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EVALUATING THE ACCURACY OF GRIDDED CLIMATE DATASETS FOR PRECIPITATION, SURFACE AIR TEMPERATURE, AND SEA SURFACE TEMPERATURE IN CENTRAL JAVA, INDONESIA

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ABSTRACT

Studies of climate information that rely on accurate and reliable data are essential in hydrometeorological monitoring, early warning, and climate change impacts in areas with varied topography and limited observation data, such as Central Java, Indonesia. This study aims to assess the accuracy of gridded satellite and reanalysis on three main variables. Precipitation was analyzed utilizing CHIRPS, ERA5 Precipitation, and GSMaP products; surface air temperature (SAT) was assessed with ERA5-Land, FLDAS, and AIRS; and sea surface temperature (SST) was evaluated using OSTIA, RAMSSA, and GAMSSA. Observational data from six BMKG stations and iQuam functioned as the reference standard. The datasets were extracted using bilinear interpolation and evaluated using a bias, mean absolute error (MAE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE) for precipitation, and root mean square error (RMSE). The evaluation showed that CHIRPS performed better estimation with the lowest RMSE and SMAPE (17.20 mm/day; 111.42 mm/month; 96.97% daily; 54.09% monthly) compared to ERA5-Precipitation and GSMaP. ERA5-Land in SAT showed better accuracy in MAE and MAPE of 1.2°C and <10% at most locations. For SST evaluation, OSTIA demonstrated the highest agreement with iQuam, showing RMSE of 0.246°C and MAPE of 0.552% in the Southern Sea, while GAMSSA recorded the highest errors across all zones. This study presents a variety of gridded dataset performances based on scale and time to illustrate the importance of validation against observational data. These results can guide researchers in processing the right dataset collection in climate applications in tropical ocean areas.

Keywords: datagrid; precipitation; surface air temperature (SAT); sea surface temperature (SST); evaluation

INTRODUCTION

Anthropogenic climate change, triggered by greenhouse gas emissions, has accelerated the energy imbalance on Earth and intensified the global hydrological cycle [1-2]. The World Meteorological Organization (WMO) reports that 2024 is on track to be the warmest year on record, with global average temperatures reaching 1.55°C above pre-industrial levels, approaching the Paris Agreement threshold [3]. This warming has increased the frequency of heat waves, altered rainfall patterns, and raised sea surface temperatures, impacting agriculture, water resources, and coastal stability in tropical regions [4-8].

Southeast Asia, including Indonesia, is vulnerable to the impacts of climate variability and change due to its dense population, diverse topography, and reliance on climate-sensitive agricultural and fisheries sectors [9-11]. Previous studies have reported increases in air temperature and changes in extreme rainfall in Indonesia since the 1990s, due to global warming and regional modes of variability such as ENSO and the Indian Ocean Dipole [12]. Central Java is key to climate research due to its contrasting geographical diversity, ranging from coastal areas to highlands, and its economy, which depends on climate-affected resources [13-14].

The reliability and consistency of climate information are pretty practical and very important in monitoring and measuring impacts. Meanwhile, ground-based and in-situ observations from BMKG and iQuam are limited, especially in complex areas or waters not covered by ocean observations. Dataset grids such as CHIRPS, ERA5, GSMaP, FLDAS, AIRS, OSTIA, RAMSSA, and GAMSSA are very helpful across a broad spatial and temporal range. However, each dataset may be biased by the recording models, algorithms, and assimilation assumptions used [15-17]. Therefore, independent validation of ground-based and in situ observational datasets is required to assess accuracy and determine suitability for regional applications [18-19].

Several previous validation studies across different regions underscore the need for local assessment. For example, CHIRPS shows high seasonal accuracy in semi-arid regions [20] and outperforms ERA5 in detecting heavy rainfall in the Ethiopian highlands [21]. FLDAS shows strong spatial-temporal consistency in simulating land surface temperature and soil moisture in Africa and the Mediterranean [22], while OSTIA demonstrates reliability in SST accuracy in Indonesian seas [17]. However, all of these studies were conducted separately, with specific variables and regions. They were not integrated into a single regional framework for evaluating rainfall, air temperature, and sea surface temperature.

Although the use of these global datasets has increased, a comprehensive study simultaneously evaluating rainfall, surface temperature, and sea surface temperature has not yet been conducted in Central Java, using consistent statistical metrics and within an integrated spatial interpolation framework. This study fills the gap by evaluating the commonly used grid products CHIRPS, ERA5, GSMaP, FLDAS, AIRS, OSTIA, RAMSSA, and GAMSSA against BMKG and iQuam observations. The expected outcome of this research is to provide a strong scientific basis for selecting appropriate datasets for climate analysis, model calibration, and long-term climate change studies in the tropical maritime environment of Central Java.

METHOD

Data and Sources

This study combines a variety of observational and gridded datasets to assess the accuracy of precipitation, surface air temperature (SAT), and sea surface temperature (SST) in Central Java. Precipitation observations (2010-2024) and surface air temperature data (2000-2024) have been obtained from six representative BMKG stations in the northern, midland highland, and southern coastal regions. Sea surface temperature observations have been collected from the iQuam system through in-situ buoy and ship-based daily measurements taken between 2008 and 2024 in the Northern and Southern Java Seas.

All evaluated gridded datasets are CHIRPS, ERA5 Precipitation, and GSMaP for precipitation; ERA5-Land, FLDAS, and AIRS for surface air temperature; and OSTIA, RAMSSA, and GAMSSA for sea surface temperature (Table 1). The datasets display resolutions in space that vary between 0.05° to 1.0°, all supplied from official data repositories such as CDS Copernicus, NASA GESDISC, JAXA, and Copernicus Marine.

Table 1. Gridded Dataset Attribute

Variable	Dataset	Source	Period	Resolution
Precipitation	Observation	BMKG, 6 Stations	2014–2024	Level 1
	CHIRPS V2.0	https://www.chc.ucsb.edu/data/chirps	2014–2024	0.05°
	ERA5 Precipitation	https://cds.climate.copernicus.eu	2014–2024	0.25°
	GSMaP-V8_Gauge	https://sharaku.eorc.jaxa.jp	2014–2024	0.1°
SAT	Observation	BMKG, 6 Stations	2009–2024	Level 1
	ERA5-Land	https://cds.climate.copernicus.eu	2009–2024	0.1°
	FLDAS	https://disc.gsfc.nasa.gov	2009–2024	0.1°
	AIRS v7	https://acdisc.gesdisc.eosdis.nasa.gov	2009–2024	1°
SST	iQuam	https://www.star.nesdis.noaa.gov	2008–2024	In Situ
	OSTIA	https://marine.copernicus.eu	2008–2024	0.05°
	RAMSSA	https://podaac.jpl.nasa.gov	2008–2024	0.083°
	GAMSSA	https://podaac.jpl.nasa.gov	2008–2024	0.25°

It should be emphasized that this study presents a validation analysis, not data assimilation. All satellite and reanalysis datasets extracted independently are consistent with in-situ observational data from BMKG and iQuam without any merging, bias correction, or assimilation processing. Therefore, the accuracy metric in this study describes the intrinsic performance of each dataset compared to ground-based observations.

Study Area

The study area covers the Central of Java, with precipitation and SAT compared at six stations (Ahmad Yani, Maritim Semarang, Tegal, Banjarnegara, Cilacap, and Yogyakarta) representing the northern, midland/highland, and southern coastal zones. SST was evaluated based on iQuam observations in the North and South Seas of Central Java. Images of station locations and distribution are presented in Figure 1.

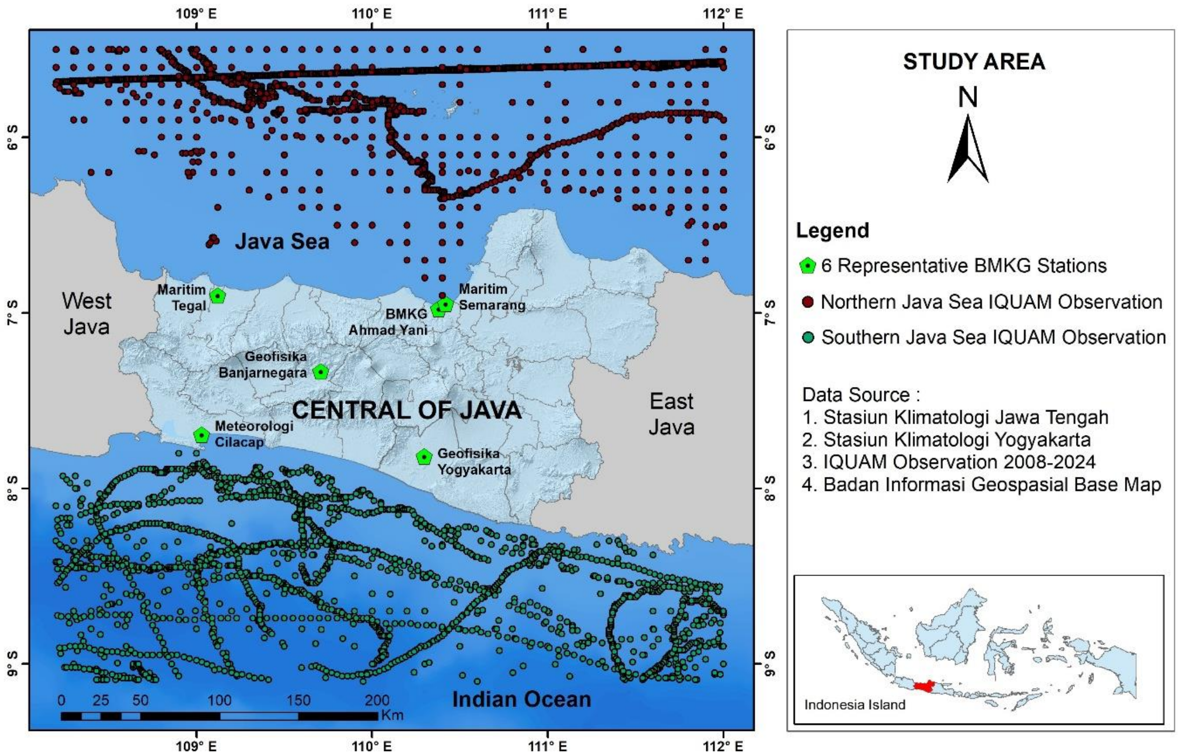

Figure 1. BMKG Station Comparative Data Location for Precipitation, SAT and iQuam SST Observation Point

Bilinear Interpolation

Grid data were adjusted to station coordinates using the bilinear interpolation method as illustrated by Figure 2. This technique calculates a value's location as a weighted function from the four nearest grids based on their spatial distance [23]. This method provides continuous data and prevents unreasonable value increases between grids [24].

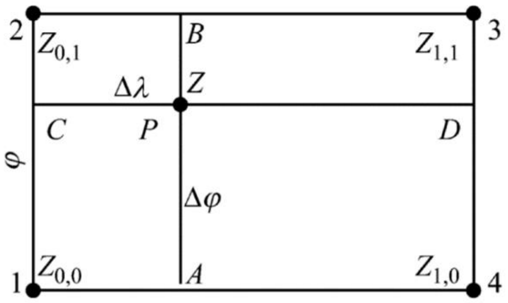

Figure 2. Interpolation of 4 points around [23]

The bilinear interpolation method in this study, in addition to being applied to adjust the base grid points, is also implemented within the integrated spatial harmonization framework for all analyzed rainfall, surface air temperature, and sea surface temperature variables. This approach aims for consistency across all datasets with varying resolutions, as well as ground-based and in-situ marine observations. The uniqueness of this research lies in its cross-variable application and spatial harmonization, which allows for multi-domain validation of land, atmosphere, and sea within a single methodological framework suitable for the varied topographic and climatic characteristics of Central Java.

Accuracy Evaluation

The precision of the gridded dataset relative to observations is evaluated using four statistical metrics: Bias, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) [25]. Symmetric MAPE (SMAPE) is used as an alternative method to avoid due to zero divisors in precipitation data [26].

$$\text{Bias}=\frac{1}{n}\sum_{i=1}^{n}(\text{Data Grid-Observation}) \tag{1}$$

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|\text{Data Grid-Observation}| \tag{2}$$

$$\text{MAPE}=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right|\times 100 \tag{3}$$

$$\text{SMAPE}=\frac{100\%}{n}\sum_{i=1}^{n}\frac{|\text{Data Grid-Observation}|}{(|\text{Data Grid}|+|\text{Observation}|)/2} \tag{4}$$

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{Data Grid-Observation})^2} \tag{5}$$

Bias measures the systematic tendency of differences between estimates and observations, MAE describes the average magnitude of absolute errors, MAPE expresses errors as a percentage of the observed value, SMAPE corrects the weakness of MAPE towards the null value, and RMSE is sensitive to significant errors because it uses the square of the difference.

Referring to the classification developed by Moreno [27] in Table 2, the MAPE value can be interpreted in the following table:

Table 2. Interpretation of typical MAPE values

MAPE	Interpretation
< 10	Highly accurate forecasting
10-20	Good forecasting
20-50	Reasonable forecasting
>50	Inaccurate forecasting

RESULTS AND DISCUSSION

Precipitation

The reliability of gridded dataset products in tropical maritime areas such as Central Java depends on the quality of precipitation datasets. This study compares three primary datasets, CHIRPS, ERA5 Precipitation, and GSMaP, representing the northern coast, southern coast, and central highland areas, against monthly and daily observation data from six BMKG Stations.

In particular for low to moderate rainfall intensity, the scatter plot visualization shows CHIRPS displaying the closest grouping along the identity line (x=y) as shown by Figure 3. While

GSMaP shows greater fluctuations, suggesting variances in low and high rainfall levels, ERA5 Precipitation frequently underestimates in periods of high precipitation.

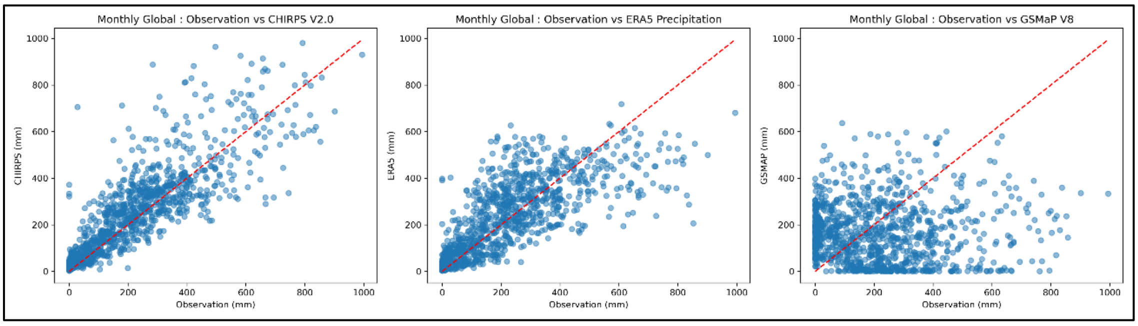

Figure 3. Scatter Plot Datagrid against Monthly Observation Precipitation Data

With lower MAE, SMAPE, and RMSE of 75.41 mm, 54.09%, and 111.42 mm, CHIRPS performed better than ERA5 Precipitation and GSMaP (Table 3). While ERA5 Precipitation showed a smaller bias (+7.44 mm), absolute errors were higher. Indicating lower estimation stability, GSMaP had the highest RMSE and SMAPE and the most severe negative bias (-56.36 mm).

Table 3. Statistical Evaluation of Datagrid on Monthly Observation

Datagrid	BIAS	MAE	SMAPE	RMSE
CHIRPS V2.0	28.89	75.41	54.09	111.42
ERA5 Precipitation	7.44	89.07	61.29	126.51
GSMaP-V8_Gauge	-56.36	186.63	111.68	234.01

The scatter plot displays a wider dispersion on the daily level as shown by Figure 4. CHIRPS remained near the identity line, while some outliers showed themselves at a more intensive level. More significant variations in ERA5 Precipitation and GSMaP suggest an inconsistency in light precipitation recognition, especially in low rainfall events.

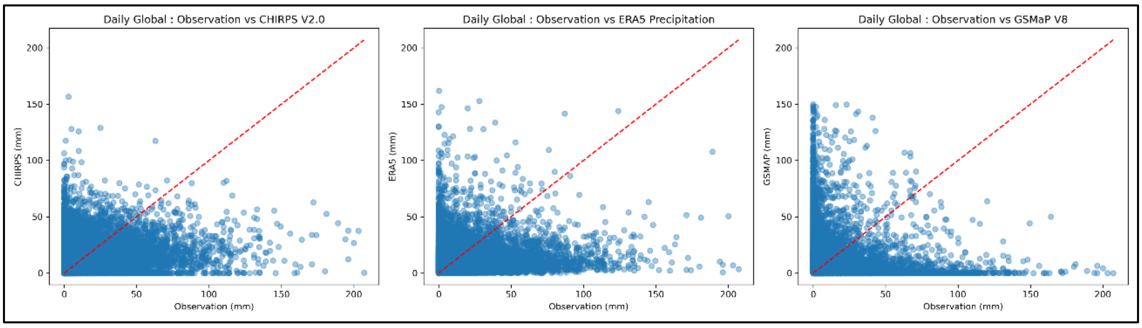

Figure 4. Scatter Plot Datagrid against Daily Observation Precipitation Data

Table 4 summarizes the statistical metrics for all gridded precipitation datasets. While SMAPE was reasonably good (96.97 %), CHIRPS indicated the lowest daily MAE (9.28 mm) and RMSE (17.20 mm). Although ERA5 Precipitation had the highest SMAPE (154 %), it showed the lowest daily bias (0.24 mm). Through daily RMSE obtaining 21.35 mm and SMAPE 154.92%, GSMaP performed less consistently and indicated uncertain and fluctuating estimates.

Table 4. Statistical Evaluation of Datagrid on Daily Observation

Datagrid	BIAS	MAE	SMAPE	RMSE
CHIRPS V2.0	0.95	9.28	96.97	17.20
ERA5 Precipitation	0.24	8.89	154.87	16.96
GSMaP-V8_Gauge	-1.86	10.68	154.92	21.35

The daily figures from six BMKG stations reveal how significantly geographical characteristics affect the accuracy of gridded data. With MAE between 8.3 and 13.9 mm, around 100% SMAPE good on absolute terms but significant on proportional terms (Table 5), CHIRPS tends to be excessively optimistic on the north shore (Ahmad Yani, Maritim Semarang, Tegal). On the lower side of MAE (8.4 - 11.3 mm), ERA5 Precipitation is also better; nonetheless, a larger SMAPE (137 - 160%) results in fewer absolute mistakes but does exist proportionately. With significant negative biases (up to -6.0 mm) and percentiles exceeding 150% of most other measurements, GSMaP is worst in this region.

ERA5 Precipitation displays superior performance, evidenced by the lowest MAE of 9.85 mm and negligible bias, demonstrating strong concordance with daily observations. Conversely, GSMaP significantly underestimates precipitation, reflected in a high SMAPE of 154.85%, thereby underscoring its inadequacy in capturing rainfall variability in the elevated regions of the highland station of Banjarnegara.

Table 5. Statistical Evaluation of Datagrid on Daily Precipitation per Stations

Stations	Evaluation	CHIRPS	ERA5-P	GSMaP	Zone
BMKG Ahmad Yani	BIAS	2.30	-2.07	-6.04	North Coastal
	MAE	13.92	11.35	14.25	
	SMAPE	100.27	137.93	157.74	
	RMSE	22.18	19.87	25.28	
Maritim Semarang	BIAS	0.60	0.53	-1.18	North Coastal
	MAE	8.79	8.76	9.79	
	SMAPE	101.36	159.66	153.18	
	RMSE	16.11	16.76	19.91	
Meteorologi Tegal	BIAS	1.09	0.96	-0.74	North Coastal
	MAE	8.35	8.40	9.49	
	SMAPE	99.89	160.51	152.67	
	RMSE	15.45	16.03	19.57	
Geofisika Banjarnegara	BIAS	1.02	-1.20	-2.99	Middle/Highland
	MAE	11.05	9.85	11.86	
	SMAPE	101.49	150.99	154.85	
	RMSE	20.41	19.55	23.78	
Meteorologi Cilacap	BIAS	0.09	2.29	-0.03	South Coastal
	MAE	5.87	7.39	8.73	
	SMAPE	89.67	161.22	156.47	
	RMSE	12.47	13.91	18.48	
Geofisika Yogyakarta	BIAS	0.61	0.97	-0.16	South Coastal
	MAE	7.66	7.60	9.95	
	SMAPE	89.15	158.95	154.59	
	RMSE	14.57	14.78	20.21	

Although all the datasets show modest bias in the southern coastal area, which comprises Cilacap and Yogyakarta, ERA5 Precipitation performs best in Yogyakarta with an MAE of 7.60 mm and a SMAPE of 158.95%. GSMap has consistently registered the largest RMSE among all the stations, so significant and random mistakes are verified.

Overall, CHIRPS results appear to be the most accurate and consistent precipitation dataset for Central Java, both spatially and temporally. ERA5 Precipitation is competitive in selected locations but unreliable in capturing extreme rainfall. GSMaP, although showing near-zero bias, requires further correction to be viable for operational precipitation monitoring.

Surface Air Temperature

The scatter plots (Figure 5) show SAT-gridded data against observations, agreeing on how well-accurate estimates are. ERA5-Land and FLDAS agree well, though ERA5-Land underestimates slightly at higher temperatures while FLDAS aligns more at about the same line. AIRS shows much more spread and tends to overestimate, especially above 28°C. The deviation from the identity line in AIRS shows some instability. FLDAS has the highest correlation, giving a more reliable temperature estimate over the observed spectrum.

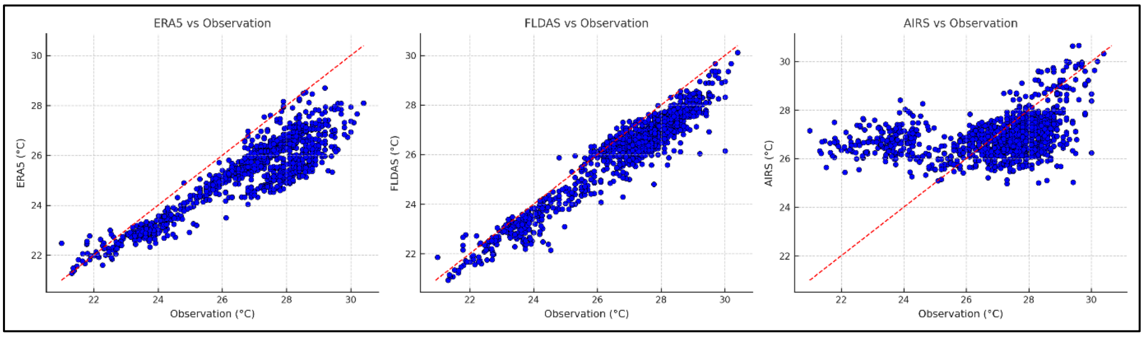

Figure 5. Comparison of Overall Observation Data and Grid Data

The zoning results for SAT show that, indeed, FLDAS proves to be the most reliable dataset over that region (see Table 6). In the northern coastal zoning Ahmad Yani, Maritim Semarang, Tegal, the MAE ebbs and flows between 0.81 to 1.10°C based on FLDAS, concomitant with a moderate negative bias. Highland zoning, i.e., Banjarnegara, in FLDAS uniformity shows reliability having an MAE of 0.56°C and a Bias of -0.51°C. In the southern coastline of Cilacap and Yogyakarta, the performance of FLDAS proves stable, having an MAE of 0.40 to 1.00°C and minimal bias. The reliability of FLDAS makes it a perfect choice for tropical areas with different types of landscapes.

ERA5-Land showed a larger negative bias on the north coast, -2.50°C in Ahmad Yani and -2.57°C in Maritim Semarang, but is more stable in the highlands and south coast. MAE ranges from 1.10 - 2.57°C, and RMSE reaches 2.63°C in extreme locations. This indicates that ERA5 tends to underestimate maximum temperatures but is still reliable in highland areas.

The results show that performance might be unstable. In Banjarnegara, a considerable overestimation is seen with a bias of 3.35°C and an RMSE of 3.46°C. However, it improves at about -0.6°C in Cilacap and Yogyakarta. Big swings between areas make AIRS less appropriate for use in these places.

Table 6. Statistical Evaluation Results of SAT Grid Data

Stations	Evaluation	ERA5-Land	FLDAS	AIRS	Zone
BMKG Ahmad Yani	BIAS	-2.50	-0.81	-0.69	North Coastal
	MAE	2.50	0.81	0.87	
	MAPE	8.85	2.87	3.06	
	RMSE	2.55	0.92	1.08	
Maritim Semarang	BIAS	-2.57	-0.88	-0.71	North Coastal
	MAE	2.57	0.88	0.90	
	MAPE	9.08	3.11	3.17	
	RMSE	2.63	0.96	1.09	
Meteorologi Tegal	BIAS	-1.15	-1.10	-1.58	North Coastal
	MAE	1.16	1.10	1.58	
	MAPE	4.14	3.94	5.65	
	RMSE	1.25	1.20	1.70	
Geofisika Banjarnegara	BIAS	-0.57	-0.51	3.35	Middle/Highland
	MAE	0.65	0.56	3.35	
	MAPE	2.75	2.39	14.45	
	RMSE	0.76	0.71	3.46	
Meteorologi Cilacap	BIAS	-1.25	-1.00	-0.61	South Coastal
	MAE	1.25	1.00	0.69	
	MAPE	4.58	3.69	2.50	
	RMSE	1.31	1.07	0.82	
Geofisika Yogyakarta	BIAS	-1.09	-0.29	0.50	South Coastal
	MAE	1.10	0.40	0.60	
	MAPE	4.15	1.53	2.32	
	RMSE	1.16	0.58	0.71	

FLDAS demonstrated the most consistent and reliable performance in estimating SAT across various station zones, showing reduced error metrics and higher correlation values. The highland and the southern coastal areas might receive good performance from ERA5, though the temperatures in the north coastal region seem underestimated. The AIRS shows strong local accuracy but with spatial instability. These indicate that FLDAS may be the more appropriate gridded product for SAT applications in Central Java, especially given the region's varied topographical and climatic circumstances.

Sea Surface Temperature

Reflecting the possibility of a strong agreement with iQuam observations, OSTIA seems to cluster most precisely around the identity line, or line of complete agreement, in the combined scatter plot of the Northern and Southern Seas, as shown in Figure 6. Though with a somewhat wider spread, RAMSSA also exhibits good alignment. GAMSSA reveals more aberrations, particularly at severe temperatures, when dispersion leads away from the identity line.

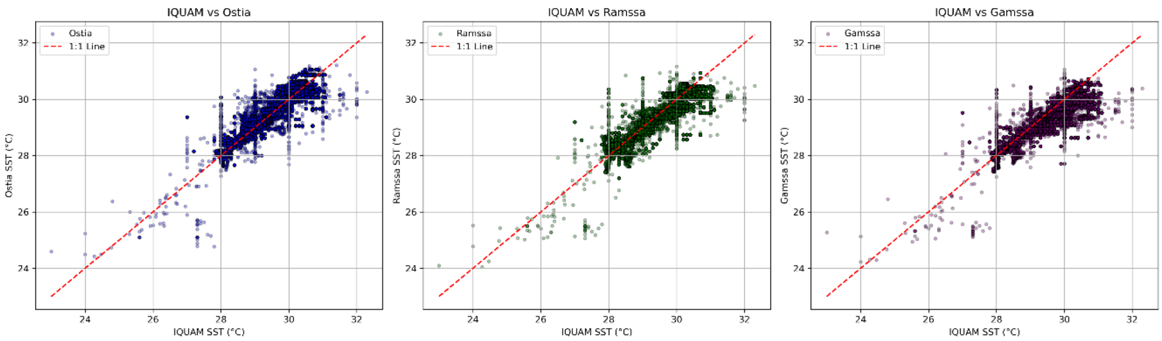

Figure 6. Scatter Plot of Datagrid SST against iQuam

With 0.285°C and 0.51%, RAMSSA recorded the lowest MAE and MAPE in the combined analysis; OSTIA had the lowest bias, and RMSE had -0.069°C 0.454°C. With -0.300°C 0.358°C 1.194% 0.556°C, the evaluation by GAMSSA was the lowest among OSTIA and RAMSSA in bias, MAE, MAPE and RMSE (Table 7). While GAMSSA is generally less accurate, these results suggest that OSTIA and RAMSSA are generally accurate and stable producers of SST estimations over the research region.

OSTIA and RAMSSA demonstrate a reasonable drop in accuracy in the Southern Sea compared to the Northern Sea. In this scenario, the three datasets have relatively low accuracy. While GAMSSA once more ranks highest in error, RMSE = 0.633°C, they register MAEs above 0.33°C and MAPEs exceeding 1%. Increased complexity of coastal currents at the point of the river inflow and daily temperature variability affect satellite SST retrievals in the coastal zones, which explains this lowered performance.

In contrast, the Southern Sea markedly enhanced the precision across all datasets. OSTIA achieves this with an MAE of 0.162°C, a MAPE of 0.552%, and an RMSE of 0.246°C. Despite the markedly decreased accuracies, the regional model-assumed and global telecommunication assimilation systems for RAMSSA and GAMSSA showed commendable performance. The enhanced consistency in this region is likely attributable to the stability of the sea surface, minimal freshwater influence, and reduced anthropogenic disturbance, thereby increasing the precision of satellite measurements.

Table 7. Evaluation of SST Datagrid Statistics against iQuam

Zone	Datagrid	BIAS	MAE	MAPE	RMSE
North and South Sea	OSTIA	-0.069	0.293	0.985	0.454
	RAMSSA	-0.203	0.285	0.951	0.482
	GAMSSA	-0.300	0.358	1.194	0.556
North Sea	OSTIA	-0.109	0.362	1.211	0.531
	RAMSSA	-0.233	0.331	1.099	0.559
	GAMSSA	-0.337	0.404	1.338	0.633
South Sea	OSTIA	0.008	0.162	0.552	0.246
	RAMSSA	-0.147	0.196	0.667	0.284
	GAMSSA	-0.231	0.271	0.920	0.366

As an SST product in the Southern Ocean area of this study, the OSTIA has generally shown rather excellent accuracy and consistency. With minimal absolute errors, the RAMSSA seems to be a reasonable substitute; yet, the GAMSSA should be utilized carefully because of its inclination towards greater deviations, particularly in the northern coastal area. These results underscore the need to select the appropriate SST datasets for tropical climate monitoring and regional oceanographic uses.

CONCLUSION

This study achieved its objective by evaluating the accuracy of an integrated dataset comprising nine rainfall, surface air temperature, and sea surface temperature datasets in Central Java. The results of this analysis combine various observations from BMKG and iQuam using an interpolation and validation framework to gain a more comprehensive regional understanding. This integrated approach connects the atmospheric and oceanic domains and provides insights into selecting datasets for climate change studies and operational monitoring in tropical maritime regions.

Compare the reliability of gridded datasets on precipitation, SAT, and SST by evaluating them against ground-based observations in Central Java and around. Bilinear interpolation and a multi-metric statistical framework were used to set up a complete validation framework appropriate for tropical maritime conditions.

In the rainfall data, CHIRPS demonstrated robust performance across spatial and temporal dimensions, succeeded by ERA5 Precipitation, whereas GSMaP may have challenges, particularly in accurately capturing adverse conditions in proximity. ERA5-Land showed excellent performance dataset for SAT, providing consistent and equitable data over sea and land. Concurrently, OSTIA demonstrates itself as a highly accurate SST product, with most South Seas products produced by RAMSSA showing consistency. In contrast, GAMSSA reveals noticeable discrepancies throughout the coastline.

These results suggest that dataset selection should be context spesific based on regional characteristics and application needs. It is being revealed that no single dataset performs best under all conditions, and validation with care is needed when integrating satellite-based data into climate monitoring, environmental planning, and early warning systems.

In long-term climate change and variability research, precipitation estimates from CHIRPS are preferred for their high stability and compatibility with ground-based observations. FLDAS and ERA5-Land accurately represent seasonal and spatial air temperatures, but ERA5-Land provides the longest and most continuous data series, making it more suitable for long-term climate change and global warming analysis. The OSTIA for sea surface temperature dataset is the most reliable, with low bias and consistent accuracy across the waters north and south of Central Java.

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