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Correlation-Based Spatiotemporal Analysis of Satellite and In-situ Derived Sea Surface Temperature (SST) in Semarang Coastal Waters (2022–2024)

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Abstract: Monitoring sea surface temperature (SST) variability is essential for understanding coastal climate processes, marine ecosystem stability, and regional ocean–atmosphere interactions. Coastal regions such as those along the northern coast of Java, Indonesia, are highly vulnerable to temperature fluctuations that influence water column stratification, nutrient availability, and biological productivity. Continuous and accurate SST monitoring is therefore crucial for assessing environmental change and supporting sustainable coastal resource management. This study aims to analyze the spatial and temporal characteristics of sea surface temperature in Semarang coastal waters and to evaluate the degree of consistency between satellite-derived and in-situ measurements obtained from the national meteorological observation station during the period 2022–2024. Monthly mean sea surface temperature values were computed from both datasets and analyzed using correlation-based statistical techniques, including Pearson correlation, determination coefficient, root mean square error (RMSE), and bias. The results revealed a strong linear relationship between the two datasets, with a correlation coefficient of 0.812 and a determination coefficient of 0.659, indicating that about 65.9% of the observed temperature variability in the in-situ record is explained by satellite observations. The RMSE value of 0.426 °C confirms high agreement, while the small negative bias (–0.093 °C) suggests a slight underestimation by the satellite-derived temperature. Both datasets exhibit similar seasonal variations, characterized by warming during mid-year months and cooling associated with the monsoonal transition. These consistent temporal patterns confirm that satellite-derived sea surface temperature provides an accurate and reliable representation of nearshore thermal dynamics. The integration of satellite and in-situ observations enhances coastal temperature monitoring, supports marine climate analysis, and provides a strong scientific basis for future environmental assessments and adaptation strategies in response to climate variability across Indonesia's northern coastal regions.

Keywords: Coastal Monitoring, Correlation Analysis, Remote Sensing, Sea Surface Temperature, Statistical Validation.

Introduction

Sea surface temperature (SST) plays a crucial role in regulating the exchange of heat and moisture between the ocean and the atmosphere. It influences large-scale climate processes, including monsoons, cyclones, and oceanic circulation, which in turn shape global and regional climate variability. As one of the most sensitive indicators of climate change, SST not only reflects the physical state of the ocean but also controls biological productivity and the stability of marine ecosystems. Variations in SST can alter weather patterns, shift marine habitats, and affect fisheries production, particularly in coastal zones where human and environmental systems are closely connected.

The global trend of ocean surface warming has become more evident over recent decades. According to Embury et al. (2024), global SST has increased steadily since the 1980s, leading to more frequent and intense marine heatwaves. This rise in surface temperature disrupts ocean–atmosphere

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feedback mechanisms and contributes to sea level changes and altered circulation. The Intergovernmental Panel on Climate Change has reported that the upper ocean has warmed by approximately 0.88 °C over the last century, making SST an essential climate variable for detecting and attributing global warming impacts. Such changes are particularly critical in tropical coastal regions where slight thermal shifts can have substantial ecological and socio-economic implications.

Monitoring SST accurately is vital for assessing the health of the ocean and its influence on atmospheric processes. Traditional in-situ methods such as shipboard measurements and buoy networks provide high accuracy but are limited in spatial and temporal coverage. The advancement of satellite remote sensing has enabled scientists to overcome these limitations by offering near-global SST observations at regular intervals. Sensors like the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Aqua satellite have become indispensable for tracking SST variability at regional and global scales (Koutantou et al., 2023). The integration of satellite and field data has thus become a standard approach for environmental monitoring and climate research.

Despite their broad coverage, satellite SST products face challenges in coastal environments. Shallow waters, suspended sediments, and land contamination within the sensor's field of view can reduce retrieval accuracy. Atmospheric effects such as aerosols and cloud interference further complicate temperature estimation. Therefore, validation using in-situ observations is necessary to ensure the reliability of satellite data before it is applied in local-scale climate analysis. Studies such as Castro et al. (2016) and Moteki (2022) have demonstrated that correlation-based validation methods can effectively assess the accuracy of satellite SST in both polar and tropical regions.

Validation relies on statistical techniques that quantify the consistency between datasets. The Pearson correlation coefficient measures the strength of association, while the coefficient of determination (R^2) indicates the proportion of variance explained by satellite observations. The root mean square error (RMSE) expresses the average deviation, and the bias describes systematic over- or underestimation. These indicators together provide a comprehensive evaluation of data reliability. Recent developments in integrated time-series analysis have further improved the interpretation of SST dynamics. Dash et al. (2024) applied spectral decomposition to assess long-term SST trends, demonstrating the effectiveness of multi-scale statistical analysis in understanding ocean variability.

In Indonesia, SST variations are closely linked to monsoonal cycles and regional oceanography. The archipelagic setting exposes Indonesian waters to alternating wind regimes, with the west monsoon bringing cooler and wetter conditions, and the east monsoon characterized by stronger solar heating and higher SST. These seasonal changes affect fisheries productivity, coral reef health, and nearshore hydrodynamics. The northern coast of Java, including the city of Semarang, provides a distinct environment where monsoonal forcing, tidal mixing, and river discharge interact. Tresnawati et al. (2022) emphasized that SST fluctuations along the northern Java Sea are primarily controlled by seasonal winds and local sedimentation, making this region a valuable case for studying spatiotemporal SST behavior.

Semarang's coastal area is a semi-enclosed shallow system influenced by both oceanic and terrestrial processes. The combination of shallow bathymetry, river inflow, and anthropogenic activity leads to spatially heterogeneous SST patterns. The city's proximity to industrial and port operations introduces additional heat and sediment into the nearshore waters. Consequently, validating satellite SST products under these dynamic and turbid conditions is essential for ensuring their reliability in local monitoring. The Tanjung Emas Maritime Meteorological Station operated by BMKG provides consistent in-situ SST data that can serve as a ground reference for satellite validation.

Accurate SST information from satellite data contributes to various operational and scientific purposes. It supports the detection of climate anomalies, aids fisheries forecasting, and helps in identifying marine heatwaves that threaten coral reef systems. In coastal management, validated SST datasets can indicate zones of pollution or reduced water circulation. The combination of spatial and temporal SST analysis thus provides insights not only into environmental variability but also into socio-economic resilience along coastal regions. López-Ramírez et al. (2024) highlighted that comparing satellite and in-situ SST is particularly valuable in socio-ecological zones where environmental monitoring guides policy decisions.

Globally, correlation-based SST validation has proven successful in different environmental settings. Guo et al. (2025) used Landsat-8 TIRS data to analyze decadal SST patterns in temperate coastal waters, while Wachmann et al. (2024) applied Landsat analysis-ready data to validate nearshore SST in the Northeast Pacific. Both studies confirmed that multi-source validation enhances the precision of satellite-derived SST, particularly in regions with complex coastal processes. Similarly, Zuo et al. (2023) demonstrated that high-resolution satellite observations can capture fine-scale SST variations in coral reef habitats, emphasizing the importance of integrating different spatial scales of analysis.

Although these international studies have established solid frameworks for SST validation, research focusing on the Indonesian coastal context remains limited. Local factors such as monsoon variability, sediment load, and anthropogenic modification introduce unique challenges that cannot be generalized from other regions. Semarang, as a rapidly developing coastal city, exemplifies how urbanization interacts with natural climate variability. Understanding its thermal characteristics is therefore essential for designing adaptive coastal management strategies and improving regional climate resilience.

From a methodological perspective, correlation-based validation not only quantifies the agreement between satellite and in-situ datasets but also helps interpret physical mechanisms underlying temperature differences. By assessing the temporal alignment and magnitude of deviations, it becomes possible to identify conditions that cause retrieval errors, such as turbidity or rainfall events. Furthermore, the integration of spatial analysis allows researchers to visualize SST gradients, upwelling zones, and river plume effects, offering a more comprehensive understanding of coastal dynamics.

Reliable SST monitoring is also important in the context of global climate programs. Datasets that combine in-situ and satellite observations contribute to the Global Ocean Observing System (GOOS) and the Copernicus Marine Environment Monitoring Service (CMEMS), which rely on validated SST inputs for model calibration. Studies like this provide localized insights that enrich global datasets, ensuring that tropical coastal conditions are adequately represented in climate assessments. Rahman and Rahaman (2024) emphasized that such validation efforts are crucial for improving reanalysis products and reducing uncertainty in ocean temperature projections.

The present study focuses on the spatiotemporal analysis and validation of satellite-derived SST against in-situ measurements in Semarang's coastal waters from 2022 to 2024. It applies correlation-based statistical methods to quantify data accuracy and interprets thermal patterns in relation to monsoon variability and local hydrodynamics. The integration of statistical validation with spatial visualization provides a robust approach to understanding the relationship between climatic drivers and coastal temperature behavior.

By linking large-scale satellite observations with local ground measurements, this study aims to strengthen the reliability of SST datasets for Indonesian waters. The outcomes are expected to enhance national climate services, particularly those supporting fisheries, coastal resource management, and early warning systems for environmental changes. Through this effort, the study contributes to Indonesia's broader goals of sustainable coastal development and the achievement of Sustainable Development Goals 13 (Climate Action) and 14 (Life Below Water).

Materials And Methods

Study area

The research was conducted in the northern coastal waters of Semarang, Central Java, Indonesia, approximately between 6°50′–7°00′ S and 110°20′–

110°30′ E. This shallow nearshore environment is influenced by monsoonal winds, tidal dynamics, and river discharge, which together create pronounced spatial and temporal variability of sea surface temperature (SST). The seasonal cycle in the study area is characterized by the west monsoon (December–February) that brings increased cloud cover and rainfall, and the east monsoon (June–August) associated with clearer skies and higher SST values. These features are consistent with previous findings on monsoonal influences along the northern coast of Java (Tresnawati et al. 2022; López-Ramírez et al. 2024).

The Tanjung Emas Maritime Meteorological Station (BMKG), located within Semarang Harbor, served as the in-situ observation site for near-surface SST monitoring. These observations were used to validate the satellite-derived SST obtained from NASA Ocean Color MODIS Aqua products, which have been widely applied in tropical coastal studies (Koutantou et al. 2023; Moteki et al. 2022). The location provides continuous and representative coastal measurements suitable for assessing satellite accuracy.

Figure 1 presents the general research area along the Semarang coastline and the mapped grid used for extracting satellite SST data, while Figure 2 illustrates the detailed position of the Tanjung Emas Maritime Meteorological Station (BMKG) within the harbor area, indicating the point of in-situ measurement.

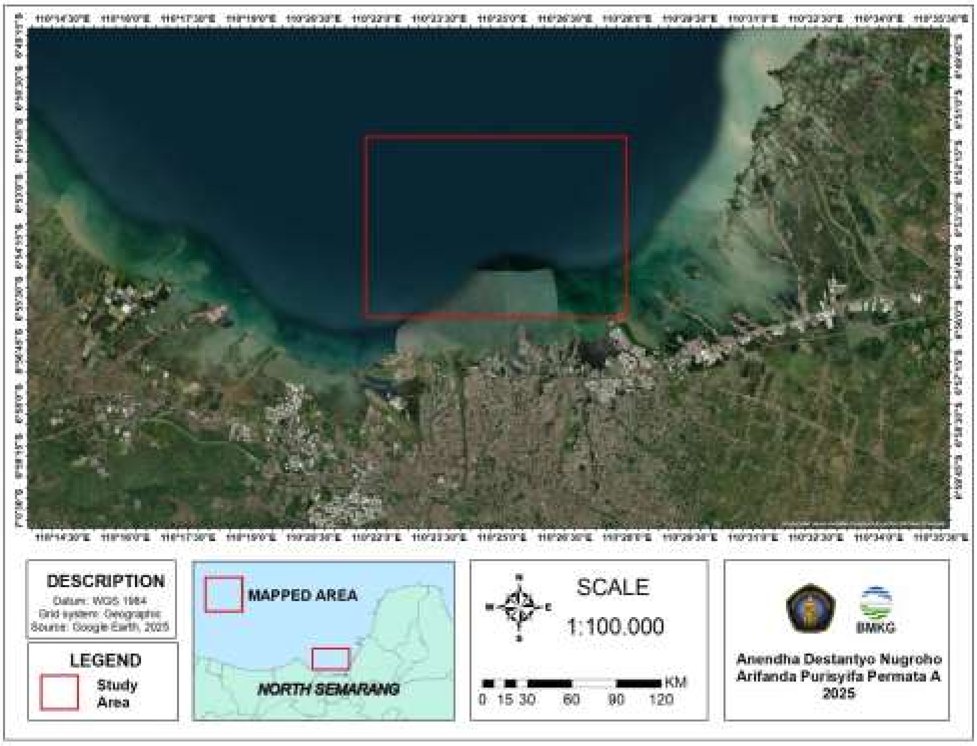

Figure 1. Study area in the northern coastal waters of Semarang showing the mapped grid used for satellite SST extraction (Source: Google Earth 2025).

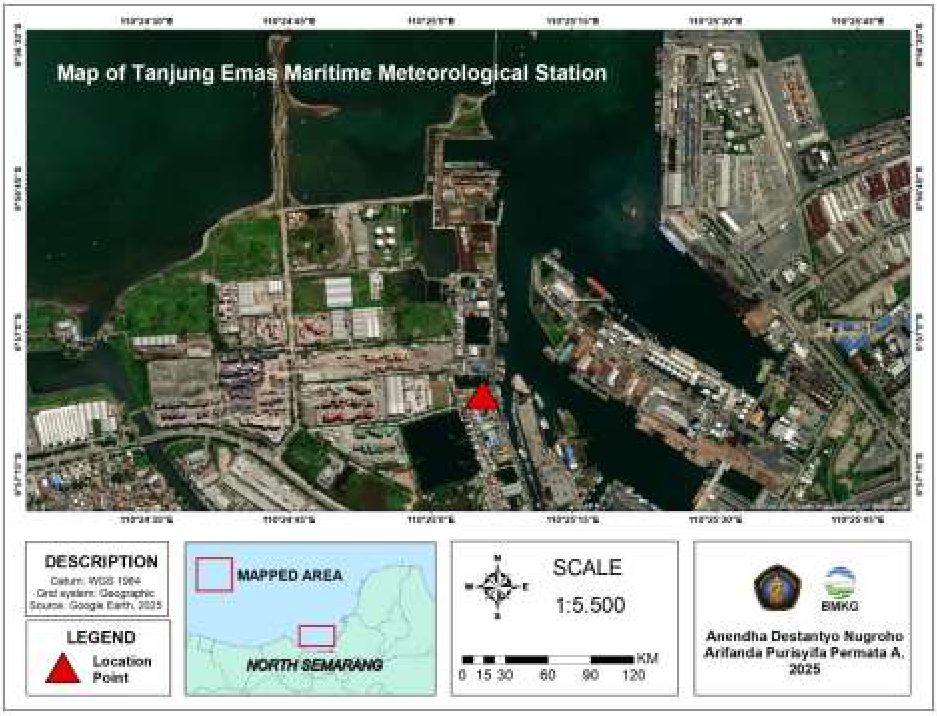

Figure 2. Detailed map of the Tanjung Emas Maritime Meteorological Station (BMKG) in Semarang Harbor, showing the in-situ observation site. (Source: Google Earth 2025).

Procedures

The workflow of this study consisted of five sequential stages. The first stage involved the acquisition of satellite-derived SST data from MODIS Aqua Level-3 monthly composites provided by NASA Ocean Color, with a spatial resolution of 4 km covering 2022–2024 (Koutantou et al. 2023). The second stage focused on the collection of in-situ SST data from the Tanjung Emas Maritime Meteorological Station (BMKG), representing near-surface temperature measurements within Semarang Harbor. In the third stage, both datasets underwent preprocessing, including quality control, temporal alignment to a monthly timescale, spatial subsetting to match the study grid, and unit harmonization in °C (Rahman et al. 2024). The fourth stage comprised the generation of spatial SST maps and monthly time-series plots to visualize temporal fluctuations and spatial distributions throughout the study period. Finally, the fifth stage involved statistical validation and interpretation, where correlation and error analyses were performed to assess the accuracy and consistency between satellite-derived and in-situ SST datasets.

The overall flow of the research procedures is summarized in Figure 3, which outlines the sequential relationship among data acquisition, preprocessing, spatial analysis, statistical validation, and interpretation. All data processing and visualization were carried out using Python 3.12 in the Google Colab environment, utilizing the libraries pandas, numpy, matplotlib, and xarray (Woo et al. 2020).

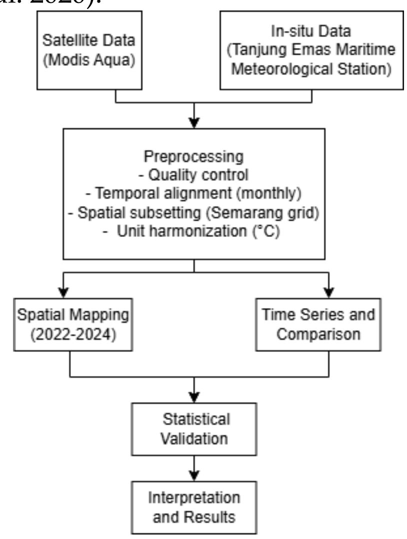

Figure 3. Procedural flow of data acquisition, preprocessing, analysis, and validation in the SST study (Semarang Coastal Waters 2022–2024).

Data analysis

The data analysis in this study was designed to evaluate the accuracy and reliability of satellite-derived sea surface temperature (SST) in representing nearshore thermal conditions in Semarang's coastal waters. To achieve this objective, a correlation-based statistical validation approach was applied by comparing MODIS Aqua Level-3 satellite SST data with in-situ observations obtained from the Tanjung Emas Maritime Meteorological Station (BMKG). This method allows for a quantitative assessment of the degree of similarity and consistency between the two datasets, which differ in both spatial resolution and measurement technique.

The first stage of the analysis involved preprocessing of both datasets to ensure comparability. Satellite SST data, originally in a gridded format with a 4 km spatial resolution, were spatially subset to cover the coordinate extent of Semarang's nearshore waters (6°50′–7°00′ S; 110°20′–110°30′ E). The in-situ data, measured at approximately one-meter depth, were converted into monthly mean values to match the temporal resolution of the satellite data. Quality control was performed by identifying and excluding outlier values and by verifying data continuity to avoid bias in statistical computation.

After both datasets were temporally aligned, descriptive statistics were generated to summarize their mean, minimum, and maximum values as an initial check of consistency. Following this, a series of statistical validation metrics were applied to quantify their agreement. The main indicators used were the Pearson correlation coefficient (r), coefficient of determination (R^2), root mean square error (RMSE), and mean bias. These parameters were selected because they provide complementary perspectives on data performance and are widely used in oceanographic validation studies (Castro et al., 2016; Dash et al., 2024).

The Pearson correlation coefficient (r) measures the strength and direction of the linear relationship between satellite-derived and in-situ SST values. It is calculated using the equation:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

where X_i and Y_i represent the paired satellite and in-situ SST values, and $\bar{X}$ and $\bar{Y}$ are their respective mean values. A correlation coefficient close to +1 indicates a strong positive relationship, meaning that temperature variations detected by satellite are consistent with those recorded by direct measurements.

The coefficient of determination (R^2) was derived from the square of the correlation coefficient and represents the proportion of in-situ SST variance explained by the satellite dataset. Higher R^2 values signify stronger model predictability and better agreement between the two datasets. This parameter is particularly useful for evaluating how much of the observed in-situ variability can be accounted for by satellite measurements.

The root mean square error (RMSE) quantifies the average magnitude of error between the two datasets. It was calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2}$$

where n is the number of paired observations. A lower RMSE value reflects better satellite performance and indicates minimal deviation from in-situ observations. For coastal SST validation, RMSE values below 0.5 °C are typically considered acceptable for scientific and operational use (Yin et al., 2023).

The mean bias (MB) measures the systematic difference between satellite and in-situ datasets and is given by:

$$MB = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)$$

A positive bias implies overestimation by the satellite data, whereas a negative bias indicates underestimation relative to in-situ measurements. Identifying bias is critical for understanding the direction and nature of retrieval errors that may arise from factors such as sensor calibration, atmospheric correction, or local environmental influences like turbidity and surface heating.

All statistical computations were conducted using the Python 3.12 programming environment. The libraries numpy and pandas were employed for numerical operations and data handling, while matplotlib was used for visualization of scatter plots and time-series graphs. The xarray library was utilized for managing the gridded satellite data. Data validation scripts were written to automate the computation of r, R^2, RMSE, and bias for the 36-month period between January 2022 and December 2024.

In addition to statistical validation, graphical analyses were performed to visualize data behavior and support interpretation. Scatter plots were generated to illustrate the degree of linear association between satellite and in-situ SST, with the 1:1 reference line indicating perfect agreement. Time-series plots were used to examine the temporal alignment between the two datasets and to identify any seasonal discrepancies. Boxplots were also produced to evaluate the spread and median differences of monthly SST values across the study period.

The interpretation of results followed oceanographic validation standards (Castro et al., 2016; Dash et al., 2024; Yin et al., 2023). Correlation coefficients above 0.7 were classified as strong, RMSE values below 0.5 °C as acceptable, and biases within ±0.2 °C as negligible. The analysis also considered physical and environmental factors that could influence the observed relationship, including seasonal monsoon patterns, atmospheric conditions, and surface mixing processes.

Finally, to contextualize the numerical findings, the results were interpreted alongside the spatial and temporal variability of SST derived from MODIS Aqua imagery. This integration allowed for a comprehensive understanding of how well satellite data captured both large-scale and localized temperature patterns. Validation results were summarized in Table 1 and further discussed in the subsequent section to link the quantitative outcomes with environmental interpretation.

Results And Discussion

Statistical Validation

The validation results show a strong consistency between satellite-derived and in-situ SST datasets (Table 1). The correlation coefficient (r = 0.812) and the coefficient of determination ($R^2 = 0.659$) indicate a robust linear relationship, meaning that approximately 65.9 % of SST variance measured in situ is explained by satellite estimates. The low RMSE value (0.426 °C) demonstrates that the MODIS Aqua data maintain a high degree of accuracy, while the small negative bias (–0.093 °C) reveals only a slight underestimation of SST compared with direct observations.

Such validation performance is within the accuracy range commonly reported for coastal tropical waters. Koutantou et al. (2023) observed comparable correlations when validating MODIS Aqua SST in the Mediterranean, whereas Moteki et al. (2022) found similar patterns along western Sumatra. Slight cold biases are typical of MODIS retrievals in shallow or turbid zones because of sub-pixel mixing and water-column effects (Woo et al. 2020). These results confirm that the MODIS Aqua dataset can represent SST variability in Semarang's nearshore area reliably.

Table 1. Statistical validation between satellite and in-situ SST datasets (2022–2024).

Parameter	Symbol	Value	Interpretation
Correlation coefficient	r	0.812	Strong positive linear relationship
Coefficient of determination	R^2	0.659	65.9 % of variance explained
Root Mean Square Error	RMSE (°C)	0.426	Low average deviation
Mean Bias	Bias (°C)	–0.093	Slight underestimation by satellite

Note: Validation metrics computed following Castro et al. (2016) and Dash et al. (2024).

The statistical summary presented in Table 1 demonstrates the overall reliability of the MODIS Aqua product; however, visualization of data dispersion further supports this finding. The scatter plot in Figure 4 displays the relationship between satellite-derived and in-situ SST values, illustrating that data points are tightly grouped along the 1:1 reference line. The narrow spread confirms the high linear correlation indicated by the computed coefficients and low residual error.

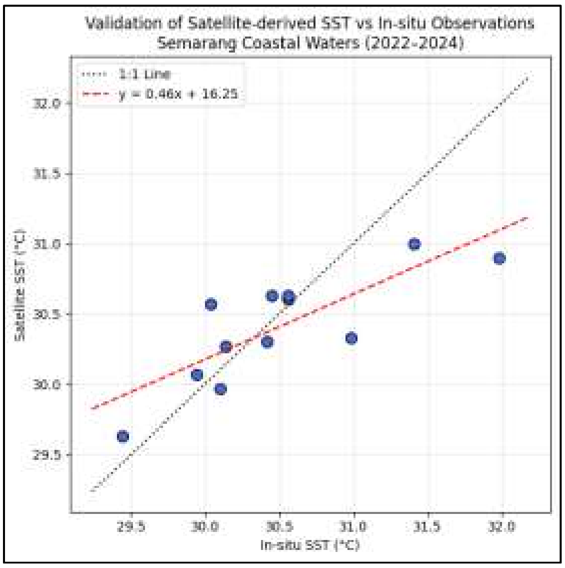

Figure 4. Scatter plot comparing satellite-derived and in-situ SST (2022–2024).

Temporal Variation of SST

The monthly SST time series during 2022–2024 (Figures 5–7) reveals a clear monsoon-driven seasonal cycle. Satellite-derived SST (Figure 5) shows cooling during the west monsoon (December–February), when cloud cover and rainfall reduce solar heating, and warming during the east monsoon (June–August), when clearer skies enhance incoming solar radiation. Throughout the study period, satellite SST ranged from about 29 °C to 31.5 °C, indicating moderate intra-annual variability characteristic of northern Java's coastal waters.

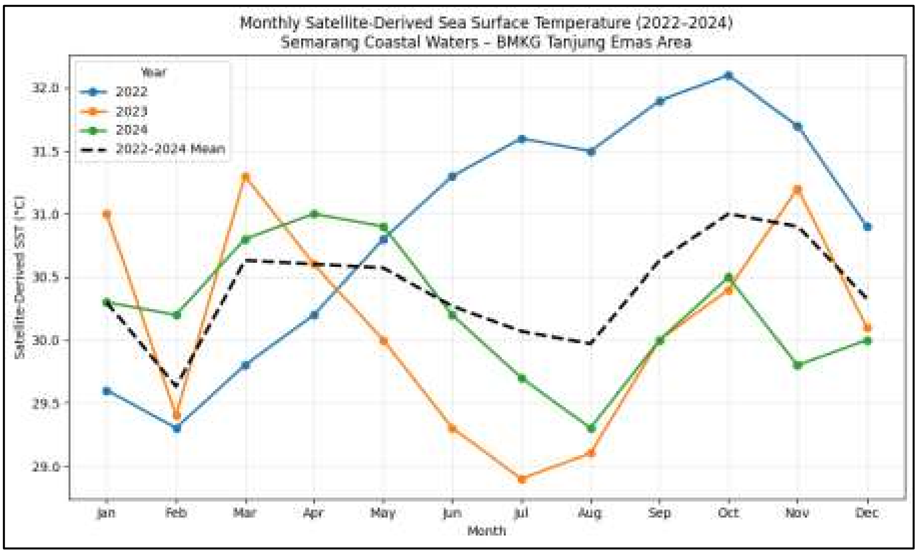

Figure 5. Monthly satellite-derived SST in Semarang coastal waters from MODIS Aqua (2022–2024).

In-situ observations (Figure 6) show the same general cyclical pattern but with slightly higher peaks, reaching up to 32 °C in some months. The in-situ dataset also reveals stronger short-term variability during transitional periods (April–May and October–November). These fluctuations reflect the influence of rapid monsoonal wind shifts, localized convection, and freshwater inputs from surrounding watersheds that affect thermal structure in the Semarang nearshore zone.

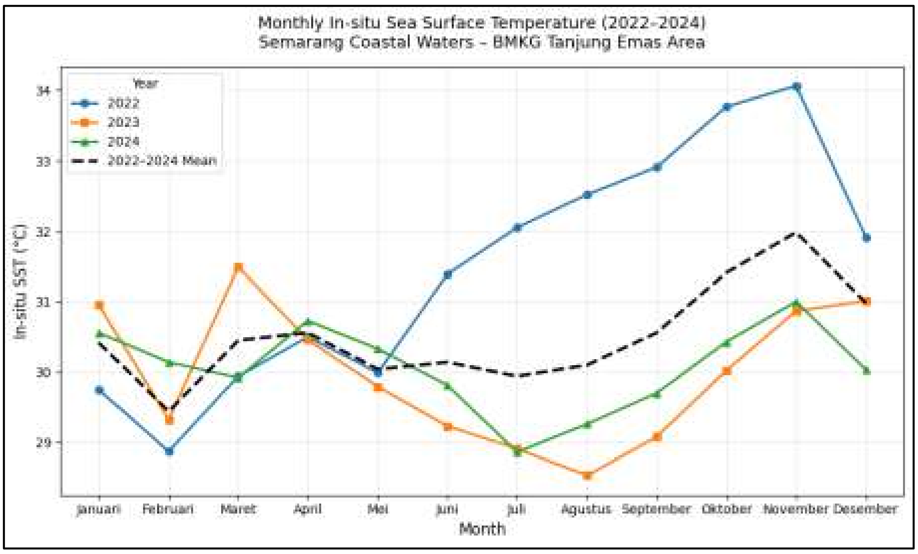

Figure 6. Monthly in-situ SST at the Tanjung Emas Maritime Meteorological Station (2022–2024).

A direct comparison between the two datasets (Figure 7) highlights their close alignment. Both series exhibit nearly identical timing of warming and cooling phases, and the differences between satellite and in-situ monthly means generally remain below 0.5 °C. This agreement indicates that MODIS Aqua provides reliable monthly SST estimates in coastal waters and can complement in-situ measurements where continuous field monitoring is limited. These results are consistent with regional findings reported by Tresnawati et al. (2022) and López-Ramírez et al. (2024) for northern Java, as well as similar monsoon-driven SST cycles in the Gulf of Thailand and northern Indian Ocean (Zuo et al. 2023; Rahman et al. 2024).

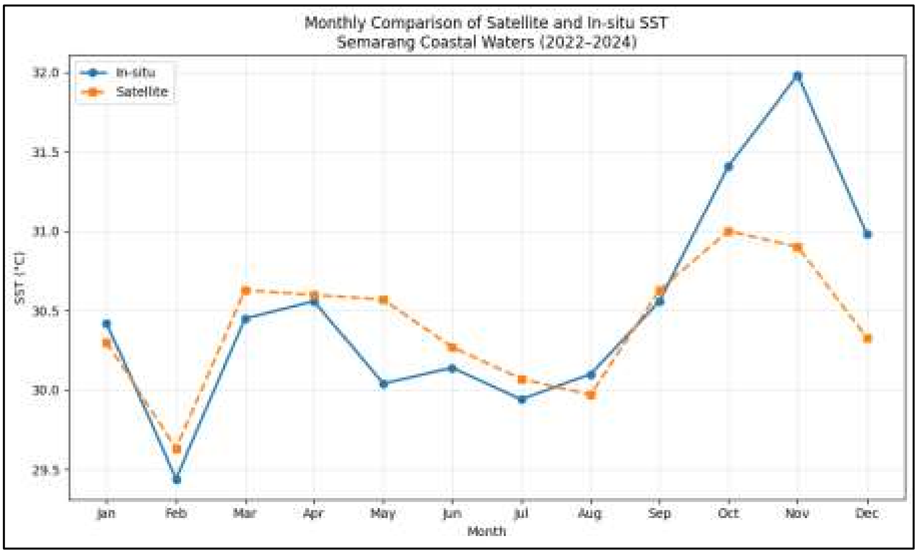

Figure 7. Monthly comparison between multi-year mean satellite and in-situ SST in Semarang coastal waters (2022–2024).

Spatial Distribution of SST

Spatial SST patterns derived from satellite imagery show that Semarang's northern waters consistently experience warmer temperatures along nearshore and southeastern sectors, and relatively cooler conditions offshore to the west (Figures 8–10). In 2022, SST values ranged from 28 °C to 31 °C, with higher temperatures adjacent to shallow coastal areas. In 2023, the spatial gradient strengthened slightly, suggesting enhanced thermal contrast due to monsoon intensity. Meanwhile, in 2024, SST distributions appeared more homogeneous, implying weaker atmospheric forcing.

These spatial differences are influenced by bathymetry, river discharge, and sediment-induced turbidity, which modulate heat absorption and vertical mixing. Similar coastal-to-offshore temperature gradients were reported by Guo et al. (2025) in Chinese estuaries and Wachmann et al. (2024) for the northeast Pacific. The general stability of spatial patterns across the three years supports Yin (2024), who observed minimal inter-annual SST anomalies under neutral ENSO conditions during this period.

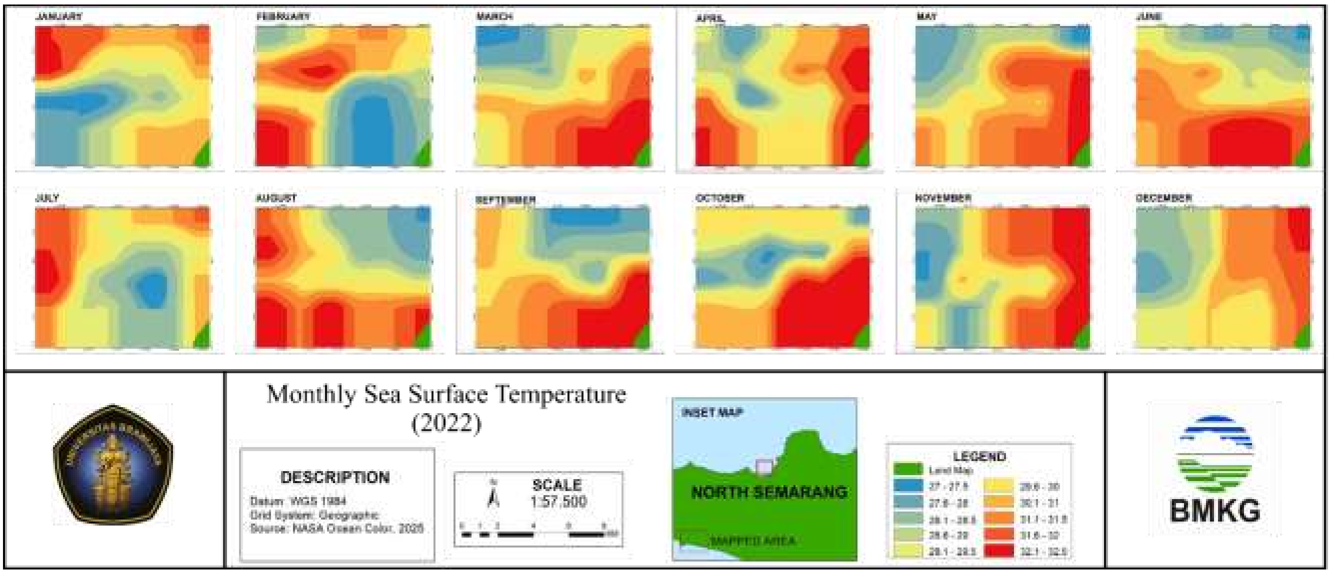

Figure 8. Spatial distribution of mean satellite-derived SST in 2022.

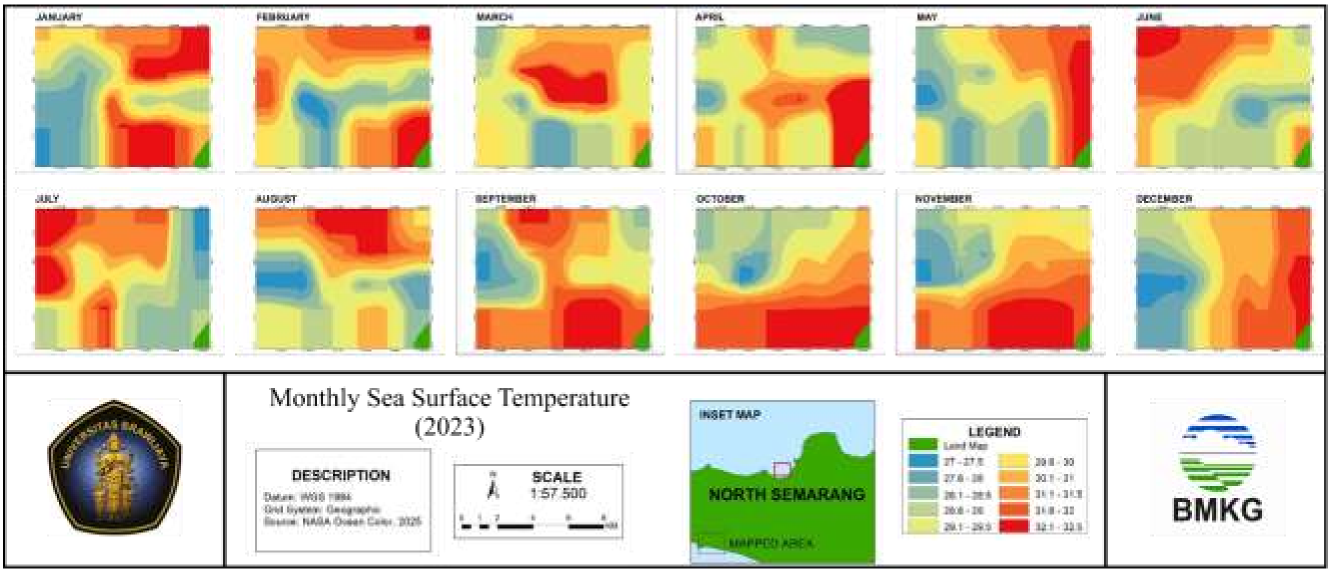

Figure 9. Spatial distribution of mean satellite-derived SST in 2023.

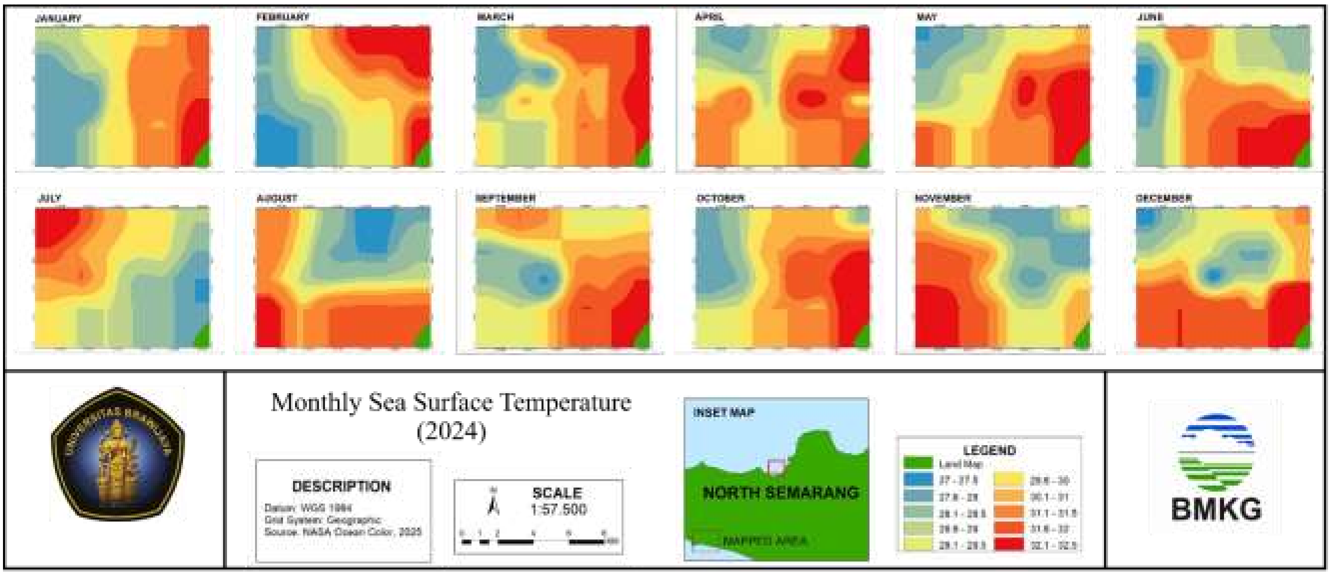

Figure 10. Spatial distribution of mean satellite-derived SST in 2024.

The composite maps of NASA Ocean Color data further illustrate intra-annual thermal dynamics across the Semarang coastal zone. Cooler patches typically appear during February–April and August, while warmer plumes dominate from September through November. The persistence of this cyclic behavior highlights the strong monsoonal control over SST, consistent with findings by López-Ramírez et al. (2024) and Guo et al. (2025) for other tropical marginal seas.

Discussion

The integration of satellite and in-situ SST data offers multiple insights beyond numerical validation. First, the strong correlation and low RMSE demonstrate that satellite remote sensing can replace or complement sparse in-situ networks in Indonesia's coastal zones. This finding supports the increasing reliance on satellite monitoring to assess climate impacts on marine environments (Koutantou et al. 2023; Dash et al. 2025).

Second, the detected seasonal cycle provides evidence of the tight coupling between monsoon dynamics and coastal thermal regimes. During the east monsoon, elevated SST enhances stratification and may reduce nutrient upwelling, potentially lowering primary productivity. Conversely, the cooling phase in the west monsoon promotes vertical mixing, which replenishes nutrients and benefits coastal fisheries—a relationship also reported by Rahman et al. (2024) for the Indian Ocean.

Third, the spatial maps suggest that urban and riverine influences amplify nearshore warming, consistent with patterns of coastal thermal pollution described by Guo et al. (2025). In Semarang, rapid industrialization around the harbor may locally intensify heat retention, implying that SST monitoring can serve as an indirect indicator of anthropogenic stress.

Finally, the integration of MODIS Aqua data with continuous BMKG observations provides a methodological framework for long-term coastal climate monitoring in Indonesia. The validation achieved here ($r > 0.8$; RMSE < 0.5 °C) meets international accuracy thresholds, suggesting that national agencies can operationalize similar approaches for early detection of marine heatwaves or coastal anomalies.

Conclusions

This study demonstrates a strong agreement between satellite-derived and in-situ sea surface temperature (SST) observations in the northern coastal waters of Semarang. Statistical validation yielded a high correlation coefficient ($r = 0.812$) and a low RMSE (0.426 °C), confirming that the MODIS Aqua dataset reliably represents nearshore thermal variability. Temporal analysis revealed a clear monsoon-driven SST cycle, with warming during the east monsoon and cooling during the west monsoon, while spatial patterns indicated persistent nearshore warming associated with shallow bathymetry and reduced mixing. The integration of satellite and in-situ observations provides a robust methodological framework for monitoring coastal temperature dynamics and assessing environmental changes in Indonesian waters. These findings contribute to improving regional climate resilience and support the implementation of SDG 13 (Climate Action) and SDG 14 (Life Below Water) through enhanced coastal observation and adaptive management strategies.

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Conflict of Interest: The authors declare that there are no conflicts of interest concerning the publication of this article.

References

Castro, S. L., Wick, G. A., & Steele, M. (2016). Validation of satellite sea surface temperature analyses in the Beaufort Sea using UpTempO buoys. *Remote Sensing of Environment*, *187*, 458–475. https://doi.org/10.1016/j.rse.2016.10.035

Dash, P., Saha, K., DiGiacomo, P., Miller, S. D., Zhang, H., Lazzaro, R., & Son, S. (2024). Trends in Satellite-Based Ocean Parameters through Integrated Time Series Decomposition and Spectral Analysis. Part I: Chlorophyll, Sea Surface Temperature, and Sea Level Anomaly. *Journal of Atmospheric and Oceanic Technology*, *42*(1), 91–123. https://doi.org/10.1175/jtech-d-24-0007.1

Embury, O., Merchant, C. J., Good, S. A., Rayner, N. A., Høyer, J. L., Atkinson, C., Block, T., Alerskans, E., Pearson, K. J., Worsfold, M., McCarroll, N., & Donlon, C. (2024). Satellite-based time-series of sea-surface temperature since 1980 for climate applications. *Scientific Data*, *11*(1), 326. https://doi.org/10.1038/s41597-024-03147-w

Guo, Y., Cherukuru, N., Lehmann, E., Qi, X., Doubell, M. J., Unnithan, S. L. K., & Feng, M. (2025). Decadal analysis of sea surface temperature patterns, climatology, and anomalies in temperate coastal waters with Landsat-8 TIRS observations. *GIScience & Remote Sensing*, *62*(1). https://doi.org/10.1080/15481603.2025.2518623

Koutantou, K., Brunner, P., & Vazquez-Cuervo, J. (2023). Validation of NASA sea surface temperature satellite products using Saildrone data. *Remote Sensing*, *15*(9), 2277. https://doi.org/10.3390/rs15092277

López-Ramírez, J. A., Morales-Zárate, M. V., Rubio-Rodríguez, U., Salinas-Zavala, C. A., & Chávez-Juárez, F. (2024). Sea surface temperature differences between in situ and GHRSST (L4) records in a socio-ecological critical area of the northeastern Pacific Ocean May 2015 to July 2016. *Latin American Journal of Aquatic Research*, *52*(4), 637–645. https://doi.org/10.3856/vol52-issue4-fulltext-3169

Moteki, Q. (2022). Validation of satellite-based sea surface temperature products against in situ observations off the western coast of Sumatra. *Scientific Reports*, *12*(1), 92. https://doi.org/10.1038/s41598-021-04156-0

Rahman, R., & Rahaman, H. (2024). Evaluation of sea surface temperature from ocean reanalysis products over the North Indian Ocean. *Frontiers in Marine Science*, *11*. https://doi.org/10.3389/fmars.2024.1461696

Tresnawati, R., Wirasatriya, A., & Wibowo, A. (2022). Accuracy Performance of Satellite-derived Sea Surface Temperature Products for the Indonesian Seas. *Geographia Technica*, *17*(2/2022), 69–83. https://doi.org/10.21163/gt_2022.172.07

Wachmann, A., Starko, S., Neufeld, C. J., & Costa, M. (2024). Validating LandsAt analysis ready data for nearshore sea surface temperature monitoring in the Northeast Pacific. *Remote Sensing*, *16*(5), 920. https://doi.org/10.3390/rs16050920

Woo, H., & Park, K. (2020). Inter-Comparisons of daily sea surface temperatures and In-Situ temperatures in the coastal regions. *Remote Sensing*, *12*(10), 1592. https://doi.org/10.3390/rs12101592

Xu, F., & Ignatov, A. (2010). Evaluation of in situ sea surface temperatures for use in the calibration and validation of satellite retrievals. *Journal of Geophysical Research Atmospheres*, *115*(C9). https://doi.org/10.1029/2010jc006129

Yin, X., Huang, B., Carton, J. A., Chen, L., Graham, G., Liu, C., Smith, T., & Zhang, H. (2023). The 1991–2020 sea surface temperature normals. *International Journal of Climatology*, *44*(2), 668–685. https://doi.org/10.1002/joc.8350

Zuo, X., Yu, K., Qin, B., Duan, X., Yao, Z., & Su, F. (2023). Deriving fine-scale patterns of sea surface temperature in coral reef habitats using the Landsat 8 thermal infrared sensor. *Frontiers in Marine Science*, *10*. https://doi.org/10.3389/fmars.2023.1293414

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