International Journal of Marine Science, 2025, Vol.15, No.1, 45-52
http://www.aquapublisher.com/index.php/ijms

Research Perspective Open Access

# Mechanisms and Applications of Ocean Remote Sensing: Inversion Algorithms

Linhua Zhang, Lingfei Jin
Institute of Life Science, Jiyang College of Zhejiang A&F University, Zhuji, 311800, Zhejiang, China
Corresponding author: lingfei.jin@jicat.org

International Journal of Marine Science, 2025, Vol.15, No.1, doi: 10.5376/ijms.2025.15.0005
Received: 17 Jan., 2025
Accepted: 20 Feb., 2025
Published: 28 Feb., 2025



**Preferred citation for this article**:
Zhang L.H., and Jin L.F., 2025, Mechanisms and applications of ocean remote sensing: inversion algorithms, International Journal of Marine Science, 15(1): 45-52 (doi: 10.5376/ijms.2025.15.0005)

**Abstract** This study reviews the fundamental mechanisms of ocean remote sensing, with a focus on the interaction between electromagnetic waves and the ocean surface, as well as the importance of atmospheric correction. It systematically analyzes inversion algorithms used to extract oceanic parameters such as chlorophyll concentration, sea surface temperature, and seafloor topography. The study also explores the integrated application of machine learning and artificial intelligence to optimize inversion accuracy and address algorithmic challenges. The findings indicate that advanced inversion algorithms can significantly enhance the accuracy of oceanic parameter extraction, which is crucial for obtaining key data on sea surface temperature, chlorophyll concentration, and seafloor topography. Case studies demonstrate the application of inversion algorithms in monitoring coral reef degradation, tracking marine oil spills, and assessing sea level rise. This study highlights the importance of inversion algorithms in improving the precision of ocean observations, aiming to provide a scientific basis for the optimization of ocean observation technologies and promote higher accuracy and broader-scale ocean monitoring capabilities.
**Keywords** Ocean remote sensing; Inversion algorithms; Sea surface temperature; Chlorophyll concentration; Machine learning

## 1 Introduction

Ocean remote sensing is an important tool for observing and understanding the sea. The ocean is huge and changes quickly. A lot of information is not easy to measure by traditional methods, and remote sensing can help us collect this data more easily. It has many uses in areas such as climate research, marine biology and marine science. Through remote sensing technology, we can obtain information such as the color, temperature, wave height of sea water, and can continuously observe it on a large scale and for a long time. For example, parameters such as chlorophyll a concentration and water transparency are directly related to whether the water quality is good. Remote sensing of these indicators can help us make more accurate ecological and geochemical models (Zhu and Huang, 2021; Zhao et al., 2022; Bisson et al., 2023).

Remote sensing technology has developed rapidly in recent years. At first, people mainly used some empirical formulas to calculate, but now there are new methods, such as semi-analytical methods and machine learning algorithms, which can make the data we obtain more accurate and wider (D'Alimonte et al., 2016; Kolluru et al., 2021). Now, researchers have developed some hybrid algorithms to better analyze ocean color data, especially the distribution of absorbent substances. These technologies allow us to see the changes in light in seawater. In addition, machine learning methods such as support vector machines and deep learning models are also used to estimate parameters such as chlorophyll a concentration and seawater sound speed, and the effect is better than traditional methods (Chen et al., 2024).

This study reviews the latest advances in these inversion algorithms, including hybrid models and machine learning methods, to see how they perform in ocean parameter inversion. We will also analyze their working mechanisms and practical applications, and discuss how to use new technologies to improve the accuracy and reliability of data. The ultimate goal is to promote the development of more powerful and more general inversion algorithms to make ocean remote sensing more useful and efficient.

## 2 Fundamental Mechanisms of Ocean Remote Sensing

### 2.1 Electromagnetic spectrum utilization in ocean observations

Ocean remote sensing mainly relies on electromagnetic spectrum to collect data. Simply put, it is to use different bands of light to "see" the ocean. Different wavelengths can see different information. For example: the near-infrared (NIR) band is more suitable for observing clear sea water; the short-wave infrared (SWIR) band is more suitable for observing turbid waters (Liu et al., 2019). These bands are important when performing atmospheric correction, which means that when processing images, they can help us "filter" air interference to data. Choosing the right wavelength is very important, especially in some places with complex water quality. If you choose the wrong one, the data will be inaccurate (Wang et al., 2023).

### 2.2 Interaction between ocean surface and electromagnetic waves

Remote sensing depends on the interaction between electromagnetic waves and the sea surface. When the light hits the sea surface, part of it will be reflected back. Through these reflected lights (also known as remote sensing reflectivity Rrs), we can know what is happening in the water. Scientists use some algorithms (such as the semi-analytical algorithm SAA) to convert Rrs data into "optical properties" in seawater. These characteristics can tell us whether there are phytoplankton, debris, colored substances, etc. in the water (Kolluru et al., 2021). This method is particularly important for monitoring seawater color and chlorophyll concentration (He et al., 2024). If the data is inaccurate, it is easy to judge the wrong water quality.

### 2.3 Atmospheric correction and its role in accurate data retrieval

Atmospheric correction (AC) is a critical preprocessing step in ocean remote sensing because it eliminates atmospheric effects in satellite data to obtain accurate ocean information. Various AC algorithms have been developed to deal with challenges posed by different atmospheric conditions. For example, the Intelligent Polarized AC (IPAC) algorithm significantly improves the accuracy of marine color products by processing multi-angle, multi-spectral and polarized data. Similarly, the use of models such as ACOLITE and SeaDAS has been shown to enhance retrieval of remote sensing reflectivity in coastal waters, and general AC methods often fail (Ilori et al., 2019). The development of advanced AC algorithms based on neural networks and other advanced AC algorithms has further improved data accuracy, especially in high-latitude areas where the solar zenith angle is large (Li et al., 2022).

## 3 Inversion Algorithms in Ocean Remote Sensing

### 3.1 Principles of ocean parameter inversion

3.1.1 Optical inversion for chlorophyll concentration

Remote sensing technology can be used to estimate how much chlorophyll a is in water, which is very useful for understanding water quality. The commonly used method now is to analyze the optical properties of water based on remote sensing reflectivity data. These methods can determine whether there are many phytoplankton in the water, because phytoplankton contains chlorophyll. In the past, people used traditional algorithms, such as the ocean color index. But now, scientists are starting to use machine learning models, like Support Vector Machine (SVM) and XGBoost, which are more accurate when processing MODIS/Aqua satellite data. Some people have combined semi-analytical algorithms (SAA) and absorption decomposition algorithms (ADA) to develop a hybrid algorithm. This method can better analyze absorbent substances like chlorophyll in water (Kolluru et al., 2021).

3.1.2 Microwave inversion for sea surface temperature and salinity

To understand the temperature and salinity of the ocean, scientists generally use microwave remote sensing. This type of approach combines multiple remote sensing data, coupled with machine learning models, to estimate temperature, salinity, and the sound velocity profiles associated with them. In order to improve efficiency, they will also use a method called empirical orthogonal function (EOF) to first "simplify" the data, so that the calculation is faster and the results are more accurate (Feng et al., 2024).

3.1.3 Acoustic inversion for seafloor topography and subsurface features

To know what the seabed looks like, you can use acoustic inversion technology. This type of technology will analyze the changes in the speed of sound in seawater, draw the seabed topography through it, and even see some structures under the seabed. There is now a new method called self-organizing mapping (SOM), which is a nonlinear algorithm. It can handle relatively complex data relationships, and the results are more accurate than traditional linear algorithms (Li et al., 2021).

### 3.2 Machine learning and ai in inversion algorithm development

Now, more and more research is using machine learning and artificial intelligence (AI) in inversion algorithms for ocean remote sensing. These technologies can find complex laws from massive data, so that the parameter inversion results are more accurate. For example, scientists use deep learning models to estimate effective wave heights based on the backscattering coefficient of the sea surface, and the results are very accurate (Wu et al., 2019). Some people also use machine learning methods to optimize the process of inverting water quality from satellite images, such as chlorophyll a concentration and water turbidity, which can also get good results (Zhu and Huang, 2021).

### 3.3 Challenges in inversion algorithm accuracy and validation

Although inversion algorithms are becoming more and more advanced now, there are still many challenges in ensuring they are accurate and reliable. The performance of the algorithm depends heavily on data quality. The better and richer the data, the more stable the algorithm effect. Sometimes, if some additional observational data, such as on-site sampling data, can be added, not just rely on satellite images, the inversion results will usually be more accurate (Bisson et al., 2023). But the problem is that the marine environment is very complex. Not only are there algae in the water, but there are also many colored dissolved substances and non-algae particles. These will affect the inversion results and make the algorithm more difficult to do. So, we may need to develop more complex models to deal with these distractions. In order to verify whether an inversion algorithm is reliable, a large amount of field measurements are usually required and then compared with the existing standard model to ensure that the results are reliable (Zhao et al., 2022).

## 4 Applications of Inversion Algorithms in Ocean Studies

### 4.1 Monitoring ocean productivity and ecosystem health

Inversion algorithms are very useful in understanding marine ecological situations. It can extract some important parameters from remote sensing data, such as how much chlorophyll is in the water, how clear the water is, etc. Commonly used algorithms now include semi-analytical algorithms (SAA) and absorption spectral decomposition algorithms (ADA). They can calculate the optical properties and types of absorbents in water from the data on seawater color (Zhao et al., 2022; Jin and Pan, 2024). With these algorithms, scientists can more accurately estimate chlorophyll concentration and transparency, thereby judging whether seawater is healthy and whether there are ecological changes. In addition, machine learning technology has also been added. It can further improve the inversion accuracy, allowing us to better monitor water quality and ecological vitality.

### 4.2 Ocean dynamics and climate studies

Inversion algorithms are also helpful in studying ocean motion and climate change. For example, it can inversely deduce the sound speed profile (SSP) from remote sensing data from different sources. This parameter is important and can help us understand the acoustics and seawater flow underwater (Feng et al., 2024; Jiang and Wang, 2024). Some algorithms can also reconstruct clearer ocean color images, which is very critical for studying ocean motion and climate change in coastal waters (Yang et al., 2024). Some hybrid models will combine different types of remote sensing data, which will make the results more accurate and the image resolution higher. This way we can see more clearly how the ocean flows and how it has something to do with climate change (Kolluru et al., 2021).

### 4.3 Marine resource management and exploration

Inversion algorithms are also used to manage and detect marine resources. We can use it to analyze the color of the ocean to determine whether there are fish in the water, or whether there are coral reefs in certain places. This is very helpful for both fisheries and ecological protection. In order to make the analysis results more accurate, researchers will also add some auxiliary observation data, such as on-site sampling data to assist in judgment (Bisson et al., 2023). Now, there are still people who combine deep learning technology with remote sensing images to improve the ability to draw and track marine resources. This allows us to better carry out sustainable development and conservation efforts.

## 5 Technological Advances in Ocean Remote Sensing Platforms

### 5.1 Satellite-based remote sensing systems

Now, satellite remote sensing has greatly changed the way we study and observe the ocean. These satellites can provide continuous and long-term data that can be used to monitor winds, ocean currents, wave heights, and sea level changes on the sea surface. One of these tools, called satellite altimeter technology, can cover a large sea area and help us continuously track sea level rise and current changes. In addition to satellites, technologies such as high-frequency radar (HF radar), submarine cable measurement and acoustic doppler flowmeter (ADCP) can also provide more refined data in a small range. By combining these ground and underwater observation technologies with satellite data, a more comprehensive observation network can be formed (Figure 1) (Amani et al., 2022). Of course, satellites have advantages of large range and long time, but they sometimes have limitations in image clarity and data update speed.

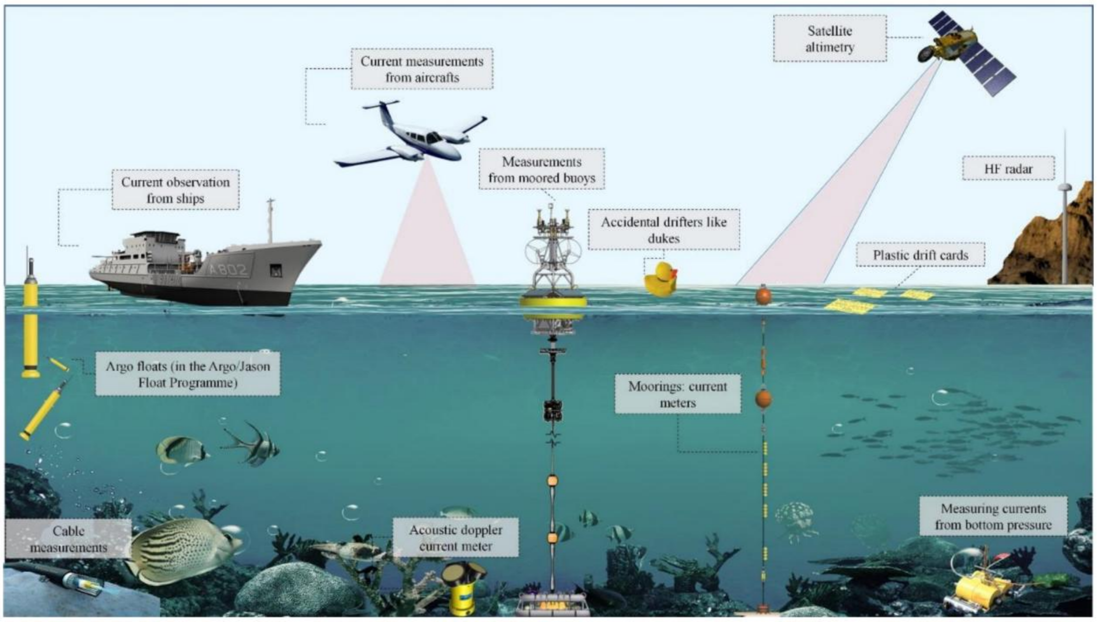


Figure 1 Different methods for ocean current estimation (Adopted from Amani et al., 2022)

### 5.2 Airborne remote sensing technologies

In addition to satellites, remote sensing equipment on aircraft and drones has also made great progress. These devices can take high-resolution images and are particularly suitable for observing shallow sea areas, such as coral reefs. There are now some advanced systems, such as FluidCam and MiDAR, that can clearly pass through the waves and provide multispectral images, which are ideal for ecological monitoring and mapping (Chirayath and Li, 2019). In addition, drones can also combine ordinary RGB images with multispectral images to measure water depth. This method is particularly suitable for use in small shallow water areas, and can draw very detailed water depth maps (Alevizos et al., 2022).

### 5.3 Autonomous underwater vehicles (AUVs) and drones

AUVs (autonomous underwater vehicles) are now increasingly important in marine research. In the past, tasks that had to be done by people in the water could be completed, but now AUV can also be completed. They are equipped with advanced sonar and laser sensors, which can perform very fine mapping underwater and can also collect various data (Sahoo et al., 2019; Hasan et al., 2024). AUV can also be used for directional sampling. For example, if there is a problem in a sea area, it can automatically go over to view and sample. This is especially useful when studying harmful algae outbreaks or ascending flow fronts ( Zhang et al., 2019 ). AUVs are also used in the construction of underwater Internet of Things, such as helping detect pollution, observing ocean changes, arranging tasks and division of labor. It can also combine remote sensing data to make smarter decisions (Ullah et al., 2024).

## 6 Case Studies of Inversion Algorithm Applications

### 6.1 Monitoring coral reef degradation

Remote sensing technology has now become an important means to observe changes in coral reefs. Researchers will use hyperspectral images and inversion algorithms to determine the health status and species composition of coral reefs. There is an algorithm called semi-analytical model that is very commonly used. It can extract underwater information from images, such as what type of seabed is, how deep is the water, and what components are there. This method can combine images with actual physical and biological characteristics to draw a fine three-dimensional seabed structure diagram. This approach is particularly practical for ecosystems that are particularly sensitive and changeable, as fast as coral reefs. It can detect even small environmental changes, whether it is due to climate change or human interference. The study found that this model can clearly distinguish different seabed types when estimating water depth, such as sand bottoms, rocky areas, or places covered by coral debris. This technology has been successfully used in Hawaii, Reunion Island and other places, and the effect is very good. It can also help us better understand the habitat composition of benthic organisms (Figure 2) (Petit et al., 2017; Goodman et al., 2020). In addition, a device called RASC-LSD is also used to improve the estimation accuracy and stability of water depth in shallow sea areas.

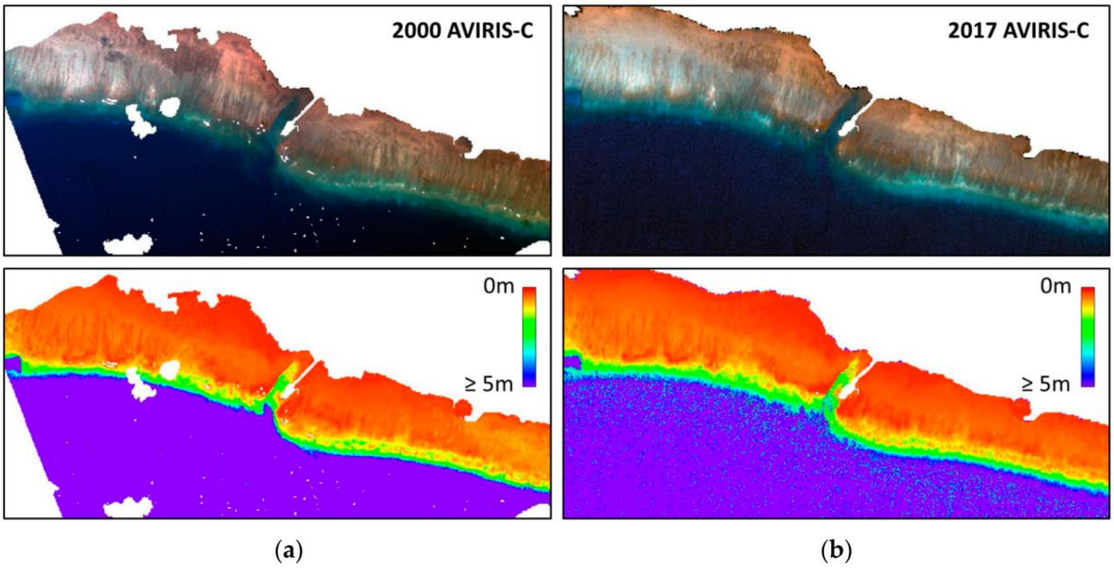


Figure 2 Derived bathymetry for 2001 and 2017 Molokai data at 18 m spatial resolution: (a) 2001 true-color image and derived water depth; (b) 2017 true-color image and derived water depth. Areas with no data and masked areas of land, cloud, cloud shadow, and wave breaks are shown in white (Adopted from Goodman et al., 2020)

### 6.2 Tracking oil spills and marine pollution

Remote sensing and inversion algorithms can also be used to monitor ocean pollution, especially oil spills. Through hyperspectral remote sensing images and some spectral separation algorithms, scientists can estimate the amount of oil in the water. Even at low concentrations, these methods can be detected (Lu et al., 2023). In addition, polarization remote sensing technology can also measure the refractive index of the oil film. This is helpful in eliminating sun-reflective interference, allowing us to more accurately estimate the area and thickness of oil leakage (Zhou et al., 2020). There are still some deep learning algorithms, such as multi-scale multi-dimensional residual CNN, which are also used to identify oil pollution. This type of method can process images more finely and the recognition accuracy can reach more than 95% (Seydi et al., 2021).

### 6.3 Assessing polar ice melt and sea level rise

Inversion algorithms can also be used in polar regions to help us understand ice melting and sea level rise trends. By analyzing ocean color data, scientists can better judge the changes in ice. If some auxiliary observation data are added, such as field measurements, the results will be more accurate (Bisson et al., 2023). There are also researches that combine deep learning technology with remote sensing data. This approach tracks changes in icebergs and sea ice more accurately, helping us analyze seasonal changes and long-term trends (Li et al., 2020). These studies are very valuable in predicting future climate and sea level changes.

## 7 Future Directions in Ocean Remote Sensing and Inversion Algorithms

### 7.1 Enhancing algorithm precision through data assimilation

Now, data assimilation is a new way to improve the accuracy of ocean remote sensing algorithms. Simply put, putting data from different sources together will have better results. For example, we can combine information such as seawater temperature, salinity, and sea surface height in satellite data to invert the temperature and salinity distribution underwater (Zhao et al., 2024). There is also a technology called neural network observation operator, which can also integrate complex data such as underwater acoustic propagation. Research has found that this approach can greatly improve the accuracy of forecasting ocean states (Storto et al., 2021). At the same time, combining semi-analytical algorithms and absorption decomposition algorithms can also reduce errors and make the inversion result more reliable (Kolluru et al., 2021).

### 7.2 Integration of quantum remote sensing technologies

Quantum remote sensing is a "new direction" in current remote sensing technology. It uses quantum technology to improve sensitivity and resolution, that is, it can see more clearly and measure more accurately. If this technology is used in ocean remote sensing, it may make the inversion algorithm more accurate, and it can also help us see more and understand more. Although this aspect is still developing, the prospects are worth looking forward to.

### 7.3 Expanding global collaboration for comprehensive ocean monitoring

Cooperation among countries is key to more comprehensively monitoring the global ocean. Through cooperation, different countries can share data, technology and experience and develop stronger models together. A research team has used machine learning to develop a global chlorophyll a concentration inversion model, which is inseparable from large international databases like the SeaWiFS dataset (Chen et al., 2024). Cooperation can also help develop a more stable sound speed inversion framework, use a variety of remote sensing data, and combine it with AI methods, which can improve monitoring capabilities for large-scale sea areas (Feng et al., 2024). With these international cooperation projects, scientists can better understand the motion patterns of the ocean, while making the application of remote sensing more accurate and useful.

## Acknowledgments

Thanks Mr F. Zhou from the Institute of Life Science of Jiyang College of Zhejiang A&F University for his reading and revising suggestion.

## Conflict of Interest Disclosure

The authors affirm that this research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

### References

Alevizos E., Oikonomou D., Argyriou A., and Alexakis D., 2022, Fusion of drone-based RGB and multi-spectral imagery for shallow water bathymetry inversion, Remote Sensing, 14: 1127.
https://doi.org/10.3390/rs14051127

Amani M., Moghimi A., Mirmazloumi S.M., Ranjgar B., Ghorbanian A., Ojaghi S., Ebrahimy H., Naboureh A., Nazari M., Mahdavi S., Moghaddam S., Asiyabi R., Ahmadi S., Mehravar S., Mohseni F., and Jin S., 2022, Ocean remote sensing techniques and applications: a review, Water, 14(21): 3400.
https://doi.org/10.3390/w14213400

Bisson K., Werdell P., Chase A., Kramer S., Cael B., Boss E., McKinna L., and Behrenfeld M., 2023, Informing ocean color inversion products by seeding with ancillary observations, Optics Express, 31(24): 40557-40572.
https://doi.org/10.1364/oe.503496

Chen K.H., Zhang J.L., Zheng Y., and Xie X.T., 2024, A study on global oceanic chlorophyll-a concentration inversion model for MODIS using machine learning algorithms, IEEE Access, 12: 128843-128859.
https://doi.org/10.1109/ACCESS.2024.3456481

Chirayath V., and Li A., 2019, Next-generation optical sensing technologies for exploring ocean worlds-NASA FluidCam MiDAR and NeMO-Net, Frontiers in Marine Science, 6: 521.
https://doi.org/10.3389/fmars.2019.00521

D'Alimonte D., Kajiyama T., and Saptawijaya A., 2016, Ocean color remote sensing of atypical marine optical cases, IEEE Transactions on Geoscience and Remote Sensing, 54: 6574-6586.
https://doi.org/10.1109/TGRS.2016.2587106

Feng X., Tian T., Zhou M.Z., Sun H.X., Li D.Z., Tian F., and Lin R.B., 2024, Sound speed inversion based on multi-source ocean remote sensing observations and machine learning, Remote Sensing, 16(5): 814.
https://doi.org/10.3390/rs16050814

Goodman J.A., Lay M., Ramirez L., Ustin S.L., and Haverkamp P., 2020, Confidence levels sensitivity and the role of bathymetry in coral reef remote sensing, Remote Sensing, 12(3): 496.
https://doi.org/10.3390/rs12030496

Hasan K., Ahmad S., Liaf A., Karimi M., Ahmed T., Shawon M., and Mekhilef S., 2024, Oceanic challenges to technological solutions: a review of autonomous underwater vehicle path technologies in biomimicry control navigation and sensing, IEEE Access, 12: 46202-46231.
https://doi.org/10.1109/ACCESS.2024.3380458

He X.Q., Pan T.F., Bai Y., Shanmugam P., Wang D.F., Li T., and Gong F., 2024, Intelligent atmospheric correction algorithm for polarization ocean color satellite measurements over the open ocean, IEEE Transactions on Geoscience and Remote Sensing, 62: 1-22.
https://doi.org/10.1109/TGRS.2023.3348159

Ilori C.O., Pahlevan N., and Knudby A., 2019, Analyzing performances of different atmospheric correction techniques for landsat 8: application for coastal remote sensing, Remote Sensing, 11(4): 469.
https://doi.org/10.3390/rs11040469

Jiang X.L., and Wang W.F., 2024, Climate change and aquatic ecosystem health: impacts adaptation strategies and future challenges, International Journal of Aquaculture, 14(4): 221-231.
https://doi.org/10.5376/ija.2024.14.0022

Jin C., and Pan Y.L., 2024, Application of algae biomarkers in water quality monitoring, International Journal of Aquaculture, 14(1): 29-36.
https://doi.org/10.5376/ija.2024.14.0004

Kolluru S., Tiwari S.P., and Gedam S.S., 2021, Hybrid inversion algorithms for retrieval of absorption subcomponents from ocean colour remote sensing reflectance, Remote Sensing, 13(9): 1726.
https://doi.org/10.3390/rs13091726

Li H., He X., Ding J., Bai Y., Wang D., Gong F., and Li T., 2022, The inversion of HY-1C-COCTS ocean color remote sensing products from high-latitude seas, Remote Sensing, 14(22): 5722.
https://doi.org/10.3390/rs14225722

Li H., Qu K., and Zhou J., 2021, Reconstructing sound speed profile from remote sensing data: nonlinear inversion based on self-organizing map, IEEE Access, 9: 109754-109762.
https://doi.org/10.1109/ACCESS.2021.3102608

Li X., Liu B., Zheng G., Ren Y., Zhang S., Liu Y., Gao L., Liu Y., Zhang B., and Wang F., 2020, Deep-learning-based information mining from ocean remote-sensing imagery, National Science Review, 7: 1584-1605.
https://doi.org/10.1093/nsr/nwaa047

Liu H., Zhou Q., Li Q., Hu S., Shi T., and Wu G., 2019, Determining switching threshold for NIR-SWIR combined atmospheric correction algorithm of ocean color remote sensing, ISPRS Journal of Photogrammetry and Remote Sensing, 153: 59-73.
https://doi.org/10.1016/J.ISPRSJPRS.2019.04.013

Lu H., Li Y., and Liu B., 2023, Energy-based unmixing method for low background concentration oil spills at sea, Remote Sensing, 15(8): 2079.
https://doi.org/10.3390/rs15082079

Petit T., Bajjouk T., Mouquet P., Rochette S., Vozel B., and Delacourt C., 2017, Hyperspectral remote sensing of coral reefs by semi-analytical model inversion - comparison of different inversion setups, Remote Sensing of Environment, 190: 348-365.
https://doi.org/10.1016/J.RSE.2017.01.004

Sahoo A., Dwivedy S.K., and Robi P.S., 2019, Advancements in the field of autonomous underwater vehicle, Ocean Engineering, 181: 145-160.
https://doi.org/10.1016/J.OCEANENG.2019.04.011

Seydi S.T., Hasanlou M., Amani M., and Huang W., 2021, Oil spill detection based on multiscale multidimensional residual CNN for optical remote sensing imagery, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14: 10941-10952.
https://doi.org/10.1109/jstars.2021.3123163

Storto A., De Magistris G., Falchetti S., and Oddo P., 2021, A neural network-based observation operator for coupled ocean-acoustic variational data assimilation, Monthly Weather Review, 149(6): 1967-1985.
https://doi.org/10.1175/MWR-D-20-0320.1

Ullah I., Ali F., Sharafian A., Ali A., Naeem H.M.Y., and Bai X., 2024, Optimizing underwater connectivity through multi-attribute decision-making for underwater IoT deployments using remote sensing technologies, Frontiers in Marine Science, 11: 1468481.
https://doi.org/10.3389/fmars.2024.1468481

Wang Y., Liu H., Zhang Z., Wang Y., Zhao D., Zhang Y., Li Q., and Wu G., 2023, Ocean colour atmospheric correction for optically complex waters under high solar zenith angles: facilitating frequent diurnal monitoring and management, Remote Sensing, 16(1): 183.
https://doi.org/10.3390/rs16010183

Wu T., Cao Y.H., Wu Z.S., Wu J.J., Qu T., and Zhang J.P., 2019, Deep learning for inversion of significant wave height based on actual sea surface backscattering coefficient model, Multimedia Tools and Applications, 79: 34173-34193.
https://doi.org/10.1007/s11042-019-07967-6

Yang Y., Wang Z., Chen P., Shen X., Kong W., Huang G., and Shu R., 2024, High-resolution ocean color reconstruction and analysis focusing on Kd490 via machine learning model integration of MODIS and Sentinel-2 (MSI), Frontiers in Marine Science, 11: 1464942.
https://doi.org/10.3389/fmars.2024.1464942

Zhang Y., Ryan J.P., Kieft B., Hobson B.W., McEwen R., Godin M., Harvey J., Barone B., Bellingham J., Birch J., Scholin C., and Chavez F., 2019, Targeted sampling by autonomous underwater vehicles, Frontiers in Marine Science, 6: 415.
https://doi.org/10.3389/fmars.2019.00415

Zhao C., Yu D., Yang L., Zhou Y., Gao H., Bian X., and Li Y., 2022, Remote sensing algorithms of seawater transparency: a review, 2022 3rd International Conference on Geology Mapping and Remote Sensing (ICGMRS), 2022: 744-749.
https://doi.org/10.1109/ICGMRS55602.2022.9849274

Zhao Y., He Z., and Jiang Y., 2024, The inversion of three-dimensional ocean temperature and salinity fields for the assimilation of satellite observations, Journal of Marine Science and Engineering, 12(4): 534.
https://doi.org/10.3390/jmse12040534

Zhou Y., Lu Y.C., Shen Y.F., Ding J., Zhang M.W., and Mao Z.H., 2020, Polarized remote inversion of the refractive index of marine spilled oil from PARASOL images under sunglint, IEEE Transactions on Geoscience and Remote Sensing, 58(4): 2710-2719.
https://doi.org/10.1109/TGRS.2019.2953640

Zhu X., and Huang J.J., 2021, Remote sensing inversion of water quality in coastal sea area based on machine learning: a case study of Shenzhen bay China, 2021: EGU21-1972.
https://doi.org/10.5194/egusphere-egu21-1972