well-being perceptions. *Global Environmental Change, 52*, 181–189. https://doi.org/10.1016/j.gloenvcha.2018.07.004

Wongsai, N., Wongsai, S., & Huete, A. R. (2017). Annual seasonality extraction using the cubic spline function and decadal trend in temporal daytime MODIS LST data. *Remote Sensing, 9*(12), Article 1254. https://doi.org/10.3390/rs9121254