

Article

A Day–Night-Differentiated Method for Sea Surface Temperature Retrieval with Emissivity Correction

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Highlights

What are the main findings?

- An emissivity-corrected, day–night-differentiated sea surface temperature (SST) retrieval method is developed by explicitly accounting for the angular and wind speed dependence of sea surface emissivity and integrating mid-infrared observations for nighttime retrieval.
- The proposed method achieves high and consistent SST accuracy under both daytime and nighttime conditions, outperforming fixed-emissivity and existing SST retrieval approaches, especially at large view zenith angles.

What are the implications of the main findings?

- Incorporating a physically consistent emissivity parameterization effectively reduces angular-dependent biases, significantly improving SST retrieval stability over rough sea surfaces and high-latitude regions.
- The synergistic use of mid-infrared and thermal infrared bands enhances resistance to atmospheric water vapor effects at night, providing a reliable solution for large-scale and long-term SST monitoring applications.

Abstract

Sea surface temperature (SST) is widely used to characterize marine productivity, environmental pollution, and climate variability, and is commonly derived from thermal infrared measurements obtained by optical satellite sensors. However, accurately retrieving large-scale SSTs remains challenging due to the complexity of air–sea coupling processes and the difficulty of accurately obtaining key intermediate parameters. This study proposes a day–night-differentiated SST retrieval method with emissivity correction rather than treating it as a fixed value. Specifically, radiance characteristics from the mid-infrared band are integrated alongside those from thermal infrared bands. The retrieved SSTs are then validated against the MODIS SST product and in situ measurements. The results demonstrate strong consistency between the retrieved SST and the MODIS SST product, with overall root mean square errors (RMSEs) of 0.66 K and 0.82 K for daytime and nighttime, respectively. In winter the RMSEs improve to 0.37 K (day) and 0.42 K (night). In situ validation against Argo measurements in 2019 shows that the RMSEs of the retrieved SSTs are approximately 0.26 K for both day and night. This confirms the efficacy of the proposed



Academic Editor: Enric Valor

Received: 6 January 2026

Revised: 7 February 2026

Accepted: 12 February 2026

Published: 14 February 2026

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SST retrieval approach, providing a feasible solution for high-precision SST retrieval in high-latitude regions with large view zenith angles.

Keywords: sea surface temperature; emissivity; mid-infrared-thermal; in situ data; cross-validation

1. Introduction

Sea surface temperature (SST), a core parameter of the ocean's thermodynamic state, serves as a critical link connecting the ocean, atmosphere, and biosphere. Its accuracy directly affects the reliability of global climate system simulations, marine ecological dynamics research, and disaster early warning systems [1]. SST strongly influences the formation of climate patterns, examples being the El Niño–Southern Oscillation [2] and the North Atlantic Oscillation [3], which have profound effects on weather systems worldwide. Moreover, SST serves as a key indicator of marine ecosystem health, affecting species distribution [4], primary productivity [5], and biogeochemical cycles [6]. It also contributes to the intensification of tropical cyclones and other extreme marine meteorological events through its control of heat and moisture fluxes [7]. Therefore, continuous and precise monitoring of SST is crucial for advancing our understanding of climate dynamics, supporting ecosystem management, and improving predictive capabilities for extreme weather events.

Thermal infrared (TIR) remote sensing enables SST estimation with enhanced spatial coverage and revisit frequency compared with ship- and buoy-based observations. Currently, TIR-based SST retrieval methods could be primarily classified into three main types: single-channel algorithms, multi-channel algorithms, and machine learning algorithms. The single-channel algorithm assumes a known emissivity and requires precise atmospheric data. Since sea surface emissivity (SSE) is typically greater than 0.96, a simplified representation of atmospheric effects was introduced by integrating upwelling and downwelling atmospheric radiance components into a single mean atmospheric effect temperature [8]. This simplification reduces the number of required input parameters, but the method remains highly dependent on the accuracy of atmospheric profiles. Furthermore, multi-channel algorithms, particularly split-window (SW) algorithms, are widely used for SST retrieval. Atmospheric correction in SST retrieval was achieved in early studies by leveraging the contrast in absorption characteristics of two adjacent thermal infrared bands around 11–12 μm , forming the basis of the SW algorithm [9]. Subsequent studies extended the SW framework into multiple formulations by accounting for different atmospheric and surface effects, and have been applied to the Advanced Very-High-Resolution Radiometer (AVHRR) [10,11], and the Moderate-Resolution Imaging Spectroradiometer (MODIS) [12]. In addition, mid-infrared (MIR) bands have also been used to retrieve SST during nighttime, benefiting from their reduced sensitivity to water vapor [13]. More recently, machine learning algorithms have been introduced for SST retrieval, demonstrating their potential in handling complex nonlinear relationships [14], as they offer advantages for handling complex retrieval problems. However, these algorithms suffer from limitations such as the high demand for training data and interpretability issues.

Traditional TIR-based SST algorithms now achieve global coverage, but their accuracy is still affected by various key intermediate parameters, such as SSE [15]. Due to the sea's relative uniformity compared to land, traditional algorithms treat the sea surface as a graybody and retrieve SST by setting SSE as a fixed value [16]. However, the emissivity of the actual dynamic, rough sea surface is strongly influenced by view zenith angle (VZA), wind speed, and wave morphology. For example, SSE exhibits a pronounced angular dependence, decreasing by approximately 1.5% at 11 μm and 2.4% at 12 μm as the view

zenith angle increases to 55° [17]. This must be explicitly considered in SST retrievals, as a decrease in SSE can cause a large systematic SST error, for example, approximately -1.2 K at a viewing angle of around 55° [18]. Consistent with this, Jia and Minnett demonstrate via radiative transfer simulations that SSE can introduce non-negligible biases in MODIS infrared SST retrieval and further introduce an emissivity-related correction term, demonstrating its effectiveness for improving SST retrieval accuracy [19]. To mitigate emissivity-induced errors, a series of SSE models have been developed, including both empirical and theoretical approaches. Empirical models, such as the classical Wilson fifth-power model [20], typically parameterize VZA but neglect wind-driven sea surface roughness, limiting their accuracy under varying ocean conditions. In contrast, advanced theoretical models incorporate additional factors such as wavelength, VZA, and wind speed, enabling a more realistic representation of ocean emissivity. Specifically, a rough sea surface model was established by relating the standard deviation of the sea wave slope distribution to wind speed [21]. Based on the rough sea surface model, a theoretical SSE model was formulated and applicable to the infrared window regions of $3.5\text{--}4.1\text{ }\mu\text{m}$ and $8\text{--}13\text{ }\mu\text{m}$. Subsequent studies further improved the physical representation by incorporating sea surface reflection [22] and wave-shadowing effects [23]. For instance, Wu improved the Masuda-based model by accounting for single reflection from the sea surface [24], thereby reducing large biases in SSE at large VZAs and enhancing estimation accuracy. The theoretical models offer strong physical interpretability and high accuracy within a 60° VZA [25], but their complex input requirements limit their applicability for global SST retrieval [26]. To address the high computational cost of theoretical SSE models, a simple parametrization that expresses SSE in terms of wind speed and VZA was proposed to balance accuracy and efficiency [27]. Building on this concept, Ma et al. further developed a simplified SSE model for SST retrieval using Sentinel-3 SLSTR TIR data and highlighted its potential applicability in the MIR region [26]. However, both approaches neglect the nonlinear response of SSE to wind speed at large VZAs, namely first increasing and then decreasing, thereby reducing the accuracy of SSE estimation and SST retrieval.

Inspired by simplified sea surface emissivity modeling, we propose an emissivity-corrected, day–night-differentiated sea surface temperature (SST) retrieval framework that accounts for the nonlinear dependence of emissivity on viewing geometry and surface roughness. A wind speed grouping strategy is introduced to parameterize sea surface emissivity as a function of view zenith angle and wind speed, enabling accurate representation of emissivity variations at large viewing angles with low computational cost. Based on this refined emissivity model, a day–night-differentiated SST retrieval scheme is developed, in which an emissivity-corrected thermal infrared split-window algorithm is applied during daytime, while a mid-infrared-enhanced triple-channel algorithm is adopted at night to mitigate atmospheric water vapor effects. This integrated framework effectively reduces angular-dependent and atmospheric uncertainties, improving SST retrieval accuracy and robustness.

The main contributions of this study are summarized as follows:

1. An emissivity-corrected, day–night-differentiated SST retrieval framework is proposed to jointly address angular effects, surface roughness variability, and diurnal differences in atmospheric sensitivity.
2. A simplified sea surface emissivity parameterization with wind speed grouping is developed, capturing the nonlinear wind speed dependence of emissivity at large view zenith angles with high efficiency.
3. A MIR-TIR synergistic nighttime retrieval strategy is introduced, effectively suppressing water vapor interference and enhancing nighttime SST retrieval stability.

2. Datasets

2.1. EOS-MODIS Data

MODIS carried by the Terra and Aqua platforms acquire observations across 36 bands spanning the visible, near-infrared, and thermal infrared regions. It offers spatial resolutions of 250 m, 500 m, and 1000 m, with a 1–2 day revisit cycle, enabling comprehensive Earth system monitoring. In this study, MODIS bands 22 (B22), 23 (B23), 31 (B31) and 32 (B32), with a spatial resolution of 1 km, are used to retrieve SST. Band details are listed in Table 1 [28].

Table 1. Details of the MODIS sensor for bands 22, 23, 31 and 32.

Band Number	Center Wavelength (μm)	Bandwidth (μm)	NEAT (K)
22	3.959	0.0594	0.07
23	4.050	0.0608	0.07
31	11.030	0.5000	0.05
32	12.020	0.5000	0.05

Furthermore, four MODIS products from 2019 are used, including the MODIS Level-1B dataset (MOD021KM), the MODIS Level-1 Geolocation product (MOD03), the MODIS Cloud Mask product (MOD35_L2) and the MODIS SST product (MOD28). Among these, the brightness temperatures for B22, B23, B31 and B32 are extracted from MOD021KM for global SST retrieval, while MOD03 and MOD35 are collocated with MOD021KM. The MOD03 product includes per-pixel geolocation information at a 1 km resolution for all MODIS overpasses, providing longitude and latitude for spatial collocation together with the corresponding VZA required for SST retrieval. MOD35 supplies cloud, land–sea, and ice masks, together with quality flags, aiming to identify scenes where land, ocean and atmosphere products should be retrieved based upon the amount of obstruction of the surface due to clouds and thick aerosol. Furthermore, a cloud edge dilation of two pixels is implemented to minimize cloud edge contamination [29]. In addition, MOD28 offers daily, 8-day, monthly, and annual global SST data, with a quality-assessment parameter assigned to each pixel, from which the daily SST data at a 4.62 km resolution are extracted for cross-validating the retrieved SST in this study. To ensure data reliability, pixels with quality flags of ‘0’ or ‘1’ (indicating good quality) are selected, and two-dimensional bilinear interpolation is applied for spatial matching between MOD021KM and MOD28.

2.2. Simulated Data

In this study, the Seebor V5.0 atmospheric profile dataset is utilized to simulate TIR and MIR brightness temperatures at the top of the atmosphere (TOA) for MODIS across diverse atmospheric and SST conditions. The dataset contains 15,704 global profiles, including 7156 representative marine profiles [30]. Each profile is defined on 101 vertical layers, providing pressure, temperature, water vapor concentration, and ozone density. A profile is classified as cloudy if the relative humidity exceeds 90% in any single layer, or exceeds 85% in two adjacent layers, while foggy profiles are characterized by a relative humidity exceeding 80% within 2 m of the surface. Based on these criteria, only cloud-free ocean profiles are retained. Abnormal cases, such as those exhibiting temperature inversion with decreasing pressure in adjacent layers, are also removed. Ultimately, as shown in Figure 1, a total of 1604 cloud-free marine profiles are selected, with bottom atmospheric temperature (T_a) ranging from 221.18 K to 309.59 K and total column water vapor (TCWV) spanning from 0.0299 g/cm² to 6.2935 g/cm².

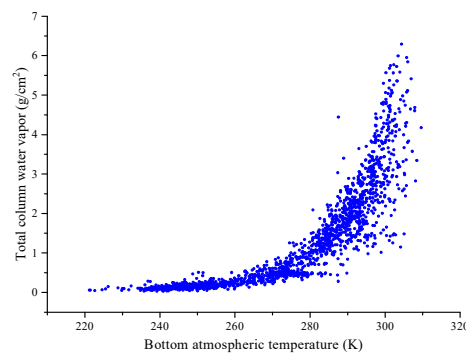


Figure 1. Distribution of bottom atmospheric temperature versus total column water vapor for the 1604 cloud-free profiles.

Subsequently, the MODTRAN 5 model is driven by the 1604 atmospheric profiles to simulate the atmospheric parameters: the atmospheric upwelling radiance, the atmospheric downwelling radiance, and atmospheric transmittance under various surface and viewing geometries. Furthermore, based on radiative transfer theory, TOA radiance is simulated and subsequently transformed into brightness temperature via the Planck function, thereby generating the simulated dataset for coefficient fitting in the SST retrieval algorithm (training dataset) and validating its performance (validation dataset). In this study, a training dataset is simulated using 1604 atmospheric profiles. Specifically, the SSTs are determined according to the sea–air temperature difference ($T_s - T_a$). Daytime temperature differences span -4 to 16 K, whereas nighttime values extend from -16 to 4 K, using a uniform 4 K interval. Furthermore, as the pixel overlap and image distortion are severe at large VZAs for MODIS [31], the VZA for each atmospheric profile varies from 0° to 60° with a step of 5° . Furthermore, to cover a wide range of SSE values, the SSE for each band is calculated using the Wu and Smith model with inputs of VZA and wind speed [23], and 10 different SSEs values are set at equal intervals for each profile, ranging from 0.932 to 0.977 for B22, 0.933 to 0.978 for B23; 0.964 to 0.993 for B31; and 0.948 to 0.990 for B32. Additionally, a marine aerosol model is used. With these inputs and the spectral response function of MODIS, the simulated TOA radiance for various surface and atmospheric conditions is generated. Notably, the validation dataset is also generated using 200 randomly selected atmospheric profiles and wind speed varies over a range of 0 – 15 m/s with 3 m/s intervals, resulting in a set of 78 SSEs for each profile in combination with the 13 VZAs.

2.3. ERA5 Reanalysis Data

The fifth-generation atmospheric reanalysis (ERA5) data from the European Centre for Medium-Range Weather Forecasts (ECMWF) provide hourly estimates of global climate variables from 1940 onward and have been broadly applied in temperature retrieval studies [32]. In this study, the following parameters are extracted from ERA5 reanalysis products at a $0.25^\circ \times 0.25^\circ$ grid for SST retrieval from MODIS observations: (1) 2 m air temperature (T_{2m} , K), which is interpolated between the lowest model level and the surface; (2) TCWV (kg/m^2), representing the total amount of water vapor from the Earth’s surface to the TOA, which needs to be converted to g/cm^2 when used; (3) 10 m eastward (U_v) and northward (U_u) wind components (m/s), which are used to calculate total wind speed by vector summation ($U = \sqrt{U_u^2 + U_v^2}$). Among these parameters, T_{2m} and TCWV are used to determine the optimal coefficients for SST retrieval, while wind speed is employed for the computation of SSE. Additionally, the ERA5 data closest in time to the MODIS data are selected, and two-dimensional bilinear interpolation is used to achieve spatial matching.

2.4. Argo In Situ Data

The Argo program consists of a near real-time, globally distributed array of profiling floats that record temperature, salinity, and pressure from the near-surface down to 2000 dbar [33]. Initiated in 2000, the program now maintains nearly 4000 active floats operating across the world's oceans. To evaluate the quality of the data, each profile is labeled using quality flags from 1 (good) to 4 (bad). In this study, core Argo profiles from 2019 containing temperature and pressure with a quality flag of '1' are extracted from the Global Ocean Argo Profile Dataset Version 3.0 [34], along with the corresponding latitude, longitude, and date for in situ validation. To avoid contamination, Argo floats are configured to end profiling at approximately 5 m depth [33]. To estimate in situ SST, we extrapolate each temperature–depth profile to the sea surface by fitting the upper-ocean segment using locally polynomial regression (LOESS) [35]. During data processing, the measurements from 5 m to 150 m are first used to perform an initial LOESS fit and compute the residuals; and then those samples with absolute residuals exceeding $3 \times \text{RMSE}$ (RMSE calculated from the initial fit) are removed, and LOESS is refitted using the remaining data. Specifically, as denoted in reference [36], a span of 0.20 (each local regression uses the nearest 20% of samples within the segment) and a polynomial degree of 3 is adopted for the LOESS. This procedure provides a robust estimation of the extrapolated SST while accounting for vertical temperature variations in the upper ocean. Spatial matching with MODIS imagery is performed using the nearest-neighbor method based on geographic coordinates, while temporal matching requires the time difference between in situ measurements and satellite overpasses to be within 0.5 h [37]. Ultimately, as shown in Figure 2, a total of 505 daytime and 537 nighttime samples are selected for validation. Daytime and nighttime samples are primarily distributed across the central regions of the Pacific, Atlantic, and Indian Oceans, with additional clusters observed near the western Pacific and northern Indian Ocean coastlines.

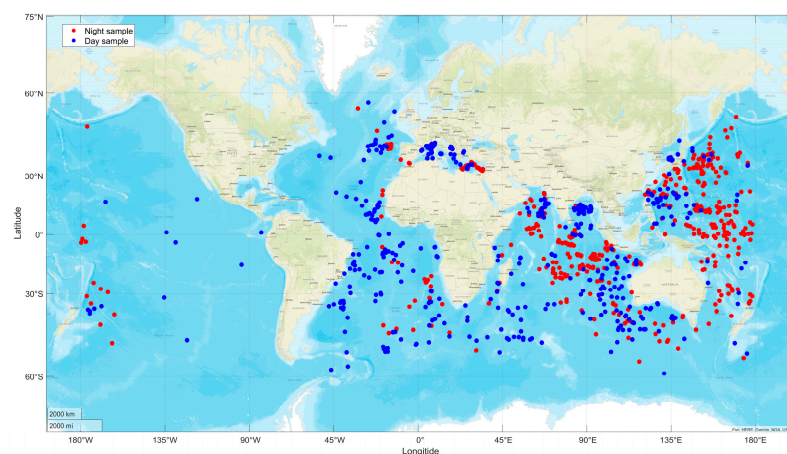


Figure 2. Distribution of Argo in situ samples for daytime and nighttime scenarios.

3. Methodologies

3.1. Simplified Sea Surface Emissivity Model

To address the limitation of insufficient accuracy in SSE estimation at large viewing angles, Wu and Smith proposed an enhanced model that incorporates a single-reflection mechanism. Building upon the Masuda's model, this refinement delivers improved accuracy under a wide range of viewing geometries. Furthermore, the model effectively repre-

sents SSE within the infrared atmospheric window regions, specifically in the 3.5–4.1 μm and 8–13 μm bands. The revised effective emissivity is expressed as

$$\varepsilon(n, \theta, U) = \varepsilon_{\text{Masuda}}(n, \theta, U) + \Delta\varepsilon_{\text{reflection}}(n, \theta, \theta_r, U) \quad (1)$$

where ε is the SSE corrected for single reflection; n is the complex refractive index; θ is the VZA; U is the 10 m near-surface wind speed; $\varepsilon_{\text{Masuda}}$ is the SSE from the Masuda model; $\Delta\varepsilon_{\text{reflection}}$ is the reflected radiation from surrounding wave facets that reaches the sensor after a single reflection; and θ_r is the VZA in the reflection direction $\vec{r}$.

Due to the high computational cost of theoretical models, simplified models are used to enhance efficiency. Specifically, SSE is treated as a constant ($\varepsilon = \varepsilon_0$, where ε_0 is the SSE at nadir under zero wind speed, denoted as Model 1) [16], or varies with VZA ($\varepsilon = \varepsilon_0(1 - (1 - \cos \theta)^5)$, denoted as Model 2) [20], and further varies with VZA and wind speed ($\varepsilon = \varepsilon_0(\cos(\theta^{c_1 U + c_2}))^{c_3}$, $\varepsilon = \varepsilon_0(1 - (1 - \cos(\theta^{c_3 U + c_4}))^{c_5 U + c_6})$, where c_i is the coefficient, denoted as Model 3 and Model 4, respectively) [26,27]. To determine the coefficients of the simplified models, a series of SSEs is simulated using the Wu and Smith model with VZAs ranging from 0° to 60° with a step size of 1° , and the wind speed ranging from 0 to 15 m/s with a step of 1 m/s (Figure 3), yielding 976 samples for each band. Furthermore, to better capture characteristic SSE behavior, decreasing and then increasing with wind speed at large VZAs, a wind speed-grouped fitting strategy is further applied to Models 3 and 4, which are denoted as Model 5 and Model 6, respectively. The wind speed interval boundaries are determined based on statistical analysis of the experimental results. Uneven grouping of wind speeds (0–3, 3–11, and 11–15 m/s) results in smaller SSE fitting errors across all four bands compared to evenly spaced groups. Table 2 shows the root mean square error (RMSE) and determination coefficient (R^2) for Models 1–6. Notably, Models 1 and 2 exhibit larger errors; in particular, Model 1 yields negative R^2 values across the four bands, indicating that it performs worse than a mean-based baseline. In contrast, Models 3–6 achieve substantially improved accuracy, with RMSE values below 0.0006 and R^2 exceeding 0.99 across all four bands.

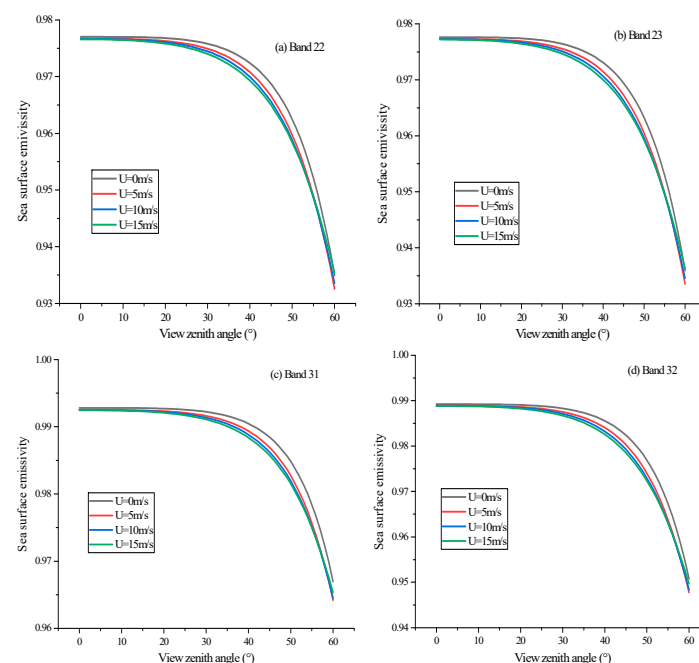
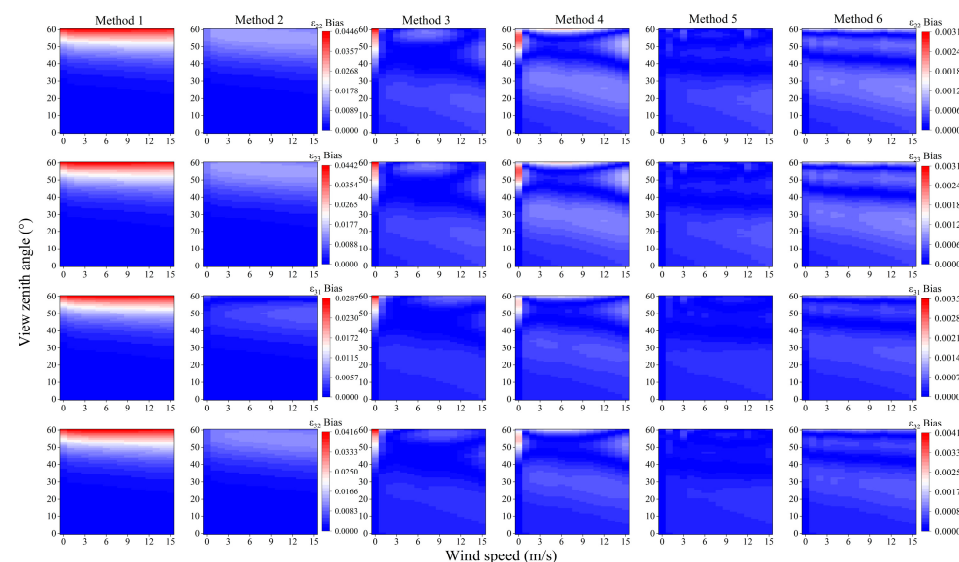


Figure 3. Sea surface emissivity under different view zenith angles and wind speeds for B22, B23, B31 and B32 based on the Wu and Smith model.

Table 2. The root mean square error and determination coefficient of six simplified sea surface emissivity models for bands 22, 23, 31 and 32.

	Band	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
RMSE	B22	0.0137	0.0069	0.0006	0.0004	0.0003	0.0005
	B23	0.0135	0.0068	0.0006	0.0004	0.0003	0.0005
	B31	0.0085	0.0023	0.0005	0.0004	0.0002	0.0004
	B32	0.0125	0.0056	0.0006	0.0005	0.0003	0.0005
R^2	B22	−0.4844	0.6105	0.9970	0.9984	0.9992	0.9978
	B23	−0.4844	0.6184	0.9970	0.9984	0.9992	0.9978
	B31	−0.5154	0.8875	0.9954	0.9966	0.9984	0.9966
	B32	−0.5147	0.6979	0.9968	0.9979	0.9991	0.9977

Furthermore, Figure 4 shows the absolute bias of SSE between the six simplified models and the Wu and Smith model for each band under different VZAs and wind speeds. Overall, the absolute bias of Model 1 and Model 2 increases progressively with VZA, reaching maximum values of 0.045 and 0.015, respectively, which fall short of the SSE accuracy required for SST retrieval. A detailed comparison reveals that Model 3 and Model 4 exhibit pronounced biases when VZA exceeds 40° with near-zero wind speed, as well as at around 60° . In addition, Model 4 displays considerable errors at VZAs of $20\text{--}40^\circ$ and $45\text{--}55^\circ$ under wind speeds above 12 m/s. By contrast, Model 5 and Model 6 effectively suppress the errors at large VZAs, particularly when VZA is greater than 40° and wind speed is near 0 m/s, where the maximum bias reduction reaches 0.0039. Among all models, Model 5 achieves the best performance, with band-specific RMSE values ranging from 0.0002 to 0.0003 and R^2 values above 0.998. Specifically, for all four bands, the absolute bias remains consistently below 0.0008 and the RMSEs are 3×10^{-4} at VZA = 0° , and are 0.001, 0.001, 8.4×10^{-4} , and 0.001 at VZA = 60° .

**Figure 4.** Absolute bias of sea surface emissivity between the six simplified models and the Wu and Smith model for the four bands under different wind speeds and view zenith angles.

3.2. Day–Night-Differentiated SST Retrieval Algorithm

In 1975, McMillin demonstrated that atmospheric effects on surface radiance can be compensated for by exploiting absorption differences between measurements at two wavelengths or viewing angles, forming the basis for subsequent developments of SW algorithms, incorporating different considerations of atmospheric and surface emission effects. It has also been reported that SW algorithms originally developed for land surface temperature can achieve good performance under ocean conditions [26,38,39]. In this study, for daytime, we adopt the algorithm proposed by Galve et al. (denoted as Day-Algorithm-1, DA-1) [40]. Its expression is given as follows:

$$T_S = A_0 + A_1 T_i + A_2 (T_i - T_j) + A_3 (T_i - T_j)^2 + (A_4 + A_5 \omega + A_6 \omega^2)(1 - \varepsilon) + (A_7 + A_8 \omega) \Delta \varepsilon \quad (2)$$

where T_S is the sea surface temperature; T_i and T_j are the corresponding brightness temperatures of MODIS B31 and B32, respectively; ε is the average of the sum of the SSE values of MODIS B31 and B32; $\Delta \varepsilon$ is the difference between the SSE values of MODIS B31 and B32; ω is the TCWV; and A_i ($i = 0-8$) are the coefficients.

For nighttime, the three-channel algorithm proposed by Sun et al. is adopted (denoted as Night-Algorithm-1, NA-1), which enhances atmospheric correction through the use of the MIR band [41]. Its expression can be written as follows:

$$T_S = B_0 + (B_1 + B_2(1 - \varepsilon_i)/\varepsilon_i)T_i + (B_3 + B_4(1 - \varepsilon_j)/\varepsilon_j)T_j + (B_5 + B_6(1 - \varepsilon_m)/\varepsilon_m)T_m \quad (3)$$

where ε_i and ε_j are the corresponding SSE values for MODIS B31 and B32, respectively; ε_m is the SSE of the MIR band (B22 or B23) and T_m is the corresponding brightness temperature; and B_i ($i = 0-6$) are the coefficients. Notably, SSE is parameterized and can be derived from the simplified SSE model presented in this study.

To determine the algorithm coefficients in Equations (2) and (3), the simulated data described in Section 2 are used, and for a given VZA, the T_a and atmospheric TCWV are grouped into discrete sub-ranges to improve SST retrieval accuracy [42]. The T_a is divided into three sub-ranges with an overlap of 5 K, namely: $T_a \leq 285$ K (cold), $280 \text{ K} \leq T_a \leq 295$ K (warm), and $T_a \geq 290$ K (hot); the TCWV is divided into six sub-ranges with an overlap of 0.5 g/cm^2 . However, as shown in Figure 1, low T_a is often accompanied by low TCWV, and vice versa. Therefore, for a cold atmosphere, TCWV is divided into two sub-ranges, namely $[0, 1.5]$ and $[1, 2.5] \text{ g/cm}^2$; for warm atmosphere, TCWV is divided into four sub-ranges, including $[0, 1.5]$, $[1, 2.5]$, $[2, 3.5]$, and $[3, 4.5] \text{ g/cm}^2$; and for a hot atmosphere, the TCWV intervals include $[0, 1.5]$, $[1, 2.5]$, $[2, 3.5]$, $[3, 4.5]$, $[4, 5.5]$ and $[5, 6.5] \text{ g/cm}^2$. In addition, to ensure physical realism, samples with SSTs below 270 K or above 310 K are excluded. Therefore, coefficients for each sub-range are derived from simulated data using Levenberg–Marquardt regression, which provides robust convergence for non-linear least-squares fitting by combining the fast local convergence of the Gauss–Newton method with the stability of gradient descent updates. The coefficients at intermediate VZAs are obtained in practice through linear interpolation.

In addition, with the aid of a simulated training dataset, the B22 and B23 are individually applied in conjunction with NA-1 for nighttime SST retrieval to identify the optimal MIR band. As shown in Figure 5, B22 consistently outperforms B23 across all VZAs, yielding RMSE values below 1.2 K, which reflects its lower sensitivity to VZA. A more detailed comparison under various atmospheric conditions is provided in Table 3. Under cold conditions, both bands perform comparably, with RMSE values remaining below 0.15 K, indicating minimal sensitivity to TCWV. In contrast, under warm conditions, the errors increase with TCWV for both bands; however, B22 consistently outperforms B23. For instance, at a TCWV of $3.0-4.5 \text{ g/cm}^2$, the RMSE of B22 remains below 0.40 K, while that of

B23 reaches 0.65 K, highlighting the higher stability of B22. This performance gap becomes even more pronounced under hot conditions: when TCWV exceeds 3.5 g/cm^2 , B23 exhibits substantial error growth, with RMSE values exceeding 0.90 K, whereas B22 maintains lower errors, typically within 0.40–0.50 K. Collectively, these findings demonstrate that B22 provides enhanced robustness, thereby representing a more reliable choice for nighttime SST retrieval.

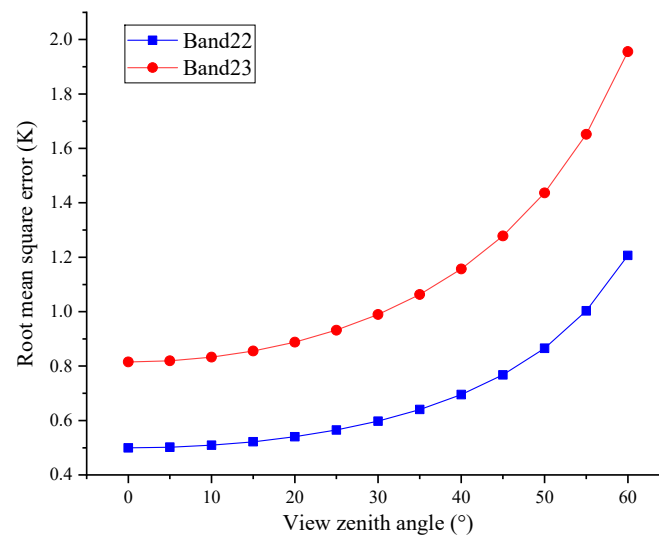


Figure 5. Variation in root mean square errors with view zenith angles for Night-Algorithm-1 using B22 and B23.

Table 3. SST fitting error (root mean square error) for Night-Algorithm-1 using bands 22 and 23 under different atmospheric conditions.

Atmospheric Conditions		SST Fitting Error (RMSEs) (K)	
T_a (K)	TCWV (g/cm^2)	B22	B23
Cold	[0, 1.5]	0.1225	0.1233
	[1, 2.5]	0.1449	0.1486
Warm	[0, 1.5]	0.1977	0.2080
	[1, 2.5]	0.3044	0.3605
	[2, 3.5]	0.3660	0.5151
	[3, 4.5]	0.3890	0.6536
Hot	[0, 1.5]	0.3861	0.4848
	[1, 2.5]	0.4126	0.5528
	[2, 3.5]	0.4879	0.7604
	[3, 4.5]	0.5046	0.8998
	[4, 5.5]	0.4253	0.7549
	[5, 6.5]	0.3665	0.6069

Furthermore, the variation in RMSE associated with the fitting errors ($u_{\text{Algorithm}}$) with respect to VZAs across all sub-ranges is presented in Figure 6. It is worth noting that an increase in RMSE is observed with an increase in the VZA. For DA-1, the coverage ranges of RMSE are 0.06–0.22 K, 0.07–0.79 K, and 0.13–1.50 K under cold, warm, and hot atmospheric conditions, respectively. For NA-1, the corresponding ranges are 0.08–0.21 K, 0.12–0.58 K, and 0.22–0.82 K, respectively.

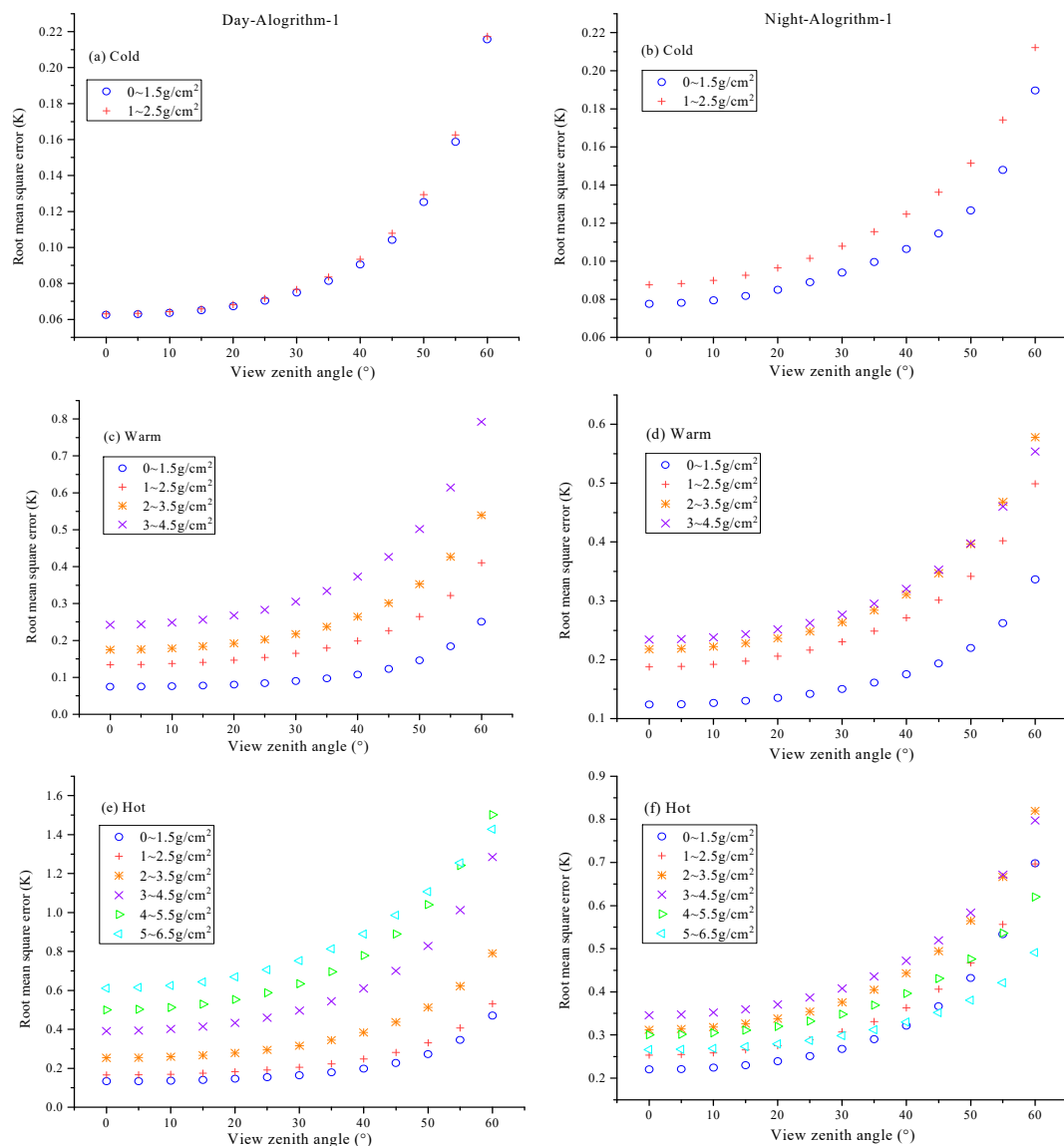


Figure 6. Variation in root mean square errors with view zenith angles for DA-1 and NA-1 under twelve sub-ranges.

4. Sensitivity Analysis

SST estimation errors originate from multiple sources, including uncertainties in the brightness temperature, T_b , TCWV and SSE, and the SST retrieval algorithm itself. Accordingly, a sensitivity analysis is conducted based on the simulated training dataset under the assumption that the input parameters are mutually independent.

4.1. Uncertainty of Brightness Temperature

The expected instrument noise ($NE\Delta T$) in MODIS bands 22, 31, and 32 is 0.07 K, 0.05 K and 0.05 K, respectively, which is extremely important for the high radiometric fidelity of brightness temperature. The influence of $NE\Delta T$ uncertainty on SST retrieval is assessed by perturbing the simulated TOA brightness temperatures with zero-mean Gaussian noise, the standard deviation of which corresponds to the $NE\Delta T$ of each spectral band [43], and SSTs are subsequently retrieved using DA-1 and NA-1. Figure 7 presents the distribution of SST differences obtained by comparing retrievals based on noise-perturbed and noise-free brightness temperatures. It is noted that the means of the differences are both 0.0 K during daytime and nighttime. For DA-1, the standard deviation (STD) is 0.12 K and 0.15 K at

VZA = 0° and 60°, respectively; for NA-1, the STD is 0.08 K and 0.09 K at VZA = 0° and 60°, respectively.

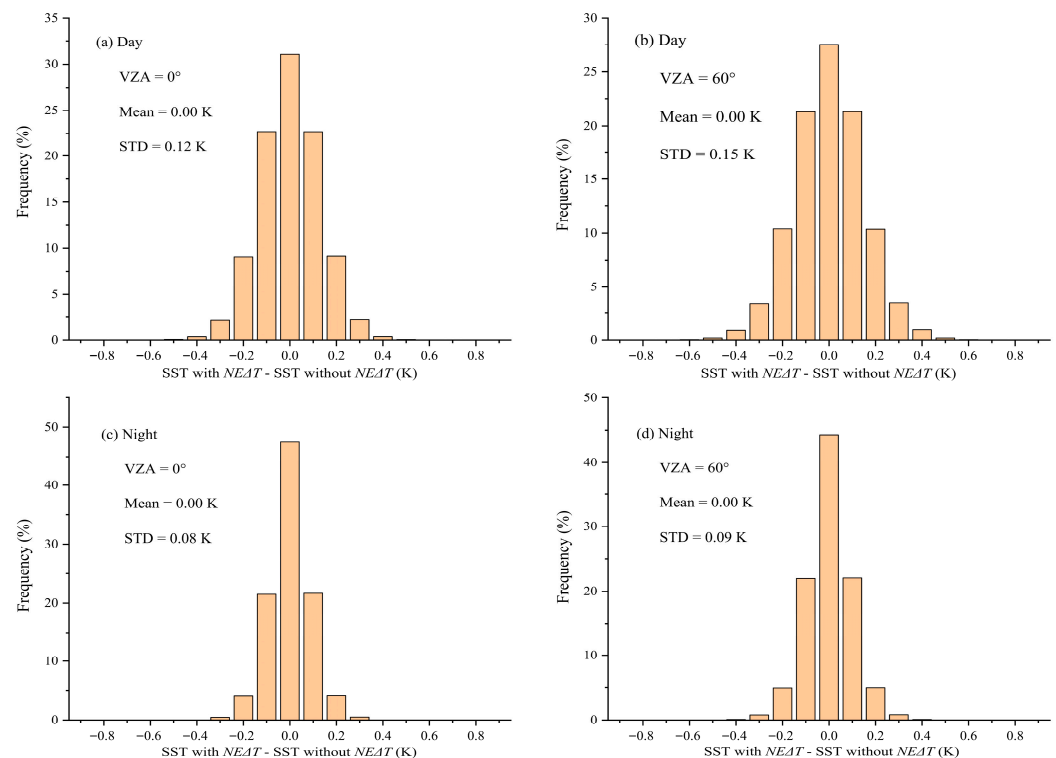


Figure 7. Uncertainty caused by *NEAT* for daytime and nighttime scenarios.

Furthermore, the uncertainty of radiometer calibration also determines the uncertainty in the nominal brightness temperature of the unknown scene. It is reported that the calibration uncertainty for MODIS B22, B31, and B32 is 0.5 K, 0.2 K, 0.2 K, respectively [44], and this source of uncertainty in SST retrieval is also analyzed following a similar approach to that used for instrument noise. Figure 8 presents the histogram of SST differences obtained with and without calibration uncertainty. It is noted that the means of the differences are both 0.0 K during daytime and nighttime. For DA-1, the STD is 0.48 K and 0.56 K at VZA = 0° and 60°, respectively; for NA-1, the STD is 0.41 K and 0.46 K at VZA = 0° and 60°, respectively.

4.2. Uncertainty of T_a

The T_a is primarily used to divide the atmospheric conditions into cold, warm, and hot, and it is used to select the coefficients in Equations (2) and (3). T_a uncertainty may cause misidentification of the corresponding sub-range, which may introduce substantial errors into the retrieved SST. A 5 K overlap is therefore imposed between neighboring T_a sub-ranges. As noted in [45], the hourly ERA5 2 m air temperature tends to be systematically higher than three-buoy observations, MOSAic, IABP, and CRREL, with RMSEs of 1.76 K, 5.72 K, and 3.36 K, respectively. Therefore, to numerically analyze the sensitivity of the retrieved SST, a perturbation of 2% on the T_a originally used to simulate the MODIS data in Section 2 is added, and the new values are then used to select the coefficients in Equations (2) and (3) to retrieve the SST. The histogram of SST error (u_{T_a}) generated by a 2% increase in the T_a is illustrated in Figure 9. For DA-1, the mean is 0.02 K and 0.05 K, and the STD is 0.08 K and 0.25 K at VZA = 0° and 60°, respectively. For NA-1, the mean is 0.00 K and 0.01 K, and the STD is 0.11 K and 0.32 K at VZA = 0° and 60°, respectively.

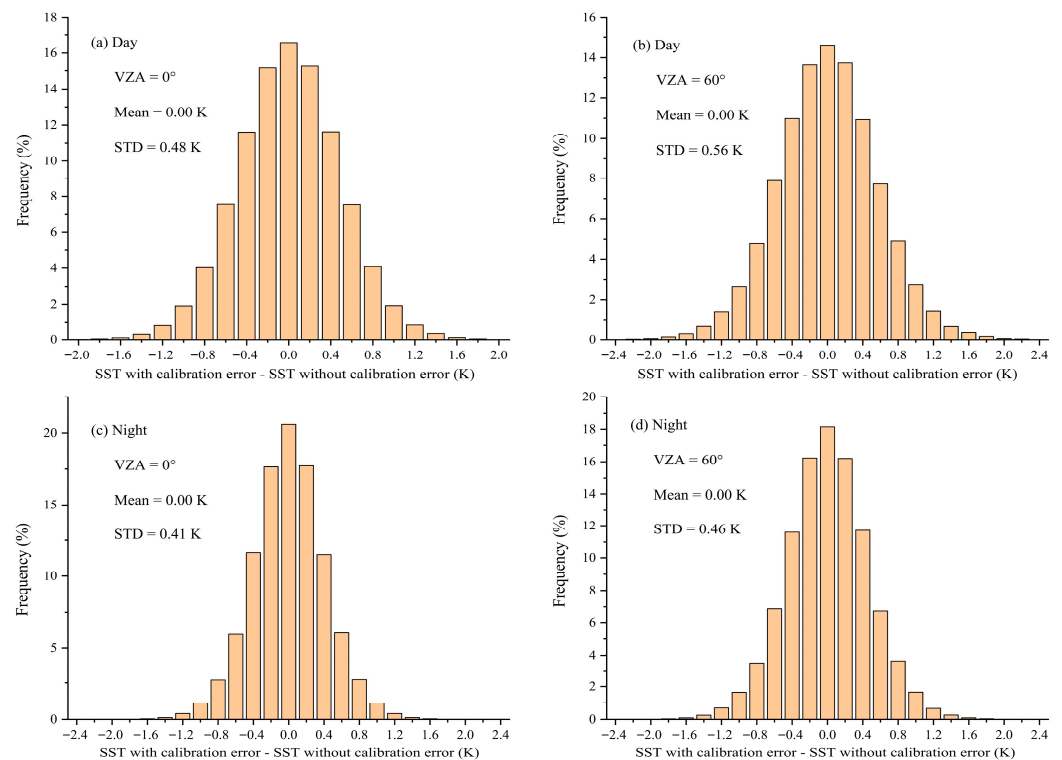


Figure 8. Uncertainty caused by radiometer calibration for daytime and nighttime scenarios.

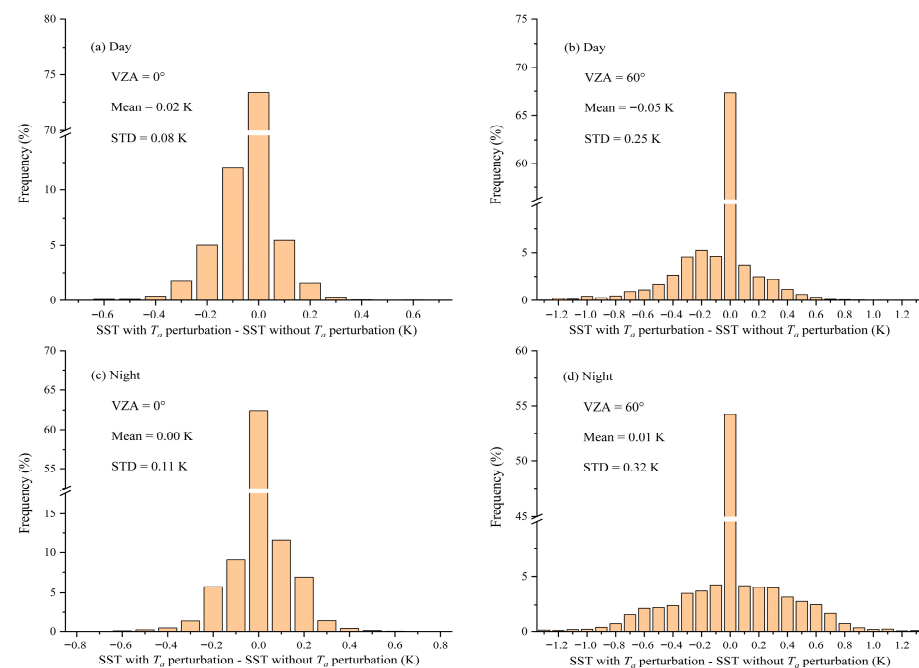


Figure 9. Uncertainty caused by T_a perturbation for daytime and nighttime scenarios.

4.3. Uncertainty of TCWV

In the SST retrieval algorithm, atmospheric TCWV functions both as an input parameter to Equation (2) and as a determinant for the selection of coefficients in Equations (2) and (3). To numerically analyze the sensitivity of the retrieved SST to TCWV uncertainty, a perturbation of 20% is added to the original atmospheric TCWVs, and the new TCWVs are then used as input data for retrieving the SST. The histogram of SST error (u_{TCWV}) generated by a 20% increase in the TCWV is illustrated in Figure 10 [46]. It is worth noting that for DA-1, the mean is 0.01 K and 0.01 K, and the STD is 0.11 K and 0.24 K

at VZA = 0° and 60°, respectively; for NA-1, the mean is 0.06 K and 0.12 K, and the STD is 0.16 K and 0.36 K at VZA = 0° and 60°, respectively.

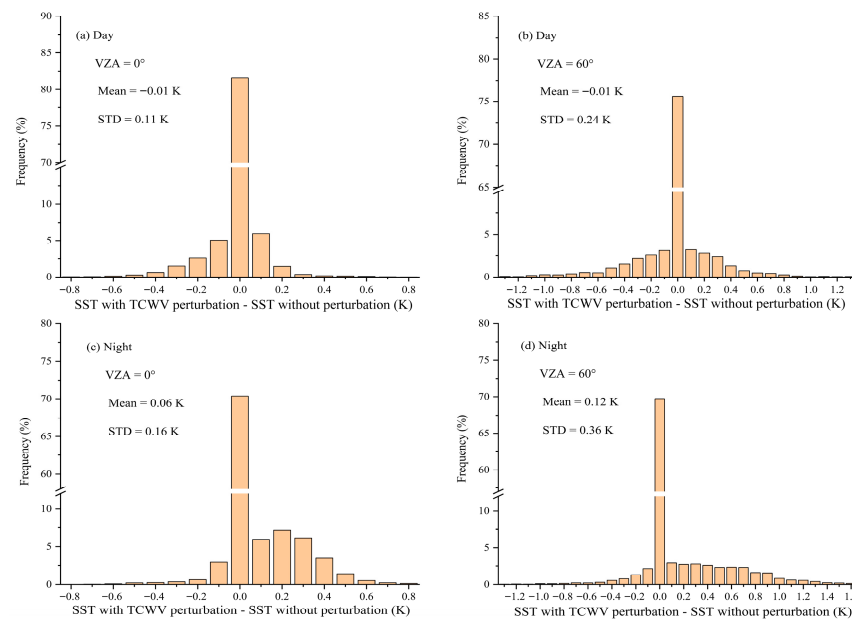


Figure 10. Uncertainty caused by total column water vapor perturbation for daytime and nighttime scenarios.

4.4. Uncertainty of SSE

To further evaluate the sensitivity of SST retrieval to SSE, quantifying the uncertainty of SSE is therefore essential, which mainly arise from the uncertainties of wind speed and the simplified model itself as indicated in Section 3. In this study, wind speed data from the ERA5 data are used to estimate SSE and as noted in [47] it tends to be systematically lower than buoy observations, with an error of 2 m/s. To account for this, an uncertainty of 2 m/s in wind speed is added and propagated through the SSE model by causing misclassification of wind speed intervals, which leads to the incorrect selection of coefficients, and through the role of wind speed as a direct input parameter to Model 5. This SSE uncertainty contributed by wind speed is quantitatively analyzed using an approach similar to that used for TCWV, and the resulting SSE uncertainties for bands 22, 31 and 32 are 0 at VZA = 0° and are 7.3×10^{-4} , 6.2×10^{-4} , 7.5×10^{-4} at VZA = 60°. Furthermore, the combined SSE uncertainties are also propagated to SST via Equations (2) and (3), and the histogram of SST differences (u_{SSE}) obtained with and without SSE uncertainty is shown in Figure 11. It is noted that for DA-1, the STD is 0.01 K and 0.03 K at VZA = 0° and 60°, respectively; for NA-1, the STD is 0.01 K and 0.16 K at VZA = 0° and 60°, respectively.

Ultimately, the overall error in the SST (u), arising from multiple error sources, can be expressed as follows:

$$u = \sqrt{u_{Algorithm}^2 + u_{BT}^2 + u_{cal}^2 + u_{T_a}^2 + u_{TCWV}^2 + u_{SSE}^2} \quad (4)$$

For DA-1, $u = \sqrt{0.06^2 + 0.12^2 + 0.48^2 + 0.08^2 + 0.11^2 + 0.01^2} = 0.52$ K and $u = \sqrt{1.5^2 + 0.15^2 + 0.56^2 + 0.25^2 + 0.24^2 + 0.02^2} = 1.65$ K at VZA = 0° and 60°, respectively. For NA-1, $u = \sqrt{0.08^2 + 0.08^2 + 0.41^2 + 0.11^2 + 0.16^2 + 0.01^2} = 0.46$ K and $u = \sqrt{0.82^2 + 0.09^2 + 0.46^2 + 0.32^2 + 0.36^2 + 0.16^2} = 1.07$ K at VZA = 0° and 60°, respectively.

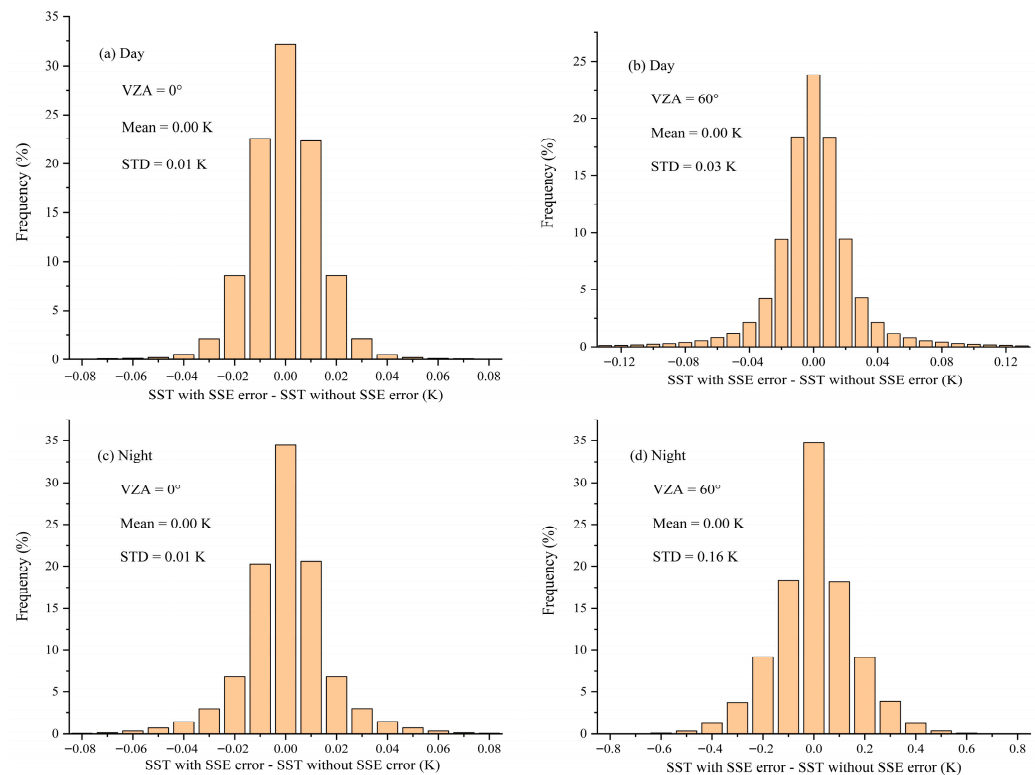


Figure 11. Uncertainty caused by sea surface emissivity error for daytime and nighttime scenarios.

5. Results

5.1. T-Based Validation Against Argo In Situ SST

This section presents a comprehensive T-based validation of the proposed day–night–differentiated SST retrieval algorithm for both daytime and nighttime cases, using Argo float observations as the reference [48]. In addition, the SST retrieval accuracies using a fixed SSE and those derived from Model 5 are compared to evaluate the advantage of emissivity correction. To ensure consistency and comparability, a standardized spatiotemporal collocation protocol is implemented. Temporal differences between satellite overpasses and reference measurements are constrained to 0.5 h, while spatial matching employs direct coordinate transformation to the nearest MODIS pixel. Furthermore, the 3σ filtering procedure is applied to suppress the impacts caused by potential atmospheric contamination [49].

The scatter plots between the retrieved SST and the Argo in situ SST for daytime and nighttime are shown in Figure 12. In the daytime (Figure 12a), 505 samples align closely with the 1:1 line, indicating a strong linear correlation. The mean bias is 0.03 K, suggesting slight overestimation, with a mean absolute error (MAE) and RMSE of 0.22 K and 0.26 K, respectively. At night (Figure 12b), 537 samples also cluster near the 1:1 line, with a mean bias of 0.01 K, again showing overestimation. The MAE and RMSE are also 0.22 K and 0.26 K, indicating similar performance to daytime conditions. This confirms that incorporating MIR radiance with TIR data enhances robustness and effectively improves SST retrieval. To further examine the adaptability of the proposed method across different oceanic regimes, we stratify the Argo samples into nearshore and tropical subsets for both daytime and nighttime conditions (Figure 12c–f). For the daytime nearshore subset (Figure 12c), 55 samples cluster around the 1:1 line, with a mean bias of -0.07 K, a MAE of 0.27 K, and an RMSE of 0.29 K. For the nighttime nearshore subset (Figure 12d), 35 samples show a mean bias of -0.11 K, a MAE of 0.22 K, and RMSE of 0.27 K. In the tropics, the daytime subset (Figure 12e) includes 241 samples with a mean bias of -0.01 K, a MAE of

0.27 K, and an RMSE of 0.30 K, while the nighttime subset (Figure 12f) contains 288 samples with a mean bias of -0.04 K, a MAE of 0.26 K, and an RMSE of 0.29 K. Compared with the overall performance (Figure 12a,b), the nearshore and tropical subsets exhibit slightly larger errors, indicating that coastal land–sea interactions and high-temperature conditions may introduce additional uncertainties in SST retrieval. Nevertheless, the retrieved SSTs in both regions still align well with the in situ measurements and preserve the same overall consistency, suggesting that the proposed method remains broadly applicable across different oceanic regimes.

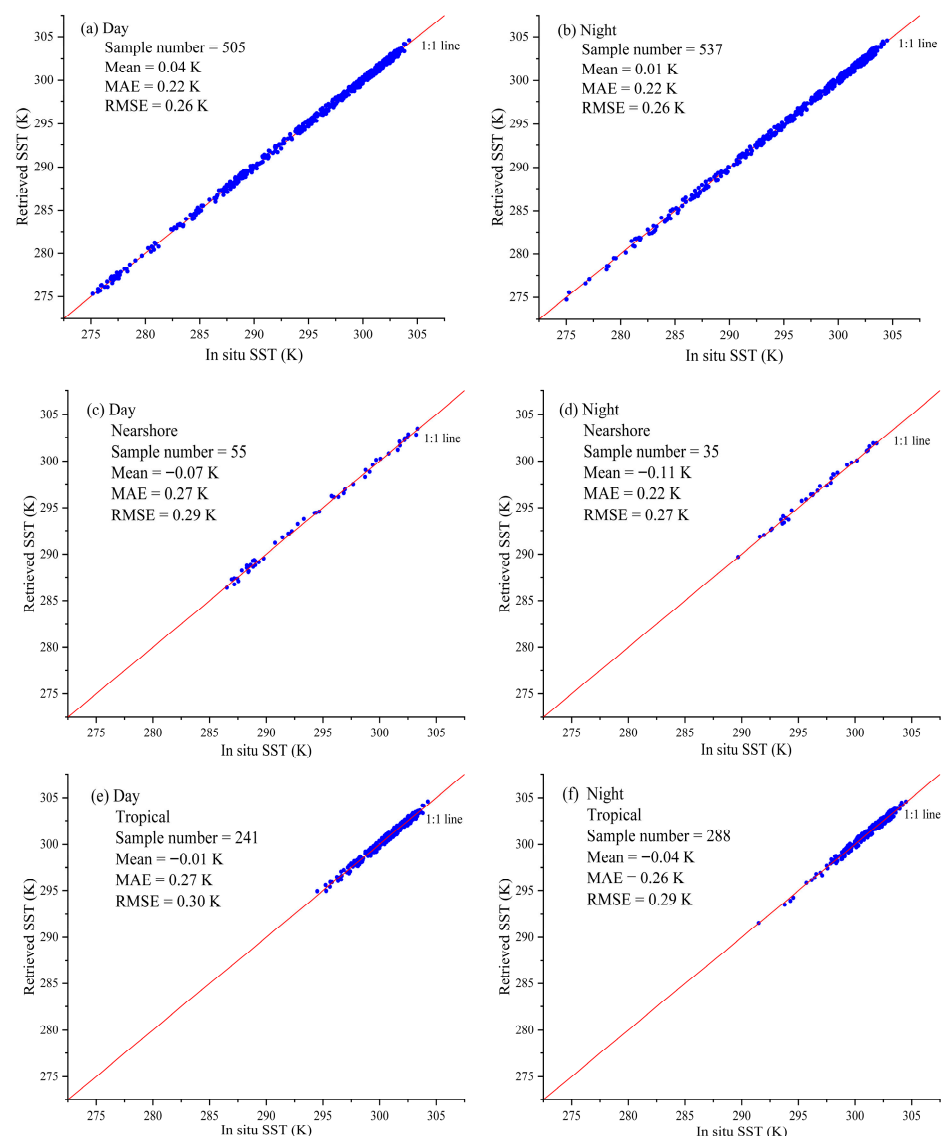


Figure 12. Scatter plots between the retrieved sea surface temperature (SST) and the Argo in situ SST: (a,b) all samples, (c,d) nearshore subset, and (e,f) tropical subset. Panels (a,c,e) correspond to daytime conditions, while (b,d,f) correspond to nighttime conditions.

Furthermore, Figure 13 shows the scatter plots of the differences between the retrieved SST and the Argo in situ SST for daytime and nighttime with different SSEs. In the daytime case (Figure 13a), adopting a fixed SSE of 0.98 (red points) leads to increasing dispersion between the retrieved and in situ SST as VZA grows from 0° to 50° – 60° , with multiple outliers exceeding 1 K. In contrast, SSTs retrieved with Model 5 SSE (blue points) remain tightly clustered around zero across all angle ranges. A similar pattern is observed at night (Figure 13b): fixed SSE produces larger dispersion and extreme bias (e.g., -6 K and $+7.5$ K)

at wide angles, whereas Model 5 maintains small and stable deviations. These results demonstrate that, by accounting for emissivity variations associated with VZA and wind speed, Model 5 more accurately captures SSE across viewing angles, thereby markedly reducing SST retrieval errors—an improvement most pronounced at large VZAs. This highlights the critical role of emissivity correction in enhancing SST retrieval accuracy.

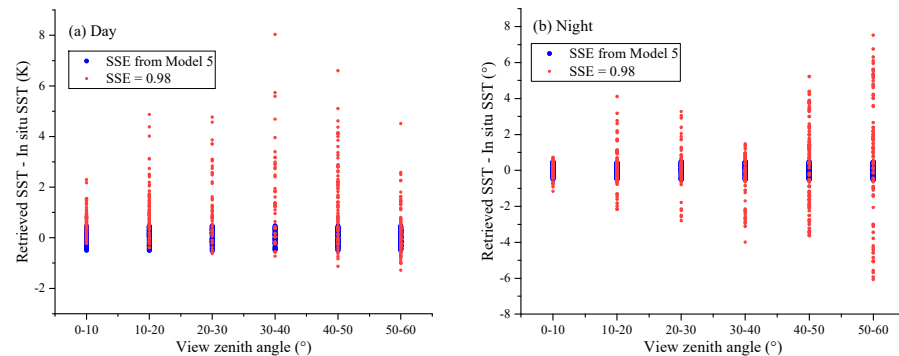


Figure 13. Scatter plots of the differences between the retrieval sea surface temperature (SSTs) and the in situ SST for daytime and nighttime using different sea surface emissivities (SSEs) under different view zenith angles.

The previous comprehensive validation confirms that the day–night-differentiated SST retrieval algorithm delivers reliable accuracy and excellent robustness under both daytime and nighttime conditions when evaluated against Argo in situ measurements. Nighttime retrievals show the same performance as those of daytime, with an RMSE of 0.26 K, reflecting enhanced stability and precision after dusk. This improvement arises from the effective integration of MIR and TIR radiance, which better suppresses atmospheric interference and sensor noise at night. Importantly, Model 5-derived SSE substantially outperforms a fixed SSE, particularly at large VZAs, where it reduces scatter and eliminates extreme deviations. These results demonstrate the critical roles of spectral integration and emissivity correction for achieving high-accuracy, diurnally consistent SST retrievals. This provides a solid foundation of data accuracy for applying sea surface temperature to marine thermal monitoring and ocean–atmosphere interaction studies. It is worth noting that in situ SST derived from Argo core temperature profiles would yield uncertainties associated with upper-ocean thermal structure and vertical temperature gradients.

5.2. Cross-Validation with MODIS SST Product

Furthermore, this study incorporates well-validated and extensively utilized MODIS SST products (MOD28) as reference benchmarks to assess the relative accuracy of the proposed day–night-differentiated SST retrieval algorithm. Due to the substantial volume of available data, fifteen MODIS images per month throughout 2019, with an interval of one day, were selected to validate the retrieval accuracy. These images cover both daytime and nighttime observations within the region from 10°N to 40°N and 100°E to 140°E. Initially, the quality-control flags from MOD35_L2 were employed to identify and retain the highest-quality and cloud-free ocean pixels. Owing to the MOD28 product and that the MODIS images are not fully consistent in terms of acquisition time and spatial resolution, data harmonization was performed prior to cross-validation. For temporal matching of remote sensing pixels, image pairs are selected in which the satellite overpass time falls within the temporal coverage of the corresponding MOD28 data. In addition, two-dimensional bilinear interpolation is employed to resample the MOD28 product from its native 4.62 km resolution to 1 km to be consistent with the retrieved SSTs from MODIS images.

Figure 14 presents the scatter plots and RMSEs between the retrieved SSTs and the MOD28 product across different seasons for both day and night. Overall, the proposed algorithm exhibits consistent and robust performance throughout four seasonal conditions, with an RMSEs of 0.66 K for daytime and 0.82 K for nighttime. The scatter points are distributed evenly along both sides of the 1:1 line, demonstrating a high level of consistency between the retrieved SSTs and the the MOD28 product. Seasonal variations in retrieval accuracy are evident: winter shows the highest accuracy (RMSEs of 0.37 K for day and 0.42 K for night), and summer the lowest (1.05 K for daytime and 0.91 K for night), while spring (0.49 K for daytime and 0.68 K for night) and autumn (0.51 K for daytime and 0.83 K for night) exhibit intermediate and comparable levels of performance. The retrieval accuracy is generally higher under low-temperature conditions, whereas the number of outliers gradually increases with rising temperature. The reduced accuracy in summer is likely attributable to higher atmospheric temperatures, which are often accompanied by increased TCWV content, thereby introducing greater uncertainty into SST retrieval. Moreover, nighttime retrievals generally exhibit slightly lower accuracy than daytime results, possibly due to the frequent occurrence of sea fog over ocean surfaces at night, introducing additional variability in the infrared signal. In addition to RMSE, the seasonal mean bias and MAE show patterns consistent with the RMSE results. The mean values indicate a positive systematic offset relative to MOD28 in all seasons, with values of 0.30–0.41 K for daytime and 0.36–0.85 K for nighttime, while the MAE shows a similar seasonal dependence to RMSE, with smaller values in winter and larger values in summer, and intermediate levels in spring and autumn.

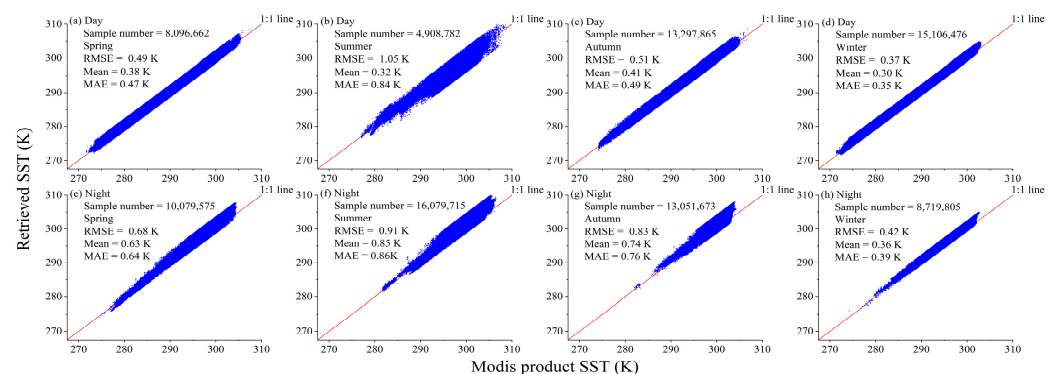


Figure 14. Scatter plots between the MODIS product sea surface temperature (SST) and the retrieved SST for daytime and nighttime across four seasons.

Figure 15 indicates that the RMSE between our retrieved SST and the MOD28 product exhibits a pronounced increase VZA for both daytime and nighttime, while its variation with wind speed is considerably weaker. The pronounced VZA dependence is consistent with the fact that SSE changes are relatively small at low VZAs but become increasingly significant at larger viewing angles. Therefore, this VZA-dependent pattern may, to some extent, indicate the effectiveness of the improved algorithm proposed in this study, given that MODIS SST products does not explicitly correct for emissivity-related effects. In addition, the RMSE varies much less with wind speed, due to the fact that wind-induced emissivity changes are generally weaker than the angular dependence.

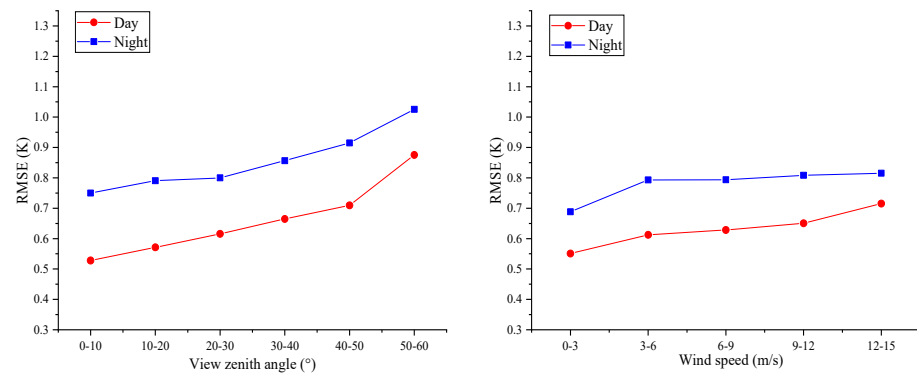


Figure 15. Root mean square errors between the retrieved sea surface temperature and the MOD28 product SST varying with view zenith angles (**left**) and wind speeds (**right**) for daytime and nighttime conditions.

6. Discussion

6.1. Accuracy Assessment of SST Retrieved Using Different SSE Models

Since SSE serves as a key parameter in the SST retrieval process, the accuracy of SST is inherently sensitive to errors in SSE. In Section 3, six SSE-simplified models are developed under different conditions, and the calculated SSE values are subsequently used to retrieve SST using Equations (2) and (3). Therefore, based on the simulated validation dataset, this section presents a comparison between the absolute biases of the emissivity-related terms derived from the six SSE models and those from the Wu–Smith model, along with the corresponding SST retrieval errors.

For daytime conditions, the emissivity-related terms consist of both the sum (ϵ) and the difference ($\Delta\epsilon$) of SSE in B31 and B32. Figure 16 shows the estimation errors of emissivity-related variables and the corresponding retrieved SST error under different wind speeds and VZAs. It is noted that when the VZA is lower than 40° , the emissivity-related term values estimated by the six models show close agreement with those derived from the Wu–Smith model, despite considerable fluctuations in wind speed. Furthermore, more pronounced discrepancies are observed when VZA is higher than 40° . Specifically, Model 1 shows the largest bias in ϵ and $\Delta\epsilon$, peaking at 0.07 and 0.01, respectively; the maximum errors in ϵ and $\Delta\epsilon$ from Model 2 are 0.02 and 0.01, respectively. For Models 3 and 4, under conditions where VZA is 60° or wind speed is near zero, the maximum bias of ϵ and $\Delta\epsilon$ can reach 0.0076 and 0.0007, respectively, while the corresponding values for Models 5 and 6 consistently remain below 0.002 and 0.0004, respectively. Regarding the accuracy of SST retrieval, when VZA is less than 40° , the six models achieve RMSE values below 0.38 K due to small emissivity errors. However, the SST retrieval error increases as the VZA increases. At larger VZAs, Model 1 yields the largest RMSE, reaching 1.69 K, while the maximum RMSE for the Model 2 is 1.27 K; the SST retrieval errors for Models 3 and 4 show a slight decrease, with a maximum error of 1.07 K. Models 5 and 6 demonstrate improved performance, achieving RMSEs below 0.76 K, attributed to their high precision in SSE estimation.

For nighttime conditions, the emissivity-related terms include ϵ_1 ($\epsilon_1 = (1 - \epsilon_{31})/\epsilon_{31}$), ϵ_2 ($\epsilon_2 = (1 - \epsilon_{32})/\epsilon_{32}$), and ϵ_3 ($\epsilon_3 = (1 - \epsilon_{22})/\epsilon_{22}$), and the estimation errors of the emissivity-related variables, along with the corresponding retrieved SST errors under different wind speeds and VZAs, are shown in Figure 17. The three aforementioned emissivity-related terms exhibit a pattern similar to that observed during daytime, with more pronounced discrepancies arising from the Wu–Smith model when the VZA is higher than 40° . For instance, Model 1 shows the largest bias in terms of ϵ_1 , ϵ_2 and ϵ_3 , peaking at 0.003, 0.044, and 0.049, respectively; the maximum errors in ϵ_1 , ϵ_2 , and ϵ_3 for Model 2

is 0.005, 0.012, and 0.015, respectively. For Models 3 and 4, when wind speed approaches zero, the maximum bias of ε_1 , ε_2 , and ε_3 can reach 0.004, 0.005, and 0.005, respectively. Models 5 and 6 demonstrate higher estimation accuracy for SSE; the maximum bias in ε_1 , ε_2 and ε_3 , and for Model 6 this reaches 0.001, while the corresponding values for Model 5 remain consistently below 0.001. Regarding SST retrieval accuracy, it is worth noting that when VZA is lower than 40° , the six models achieve RMSE values less than 0.37 K. At larger VZAs, Model 5 also delivers the best performance, with RMSEs lower than 0.55 K, whereas Model 1 yields the largest RMSE, reaching 1.93 K. The maximum RMSEs for Models 2, 3, 4, and 6 are 1.44 K, 0.75 K, 0.82 K, and 0.63 K, respectively.

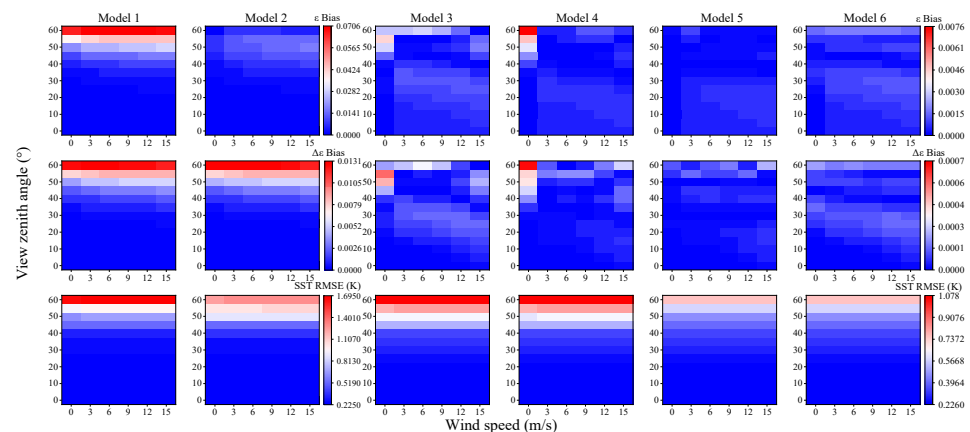


Figure 16. Biases in emissivity-related terms and sea surface temperature (SST) root mean square errors (RMSEs) for DA-1 coupled with the six sea surface emissivity (SSE) models under different wind speeds and view zenith angles.

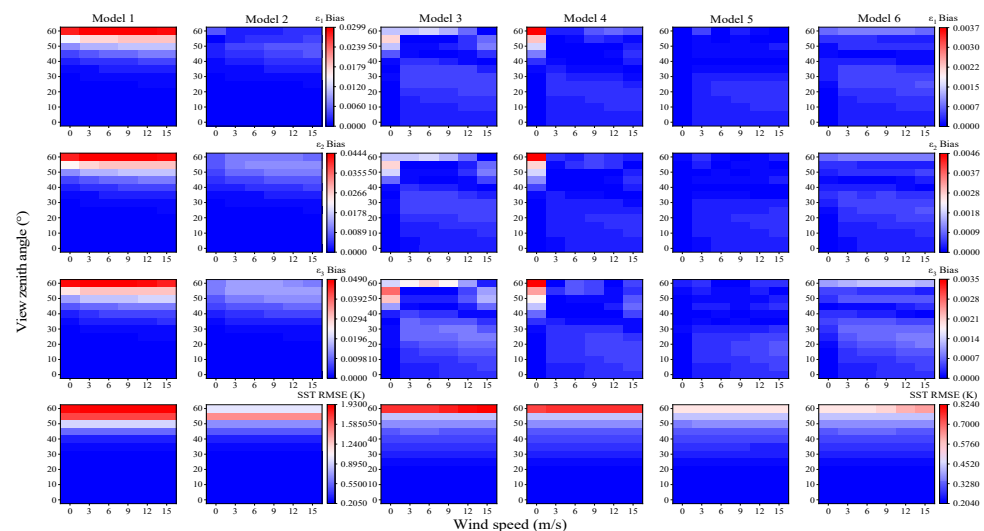


Figure 17. Biases in emissivity-related terms and sea surface temperature (SST) root mean square errors (RMSEs) for NA-1 coupled with six sea surface emissivity (SSE) models under different wind speeds and view zenith angles.

Based on comprehensive validation experiments conducted under both daytime and nighttime conditions, Model 5 demonstrates clear superiority as an SSE model, with strong physical soundness and computational efficiency. These results further confirm the stability of the proposed SST retrieval method, which achieves high retrieval accuracy (RMSEs below 0.76 K during daytime and 0.55 K at nighttime). This level of precision meets the requirements of applications demanding kelvin-scale accuracy, such as climate monitoring and operational oceanography.

6.2. Performance Comparison with Existing Method

To further evaluate the performance of our SST retrieval algorithm, we compared it against the method proposed by Ma et al. (denoted as Method 1) [26], using the simulated validation dataset under both daytime and nighttime conditions, and the comparison results are illustrated in Figure 18. It is worth noting that our method exhibits higher stability and accuracy across a range of VZAs and wind speeds.

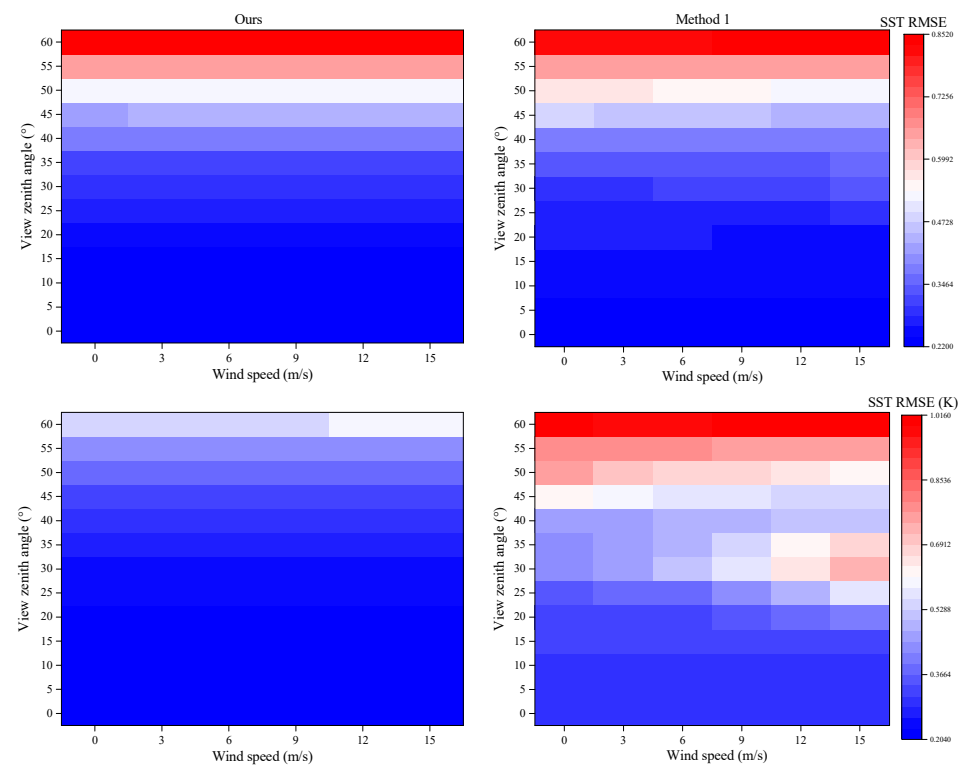


Figure 18. Root mean square errors (RMSEs) of sea surface temperature (SST) retrieval for our method and the existing method (Method 1) under different wind speeds and view zenith angles.

For daytime conditions (upper panels), both methods achieve comparable accuracy when the VZA is below approximately 30° . However, as the VZA increases, Method 1 shows a noticeable rise in retrieval error, reaching up to 0.1 K higher than our results when the VZA exceeds 40° . In contrast, our approach maintains smooth and consistent variations, with the maximum RMSE remaining below 0.76 K. This indicates superior robustness to changes in VZA. Furthermore, the advantages of our algorithm become even more pronounced during nighttime conditions (lower panels). Here, Method 1 exhibits stronger angular dependence and larger retrieval errors, reaching values up to 0.47 K higher than those of our method at a VZA of 60° , whereas our algorithm remains stable and maintains minimal error across all VZA conditions. This improvement can primarily be attributed to the integration of MIR bands, which effectively mitigate the influence of atmospheric water vapor and enhance retrieval reliability during nighttime. Therefore, these findings confirm that our SST retrieval method achieves superior stability and accuracy, providing more consistent performance under both daytime and nighttime conditions. This enhanced performance is crucial for applications requiring precise SST measurements.

7. Conclusions

This study develops a day–night-differentiated SST retrieval method that explicitly accounts for emissivity correction and leverages MIR radiance to enhance retrieval accuracy, particularly under nighttime conditions. The objective of this research is to mitigate the

angular sensitivity and uncertainties related to atmospheric water vapor that frequently compromise the accuracy and stability of traditional SW algorithms. In this study, a simplified but physically consistent parameterization SSE model (Model 5) is constructed, capturing nonlinear variations in SSE concerning both viewing geometry and surface roughness by dividing wind speed into different ranges. The proposed day–night-differentiated SST retrieval is then applied to an SST retrieval task from MODIS data, demonstrating that the algorithm enhances accuracy and reduces angular dependence compared with conventional SW schemes. Furthermore, the sensitivity analysis reveals that the method exhibits good resistance to typical uncertainty sources, such as instrument noise, calibration errors, and perturbations in input variables. Among these factors, the uncertainty in calibration errors exerts the greatest influence, whereas the impacts of TCWV and SSE perturbations are relatively limited.

To further evaluate the retrieval accuracy of the proposed method for MODIS SST, a comprehensive validation is conducted through two complementary approaches, namely T-based validation against independent ground measurements from the Argo sites and cross-validation against MOD28 SST products. T-based validation is performed using 400 samples, yielding RMSEs of 0.26 K for both daytime and nighttime, indicating robust retrieval accuracy. Moreover, stratified evaluations over representative oceanic regimes, including nearshore and tropical regions, demonstrate consistent performance, suggesting promising regional applicability of the proposed method. In addition, cross-validation results show overall RMSEs of 0.66 K for daytime and 0.82 K for nighttime. Seasonally, the retrieval accuracy follows a clear pattern: winter exhibits the highest accuracy, followed by spring and autumn, whereas summer shows the largest RMSE, primarily due to higher TCWV and surface temperatures.

Furthermore, to quantify the effectiveness of Model 5, performance comparisons are also conducted against the other five simplified models using the simulated validation dataset. The results indicate a substantial improvement in SST retrieval accuracy when employing Model 5. Specifically, at a VZA of 60° , there are notable RMSE reductions of 0.36 K for daytime and 0.15 K for nighttime, which confirms the advantages of high-accuracy emissivity estimation. Additionally, a comparative analysis with an existing method [24], which relies solely on IR bands, further demonstrates the superior performance of the proposed method, yielding RMSE reductions of 0.1 K for daytime and 0.47 K for nighttime. These results validate the benefit of incorporating MIR bands to enhance nighttime SST retrieval accuracy.

In summary, the proposed day–night-differentiated SST retrieval with emissivity correction reduces angular-dependent bias and improves robustness to atmospheric interference, making it promising for large-scale, long-term SST monitoring and potential operational use in ocean–atmosphere studies. Nonetheless, several limitations remain. First, the simplified SSE model (Model 5) may be less reliable under extreme conditions (e.g., very high winds, strong sea–air temperature gradients, or high humidity), potentially causing residual angular sensitivity, especially at VZAs $> 55^\circ$. Second, our uncertainty assessment is conducted under the assumption that the input parameters are mutually independent, and a rigorous multi-parameter coupled uncertainty analysis would be required accounting for inter-parameter correlations. Future work will therefore focus on coupling emissivity parameterization with dynamic ocean-surface models that account for wave spectra, wind direction, and air–sea flux variability, and advancing covariance-aware sensitivity approaches to better characterize coupled uncertainties under realistic scenarios.

Author Contributions: Conceptualization, C.G.; methodology, Q.Z.; software, Q.Z.; validation, Q.Z.; formal analysis, C.G. and Q.Z.; investigation, Q.Z.; resources, Q.Z.; data curation, Q.Z.; writing—original draft preparation, Q.Z.; writing—review and editing, C.G., W.L. and Y.Z.; visualization, Q.Z., Y.M. and Y.W.; supervision, E.Z.; project administration, C.G.; funding acquisition, C.G. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the General Program of the National Natural Science Foundation of China under Grant 42271395, and by the Ministry of Science and Technology of China, the National Quality Infrastructure System under Grant 2022YFF0610802.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The authors gratefully acknowledge NASA for providing the MOD021KM, MOD03, MOD35_L2 (<https://ladsweb.modaps.eosdis.nasa.gov/> (accessed on 1 February 2025)) and MOD28 products (<https://search.earthdata.nasa.gov/> (accessed on 1 March 2025)). Additionally, they thank ECMWF for offering the ERA5 reanalysis data (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels> (accessed on 15 February 2025)). The authors also acknowledge CARDC for providing the Global Argo Observational data set (V3.0) (<ftp://ftp.argo.org.cn/pub/ARGO/global/> (accessed on 1 April 2025)). Thanks are also given to the anonymous reviewers.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SST	Sea surface temperature
TIR	Thermal infrared
SSE	Sea surface emissivity
SW	Split-window
AVHRR	Advanced very-high-resolution radiometer
MODIS	Moderate-resolution imaging spectroradiometer
MIR	Mid-infrared
VZA	View zenith angle
TOA	Top of the atmosphere
TCWV	Total column water vapor
REA5	Fifth-generation atmospheric reanalysis
ECMWF	Medium-range weather forecasts
RMSE	Root mean square error
R^2	Determination coefficient
STD	Standard deviation

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