remote sensing

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Editorial

Preface: Remote Sensing Applications in Ocean Observation

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The launch of Seasat, TIROS-N and Nimbus-7 satellites equipped with ocean observation sensors in 1978 opened the way for remote sensing applications in ocean observation. After more than 40 years of development, the application of satellite remote sensing in the ocean has expanded from marine environmental observation to the extraction of ocean dynamic information, and from traditional analysis methods to the use of artificial intelligence technology. With remote sensing technology, the parameters of the ocean surface, such as ocean chlorophyll-a (Chl-a), sea surface temperature (SST), sea surface height (SSH), sea surface wind (SSW), sea surface salinity (SSS), sea ice and sea surface current, can be observed.

SST was one of the first ocean variables studied by earth observation satellites. The first satellite instrument to sense SST was an infrared sensor that used channel combining to correct for atmospheric attenuation of infrared signals from the ocean surface [1]. Besides the infrared SST, imaging microwave radiometers with SST capabilities can also be used [2]. With improvements in the performance of satellite radiometers and SST retrieval algorithms, accurate, global, high-resolution, frequently sampled SST fields have become the basis for many research and operational activities. In 1982, the first SST product was made available for operational use, was the Multi-Channel SST (MCSST), which was derived from the advanced high-resolution radiometer (AVHRR) onboard the NOAA series of satellites [1,3–5]. A nonlinear algorithm was later used to generate another SST product, named the Nonlinear SST (NLSST), or the Pathfinder SST [6]. These algorithms have also been applied to other satellite infrared sensors, such as the MODIS onboard the Aqua and Terra satellites [7]. Data from these datasets have been widely used in various ocean and atmospheric studies, such as those on ocean fronts [8–10], ocean–atmosphere interactions [11], variability and long-term changes [12–16] and ocean modeling [17,18]. This Special Issue contains several articles on SST applications, which will be introduced in the later sections.

Following the successful demonstration of quantitative estimations of Chl-a derived from the Coastal Zone Color Scanner (CZCS) onboard the Nimbus-7 satellite, the Chl-a products derived from the Sea-Viewing Wide-Field-of-View Sensor (SeaWiFS) onboard the Orbview-2 satellite were made available for public use in September 1997. The two Moderate Resolution Imaging Spectroradiometers (MODISs) onboard the Terra (since 200) and Aqua (since 2002) satellites provide the same products. The Chl-a product was derived using bio-optical algorithms such as the chlorophyll 2 algorithm (OC2) and chlorophyll 4 algorithm (OC4) for SeaWiFSs [19] and the chlorophyll 3 algorithm (OC3) for MODISs [20]. These ocean color sensors provide not only Chl-a products, but also several other ocean-water-quality products and colored dissolved organic matter, turbidity, dissolved organic carbon and suspended sediment concentration [21]. These missions provided data of exceptional quality and continuity, allowing scientific investigation of a variety oceanographic research topics [22]. For a description of remote sensing methods and statistical techniques for evaluating ocean color, refer to [23]. The good-quality SeaWiFS data were also compared with data from other ocean color sensors [24–28]. As there are several ocean color sensors, new algorithms for ocean Chl-a products have been proposed [29]. In addition to the band ratio algorithm, artificial intelligence models have been applied to retrieve Chl-a data from ocean color sensors, including models based on neural networks [30–32], machine learning [33–37] and deep learning [38,39]. This Special Issue also presents several articles detailing applied research using ocean color sensors. These will be introduced in later sections.

Satellite altimeters measure sea surface height from space with an accuracy of approximately 2 cm [40,41], making altimeter data useful for various ocean studies [42,43]. The TOPEX/Poseidon altimeter provided sea surface height data from 1992 to 2005, and its follow-up satellites, the Jason series, have since provided continuous data. These high-quality data have allowed oceanographers to conduct many studies, such as those on ocean circulation [44], ocean currents [45,46], oceanic eddies [47–49], ocean tides [50,51], sea surface waves [52,53] and sea level change [54–57]. To reflect the practicability of satellite altimeter data in the study of ocean dynamics, this Special Issue has gathered several studies using satellite altimetry, which will be introduced in later sections.

Similar to satellite altimeters using radar signal, satellite scatterometers provide wind field data over the oceans [58,59]. Satellite scatterometers are not only applied to study weather and ocean–atmosphere interactions, but also land and ice [60]. This Special Issue includes an article that introduces the application of a scatterometer onboard a China–French satellite to identify sea ice.

Besides the above-mentioned applications in ocean observation, this Special Issue presents various advanced ocean remote sensing technologies and their applications, including the use of artificial intelligence (AI) technology to explore ocean information [61–64] and reconstruct missing values [65,66]. The applications of ocean remote sensing detailed in this Special Issue include methods for the observation of changes in the ocean environment [67–77] and fishing ground [78], as well as the dynamics of the ocean, such as internal tides [79], internal waves [80,81], eddies and wakes [82,83], upwelling [84,85], ocean current [86–89] and even bibliometric analysis applied to oil detection and mapping [90]. A brief overview of the articles collected in this Special Issue is given below.

AI has been widely used for image classification. Fuzzy logic is a method of reasoning that resembles human reasoning. This approach is similar to how humans perform decision making. Thus, fuzzy logic can be treated as a kind of AI technology. The classification of seawater is very important for the study of ocean water color, because the various substances contained in seawater cause differences in seawater color. Therefore, the classification of seawater color can help us determine and systematically understand the substances contained in seawater. However, currently there is no commonly recognized template for the classification of water color. Therefore, Jia et al. [61] used a synthetic hyperspectral dataset of plankton, aerosols, clouds and marine ecosystems for unsupervised classification to categorize global ocean waters into 15 classes, resulting in a set of fuzzy logic optical water pattern schemes. These schemes were applied to several satellite multispectral sensors, including the Sea-Viewing Wide-Field-of-View Sensor (SeaWiFS), Medium-Resolution Imaging Spectrometer (MERIS), Moderate-Resolution Imaging Spectroradiometer (MODIS), Operational Land Imager (OLI), Visible Infrared Imaging Radiometer Suite (VIIRS), Multispectral Instrument (MSI) and Ocean and Land Colour Instrument (OLCI), and are considered more appropriate than existing optical water-type classification methods for global oceans.

Oil spills have always been an important issue in environmental protection efforts. However, it is difficult to automatically distinguish between man-made (spill) and natural (seep) oil slicks from synthetic aperture radar (SAR) images using limited datasets. Amri et al. [62] introduced the application of deep learning for automated offshore oil slick detection in SAR images. The data used were derived from a large database of real and recent oil slick monitoring for both types of oil slicks. Compared with the monomodal model, the proposed method yields a detection performance of up to 94% and reduces the false-positive rate by 14% to 34%. These results provide new solutions to improving the detection of natural and man-made oil slicks by providing tools that allow image interpreters to more efficiently monitor global ocean surfaces. Such a tool would speed up oil slick detection tasks, helping researchers to keep up with the continuous acquisition of sensors.

SAR images can be used not only for oil spill detection, but also for ship detection. With the development of artificial intelligence and big data technology, the data-driven convolutional neural network (CNN) has been widely used in ship detection. However, the accuracy of ship detection, feature visualization and analysis when using CNN methods need to be further improved. Geng et al. [63] proposed a two-stage ship detection method for land-contained sea area without the traditional sea–land segmentation process. Based on Sentinel-1 SAR images, the proposed method is suitable for ships smaller than 32×32 in size and can achieve a very high accuracy.

SST plays an important role in air–sea interactions, which have a significant impact on global change. Satellite-remote-sensing-derived SST data are often used as input for numerical forecasting models, but the results produced by numerical forecasting models often deviate from the observation data. In this era of big data, artificial intelligent technology can also be used to correct the bias of numerical forecast products. Fei et al. [64] presented an SST correction method with a convolutional long short-term memory network with multiple attention mechanisms. The method has been tested in the South China Sea and can effectively reduce errors.

Developing a system for accurately estimating changes below the sea surface from data on the sea surface is a challenge in ocean remote sensing. Dong et al. [65] applied the machine learning method of artificial intelligent technology to subsurface salinity reconstruction. The input parameters were SSS, SST, SSH and SSW, all of which can be obtained from satellite remote sensing. The parameters also included marine geographic information, that is, longitude and latitude. The Argo data were used to train and validate the machine learning model. The results show that reconstructed subsurface salinity is mainly affected by wind speed and its location, and better estimation accuracy is obtained in winter and autumn due to weaker stratification. This study offers new insight into oceanic observations.

Sargasso is abundant in the Caribbean Sea. To assess the presence and abundance of Sargasso algae from satellite ocean color data, atmospheric corrections are first required. However, atmospheric correction procedures commonly used in ocean waters need to be adjusted when dealing with Sargassum's emergence, because the non-zero water reflectance in the near-infrared band caused by Sargassum's optical signature may lead its misidentification as aerosols. Schamberger et al. [66] relied on the local uniformity of aerosol reflectance between Sargassum and Sargassum-free regions, overcoming this difficulty by interpolating aerosol and sunlight reflectance between nearby Sargassum-free pixels. The proposed method was shown to generate more reasonable aerosol and sunlight reflectance estimations.

The Geostationary Ocean Color Imager (GOCI) is the first operational geostationary ocean color sensor designed to monitor short-term and small-scale changes in the Northwest Pacific. Atmospheric corrections are especially important for small-scale short-term changes. To examine the uncertainty of GOCI-derived normalized water-leaving radiance (nLw) products, He et al. [67] applied the nLw data provided by Aerosol Robotic Network Ocean Color (AERONET-OC) to analyze the results of two GOCI algorithms. The results show that the nLw data generated by the GOCI Data Processing System were slightly better than those of the Sea-Viewing Wide-Field-of-View Sensor Data Analysis System (SeaDAS) in the visible band; however, the average relative error percentage in the blue band was over 30% for both algorithms. Both algorithms perform better at noon, and worse in the early morning and early evening. It is speculated that the uncertainty in the nLw measurement comes from the aerosol model, the near-infrared water-leaving radiometric correction method, and the bidirectional reflectance distribution function correction method in the corresponding atmospheric correction procedure.

In addition to atmospheric corrections, correcting detected clouds is critical for visible-light remote sensing because they severely impede the radiative transmission of visible light. However, cloud occlusion on turbid waters is prone to misjudgment, resulting in the loss of non-cloud pixel data. Lu et al. [68] proposed an improved GOCI cloud-masking method for turbid water. Compared with other existing cloud-masking methods, this improved method can more realistically identify the spatial location and shape of clouds and thus preserves more accurate turbid water pixels.

Unlike traditional passive ocean color remote sensing technology to detect phytoplankton and suspended particles on the sea surface, lidar technology is also used to simulate the biogeochemical processes of the upper ocean, providing data on the vertical distribution of suspended particles and the optical properties of the ocean. Zhang et al. [69] presented a new optical method to distinguish between water with different concentrations of algae through data generation (the initial width of the laser beam and the width decay rate) using the marine Scheimpflug lidar system. The applications of backscattered intensity and laser beam width measurements are explored with spatial resolution with millimeter accuracy over distances of up to several meters.

The application of satellite observation in studying typhoons has become a research hotspot in recent years. Strong typhoons enhance turbulent mixing, causing sediment re-suspension and promoting Chl-a blooms. Li et al. [70] found that the three late-autumn typhoons in the northwest of the South China Sea had limited responses to Chl-a, with only a slight increase of 23%, but a 280% increase in total suspended sediment (TSS). However, in the southern region, approximately 100 km away from the typhoon track, after the typhoon passed, the concentrations of TSS and Chl-a increased by 160% and 150%, respectively, showing different mechanisms for the increase in Chl-a concentration. This study contributes to a further detailed evaluation of the biological responses induced by typhoons.

The Chl-a and SST products from MODIS Aqua were used to study the events of harmful algae bloom (HAB) in the Arabian Gulf [71]. The results of the study show that the highest Chl-a concentration was in the Strait of Hormuz, with an average of 2.8 mg m^{-3}, which was 1.1 mg m^{-3} higher than the average of the entire study area. While the shallow-water region showed a strong positive correlation between Chl-a and SST, the deep-water region showed the opposite, with a negative correlation.

Seagrass meadows play a key role in supporting high levels of biodiversity, but are constantly threatened by human activity. To understand changes in the distribution of seagrass meadow, Xu et al. [72] used Landsat-8 OLI imagery (1974–2019) to assess large-scale changes in seagrass (*Zostera marina* L.) in the Caofeidian shoal port in the northern Bohai Sea from reclamation activities. By mapping changes in the distribution of seagrass meadows, it was shown that changes in seagrass meadows increased rapidly as the amount of land reclaimed increased. Storm surges caused by typhoons were shown to be causing habitat degradation. Fortunately, a land reclamation project created an artificial "coastal dam" that buffered seagrass meadows from wave action and provided relative shelter, which has resulted in a substantial increase in habitat since 2012.

In July–August 2021, a severe marine heat wave (MHW) occurred over a wide area of the Pacific Northwest, including the entire Sea of Japan and parts of the Sea of Okhotsk [73]. These MHWs are the largest observed since satellite measurements of global SST began in 1982. The MHWs in summer 2021 were observed at the sea surface and occurred with a stable shallow oceanic surface boundary layer. The distribution of MHWs is closely related to the sea surface heat flux, indicating that MHWs are mainly generated by atmospheric forcing. The atmospheric westerly jet moved extremely northward, and MHWs developed rapidly under the atmospheric high-pressure system close to the sea surface, which is related to the northwestward expansion of the North Pacific Subtropical High. Subsequently, as the westerly jet shifted southward, the MHWs weakened and then contracted abruptly, synchronizing with the rapid deepening of the ocean surface boundary layer.

Thermal discharge from power plants is a form of ocean pollution. It needs to be monitored. Zhang et al. [74] analyzed the thermal discharge of the Daya Bay Nuclear Power Plant (NPP) in China. To determine temporal and spatial patterns and factors affecting heat emissions, Landsat imagery acquired for the period 1993–2020 was used. SST data were retrieved from Landsat imagery using the radiative transfer equation and split window algorithm. The retrieved SST data were then used to analyze seasonal and interannual variations in areas affected by thermal discharge from the NPP, as well as the effects of the installed capacity of the NPP, tides and wind on the spread of thermal discharge. The analysis showed that with the increase in the installed capacity of the NPP, the SST increases. There is a significant linear correlation between SST and the installed capacity of an NPP. Tides affect areas of the warming zone, and the low tide has a greater impact. Regardless of whether the wind is favorable or adverse, the tides affect the warming zone more than the wind.

Based on satellite-observed SST data, Argo observations and model reanalysis results, Qiao et al. [75] investigated the upper ocean response to Super Typhoon Goni (2015) in the western North Pacific. The results show that the maximum SST cooling caused by Goni was larger than that caused by most typhoons, which is related to the enhancement of turbulent mixing caused by Goni. On the right side of the typhoon's path, the Goni-induced diapycnal diffusivity in the upper ocean increased by three orders of magnitude and persisted for at least 9 days after Goni's passage. In contrast, the diapycnal diffusivity on the left side of the typhoon path did not show a significant change. The enhancement of turbulent mixing was consistent with the Goni-induced near-inertial kinetic energy, which suggests that the enhanced turbulent mixing was caused by Goni-induced near-inertial waves.

Sea ice plays an important role in global climate change issues. Therefore, methods of detecting sea ice are also valued in ocean telemetry. Li et al. [76] introduced an improvement of the Bayesian Sea ice detection algorithm for the rotating fan-beam scatterometer CSCAT on the China–France Ocean Satellite (CFOSAT). This also serves as a guide for the recently launched dual-frequency rotating fan-beam scatterometer WindRAD.

Fishing grounds have a significant relationship with the marine environment. The use of satellites to observe changes in the marine environment has often been used for fishery management. Ding et al. [77] used satellite-derived SST, SSW, Chl-a and reanalysis data to explore the relationship between the observed aggregation of large fish and environmental factors. In the winter of 2017, the bottom water of the fishing grounds in the East China Sea was abnormally warm, and there was a significant cooling caused by the eastward movement of the Yellow Sea Cold Current with intensified northwesterly winds. Unusually warm fisheries may have provided a suitable environment for warm fish, resulting in the observation of large fish assemblages. This abnormal temperature change may be related to changes in local ocean circulation.

Although the ocean internal solitary wave (ISW) is a phenomenon that occurs under the sea surface, it modulates the convergence and divergence of the sea surface. Therefore, by observing the roughness of the sea surface, the characteristics of ISWs can be detected. Combining SAR images and mooring stations located between offshore islands with rough topographic features, Liu et al. [78] presented the characteristics of ISWs observed in the northern Yellow Sea during the summers of 2018 and 2019. ISWs with vertical displacements of up to 10 m induced prevailing high-frequency temperature variations. SAR images show that ISW intensity exhibits a clear spring–neap cycle corresponding to the local tidal forcing. The propagation speed derived from SAR images is consistent with the Korteweg–de Vries (KdV) model. The prevalence of ISWs in the study area is believed to play a crucial role in the regulation of vertical heat and nutrient transport and thus the biogeochemistry cycle.

Multi-satellite altimeter data from 1993 to 2020 were used to study the model-1 semidiurnal diurnal tides in the Sulu and Sulawesi Seas [79]. To extract multiple coherent internal tides separately, a practical plane wave analysis method was used. The complex radiation paths and interference patterns of internal tides were revealed, showing the spatial contrast between the Sulu and Sulawesi Seas. Mode-1 semidiurnal tides in the Sulawesi Sea are efficiently generated by the Sulu and Sangchi island chains, creating a spatially inhomogeneous disturbance pattern in the deep basin. These high-energy semidiurnal internal tidal beams contribute to the frequent occurrence of solitary waves (ISWs) in the study area.

Following similar techniques to [79], Wang et al. [80] used satellite altimeter data to study internal tides and explore the difference between the semidiurnal and diurnal internal tides on the East China Sea Shelf. The semidiurnal and diurnal internal tides exhibited distinct temporal trends. The semidiurnal internal tides increased by an order of magnitude, while the diurnal internal tides followed quasi-spring–neap cycles with a generally stable intensity. These internal tides probably originated from the shelf–slope area in northeastern Taiwan. Time-varying stratification was the most important factor for the internal tidal magnitude. Although both semidiurnal and diurnal internal tides were mode-1-dominated, the semidiurnal internal tide intensified at the sea surface and the diurnal internal tide intensified at the bottom.

Satellite altimeter data can be used not only to observe internal tides but also to observe core rings. Meunier et al. [81] reconstructed the 3D structure of the Loop Current Rings (LCRs) in the Gulf of Mexico using satellite altimeter data and a large set of ARGO float profiles. Between 1993 and 2021, 40 LCRs were detected in altimetry, and their 3D thermohaline structures were determined. The dynamically correlated variables and their cumulative effects on the heat, salt and energy balances in the Gulf of Mexico were discussed. The results show that LCRs have a significant effect on these balances.

Satellite altimeter data can also be used to detect mesoscale eddies. Mesoscale eddies can be found in the global ocean and have been studied on global and regional scales. Hao et al. [82] investigated the spatiotemporal variation and generation mechanism of mesoscale eddies across Indonesian seas. Eddies were detected from altimetry sea-level anomalies. The Sulu Sea, Sulawesi Sea, Maluku Sea and Banda Sea were the main eddy-generating areas. More than 80% of eddies are short-lived, with a lifespan of less than 30 days. The eddies exhibit high spatial inhomogeneity, with typical amplitudes and radii of 2–6 cm and 50–160 km, respectively. Approximately 48% of the eddies in the Sulawesi Sea are highly nonlinear, compared to less than 30% in the Sulu and Banda Seas. In the Sulu and Sulawesi Seas, barotropic instability of the mean flow dominates the eddy generation, while in the Maluku and Banda Seas, baroclinic instability is slightly greater.

As the visible trajectory information left by moving objects on the sea surface, wake has developed into one of the key detection targets of ocean visible-light remote sensing. In the case of slow ship speed, deep draft and the existence of clouds and fog, due to the low reflectivity of the sea surface and interfering objects, the wake target signal is weak and the signal-to-noise ratio is low. To solve the above problems, Ying et al. [83] calculated the difference in noise equivalent reflectance of eight bands commonly used in oceanographic remote sensing and found that the index is generally in the order of 10^{-4} and stabilizes within a certain range of values. This research has helped to improve the ability of imaging systems to detect weak wake signals.

Coastal upwelling is important for coastal ecosystems because it increases nutrients and supports plankton growth in the upper ocean. Huang et al. [84] used the SST data of the Himawari-8 geostationary satellite to map the upwelling area on the east coast of Taiwan in summer during the southwest monsoon season, which provides favorable conditions for upwelling. The results show that the range of upwelling was larger from June to August, but the upwelling duration was longest in the north center from May to September.

In addition to using satellite remote sensing SST data, data from other sources can also be applied for the study of upwelling. Li et al. [85] analyzed the spatial distribution, variability and possible forcing mechanisms of the upwelling off Manaung Island, Myanmar, using multisource satellite remote sensing data and the World Ocean Atlas 2018 (WOA18) temperature and salinity dataset. The results show that upwelling occurs in February, peaks in March and decays in May, and this upwelling is caused by the rise of seawater at depths below 100 m. The evolution of upwelling was mainly induced by remote forcing from the equator, while local wind forcing also contributed to enhancing the strength of the upwelling.

Whether the East Australian Current (EAC) has a seasonal intrusion has been debated. Xie et al. [86] applied Topographic Position Index (TPI)-based image processing techniques and a 26-year satellite SST dataset to quantitatively map the EAC in northern New South Wales (NSW). The results show that EAC intrusion exhibited seasonal cycles, being closer to the coast in austral summer than winter. The spatial analysis also showed that the EAC had a seasonal shift upstream of 29°40′S latitude and a seasonal expansion downstream. This study confirmed the seasonality of EAC intrusion observed in long-term remote sensing data. The findings provide new information on seasonal upwelling and shelf circulation off the NSW coast.

During June and July 2010, an anomalous branch of the Kuroshio Current near Taiwan in the western North Pacific was observed meandering eastward around 21°N [87]. This branch carries high-Chl-a waters into the nutrient-poor North Pacific Subtropical Gyre from 125°E. The thermohaline characteristics of this branch are similar to those of the Kuroshio. This branch has an average surface speed of 0.5 m s^{-1}, as shown by satellite altimeter data, Lagrangian drifters and Japan Meteorological Agency meridian cruise transects at 137°E. The branch appears to be associated with a surface cyclonic wind anomaly to the north at approximately 22–24°N.

The change that occurs in the Kuroshio Current as it passes through the Luzon Strait is a frequently discussed topic. Sun et al. [88] used multiple remote sensing datasets, combined with in situ drift observations, to analyze the Kuroshio intrusion into the South China Sea through the Luzon Strait. The results show the presence of a strong Kuroshio branch and accompanying anticyclonic eddy (ACE) in the winter of 2020–2021. Both the orographic negative wind stress curl southwest of Taiwan and the westward Ekman transmission through the Luzon Strait had higher values than the historical maximum. Hence, wind forcing is considered to be the main mechanism of this event.

Using coastal radar to observe the oceans is another form of ocean remote sensing technology. Lu et al. [89] used coastal high-frequency radar observations, satellite tracking drifters and numerical models to explore the ocean current variations in the northern Taiwan Strait in summer. The results show an obvious interaction between the intra-diurnal tides and ocean currents northwest of Taiwan. As the tide changed f high tide and low tide, the change in direction of the nearshore current occurred before the change in the offshore current. The drifter trajectories showed that there were three different drifting paths in the Taiwan Strait in summer. The regional ocean modeling system model was applied to clarify the factors influencing the three pathways. Simulation results and high-frequency radar data show that the difference in the drift path is caused by the transition of tidal ebb and flood and the difference in the speed of nearshore and offshore ocean currents.

In addition to analyzing observed data or using numerical models, marine researchers can also apply bibliometric and network analysis to analyze research trends. Oil spill detection and mapping (OSPM) is an extremely relevant problem due to spills' environmental impact on coastal and marine ecosystems. Vasconcelos et al. [90] evaluated the scientific literature from the last 50 years from a scientific point of view. The authors conducted a literature review on OSPM applications to perform bibliometric and network analysis to assess research and trends in this scientific field. Data were taken from the Scopus database, and then bibliometric tools were used to obtain information and reveal quantitative patterns in the literature. The findings indicate that the detection of oil in the ocean has undergone tremendous development over the past few decades and that there is a close relationship between technological developments aimed at detection and improvements in remote sensing data acquisition methods.

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