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Google Earth Engine for Sea Surface Temperature Mapping in Marine Environments: A Review

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Abstract. Sea surface temperature (SST) is a fundamental oceanographic variable for describing air–sea exchange, ocean circulation, fisheries habitat, coral thermal stress, coastal processes, and climate variability. The rapid expansion of satellite archives has improved SST observation, but conventional desktop workflows remain constrained by data volume, preprocessing requirements, and reproducibility. This review evaluates the role of Google Earth Engine (GEE) as a cloud-computing environment for SST mapping in marine and coastal research. A structured narrative review was conducted using peer-reviewed literature and authoritative dataset documentation published mainly between 2017 and 2026, with emphasis on studies that employed GEE, satellite-derived SST products, validation procedures, or marine applications. The synthesis shows that GEE substantially reduces data-handling barriers and supports scalable time-series analysis through readily accessible products such as MODIS Aqua/Terra Ocean Color L3, NOAA OISST v2.1, NOAA WHOI SST, and JAXA GCOM-C/SGLI SST. However, dataset choice remains application-dependent. Coarse, gap-filled products are effective for climate-scale trends and anomalies, whereas thermal infrared sensors with kilometre- to hectometre-scale observations are more appropriate for coastal gradients but require stricter cloud screening, atmospheric correction, and validation. The principal methodological risks are confusion between land surface temperature and true marine SST, inadequate quality-flag filtering, nearshore mixed pixels, inconsistent temporal compositing, and weak validation. A reproducible workflow is proposed that integrates dataset selection, quality assurance, temporal compositing, anomaly analysis, in-situ or multi-product validation, and uncertainty reporting. GEE is therefore best regarded as an analytical infrastructure rather than an SST algorithm itself; scientific reliability ultimately depends on sensor physics, product quality, validation design, and transparent code-based processing.
Keywords: Google Earth Engine; sea surface temperature; marine remote sensing; cloud computing; ocean monitoring

Abstrak. Suhu permukaan laut (SPL) merupakan variabel oseanografi penting untuk menjelaskan pertukaran udara–laut, sirkulasi laut, habitat perikanan, tekanan termal terumbu karang, proses pesisir, dan variabilitas iklim. Perkembangan arsip satelit telah memperluas kemampuan observasi SPL, tetapi pengolahan konvensional berbasis komputer lokal masih menghadapi kendala volume data, kebutuhan praproses, dan reproduktibilitas. Artikel tinjauan ini mengevaluasi peran Google Earth Engine (GEE) sebagai lingkungan komputasi awan untuk pemetaan SPL dalam penelitian kelautan dan pesisir. Tinjauan naratif terstruktur dilakukan terhadap literatur ilmiah bereputasi dan dokumentasi resmi dataset yang terutama terbit pada 2017–2026, dengan penekanan pada penelitian yang menggunakan GEE, produk SPL satelit, prosedur validasi, atau aplikasi kelautan. Sintesis menunjukkan bahwa GEE mampu mengurangi hambatan pengelolaan data dan mendukung analisis deret waktu melalui produk seperti

MODIS Aqua/Terra Ocean Color L3, NOAA OISST v2.1, NOAA WHOI SST, dan JAXA GCOM-C/SGLI SST. Meskipun demikian, pemilihan dataset harus disesuaikan dengan tujuan. Produk beresolusi kasar dan tanpa celah lebih sesuai untuk tren serta anomali skala iklim, sedangkan sensor inframerah termal beresolusi lebih tinggi lebih relevan untuk gradien pesisir tetapi memerlukan penyaringan awan, koreksi atmosfer, dan validasi yang lebih ketat. Risiko metodologis utama meliputi kekeliruan antara suhu permukaan daratan dan SPL, penggunaan quality flag yang tidak memadai, piksel campuran di pesisir, komposit temporal yang tidak konsisten, dan validasi yang lemah. Artikel ini mengusulkan alur kerja reproduktif yang menggabungkan pemilihan dataset, penjaminan mutu, komposit temporal, analisis anomali, validasi, serta pelaporan ketidakpastian. Dengan demikian, GEE merupakan infrastruktur analitis, bukan algoritma SPL; keandalan ilmiah tetap ditentukan oleh karakteristik sensor, mutu produk, desain validasi, dan transparansi pengolahan berbasis kode.
Kata kunci: Google Earth Engine; suhu permukaan laut; penginderaan jauh kelautan; komputasi awan; pemantauan laut

1. Pendahuluan

Sea surface temperature (SST) is one of the most widely observed physical variables in oceanography because it connects processes operating at the ocean–atmosphere interface with ecological and socioeconomic responses. Variations in SST influence surface heat fluxes, stratification, circulation, primary productivity, species distributions, coral bleaching risk, and the occurrence of marine heatwaves. Long-term satellite SST records have consequently become essential for climate monitoring and marine ecosystem assessment (Merchant et al., 2019; Frölicher et al., 2018). In fisheries and coastal science, SST is frequently analysed together with chlorophyll-a, currents, bathymetry, and catch data to identify potential fishing grounds and to interpret habitat variability.

Satellite observation provides the spatial continuity that is difficult to achieve using ships, coastal stations, and autonomous platforms alone. Nevertheless, SST is not a single uniform measurement. Thermal infrared radiometers typically retrieve the temperature of the ocean skin or sub-skin under clear-sky conditions, whereas gridded analyses such as NOAA Optimum Interpolation SST (OISST) combine satellite and in-situ observations and use interpolation to construct spatially complete fields. The resulting products differ in spatial resolution, temporal sampling, cloud sensitivity, depth representation, uncertainty, and suitability for nearshore applications (Donlon et al., 2012; Huang et al., 2021; Merchant et al., 2019). Therefore, the ease of accessing a dataset should not be confused with its fitness for a particular scientific question.

Google Earth Engine (GEE) has changed the practical environment in which these datasets can be analysed. GEE integrates a large geospatial data catalogue with cloud-based parallel computation and APIs for JavaScript and Python, enabling researchers to process long time series without downloading every scene to local storage (Gorelick et al., 2017). Reviews of GEE applications show rapid growth in environmental research and extensive use of Landsat, MODIS, and Sentinel data, although marine applications remain less represented than terrestrial mapping (Kumar & Mutanga, 2018; Tamiminia et al., 2020; Amani et al., 2020; Pérez-Cutillas et al., 2023). This imbalance is important because the ocean presents specific methodological challenges: clouds obscure thermal infrared observations, coastal pixels are affected by land adjacency and mixed-water conditions, atmospheric correction can dominate retrieval error, and different SST products represent different temperature definitions.

Several studies have demonstrated the practical use of GEE for SST. Ramdani et al. (2021) processed more than 600 Landsat 8 images to examine SST dynamics over the Timor Sea, Van Diemen Gulf, and Beagle Gulf, illustrating the computational advantages of cloud-based processing. Rusydi et al. (2023) used a NOAA SST climate data record in GEE to examine temperature anomalies around earthquakes south of Java, while Indonesian coastal studies have combined GEE-derived SST and chlorophyll-a for fisheries-oriented interpretation. GEE has also been applied to coral bleaching assessment through SST anomalies and accumulated thermal stress metrics (Mhalaskar et al., 2024). These examples indicate that the platform can support both high-resolution coastal analysis and multi-decadal regional studies, but the methodological requirements differ substantially between applications.

Accordingly, this review aims to: (1) explain the principal SST datasets and retrieval options that are relevant to GEE; (2) compare their strengths and limitations for marine and coastal mapping; (3) synthesize representative GEE-based SST applications; (4) identify recurring methodological errors and validation needs; and (5) propose a reproducible workflow for future studies, with particular relevance to tropical and Indonesian waters.

2. Review Method

2.1 Review design and literature selection

A structured narrative review was adopted because the objective was methodological synthesis rather than estimation of a pooled effect size. Literature was identified through targeted searches of scholarly publisher pages, journal databases, institutional repositories, and authoritative data documentation using combinations of the terms “Google Earth Engine”, “sea surface temperature”, “SST”, “marine”, “coastal”, "MODIS", "OISST", "GCOM-C", "Landsat thermal", "validation", and "coral bleaching". Priority was given to peer-reviewed studies published from 2017 onward, while older foundational SST validation and analysis papers were retained when they were necessary to explain retrieval physics, operational SST products, or established validation concepts.

Sources were included when they met at least one of four criteria: (i) they described GEE architecture or its development for geospatial big-data analysis; (ii) they used GEE directly for SST or a closely related marine thermal application; (iii) they developed or validated a satellite or blended SST product relevant to datasets available in GEE; or (iv) they documented an authoritative SST dataset available through the Earth Engine Data Catalog. Studies focused only on terrestrial land surface temperature without a marine component were excluded from the substantive synthesis. The final evidence base emphasized primary journal articles; official Earth Engine dataset pages were used only to verify current dataset identifiers, availability, pixel size, and band definitions.

2.2 Analytical framework

The selected evidence was synthesized across five dimensions: data source and sensor, spatial–temporal resolution, preprocessing and quality control, validation strategy, and marine application. Particular attention was given to the distinction between native satellite SST retrievals and blended or interpolated SST analyses. This distinction is central because a daily gap-free climate field may be ideal for anomaly detection but unsuitable for resolving a narrow coastal plume, while a higher-resolution thermal image may capture coastal gradients but have substantial data gaps because of clouds.

3. Results and Discussion

3.1 Why Google Earth Engine matters for SST analysis

GEE addresses three practical bottlenecks in satellite oceanography: archive access, computational scaling, and reproducibility. Traditional workflows often require manual scene selection, bulk download, local atmospheric or quality filtering, mosaicking, and storage of intermediate rasters. In GEE, image collections can be filtered by date and geometry, mapped through quality-control functions, reduced temporally, and exported only after analysis. This architecture is especially beneficial for tropical regions where frequent cloud cover may require processing hundreds or thousands of observations to create useful composites. The scientific benefit is not merely speed. A scripted workflow records the sequence of filters, scale factors, reducers, and thresholds, making analysis more repeatable than a largely manual desktop workflow (Gorelick et al., 2017; Amani et al., 2020).

However, cloud computing does not eliminate remote-sensing uncertainty. GEE executes the operations specified by the analyst; it does not automatically determine whether a thermal band is an appropriate SST product, whether a quality flag has been interpreted correctly, or whether an interpolation product is being compared unfairly with an instantaneous satellite observation. The platform should therefore be understood as an analytical environment, not as an SST retrieval model. This distinction is especially important for novice users who may calculate temperature from any thermal band without considering atmospheric correction, emissivity, sensor calibration, or the physical definition of SST.

3.2 SST datasets relevant to Google Earth Engine

The Earth Engine catalogue currently includes several direct or indirect sources of SST. Four groups are particularly useful: ocean-colour products that include an SST band (e.g., MODIS Aqua/Terra L3SMI), blended climate analyses (NOAA OISST v2.1), climate data records such as NOAA WHOI SST, and dedicated ocean SST products such as JAXA GCOM-C/SGLI. Landsat thermal data can also be used to estimate high-resolution surface temperature in coastal waters, but it is not equivalent to using a validated global SST product and demands more careful correction and validation.

Table 1. Main SST data options for marine analysis in Google Earth Engine

Dataset / sensor	Approx. spatial resolution	Temporal characteristics	Principal advantage	Main limitation / caution
NASA MODIS Aqua/Terra Ocean Color L3SMI	~4.6 km	Daily; long record from early 2000s	Direct ocean product; SST can be integrated with chlorophyll-a and other ocean-	Cloud-dependent thermal retrieval; coarse for narrow coastal features;

			colour variables	quality filtering required
NOAA OISST v2.1	0.25° (~28 km)	Daily; from 1981 to present	Gap-filled, long-term, stable field suited to climate trends, anomalies, and marine heatwave screening	Too coarse for local coastal gradients; interpolation means values are not purely instantaneous satellite observations
NOAA WHOI SST CDR v2	0.25° (~28 km)	High-frequency climate record	Useful for multi-decadal analysis with diurnal modelling and QC information	Coarse resolution; application should respect product definition and quality flags
JAXA GCOM-C/SGLI L3 SST v3	~4.6 km	Ongoing; multi-day product availability	Dedicated SST product with explicit SST quality flags; useful in tropical and Indonesian waters	Shorter record than MODIS/OISST; cloud and retrieval-quality screening remain necessary
Landsat 8/9 TIRS-derived water surface temperature	Native thermal resolution ~100 m (distributed/resampled products may differ)	16-day per satellite; scene-based	Resolves estuaries, nearshore fronts, plumes, and small embayments	Not a ready-made ocean SST climate product; atmospheric correction, emissivity, cloud masking, and validation are critical

Source: synthesized from Earth Engine dataset documentation and peer-reviewed SST literature (Huang et al., 2021; Merchant et al., 2019; Kurihara et al., 2021; Vanhellemont et al., 2022).

3.3 MODIS for regional and ecosystem-oriented SST mapping

MODIS remains one of the most practical SST sources for marine studies because its long record and daily sampling support seasonal climatologies, interannual analysis, and joint interpretation with ocean-colour variables. The MODIS Aqua L3SMI collection in Earth Engine contains SST together with chlorophyll-a and other marine biogeochemical bands, enabling coherent extraction of environmental variables from one collection. This is particularly attractive for fisheries studies, where thermal habitat and productivity indicators are commonly evaluated together.

The principal limitation is the trade-off between temporal frequency and clear-sky availability. Thermal infrared SST is strongly affected by cloud, and tropical maritime regions may have long periods with sparse valid observations. Monthly or 8-day composites can increase data coverage but may suppress short-lived events, and compositing must be consistent across years. Validation studies also demonstrate that MODIS bias is not spatially or temporally uniform. Gentemann (2014) identified cloud-related contamination and environmental dependencies, while Saleh and Al-Anzi (2021) showed that MODIS Aqua and Terra errors differ between day and night and that triple-collocation approaches can characterize uncertainty more robustly than simple pairwise comparison. Therefore, GEE scripts should explicitly use quality flags and report the number of valid observations contributing to each composite.

3.4 NOAA OISST for long-term trends, anomalies, and marine heat

NOAA OISST v2.1 is particularly valuable when the research question concerns climate variability rather than local coastal structure. The product combines bias-adjusted satellite observations with ship and buoy measurements on a regular 0.25° grid and fills gaps through optimum interpolation. Its continuous daily record from 1981 makes it suitable for calculating climatological means, standardized anomalies, long-term trends, and thermal stress indicators. Version 2.1 corrected biases associated with changes in drifting-buoy data ingestion and improved agreement with independent products (Huang et al., 2021).

The strength of a complete field can become a weakness if the user interprets OISST as a direct high-resolution satellite image. A 0.25° cell spans tens of kilometres and may integrate offshore and nearshore conditions, particularly around islands, narrow straits, and complex Indonesian coastlines. OISST should therefore be favoured for basin to regional scales, marine heatwave context, or anomaly baselines, while higher-resolution products should be used to characterize local thermal gradients. Multi-scale studies can profitably combine OISST for long-term context with MODIS, GCOM-C, or Landsat for spatial detail.

3.5 GCOM-C/SGLI as an emerging SST source for tropical waters

GCOM-C/SGLI provides a dedicated SST product with explicit quality information and has become increasingly relevant for tropical ocean research. Kurihara et al. (2021) described a quasi-physical split-window method for SGLI SST retrieval, emphasizing the sensor-specific physical basis of the product. In Indonesian waters, Sukresno et al. (2021) validated GCOM-C SST against iQuam in-situ data and MUR-SST and reported an estimated accuracy of approximately 0.37 °C. This regional validation is important because tropical atmospheric conditions, cloud cover, and coastal complexity can differ substantially from the conditions represented in global aggregate accuracy metrics.

For GEE users, the main implication is that GCOM-C should not merely be treated as another visually interchangeable SST layer. Quality flags, product version, and observation availability need to be incorporated into the workflow. Its shorter record compared with MODIS and OISST limits multi-decadal climatology, but it is valuable for recent-period monitoring and cross-sensor comparison.

3.6 Landsat thermal data for high-resolution coastal temperature

High-resolution coastal SST is a recurring demand in estuaries, aquaculture zones, thermal-discharge studies, and shallow embayments. Landsat 8 and 9 offer substantially finer spatial detail than global operational SST products. Jang and Park (2019) demonstrated high-resolution coastal SST retrieval from Landsat 8 OLI/TIRS, while Bradtke (2021) evaluated Landsat 8 as a source of high-resolution SST maps in the Baltic Sea. Vanhellemont et al. (2022) further validated Landsat 8 temperature against in-situ measurements collected by surfers and showed that retrieval method and atmospheric treatment can materially affect bias.

These studies support the use of Landsat in GEE for nearshore temperature mapping, but they also highlight a common conceptual error: the thermal band or standard land surface temperature product should not automatically be labelled as SST. Water emissivity, atmospheric transmittance, upwelling and downwelling radiance, cloud edges, adjacency to land, and the thermal skin effect all influence the retrieved value. For publication-quality work, the exact retrieval pathway must be documented. If a standard surface-temperature product is used over water, its limitations should be acknowledged and, where possible, validated against independent marine observations.

3.7 Representative marine applications of GEE-based SST

The literature indicates that GEE-based SST analysis is moving beyond simple mapping toward ecological interpretation and event-based monitoring. Representative studies are summarized in Table 2. These studies demonstrate the platform's flexibility, but they also reveal that the scientific quality of the result depends on matching the product to the scale and mechanism of interest.

Table 2. Representative applications of GEE in sea-surface temperature research

Study	Region / application	Data or approach	Methodological contribution / lesson
Ramdani et al. (2021)	Timor Sea, Van Diemen Gulf, Beagle Gulf; SST and suspended matter	Landsat 8 thermal processing in GEE; Sentinel-3 for TSM	Demonstrated efficient processing of hundreds of scenes and long temporal coverage in a cloud environment
Rusydi et al. (2023)	Southern Java; possible earthquake-related SST anomaly	NOAA WHOI SST CDR in GEE	Illustrated multi-decadal temporal extraction and hypothesis testing; also showed that apparent SST fluctuation should not be over-interpreted causally
Sukresno et al. (2021)	Indonesian seas; product validation	GCOM-C SST, iQuam, MUR-SST	Regional validation showed the need to quantify product-specific accuracy before operational use
Mhalaskar et al. (2024)	Lakshadweep Islands; coral bleaching vulnerability	SST anomaly and degree-heating metrics in GEE	Demonstrated ecosystem-oriented thermal stress assessment using cloud computation
Vanhellemont et al. (2022)	Nearshore coastal waters; high-	Landsat 8 TIRS compared with in-	Showed that retrieval algorithm,

	resolution validation	situ surfer measurements	atmospheric correction, and local target stability strongly influence coastal temperature accuracy

3.8 Quality control: the most important step in a GEE SST workflow

Quality control is often more important than the choice of reducer or visualization palette. Thermal infrared SST retrieval can fail or become biased at cloud edges, under aerosols, in strong atmospheric water vapour, or where land and water are mixed within a pixel. A reliable GEE workflow should therefore begin with product-specific quality masks rather than with temporal averaging. For dedicated products, bitwise QA flags should be decoded according to the data provider's documentation. For Landsat-based retrievals, cloud, cloud shadow, cirrus, and saturation flags should be applied before temperature calculation or compositing.

Nearshore masking also deserves special attention. A general coastline vector may not correspond perfectly to the sensor pixel footprint, and tidal variability can create alternating land–water classification near the shore. Analysts should consider buffering the coastline seaward by one or more pixels for validation or trend analysis when land contamination is suspected. This conservative step sacrifices some nearshore coverage but can reduce false thermal extremes caused by mixed pixels. Conversely, if the nearshore zone is the main research target, higher-resolution thermal data and explicit land-adjacency analysis are preferable to a coarse global product.

3.9 Temporal compositing and anomaly calculation

Temporal aggregation is not a neutral operation. Mean, median, minimum, maximum, and percentile reducers answer different scientific questions. Median composites can suppress residual cloud contamination and outliers, while mean composites preserve the arithmetic expectation but are more sensitive to extremes. For seasonal fisheries analysis, monthly means or medians may be appropriate; for coral bleaching, accumulated thermal stress requires threshold-based metrics rather than simple monthly averaging; for marine heatwaves, daily data relative to a climatological percentile threshold are required. Consequently, a methods section should state the temporal unit, reducer, minimum valid-pixel rule, baseline period, and treatment of missing observations.

Anomaly calculation should use a clearly defined climatology. A simple SST anomaly can be expressed as SST' = SST(t) − climatological SST for the corresponding day, week, or month. If a 30-year climate normal is unavailable at the resolution of interest, the analyst should justify the baseline period and assess whether the period includes a trend that could bias anomalies. OISST is particularly appropriate for stable long-term baselines, whereas shorter records such as GCOM-C can be compared against a longer climatology from another product only with careful cross-product calibration.

3.10 Validation and uncertainty reporting

Validation distinguishes a visually plausible temperature map from a scientifically defensible SST product. The preferred reference is quality-controlled in-situ temperature from drifting buoys, moorings, research vessels, or coastal loggers with a documented measurement depth and time. Matchups should be constrained spatially and temporally because SST can change rapidly near fronts and during daytime warming. Standard statistics include bias, mean absolute error, root mean square error (RMSE), unbiased RMSE, correlation, and sample size. The validation literature also shows the value of triple-collocation or three-way error analysis when no single dataset can be treated as error-free (Gentemann, 2014; Saleh & Al-Anzi, 2021; Sukresno et al., 2021).

When in-situ observations are unavailable, cross-product comparison can still provide useful consistency evidence, but it should not be presented as true accuracy validation. For example, a Landsat-derived coastal temperature map may be compared with MODIS or GCOM-C for regional pattern consistency, while OISST can provide temporal context. Differences are expected because the sensors have different overpass times, footprints, retrieval depths, and processing algorithms. A good paper should therefore report uncertainty sources qualitatively even when quantitative validation is limited.

3.11 Recommended reproducible workflow for marine SST mapping in GEE

Based on the reviewed literature, a defensible GEE workflow can be organized into eight sequential stages: (1) define the oceanographic question and spatial scale; (2)

choose an SST product whose resolution and temperature definition match that question; (3) filter by study area and period; (4) apply product-specific QA, cloud, and land-contamination masks; (5) apply documented scale factors and unit conversions; (6) generate temporal composites or anomalies using a stated baseline and reducer; (7) validate against in-situ data or, when unavailable, conduct transparent cross-product consistency analysis; and (8) export maps and tabular time series together with code, parameter values, and uncertainty notes. Table 3 converts these stages into a publication-oriented checklist.

Table 3. Publication checklist for reproducible SST mapping using Google Earth Engine

Stage	Minimum information to report	Common error to avoid
Research scale	Study extent, coastal/offshore focus, temporal scale, ecological or physical objective	Selecting a dataset only because it is easy to visualize
Dataset	Collection ID, sensor/product, version, native pixel size, observation period	Calling land surface temperature or brightness temperature "SST" without justification
Quality control	QA bits, cloud mask, land/water mask, valid-observation threshold	Averaging all pixels before removing clouds and poor-quality retrievals
Preprocessing	Scale factor, offset, unit conversion, atmospheric correction if required	Applying undocumented constants or mixing Kelvin and Celsius
Temporal analysis	Reducer, composite interval, baseline climatology, missing-data rule	Comparing months/years with different valid-pixel densities without checking coverage
Validation	Reference data, matchup window, sample size, bias/RMSE or comparable statistics	Using another satellite product as if it were error-free ground truth
Reproducibility	GEE code, date of access, export scale/projection, key thresholds	Reporting only map figures without sufficient processing detail
Uncertainty	Sensor/product limitations, coastal mixed pixels, cloud gaps, representativeness	Interpreting visually strong patterns as causal evidence without supporting analysis

3.12 Relevance for Indonesian marine and fisheries research

Indonesia is an especially appropriate setting for GEE-based SST research because it combines a vast archipelagic domain, strong monsoonal variability, the Indonesian Throughflow, coastal upwelling systems, coral reefs, and economically important fisheries. At the same time, persistent cloudiness and highly fragmented coastlines challenge thermal infrared remote sensing. This combination makes a multi-product strategy attractive. OISST can provide the long-term regional baseline; MODIS or GCOM-C can describe mesoscale and ecosystem-relevant spatial variability; Landsat can be reserved for specific nearshore sites requiring finer spatial detail.

Research quality would improve if Indonesian SST studies moved beyond descriptive colour maps toward explicit hypothesis testing and uncertainty assessment. Examples include quantifying SST–chlorophyll relationships by season, testing thermal habitat associations with catch-per-unit-effort, evaluating coastal upwelling indices, identifying marine heatwave exposure of coral reefs, or comparing satellite SST with low-cost temperature loggers. GEE can reduce the computational burden of these analyses, but robust field or independent observational data remain essential for validation and ecological inference.

3.13 Limitations of Google Earth Engine for marine SST research

Despite its advantages, GEE has several limitations. First, not every operational or research SST product is available in the public catalogue, and catalogue versions may lag behind specialist oceanographic archives. Second, server-side processing requires a different programming model from conventional desktop scripting, and careless use of reducers, reprojection, or scale can produce unintended outputs. Third, very high-resolution coastal work may require algorithms or atmospheric inputs that are easier to control outside GEE. Fourth, reproducibility still depends on version awareness: datasets can be deprecated, reprocessed, or replaced, and code should therefore record collection identifiers and access dates.

Finally, the accessibility of GEE can encourage methodological oversimplification. A map can be produced rapidly, but rapid production does not guarantee oceanographic validity. The most important safeguard is to connect every processing decision to the physical meaning of the data and to document uncertainty. This principle is more consequential than any particular coding technique.

4. Conclusion

Google Earth Engine has become a powerful infrastructure for sea surface temperature mapping because it combines large satellite archives, cloud computation, and script-based reproducibility. Its principal value is the ability to analyse long and spatially extensive SST records without the storage and processing constraints of conventional local workflows. MODIS Aqua/Terra is well suited to regional marine and ecosystem analysis, NOAA OISST v2.1 provides a robust basis for long-term anomalies and climate-scale variability, JAXA GCOM-C/SGLI offers a useful dedicated SST product for recent tropical monitoring, and Landsat thermal data can resolve finer coastal patterns when retrieval and validation are handled carefully. No single dataset is optimal for all objectives. The dominant scientific risks are inadequate quality masking, confusion between generic surface temperature and validated SST, land-contaminated coastal pixels, inconsistent temporal compositing, and insufficient validation. Future marine studies should therefore adopt multi-product and multi-scale designs, quantify uncertainty, publish reproducible GEE code, and integrate satellite analysis with in-situ observations whenever possible. For Indonesian waters in particular, such practices can strengthen applications in fisheries habitat mapping, coral thermal stress, coastal upwelling, marine heatwaves, and long-term ecosystem monitoring.

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Conflict of Interest

The author declares no conflict of interest.

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