

## Article

# A Novel Method for Eliminating Glint in Water-Leaving Radiance from UAV Multispectral Imagery

Jong-Seok Lee <sup>1,2</sup>, Sin-Young Kim <sup>3</sup>  and Young-Heon Jo <sup>1,\*</sup> 

<sup>1</sup> Department of Oceanography and Marine Research Institute, Pusan National University, Busan 46241, Republic of Korea; hot4027@pusan.ac.kr

<sup>2</sup> Coastal Disaster & Safety Research Department, Korea Institute of Ocean Science & Technology, Busan 46241, Republic of Korea

<sup>3</sup> BK21 School of Earth and Environmental System, Pusan National University, Busan 46241, Republic of Korea; tmzkt35@pusan.ac.kr

\* Correspondence: joyoung@pusan.ac.kr; Tel.: +82-51-510-3372

**Abstract:** Unmanned Aerial Vehicle (UAV) high-resolution remote sensing imagery has been used for unprecedented coastal environment monitoring with ground sampling distance and time intervals of a few centimeters and seconds, respectively. However, high spatial-time resolutions of UAV remote sensing data consist of unexpected signals from water surface level changes induced by wind-driven currents and waves. This leads to non-linear and non-stationary forms of sun and sky glints in the UAV sea surface image. Consequently, these surface glints interfere with the detection of water body reflections and objects, reducing the accuracy and usability of the measurements. This study employed Fast and Adaptive Multidimensional Empirical Mode Decomposition (FA-MEMD) to separate the spatial periodicity of time-continuous multispectral images of the sea surface from the original data and retain non-oscillatory signals called residual images. The residual images effectively represented the spatial-temporal radiance and flow variations in the water body by correcting the regions of surface glint. This study presents three key findings: First, homogeneous surface radiance data with surface glint removed from the raw image sequence was acquired using FA-MEMD. Second, the continuous surface glint removal effect is validated through water-leaving radiance ( $L_{w-SBA}$ ) measurements obtained via the Skylight-Blocked Approach (SBA) method. Comparisons showed that  $R^2$  values for the data obtained from clear water before and after surface glint removal were 0.02 and 0.56 with RMSE values of  $8.37 \times 10^{-5}$  and  $5.51 \times 10^{-5} \text{ W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1}$ , respectively, indicating an improvement rate of 34.19%. Third, a comparative analysis with previous study methods demonstrated that our approach yielded spatially and temporally uniform homogeneous surface radiance data with less variability than traditional methods. The spatially and temporally synchronized residual images and the  $L_{w-SBA}$  data showed high similarity, confirming that the FA-MEMD technique effectively removed the surface glint from wave-induced roughness, enhancing the reliability of high-resolution UAV sea color observations.

**Keywords:** ocean optics; sun glint; sky glint; multispectral camera; UAV; FA-MEMD; SBA



Academic Editors: Manuel Antón and Ming-Der Yang

Received: 28 November 2024

Revised: 4 February 2025

Accepted: 26 February 2025

Published: 12 March 2025

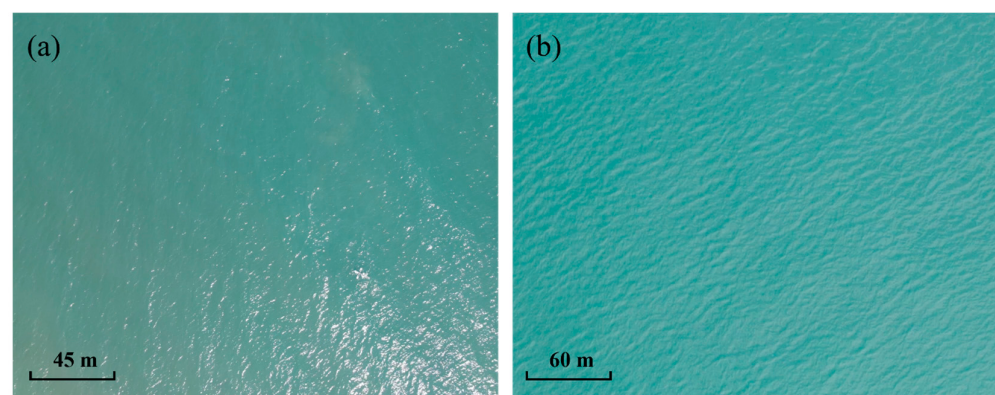
**Citation:** Lee, J.-S.; Kim, S.-Y.; Jo, Y.-H. A Novel Method for Eliminating Glint in Water-Leaving Radiance from UAV Multispectral Imagery. *Remote Sens.* **2025**, *17*, 996. <https://doi.org/10.3390/rs17060996>

**Copyright:** © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

Unmanned Aerial Vehicles (UAVs) have become an essential tool for high-resolution remote sensing, providing centimeter-scale spatial resolution and rapid temporal information [1]. These capabilities allow UAVs to capture fine-scale oceanic features and environmental variables such as turbidity [2], chlorophyll concentration [3,4], and sub-mesoscale

eddies [5–7]. Compared to traditional satellite remote sensing, UAVs offer significant advantages, including flexible deployment and the ability to avoid cloud interference [8]. However, despite these benefits, UAV-based remote sensing faces a major challenge—the presence of sun and sky glint in sea surface imagery, which can severely degrade data quality and limit its application for quantitative environmental analysis [9,10]. Sun and sky glint (Figure 1) are significant sources of noise in UAV sea surface imagery [11]. Sun glint occurs when direct sunlight reflects off the water surface, creating overexposed pixels that obscure water-leaving radiance ( $L_w$ ) signals [12]. Sky glint, on the other hand, results from scattered sky radiation reflecting off the sea surface, introducing spatially varying distortions across the image. Unlike satellite-based remote sensing, UAV imagery is characterized by higher spatial resolution and greater variability in surface roughness, making glint correction more complex [13,14]. The presence of glint reduces the signal-to-noise ratio (SNR) and affects remote sensing reflectance ( $R_{rs}$ ) calculations, which are crucial for ocean monitoring applications [15–19].



**Figure 1.** Patterns of surface glints observable in high-resolution UAV ocean surface imagery: (a) sun glint signal caused by total reflection of sunlight and (b) sky glint signal fluctuating according to the roughness of the waved surface.

As sun glint in remote sensing data cannot be eliminated [20], various studies have been conducted with regard to its reduction or correction. The most effective method to minimize sun glint is by adjusting the geometry of the UAV and camera position, aligning them in such a manner that surface reflection is minimized based on wind speed and the solar zenith angle [21–23]. However, even when accounting for solar zenith angles, wind speed, and sensor view angles, few pixels in the imagery inevitably exhibit sun glint due to the complex roughness of the water surface [24,25]. A traditional approach for correcting sun glint involves using a radiative transfer model based on statistical methods [26]. This model calculates the statistical probability distribution of solar reflection on the sea surface. However, the applicability of previous methods is limited with regard to high-resolution UAV sea surface imagery, as varying solar reflection intensities occur at different pixel locations.

Another approach involves using the near-infrared (NIR) band, which is predominantly absorbed by the water surface and measured as nearly zero in sea surface remote sensing images. Using this property, the influence of solar reflection can be estimated through NIR band images and subtracted from other wavelength bands to compensate for sun glint [27–30]. However, this method does not apply to RGB digital cameras that cannot measure the NIR band, and pixel boundaries may appear blurred depending on the surface glint intensity. Additionally, this approach is limited by the variability of NIR reflectance in shallow waters and regions with high concentrations of phytoplankton and suspended sediments [31–34].

A relatively modern approach to resolve the sun glint issue is to employ the Temporal Minimum Filter (TMF) method. The TMF method applied to each frame of a time-sequenced video can accumulate pixel values where surface glint does not occur, producing an image with minimal glint effects [35]. However, the TMF method requires substantial time and input data to produce a single corrected image, and its efficiency in reflection removal varies depending on wave conditions and seawater characteristics. Recently, machine and deep learning-based sun glint correction techniques have been proposed for high-resolution UAV images [36,37]. Deep learning can efficiently identify sun glint patterns, but the accuracy of these models significantly depends on the quality of the sun glint masks used for training. Additionally, they may encounter issues such as classification errors when sun glint occurs in small pixel regions.

Despite these existing approaches, a robust and adaptive glint correction method for high-resolution UAV imagery has yet to be established. Conventional techniques either rely on predefined environmental parameters, such as solar zenith angles and wind speeds, or require extensive computational resources and training datasets, making them difficult to implement across diverse UAV applications [21]. Additionally, many existing methods are designed for satellite-based remote sensing and struggle to accommodate the unique challenges posed by UAV imagery, including the high spatial variability of surface glint and the dynamic nature of ocean surface roughness. These limitations highlight the need for a novel correction technique that can effectively separate and remove unwanted glint signals without relying on restrictive environmental assumptions or computationally expensive models.

To address this gap, this study proposes a novel method for UAV glint correction using Fast and Adaptive Multidimensional Empirical Mode Decomposition (FA-MEMD). FA-MEMD is an advanced signal decomposition technique that separates multi-component signals based on their frequency and amplitude, allowing for the isolation and removal of glint signals while preserving the integrity of water-leaving radiance signals. Additionally, this method not only corrects strong sun glint regions, as previous studies have, but also effectively removes both sun and sky glint across the entire image. Furthermore, it has the significant advantage of ensuring stable glint correction while maintaining the statistical integrity of the original data. Unlike traditional correction approaches that depend on pre-established atmospheric or geometric models, FA-MEMD is purely data-driven, making it highly adaptable for UAV applications in various environmental conditions. This adaptability is particularly crucial for UAV-based coastal monitoring, where water surface roughness and environmental lighting conditions can vary significantly across different observation times and locations.

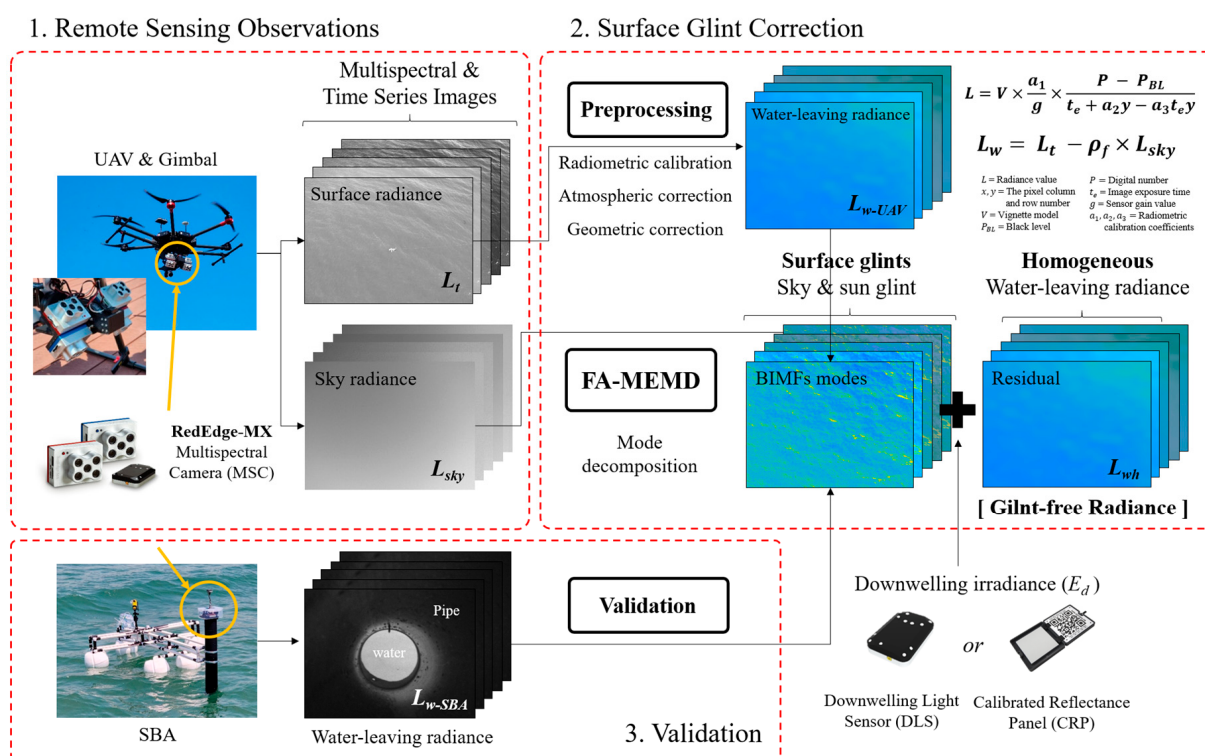
FA-MEMD operates by decomposing UAV-acquired multispectral imagery into intrinsic mode functions (IMFs) that represent different oscillatory components within the data. By leveraging its ability to identify and isolate the frequency characteristics of glint signals, FA-MEMD enables a more precise and automated correction process compared to conventional methods. The decomposition framework allows the selective removal of unwanted signals associated with glint while preserving essential radiometric features necessary for accurate water-leaving radiance estimation. Furthermore, FA-MEMD does not require prior knowledge of environmental variables such as wind speed, wave height, or incident solar angles, which makes it significantly more flexible and scalable than existing correction methods.

This study is structured to address the acquisition of high spatial resolution UAV data and the correction of sun and sky glints as follows: We illustrate the procedures of our solution in Section 2 and discuss our observations in Section 3. Next, in Section 4.1 we test whether it is possible to extract the physical signal of surface glints from the decomposed modes. To verify this, in Section 4.2, we apply the FA-MEMD technique

to consecutive imagery drawn from various regions with different seawater conditions. Specifically, we conducted a comparative analysis using water-leaving radiance ( $L_{w-SBA}$ ) measured using the Skylight-Blocked Approach (SBA) to verify the accuracy of the radiance images with surface glints removed. In Section 4.3, we demonstrate how the new approach performs better than currently available methods. In Sections 5 and 6, we discuss our results and present the summary, respectively. Notably, this approach proposes a new method for identifying and removing periodic surface glint features using only images captured continuously from a fixed location, without requiring consideration of variables such as surface wind direction, speed, roughness, or wave characteristics.

## 2. Methodology

UAV time-series data of the sea surface were captured from a fixed position and processed as outlined in Figure 2. This method includes three steps: First, the collected UAV time-series data of the sea surface (total upwelling radiance,  $L_t$ ) and the sky (sky radiance,  $L_{sky}$ ) were used to obtain the water-leaving radiance ( $L_{w-UAV}$ ); second, FA-MEMD was used for the decomposition and correction of surface glints; third, the surface glint correction results were validated. The SBA setup was moored within the observation area of the UAV to acquire time-continuous water-leaving radiance ( $L_{w-SBA}$ ), which was used to verify the de-glinted images. FA-MEMD was also employed to remove the heterogeneous sun and sky glints caused by rough surfaces, yielding glint-filtered and homogeneous reflectance images.



**Figure 2.** Flowchart of data collection and surface glint decomposition processing.

### 2.1. Preprocessing of Multispectral Images

To derive sea surface level reflectance from the raw images captured by the UAV-mounted multispectral camera, relative atmospheric correction techniques were adopted. When atmospheric correction for UAV measurements is not applied, variations in water vapor and aerosol levels in the atmosphere can produce substantial differences between the radiance measured by the sensor and the radiance at the sea surface level [38,39].

Relative atmospheric correction, following Lee et al. [40], was applied as a suitable method for UAV sea surface images. This technique enabled an assessment of the relative contribution of vertical absorption and scattering effects without requiring in situ aerosol measurements. This method involved obtaining vertical profile spectral data from the target altitude before and after UAV flights, calculating a polynomial function for radiance variations with altitude, and using this function to correct the radiance captured during the flight to the surface level. Accordingly, all UAV data were atmospherically corrected to sea surface level reflectance using vertical profile information acquired before and after flights.

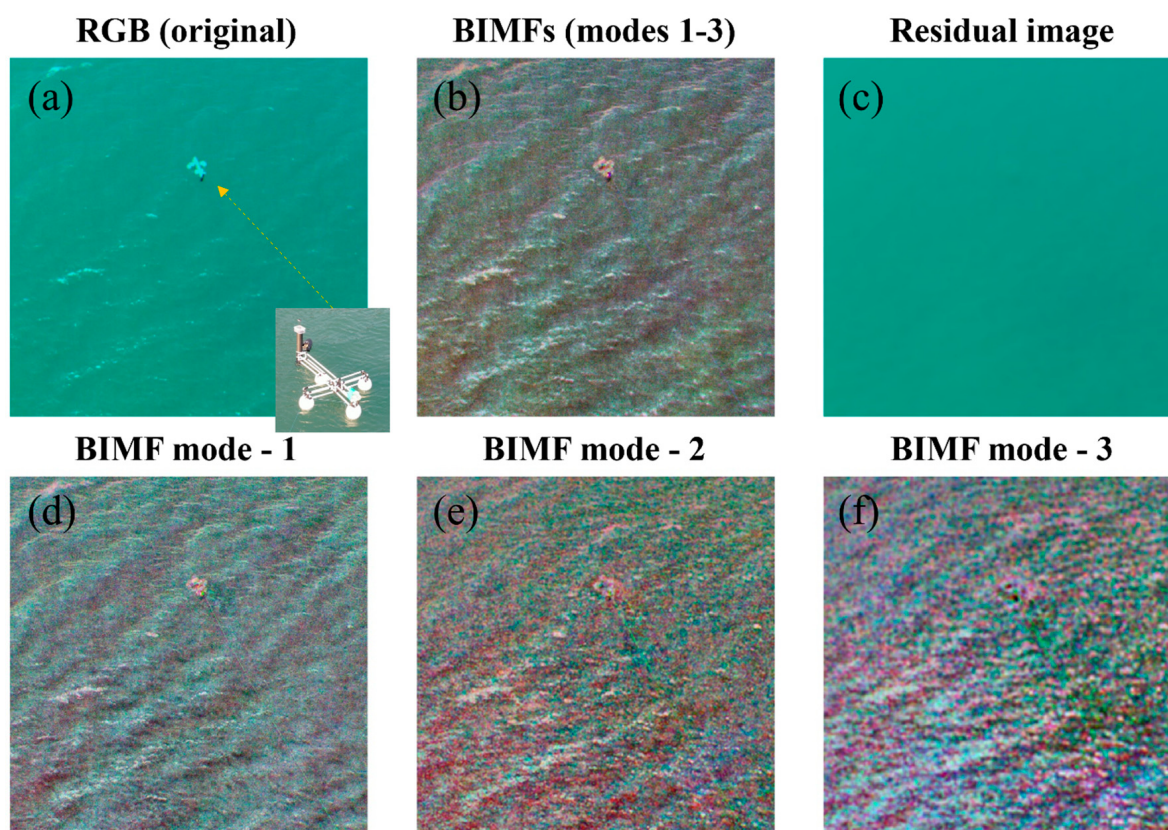
In UAV sea surface images, limitations in establishing fixed ground control points within the captured images rendered geo-referencing challenging. Therefore, in such cases, direct geo-referencing techniques can be applied using the UAV's sensor coordinates, posture information, and internal parameters to project images directly onto the sea surface [40]. Direct geo-referencing methods utilize the rotation matrix, calculated from the sensor's latitude, longitude, altitude, posture, and internal camera parameters (e.g., sensor size, focal length, and field of view), to project the observed aerial images onto the sea surface [19]. The projected images are assigned pixel-wise coordinates based on the World Geodetic System 1984 (WGS84) latitude–longitude system. It is assumed that the elevation differences due to sea surface roughness can be ignored within the UAV's observation range, allowing the aerial images to be uniformly projected at an elevation of 0 m relative to the Global Positioning System (GPS) altimeter.

## 2.2. FA-MEMD

Even if the UAV camera is aligned at zenith and azimuth angles to minimize surface reflection, as suggested by Mobley [21] and Jung and Kim [23], surface glints inevitably occur within wide observation ranges provided by wide-angle cameras. Therefore, previous studies have introduced correction methods for strong reflection signals, such as sun glints, occurring in specific areas of the images [24,35,37,41,42]. However, complex slopes on the sea surfaces, caused by wind-driven currents and waves, often lead to heterogeneous sun and sky glints across broader areas of the images. To accurately compute sea surface reflection, it is necessary to consider the angle of light incidence and the slope of the sea surface at specific points. However, such reflection signals are non-linear and non-stationary. Additionally, acquiring field observation data for these signals is highly constrained.

To address this challenge, this study employed the FA-MEMD technique, which can identify periodicity from dynamically changing sea surface observation images and decompose them accordingly [43]. FA-MEMD is an advanced method derived from the EMD method proposed by Huang et al. [44] designed for the efficient processing of multidimensional data. This technique uses order statistic filtering to rapidly decompose data, making it particularly effective for processing high-resolution time-series data, such as those obtained from UAV sea surface images (Figure 3).

FA-MEMD enables scale-based decomposition of large datasets by employing order statistic filtering instead of spline interpolation during the sifting process. This approach significantly reduces the computational burden associated with expanding the data domain, facilitating fast and adaptive multidimensional signal processing. FA-MEMD also aligns scales across Bidimensional Intrinsic Mode Functions (BIMFs) within the data's dimensional domain. This capability is especially beneficial for high-resolution time-series data such as UAV sea surface images. FA-MEMD decomposed the sea surface monitoring images into a finite number of BIMFs (Figure 3b) and residual images (Figure 3c) based on variations in the scale and frequency over time. BIMFs were decomposed mode-wise from large to small signals according to the frequency of the detected signal (Figure 3d–f).



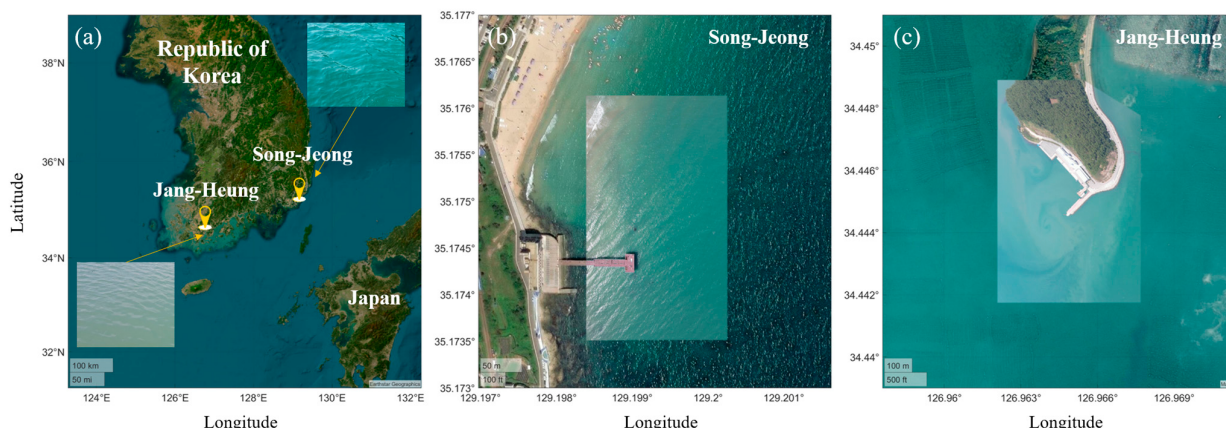
**Figure 3.** Empirical mode decomposition of time-continuous UAV ocean surface remote sensing data using FA-MEMD. (a) RGB composite image created by combining 475, 560, and 668 nm bands captured using a RedEdge-MX camera. (b) Summation of BIMF signals extracted using FA-MEMD. (c) Residual image obtained after subtracting the BIMFs from the original data. (d–f) Decomposed BIMFs arranged in order of decreasing frequency.

### 3. Study Area and Datasets

This study evaluates the effectiveness of FA-MEMD for glint correction by applying it to UAV-based remote sensing data collected from two distinct coastal environments with contrasting optical properties. The datasets include UAV multispectral imagery and in situ radiance measurements from the Skylight-Blocked Approach (SBA) (Pusan National University, Center for Remote Sensing (Busan, Republic of Korea)). These datasets provide a robust basis for testing FA-MEMD's performance in both clear and turbid waters, ensuring the method's adaptability to varying environmental conditions.

#### 3.1. Study Areas in Clear and Turbid Coastal Environments

To assess FA-MEMD under different water clarity conditions, UAV sea surface images were collected from two coastal locations in South Korea (Figure 4a). The first site, Song-Jeong Beach (Figure 4b), represents a clear-water coastal environment with low suspended sediment levels, while the second site, Jang-Heung (Figure 4c), features highly turbid waters due to well-developed tidal flats. The key reason for selecting these study areas is that water turbidity significantly affects water-leaving radiance and the appearance of glint signals. In clear waters, glint signals are more pronounced due to higher transmittance, while in turbid waters, increased scattering alters the spectral distribution of reflected sunlight. By testing FA-MEMD on both clear and turbid water datasets, this study ensures that the method is effective across different optical conditions.



**Figure 4.** (a) Two study areas. (b) Songjeong Beach off the eastern coast of Korea, characterized by clear waters and sandy beaches. (c) Noryeokdo, Jangheung, located on the southern coast of Korea, characterized by high turbidity in tidal flats.

### 3.2. Multispectral Sensor on UAV Observations

UAV imagery was collected using a Micasense RedEdge-MX multispectral camera from Micasense (Seattle, WA, USA) multispectral camera mounted on a DJI M600 UAV (DJI, Shenzhen, China). This camera captures images across five spectral bands (475, 560, 668, 717, and 840 nm) and converts them into radiance values, making it suitable for detecting glint signals and evaluating their removal using FA-MEMD. The suitability of the RedEdge-MX camera for ocean color remote sensing has been validated [45], and it has been widely used in various marine environmental studies [7]. The RedEdge-MX camera captures radiance images for each spectral band and can simultaneously obtain downwelling irradiance using an integrated Downwelling Light Sensor (DLS). Two RedEdge-MX units were mounted within a single frame, with one oriented downward toward the sea surface and the other upward toward the sky, each positioned at a 40° angle. The azimuth angle was consistently maintained at 135°, facing away from the sun. This frame was mounted on the underside of the M600 UAV, along with a two-axis gimbal (roll and pitch motors).

To obtain a diverse range of input data, the images were collected at various solar zenith angles, altitudes, ground sampling distance, and time intervals. Detailed information on the observations at each study area is provided in Table 1. All UAV sea surface images were acquired under clear sky conditions with no cloud cover. The data were collected between 10:00 a.m. and 3:00 p.m., when the effects of sun glint were relatively minimal. The UAV hovered over the target site for approximately 10 min to collect the data, maintaining a constant field of view for the sensor throughout the observation period. All sea surface images captured by the multispectral camera were processed to radiance values through a pre-processing step and geo-referenced using direct geo-referencing techniques.

The metadata of each image included observation time, location, altitude, and the downwelling irradiance ( $E_d$ ) at the time of capture. The imaging interval was set to 1 s. The raw images (digital numbers) initially observed by the RedEdge-MX cameras were radiometrically corrected and processed for vignetting effects using Equations (1)–(4) to obtain radiance values ( $W \cdot m^{-2} \cdot sr^{-1}$ ). Depending on the orientation of each camera, the captured data corresponded to sky radiance ( $L_{sky-UAV}$ ) and total upwelling radiance ( $L_{t-UAV}$ ) images.

$$L(\lambda) = V_{(x,y)} \times a_1 / g \times (P - P_{BL}) / (t_e + a_2 y - a_3 t_e y) \quad (1)$$

$$V_{(x,y)} = 1/k \quad (2)$$

$$k = 1 + k_0 r + k_1 r^2 + k_2 r^3 + k_3 r^4 + k_4 r^5 + k_5 r^6 \quad (3)$$

$$r = \sqrt{(x - c_x)^2 + (y - c_y)^2} \quad (4)$$

The radiance ( $L$ ) is computed using a vignette correction polynomial function  $V(x, y)$  for pixel position  $(x, y)$  along with radiometric calibration coefficients  $a_1$ ,  $a_2$ , and  $a_3$ , sensor gain  $g$ , normalized raw digital number  $P$ , normalized black level  $P_{BL}$ , and image exposure time  $t_e$ . The raw pixel value  $P$  is normalized to a value between 0 and 1 using metadata from the TIFF files. Vignette distortion is corrected based on the pixel distance  $r$  from the vignette center to each pixel  $(x, y)$ , using six pre-set vignette correction coefficients ( $k$ ) provided during camera manufacturing. The image dimensions are defined as  $c_x = 1280$  and  $c_y = 960$  pixels for the  $x$ - and  $y$ -axis, respectively.

$$L_{w-UAV} = L_{t-UAV} - (L_{sky-UAV} \times \rho_f) \quad (5)$$

The Fresnel reflectance ( $\rho_f$ ) was set to 0.028 based on the UAV's imaging angle, and the radiance images captured in the skyward and waterward directions were ultimately integrated into UAV-based water-leaving radiance ( $L_{w-UAV}$ ) images using Equation (5). The radiance dataset calculated through this process was used as input data for FA-MEMD.

**Table 1.** UAV observation data details.

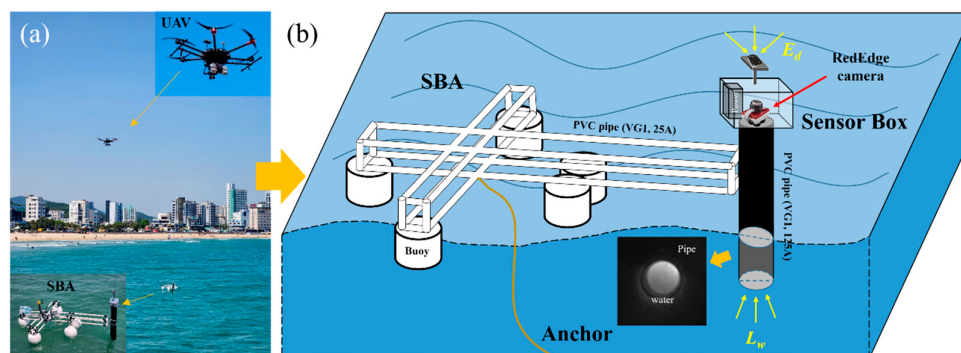
|                        | Study Area 1                              | Study Area 2          |
|------------------------|-------------------------------------------|-----------------------|
| Location               | Song-Jeong Beach                          | Jang-Heong            |
| Date of observation    | 10 May 2024                               | 5 September 2024      |
| Time of day            | 12:49 p.m.–13:04 p.m.                     | 12:11 p.m.–12:25 p.m. |
| Temporal resolution    | 1 pixel/s                                 | 1 pixel/s             |
| Spatial resolution     | 31 cm/pixel                               | 42 cm/pixel           |
| Image size             | 960 × 1280                                | 960 × 1280            |
| UAV altitude           | 50 m                                      | 120 m                 |
| Sky conditions         | Clear sky                                 | Clear sky             |
| Bottom characteristics | Mudflat                                   | Sandy beach           |
| Seawater properties    | Clear water                               | High turbidity        |
| UAV geometry           | Zenith: 45°, Azimuth: 135° (from the sun) |                       |

### 3.3. In Situ SBA Observations

To validate the FA-MEMD glint correction process, Skylight-Blocked Approach (SBA) radiance measurements were collected within the UAV observation areas. The residual ( $L_{w-UAV}$ ) decomposed through FA-MEMD represents an indirect estimation of the radiance reflected by the water itself. However, to validate this result, actual measurements of water-leaving radiance are required. Nevertheless, all ocean remote sensing data are inevitably affected by surface reflections occurring at the water–atmosphere interface. The SBA can be applied to measure  $L_w$  without interference from surface glints [46–49]. In this study, an SBA system was built and moored within the UAV observation area, enabling continuous acquisition of the  $L_{w-SBA}$  data (Figure 5a). The SBA system consisted of a cross-shaped frame with buoys attached at each corner and a sensor mounted on top of a 1.5 m long black polyvinyl chloride pipe positioned at one end of the cross (Figure 5b). The pipe was extended 30 cm below the buoy to ensure that it remained submerged. The RedEdge-MX camera attached to the pipe captured spectral images directed toward the water surface from within the shaded pipe. Additionally, a DLS module installed on the upper frame collected downwelling irradiance ( $E_d$ ) data and metadata, such as latitude, longitude, and time.

The central part of the SBA images captured the water-leaving radiance through the pipe. To avoid the influence of pipe shadows, the average value of the central 50 × 50 pixel area was extracted and applied to calculate  $L_{w-SBA}$ . The temporal variations in  $L_{w-SBA}$  measured

using the SBA system served as a reference for comparing and validating the results of surface glint removal radiance ( $L_{w-UAV}$ ) achieved via the FA-MEMD method.



**Figure 5.** (a) SBA and UAV systems operating simultaneously. (b) Schematic of the SBA system. The SBA system floats on the sea surface using buoys and can be secured in position with anchors. It is capable of measuring water-leaving radiance ( $L_w$ ) and downwelling irradiance ( $E_d$ ) from a fixed location above the water surface.

The pipe was designed to extend 30 cm below the water surface, ensuring it remained submerged. While wave-induced motion can cause the SBA system to fluctuate, leading to variations in the pipe's depth, this study assumed an average submersion depth of 30 cm. The radiance measured by the sensor may be attenuated within the water column depending on the pipe's submerged depth. To account for the attenuation effect, spectral attenuation coefficients ( $K$ ) were determined based on Pedroso et al. [50] for data from Songjeong, located along South Korea's eastern coast, and Min et al. [51] for data from Jangheung, located along South Korea's southern coast. Using these coefficients, the water-leaving radiance at the sea surface,  $L_{w-SBA}(0-)$ , was calculated according to Equation (6).

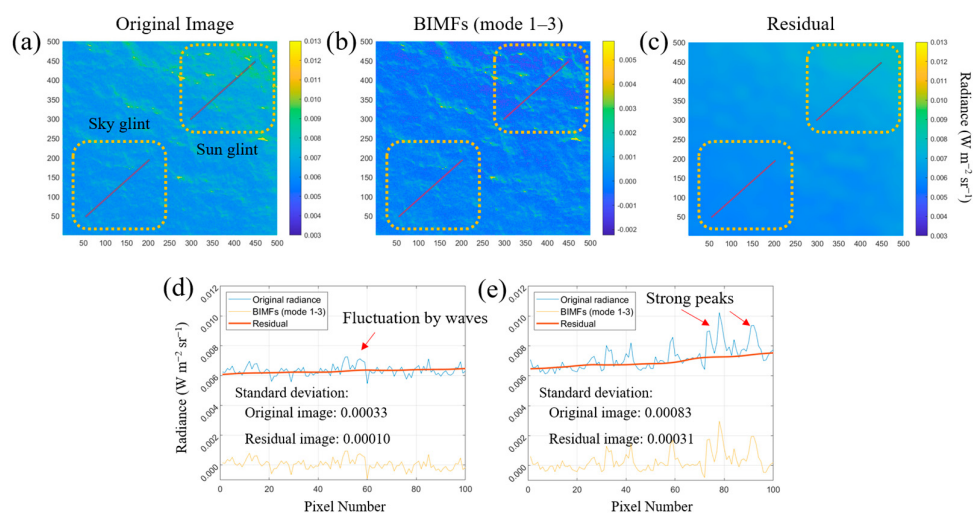
$$L_{w-SBA}(0-) = L_{w-SBA}(\text{depth}) \times e^{-K \times \text{depth}} \quad (6)$$

## 4. Results

### 4.1. Decomposition of Surface Glint Signals Through FA-MEMD

The time-varying brightness of the surface glints observed in the UAV sea surface images resulted from the combined effects of wind-driven currents, waves, and other factors. These signals manifested as non-linear and non-stationary patterns of roughness, and therefore their analysis and interpretation are challenging. FA-MEMD enabled the empirical decomposition of the physical components of such non-linear phenomena from time-continuous UAV sea surface images. By decomposing and removing the representative signals of surface glints from the original image sets using FA-MEMD, only the radiance signals reflected from the water itself remain [5]. A 60 s sequence of data, acquired at 1 s intervals using a UAV-mounted RedEdge-MX multispectral camera, was used as the input for FA-MEMD, and the EMD was configured to decompose the modes into three BIMFs and a residual image (Figure 6).

In the overall area of the original image, heterogeneous sky glints caused by surface roughness were detected, with particularly strong sun glints observed in the upper-right region (Figure 6a). The BIMF modes, decomposed using FA-MEMD, revealed frequency-specific components of surface reflections that were distinguishable in the original images. The combined output of the three modes could be considered as complete signal of the decomposed surface glints (Figure 6b). The residual images, obtained after removing the BIMFs from the original images, displayed spatially homogeneous radiance signals with the surface glints removed (Figure 6c).



**Figure 6.** Decomposition results of surface glints using FA-MEMD (475 nm). (a) Original image. (b) BIMFs combined from modes 1–3, corresponding to the decomposed surface glint signals from the original image. (c) Residual image showing homogeneous radiance. (d) Cross-sectional graph of the sky glint region. (e) Cross-sectional graph of the sun glint region.

For each image in Figure 6a–c, the transect data were extracted from areas where glints occurred, following the direction of wave propagation, to evaluate spatial variability in radiance. The transect data from the sky and sun glint regions both exhibited significant variability, depending on the roughness of the sea surface (Figure 6d,e). Particularly, regions with strong sun glints showed relatively higher fluctuation peaks (Figure 6e). Conversely, the transect data from the residual images demonstrated spatially stable radiance in both regions.

The standard deviation of the datasets extracted from the original and residual images was compared. In the region where sky glints occurred, the mean value was similar but the standard deviation of the original data were calculated as 0.00033 while the standard deviation of the residual data were 0.0001. In the region where sun glints occurred, the standard deviation of the original and residual data were 0.00083 and 0.00031, respectively. The standard deviation in the sun glint region was 2.5-times higher compared to that in the sky glint region. In other words, in the case of the estimated reflectance without glint correction, its values can be 2.5-times higher than those of the correct ones; hence, the geophysical properties can be misleading. The radiance fluctuations caused by surface glints across the image can induce significant changes in radiance even over a distance of just a few pixels, despite the similar physical characteristics of adjacent water bodies. Such unexpected variability can introduce substantial errors in algorithm outputs or validation results when investigating the optical properties of seawater.

#### 4.2. Validation of Radiance in the Residual Image over Time

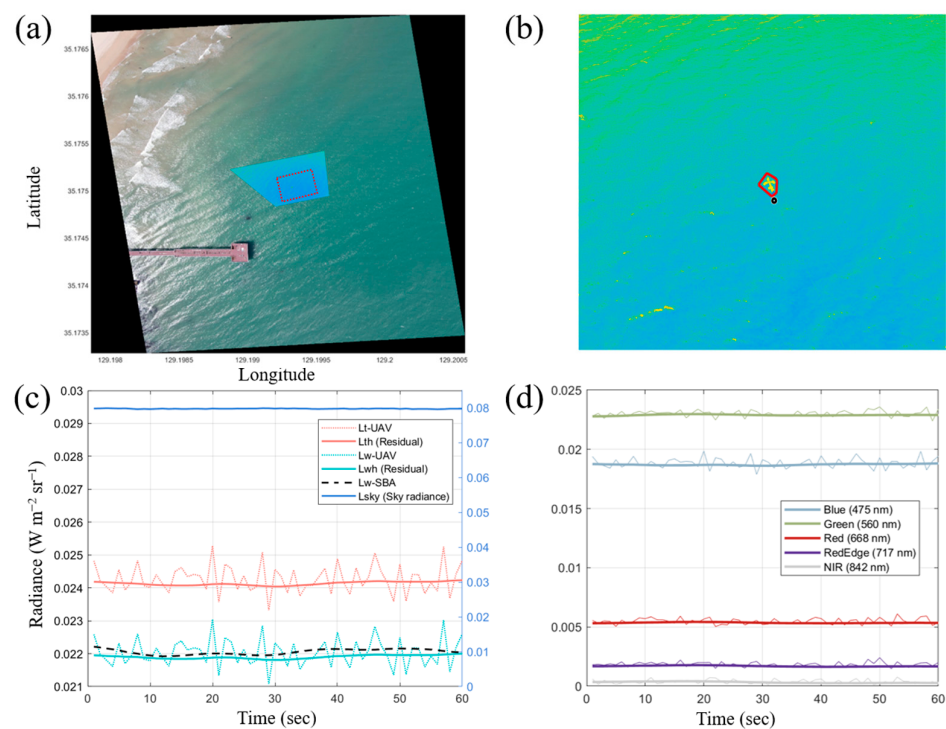
The UAV sea surface image measures the total upwelling radiance ( $L_{t-UAV}$ ), which is the sum of all reflected light from the water body, sea surface, and seabed.  $L_{w-UAV}$ , which enables the observation of the physical properties of seawater, contains only the reflection information from the water body itself. It is obtained by removing the contribution of sky radiance from the  $L_{t-UAV}$  image (Equation (7)). The  $L_{sky-UAV}$  observed using a RedEdge-MX camera was calculated as the average value of a  $15 \times 15$  pixel area at the center of the image. The Fresnel reflection coefficient  $\rho$  was set to 0.028, based on the observation geometry proposed by Mobley [11]. Owing to the complex roughness of the water surface, each pixel in high-resolution UAV sea surface images has a different angle of light reflection. Consequently, subtracting a single value for sky radiance contribution from the two-

dimensional high-resolution image, as in Equation (7), cannot uniformly account for the effects of surface roughness.

$$L_{w-UAV} = L_{t-UAV} - (L_{sky-UAV} \times \rho) \quad (7)$$

Time-series  $L_{w-UAV}$  data were decomposed into modes using FA-MEMD, and the residual image, with surface reflections (BIMFs) removed, was calculated as spatially homogeneous water-leaving radiance ( $L_{wh}$ ). To validate the calculated  $L_{wh}$ , a comparison was performed with the  $L_{w-SBA}$  data obtained using the SBA system moored within the UAV sea surface image.

Figure 7 shows the FA-MEMD analysis results of time-series UAV sea surface multi-spectral images observed under clear water conditions. The position of the SBA system identified in the UAV sea surface images was automatically detected by image processing (red box in Figure 7b). The average  $L_{wh}$  value from a 10 pixel diameter area near the pipe (black circle in Figure 7b) was extracted and synchronized with the  $L_{w-SBA}$  data from the same time and location.

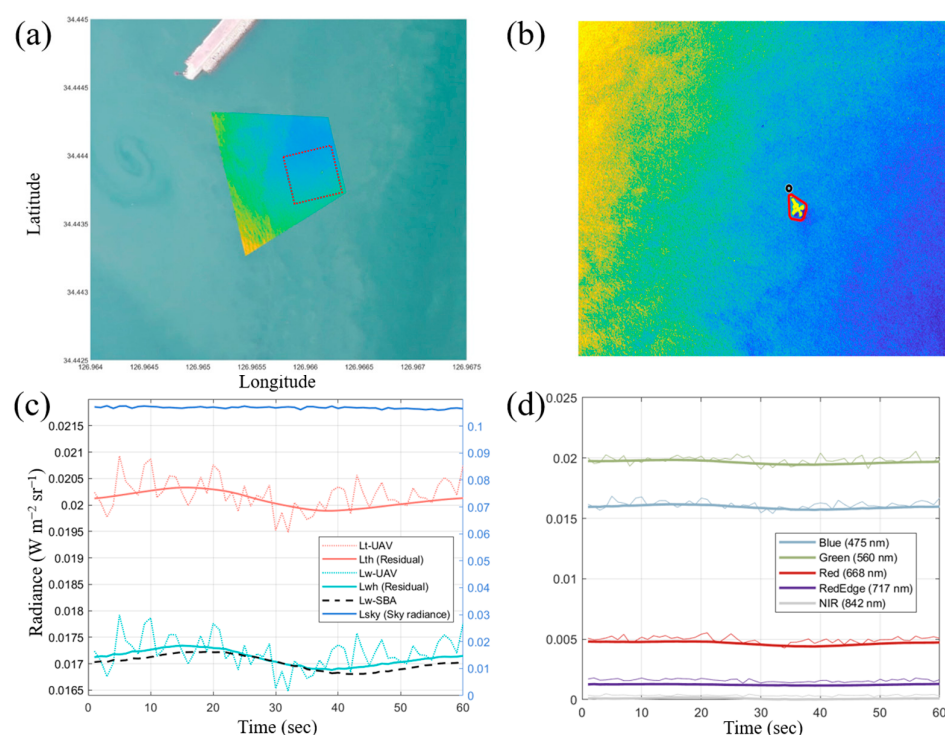


**Figure 7.** (a) Overlay image of digital and multispectral cameras at Songjeong Beach (10 May 2024). (b) Multispectral image in the blue (475 nm) wavelength band (red dashed box area in (a)). SBA (red box) and data extraction area (black circle) identified through image processing. (c) Temporal variations in variables in clear water decomposed using FA-MEMD. Residual signals (thick solid lines) were derived from original radiance (thin line) signals. (d) Temporal changes in reflectance across five spectral bands. Solid and fine lines correspond to the residual and original data of each wavelength band, respectively.

In the clear-water region, it was assumed that the physical properties of seawater would remain stable within a 1 min period. Therefore, it was expected that the radiance at a fixed point in the UAV image would be influenced by surface glints and illumination conditions only. As depicted in Figure 7c, while the average value of  $L_{w-UAV}$  remained constant over time, radiance fluctuations were observed on a second-by-second basis, indicating variations in surface roughness over time. Conversely,  $L_{wh}$  extracted from the same location maintained stable values without temporal variability.  $L_{wh}$  exhibited a similar

trend to  $L_{w-SBA}$ , which was directly measured from the water, over the time series data. When comparing  $L_{w-UAV}$  and  $L_{wh}$  based on  $L_{w-SBA}$  values, the  $R^2$  values were 0.02 and 0.56 while the RMSE values were  $8.37 \times 10^{-5}$  and  $5. \times 10^{-5} \text{ W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1}$ , respectively. Prior to correction, the correlation of radiance over time with the reference data were insignificant; however, surface glint correction significantly increased the correlation coefficient to 0.56 and reduced RMSE by 34.19%. Additionally, five wavelength data observed using the RedEdge-MX camera extracted from the same location also showed consistent radiance over time (Figure 7d).

Figure 8 illustrates the temporal variations in modes decomposed using FA-MEMD in the Jangheung region. In this area, a strong sub-mesoscale eddy was present within the UAV observation range (Figure 8b), and such coastal currents could move several centimeters per second [5]. Consequently, the radiance at fixed points in the UAV sea surface images reflected not only surface reflection and illumination but also physical changes caused by water movement.



**Figure 8.** (a) Overlay image of digital and multispectral cameras at Noryeokdo, Jangheung (5 September 2024). (b) Multispectral image in the blue (475 nm) wavelength band (red dashed box area in (a)). Detected SBA (red box) and data extraction area (black circle) identified through image processing. (c) Temporal variations in variables in turbid water decomposed using FA-MEMD. Residual signals (thick solid lines) were derived from original radiance (thin line) signals. (d) Temporal changes in reflectance across five spectral bands. Solid and fine lines correspond to residual and original data of each wavelength band, respectively.

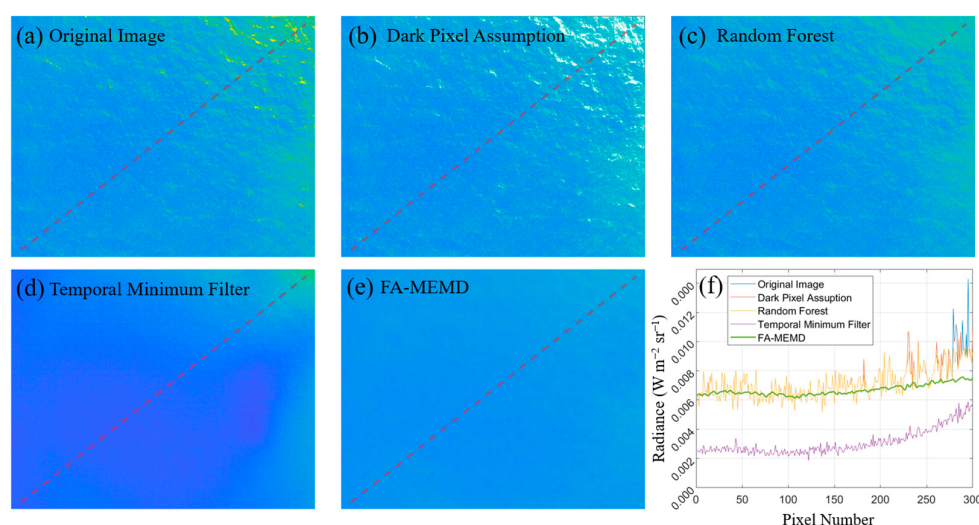
As depicted in Figure 8c,  $L_{w-UAV}$  exhibited significant variability over time when compared to  $L_{wh}$ . Even after removing the surface glints,  $L_{wh}$  in the turbid water region displayed temporal variability, effectively capturing changes in radiance due to the movement of turbid water. When comparing  $L_{w-UAV}$  and  $L_{wh}$  based on the  $L_{w-SBA}$  values, the  $R^2$  values were 0.07 and 0.87 while the RMSE values were  $13.33 \times 10^{-5}$  and  $4.87 \times 10^{-5} \text{ W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1}$ , respectively. The correction accuracy in turbid water was even more pronounced compared to that in clear water, with the correlation coefficient rising to 0.87 and the RMSE improving by 63.47%. Figure 8d illustrates the average values of  $L_{w-UAV}$  and  $L_{wh}$  for the five spectral

bands observed using the multispectral camera. Significant fluctuations were observed in all  $L_{w-UAV}$  values across each spectral band, while the  $L_{wh}$  data maintained a stable trend in radiance across the spectral ranges.

Although  $L_{w-SBA}$  and  $L_{wh}$  were synchronized by time and location, slight time lags or offsets may occur because of difficulties in precisely extracting pixels from identical positions inside and outside the pipe as well as potential differences in optical conditions during the observation process. Nevertheless, the  $L_{wh}$  observed in both regions showed a high correlation with the reference data,  $L_{w-SBA}$ , indicating that  $L_{wh}$  can effectively represent the homogeneous trend of the original  $L_{w-UAV}$  data and successfully isolate surface reflections.

#### 4.3. Comparison with Previous Studies on Glint Correction Methods

Among the various types of surface glints, sun glints are particularly intense, often strong enough to obscure reflections from the water surface. Thus, studies have mainly focused on the removal and interpolation of sun glints. While sun glint correction can increase the number of usable pixels in UAV sea surface images, the influence of surface glints that occur heterogeneously over a waved surface still disrupts the reflection information of seawater, as discussed in the previous section. Figure 9 illustrates a comparison between the conventional sun glint removal methods and the surface glint removal approach using FA-MEMD. Figure 9a–d depict, in order, the original UAV sea surface image and the sun glint removal methods using the Dark Pixel Assumption, Random Forest (RF), and TMF methods. Figure 9e depicts the residual ( $L_{wh}$ ) result obtained through FA-MEMD.



**Figure 9.** Spatial comparison results with previously reported methods for removing surface glints. (a) Original image. (b) Dark Pixel Assumption (NIR > 0). (c) Random Forest. (d) Temporal Minimum Filter. (e) FA-MEMD. (f) Cross-sectional data graphs extracted from images corrected using each method.

As shown in the original UAV sea surface image, sun glint signals occurring in specific regions of the image exhibit high intensity, often several-times stronger than the radiance of the adjacent water. In the masking and filtering method [28] using the dark pixel assumption (NIR = 0) (Figure 9b), the pixel values affected by sun glint are removed, resulting in data loss, while variability caused by surface reflections remains observable in other areas. When sun glint correction and gap-filling are performed using machine learning (e.g., RF) or artificial neural networks (Qin et al. [37]), the model can be trained with input data that include pixels affected by sun glints to remove the sun glint regions and fill the gaps (Figure 9c). However, as the pixel values affected by sun glints are considerably higher than those of the surrounding area, it is relatively easy to train a neural network model using the ground truth data for sun glint correction. Conversely, surface glints

caused by a waved surface exhibit only slight differences compared to the neighboring data, rendering it difficult to train the model with high reliability. The TMF technique [35] constructs an image with minimized surface reflection by calculating the minimum value of each pixel from temporally consecutive data (Figure 9d). While this method can minimize both sun and sky glints, it tends to underestimate radiance compared to the original image, posing limitations for quantitative remote sensing.

The surface glint decomposition technique using FA-MEMD not only corrects the sun glint regions but also provides consistent correction across the entire image, including areas affected by sky glints (Figure 9e). It performs statistical interpolation on data contaminated by glints. Additionally, while conventional sun glint detection and correction methods are limited to image processing based on pixel values affected by sun glints, FA-MEMD offers the advantage of physically decomposing optical signals reflected from the sea surface. The residual image produced using FA-MEMD effectively preserves the spatial patterns of the original data while providing a homogeneous spatial distribution (Figure 9f). The standard deviation of the cross-sectional data extracted from each image was calculated as  $6.56 \times 10^{-4}$ ,  $5.39 \times 10^{-4}$ ,  $5.26 \times 10^{-4}$ ,  $4.22 \times 10^{-4}$ , and  $1.75 \times 10^{-4} \text{ W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1}$  for the Original Image, Dark Pixel Assumption, RF, TMF, and FA-MEMD techniques, respectively. The FA-MEMD results maintained an average value close to that of the original image while exhibiting the lowest standard deviation.

## 5. Discussion

### 5.1. Parameter and Input Data Setup for FA-MEMD

FA-MEMD is a powerful technique capable of decomposing periodic components within data based on input data. However, to obtain stabilized output data under varying observational conditions, an explicit physical basis for parameter settings and input data setup is required. This study constructed the model by referring to the parameter setting guidelines provided with the FA-MEMD algorithm [44]. The maximum number of modes decomposed by FA-MEMD for extracting periodic surface glint signals was set to three. This enabled sufficient decomposition of wave frequencies in coastal areas while avoiding excessively extended computation duration. For other detailed parameter settings, such as window size and sifting tolerance for separating waves, the study referred to previous research by Kim et al. [5].

Key factors determining the physical characteristics of the input data include the spatial resolution of the image (altitude) and time intervals between images. When the spatial resolution of the input data is insufficient to identify waves within the images, or if the time interval between consecutive images is significant, FA-MEMD fails to adequately decompose surface glint signals within the dataset. The BIMFs decomposed from insufficient data can distort the brightness values of the sea surface, resulting in inaccurate residual values. By artificially altering the spatial and temporal resolutions of observed sea surface and UAV sea surface images before inputting them into FA-MEMD, the conditions of the input data can be indirectly evaluated. The evaluation criteria focused on determining whether the decomposed BIMFs can accurately separate reflection signals caused by waves. The results were organized into a lookup table based on the spatial and temporal resolutions of the input data. However, these evaluation results can vary depending on the roughness of the sea surface at the time of observation, the physical characteristics of waves (wavelength and wave height), and changes in the solar incidence and reflection angles. More comprehensive data may be established in the future by acquiring information under a variety of light conditions, seawater physical properties, and input data settings.

### 5.2. Influence of Non-Periodic Signals

FA-MEMD decomposes periodic signals within time-continuous data into BIMFs, while non-periodic signals are extracted as residuals. Therefore, if large floating objects are present in the UAV images, or if irregular wave-breaking signals occur, they can influence the decomposition into BIMFs and residuals. For example, when an object such as a buoy moves through the UAV sea surface images, traces of the path of the buoy may remain in the residual results for a certain duration. This occurs because EMD is specialized in processing non-linear and non-stationary signals, which implies that moving objects such as buoys can distort the original signal, leaving residual traces behind.

Additionally, owing to the time-continuity characteristic of the residuals, subtle changes in the sea surface caused by the passage of a buoy can affect the residuals. However, such non-periodic signals cause distortions only in specific parts of the UAV sea surface images and do not affect the overall trend of the original data. Strong non-periodic signals such as these can be indirectly addressed by removing or interpolating them based on their wavelength values.

### 5.3. Geometric Stability of Input Data for FA-MEMD

With advancements in UAV flight technology, UAVs equipped with Real-Time Kinematic (RTK)-GPS and high-performance flight controllers have recently become commercially available. These improvements have enhanced the geometric accuracy of UAV images to within a few millimeters. Nonetheless, the cumulative effect of sensor vibrations and GPS errors during UAV flights can still reduce the accuracy of direct geometric corrections for the sea surface. To analyze the UAV sea surface image observed at a fixed altitude and latitude–longitude using FA-MEMD, it is crucial to ensure that the data from the same location within the frame are consistently captured. However, slight vibrations persisted in the data collected at regular time intervals. These vibrations can introduce errors in the process of decomposing the spatial periodicity of surface glints when separating BIMFs from the original data.

However, the FA-MEMD analysis of UAV sea surface images obtained in this study was successfully conducted. This outcome is probably attributed to the minimal impact of image vibrations relative to the overall pattern of the BIMFs or the robustness of EMD to noise. To address this issue more effectively, it is recommended that the UAV be equipped with a gimbal of at least two axes to maintain a stable sensor posture, and a high-precision GPS antenna be used for accurate acquisition of the UAV and sensor orientation and position data. As an alternative, sensors could be installed at fixed positions, such as on tall buildings or bridges, to monitor the water surface.

## 6. Conclusions

To address the issue of surface glints, which inevitably occur in high-resolution sea surface UAV sea surface images, we proposed a solution using FA-MEMD, differing from conventional approaches. This method can not only correct the sun glint pixels observed on the sea surface but also sky glints occurring across broader areas of the images because of the roughness of the sea surface. To evaluate the applicability of this approach, we tested it using the data collected from both clear and turbid water regions and validated the input conditions of the model by controlling the spatial and temporal resolutions of the input data.

Additionally, to validate the surface glint correction within the UAV sea surface images, we conducted a quantitative verification of the optical properties of  $L_{wh}$  derived using the  $L_{w-SBA}$  data observed with the SBA system. The final  $L_{wh}$  images obtained were free from the influence of surface glints caused by rough sea surfaces, providing spatially homogeneous reflectance similar to that observed over a flat sea surface over time.

The acquisition of such homogeneous  $L_{wh}$  provides highly accurate optical information for understanding the characteristics of seawater. Additionally, it can significantly reduce the error margin of algorithms derived from these data. Therefore, this study proposed a correction method for surface glints caused by the complex roughness of the sea surface—a challenge previously considered unmanageable—using the FA-MEMD technique. This approach has the potential to render a substantial contribution to the precise data-correction processes in sea surface remote sensing.

**Author Contributions:** Conceptualization, J.-S.L., S.-Y.K. and Y.-H.J.; Methodology, J.-S.L. and S.-Y.K.; Software, J.-S.L. and S.-Y.K.; Validation, J.-S.L.; Formal analysis, J.-S.L. and S.-Y.K.; Investigation, J.-S.L. and S.-Y.K.; Resources, J.-S.L.; Data curation, J.-S.L.; Writing—original draft preparation, J.-S.L.; Writing—review and editing, J.-S.L. and Y.-H.J.; Visualization, J.-S.L.; Supervision, Y.-H.J.; Project administration, Y.-H.J.; Funding acquisition, Y.-H.J. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was supported by the “Development of technology using analysis of ocean satellite images (RS-2021-KS211406)” project funded by the Korea Institute of Marine Science & Technology Promotion (KIMST). Additionally, this research was supported by the Korea Institute of Marine Science & Technology (KIMST) funded by the Ministry of Oceans and Fisheries (RS-2023-00256330, Development of risk managing technology tackling ocean and fisheries crisis around Korean Peninsula by Kuroshio Current).

**Data Availability Statement:** Data are contained within the article.

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

## References

- Colomina, I.; Molina, P. Unmanned aerial systems for photogrammetry and remote sensing: A review. *ISPRS J. Photogramm. Remote Sens.* **2014**, *92*, 79–97. [\[CrossRef\]](#)
- Lee, J.S.; Baek, J.Y.; Shin, J.; Kim, J.S.; Jo, Y.H. Suspended Sediment Concentration Estimation along Turbid Water Outflow Using a Multispectral Camera on an Unmanned Aerial Vehicle. *Remote Sens.* **2023**, *15*, 5540. [\[CrossRef\]](#)
- Baek, J.Y.; Jo, Y.H.; Kim, W.; Lee, J.S.; Jung, D.; Kim, D.W.; Nam, J. A new algorithm to estimate chlorophyll-a concentrations in turbid yellow sea water using a multispectral sensor in a low-altitude remote sensing system. *Remote Sens.* **2019**, *11*, 2257. [\[CrossRef\]](#)
- Román, A.; Tovar-Sánchez, A.; Gauci, A.; Deidun, A.; Caballero, I.; Colica, E.; Navarro, G. Water-Quality Monitoring with a UAV-Mounted Multispectral Camera in Coastal Waters. *Remote Sens.* **2022**, *15*, 237. [\[CrossRef\]](#)
- Yurovsky, Y.Y.; Kubryakov, A.A.; Plotnikov, E.V.; Lishaev, P.N. Submesoscale currents from UAV: An experiment over small-scale eddies in the coastal black sea. *Remote Sens.* **2022**, *14*, 3364. [\[CrossRef\]](#)
- Specht, M. Methodology for Performing Bathymetric and Photogrammetric Measurements Using UAV and USV Vehicles in the Coastal Zone. *Remote Sens.* **2024**, *16*, 3328. [\[CrossRef\]](#)
- Kim, S.Y.; Lee, J.S.; Jeong, Y.; Jo, Y.H. Decomposition of Submesoscale Ocean Wave and Current Derived from UAV-Based Observation. *Remote Sens.* **2024**, *16*, 2275. [\[CrossRef\]](#)
- Anderson, K.; Gaston, K.J. Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Front. Ecol. Environ.* **2013**, *11*, 138–146. [\[CrossRef\]](#)
- Kay, S.; Hedley, J.D.; Lavender, S. Sun glint correction of high and low spatial resolution images of aquatic scenes: A review of methods for visible and near-infrared wavelengths. *Remote Sens.* **2009**, *1*, 697–730. [\[CrossRef\]](#)
- Gao, B.C.; Li, R.R. Correction of sunglint effects in high spatial resolution hyperspectral imagery using SWIR or NIR bands and taking account of spectral variation of refractive index of water. *Adv. Environ. Eng. Res.* **2021**, *2*, 1–15. [\[CrossRef\]](#)
- Mobley, C.D. *Light and Water: Radiative Transfer in Natural Waters*; Academic Press: San Diego, CA, USA, 1994. Available online: <https://cir.nii.ac.jp/crid/1130282269840486656> (accessed on 25 February 2025).
- NASA Earth Observatory. The Science of Sunglint. Available online: <https://earthobservatory.nasa.gov/images/84333/the-science-of-sunglint> (accessed on 27 December 2024).
- Hodgson, A.; Kelly, N.; Peel, D. Unmanned aerial vehicles (UAVs) for surveying marine fauna: A dugong case study. *PLoS ONE* **2013**, *8*, e79556. [\[CrossRef\]](#) [\[PubMed\]](#)

14. Subhan, B.; Arafat, D.; Santoso, P.; Pahlevi, K.; Prabowo, B.; Taufik, M.; Madduppa, H. Development of observing dolphin population method using Small Vertical Take-off and Landing (VTOL) Unmanned Aerial System (AUV). *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *278*, 012074. [\[CrossRef\]](#)
15. Turner, D.; Lucieer, A.; Wallace, L. Direct georeferencing of ultrahigh-resolution UAV imagery. *IEEE Trans. Geosci. Remote Sens.* **2013**, *52*, 2738–2745. [\[CrossRef\]](#)
16. Casella, E.; Collin, A.; Harris, D.; Ferse, S.; Bejarano, S.; Parravicini, V.; Rovere, A. Mapping coral reefs using consumer-grade drones and structure from motion photogrammetry techniques. *Coral Reefs* **2017**, *36*, 269–275. [\[CrossRef\]](#)
17. Dietrich, J.T. Bathymetric structure-from-motion: Extracting shallow stream bathymetry from multi-view stereo photogrammetry. *Earth Surf. Process. Landf.* **2017**, *42*, 355–364. [\[CrossRef\]](#)
18. Taddia, Y.; Stecchi, F.; Pellegrinelli, A. Using DJI Phantom 4 RTK drone for topographic mapping of coastal areas. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* **2019**, *42*, 625–630. [\[CrossRef\]](#)
19. Román, A.; Heredia, S.; Windle, A.E.; Tovar-Sánchez, A.; Navarro, G. Enhancing Georeferencing and Mosaicking Techniques over Water Surfaces with High-Resolution Unmanned Aerial Vehicle (UAV) Imagery. *Remote Sens.* **2024**, *16*, 290. [\[CrossRef\]](#)
20. Shaw, J.A.; Vollmer, M. Blue sun reflected from water: Optical lessons from observations of nature. In *Education and Training in Optics and Photonics*; Optica Publishing Group: Washington, DC, USA, 2017; p. 104523B.
21. Mobley, C.D. Estimation of the remote-sensing reflectance from above-surface measurements. *Appl. Opt.* **1999**, *38*, 7442–7455. [\[CrossRef\]](#)
22. Joyce, K.E.; Duce, S.; Leahy, S.M.; Leon, J.; Maier, S.W. Principles and practice of acquiring drone-based image data in marine environments. *Mar. Freshwater Res.* **2018**, *70*, 952–963. [\[CrossRef\]](#)
23. Jung, S.; Kim, W. Development of an unmanned aerial system for maritime environmental observation. *IEEE Access* **2021**, *9*, 132746–132765. [\[CrossRef\]](#)
24. Muslim, A.M.; Chong, W.S.; Safuan, C.D.M.; Khalil, I.; Hossain, M.S. Coral reef mapping of UAV: A comparison of sun glint correction methods. *Remote Sens.* **2019**, *11*, 2422. [\[CrossRef\]](#)
25. Tiškus, E.; Bučas, M.; Vaičiūtė, D.; Gintauskas, J.; Babrauskienė, I. An Evaluation of Sun-Glint Correction Methods for UAV-Derived Secchi Depth Estimations in Inland Water Bodies. *Drones* **2023**, *7*, 546. [\[CrossRef\]](#)
26. Ottaviani, M.; Spurr, R.; Stamnes, K.; Li, W.; Su, W.; Wiscombe, W. Improving the description of sunglint for accurate prediction of remotely sensed radiances. *J. Quant. Spectrosc. Radiat. Transf.* **2008**, *109*, 2364–2375. [\[CrossRef\]](#)
27. Hochberg, E.J.; Andréfouët, S.; Tyler, M.R. Sea surface correction of high spatial resolution Ikonos images to improve bottom mapping in near-shore environments. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 1724–1729. [\[CrossRef\]](#)
28. Hedley, J.D.; Harborne, A.R.; Mumby, P.J. Simple and robust removal of sun glint for mapping shallow-water benthos. *Int. J. Remote Sens.* **2005**, *26*, 2107–2112. [\[CrossRef\]](#)
29. Goodman, J.A.; Lee, Z.; Ustin, S.L. Influence of atmospheric and sea-surface corrections on retrieval of bottom depth and reflectance using a semi-analytical model: A case study in Kaneohe Bay, Hawaii. *Appl. Opt.* **2008**, *47*, F1–F11. [\[CrossRef\]](#)
30. Kutser, T.; Vahtmäe, E.; Praks, J. A sun glint correction method for hyperspectral imagery containing areas with non-negligible water leaving NIR signal. *Remote Sens. Environ.* **2009**, *113*, 2267–2274. [\[CrossRef\]](#)
31. Hossain, M.S.; Bujang, J.S.; Zakaria, M.H.; Hashim, M. The application of remote sensing to seagrass ecosystems: An overview and future research prospects. *Int. J. Remote Sens.* **2015**, *36*, 61–114. [\[CrossRef\]](#)
32. Kutser, T.; Jupp, D.L. On the possibility of mapping living corals to the species level based on their optical signatures. *Estuar. Coast. Shelf Sci.* **2006**, *69*, 607–614. [\[CrossRef\]](#)
33. Mumby, P.J.; Skirving, W.; Strong, A.E.; Hardy, J.T.; LeDrew, E.F.; Hochberg, E.J.; David, L.T. Remote sensing of coral reefs and their physical environment. *Mar. Pollut. Bull.* **2004**, *48*, 219–228. [\[CrossRef\]](#)
34. Vahtmäe, E.; Kutser, T.; Martin, G.; Kotta, J. Feasibility of hyperspectral remote sensing for mapping benthic macroalgal cover in turbid coastal waters—A Baltic Sea case study. *Remote Sens. Environ.* **2006**, *101*, 342–351. [\[CrossRef\]](#)
35. Partama, I.G.Y.; Kanno, A.; Ueda, M.; Akamatsu, Y.; Inui, R.; Sekine, M.; Higuchi, T. Removal of water-surface reflection effects with a temporal minimum filter for UAV-based shallow-water photogrammetry. *Earth Surf. Process. Landf.* **2018**, *43*, 2673–2682. [\[CrossRef\]](#)
36. Giles, A.B.; Davies, J.E.; Ren, K.; Kelaher, B. A deep learning algorithm to detect and classify sun glint from high-resolution aerial imagery over shallow marine environments. *ISPRS J. Photogramm. Remote Sens.* **2021**, *181*, 20–26. [\[CrossRef\]](#)
37. Qin, J.; Li, M.; Zhao, J.; Li, D.; Zhang, H.; Zhong, J. Advancing sun glint correction in high-resolution marine UAV RGB imagery for coral reef monitoring. *ISPRS J. Photogramm. Remote Sens.* **2024**, *207*, 298–311. [\[CrossRef\]](#)
38. Schlöpfer, D.; Popp, C.; Richter, R. Drone data atmospheric correction concept for multi-and hyperspectral imagery—the DROA-COR model. The International Archives of the Photogrammetry. *ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci.* **2020**, *43*, 473–478.
39. Jenerowicz, A.; Wierzbicki, D.; Kedzierski, M. Radiometric Correction with Topography Influence of Multispectral Imagery Obtained from Unmanned Aerial Vehicles. *Remote Sens.* **2023**, *15*, 2059. [\[CrossRef\]](#)

40. Lee, J.S.; Baek, J.Y.; Jung, D.; Shim, J.S.; Lim, H.S.; Jo, Y.H. Estimate of coastal water depth based on aerial photographs using a low-altitude remote sensing system. *Ocean Sci. J.* **2019**, *54*, 349–362. [[CrossRef](#)]
41. Windle, A.E.; Silsbe, G.M. Evaluation of unoccupied aircraft system (UAS) remote sensing reflectance retrievals for water quality monitoring in coastal waters. *Front. Environ. Sci.* **2021**, *9*, 674247. [[CrossRef](#)]
42. Chen, J.; Xiao, Y.; Guo, Y.; Li, M.; Li, X.; Zhang, X.; Fu, Y. Detecting sun glint in UAV RGB images at different times using a deep learning algorithm. *Ecol. Inf.* **2024**, *81*, 102660. [[CrossRef](#)]
43. Thirumalaisamy, M.R.; Ansell, P.J. Fast and adaptive empirical mode decomposition for multidimensional, multivariate signals. *IEEE Signal Process. Lett.* **2018**, *25*, 1550–1554. [[CrossRef](#)]
44. Huang, N.E.; Shen, Z.; Long, S.R.; Wu, M.C.; Shih, H.H.; Zheng, Q.; Liu, H.H. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc. R. Soc. Lond. A Math. Phys. Eng. Sci.* **1998**, *454*, 903–995. [[CrossRef](#)]
45. Kim, W.; Roh, S.H.; Moon, Y.; Jung, S. Evaluation of Rededge-M camera for water color observation after Image preprocessing. *Journal of the Korean Society of Surveying, Geodesy. Photogramm. Cartogr.* **2019**, *37*, 167–175.
46. Lee, Z.; Pahlevan, N.; Ahn, Y.H.; Greb, S.; O'Donnell, D. Robust approach to directly measuring water-leaving radiance in the field. *Appl. Opt.* **2013**, *52*, 1693–1701. [[CrossRef](#)]
47. Lee, Z.; Wei, J.; Shang, Z.; Garcia, R.; Dierssen, H.M.; Ishizaka, J.; Castagna, A. On-water radiometry measurements: Skylight-blocked approach and data processing. *IOCCG Ocean Opt. Biogeochem. Protocols Sat. Ocean Colour Sens. Valid.* **2019**, *3*, 7.
48. Shang, Z.; Lee, Z.; Dong, Q.; Wei, J. Self-shading associated with a skylight-blocked approach system for the measurement of water-leaving radiance and its correction. *Appl. Opt.* **2017**, *56*, 7033–7040. [[CrossRef](#)]
49. Gray, P.C.; Windle, A.E.; Dale, J.; Savelyev, I.B.; Johnson, Z.I.; Silsbe, G.M.; Johnston, D.W. Robust ocean color from drones: Viewing geometry, sky reflection removal, uncertainty analysis, and a survey of the Gulf Stream front. *Limnol. Oceanogr. Methods* **2022**, *20*, 656–673. [[CrossRef](#)]
50. Pedroso Curtarelli, V.; Clemente Faria Barbosa, C.; Andrade Maciel, D.; Flores Júnior, R.; Menino Carlos, F.; de Moraes Novo, E.M.L.; da Silva, E.F.F. Diffuse attenuation of clear water tropical reservoir: A remote sensing semi-analytical approach. *Res.* **2020**, *12*, 2828. [[CrossRef](#)]
51. Min, J.E.; Ryu, J.H.; Ahn, Y.H.; Lee, K.S. Development of the diffuse attenuation coefficient for down-welling irradiance ( $K_d$ ) algorithm around the Korean Sea. *Korean Soc. Remote Sens.* **2007**, 204–209. Available online: <https://koreascience.kr/article/CFKO200727465742553.do> (accessed on 25 February 2025).

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.