

Spatial-Temporal Data Mining for Ocean Science: Data, Methodologies and Opportunities

HANCHEN YANG, Tongji University, The Hong Kong Polytechnic University, China

JIANNONG CAO, The Hong Kong Polytechnic University, China

WENGEN LI^{*}, Tongji University, China

SHUYU WANG, Tongji University, China

HUI LI, Tongji University, China

JIHONG GUAN, Tongji University, China

SHUIGENG ZHOU, Fudan University, China

With the rapid amassing of *spatial-temporal* (ST) ocean data, many *spatial-temporal data mining* (STDM) studies have been conducted to address various oceanic issues, including climate forecasting and disaster warning. Compared with typical ST data (e.g., traffic data), ST ocean data presents some unique characteristics, e.g., diverse regionality and high sparsity. These characteristics make it difficult to design and train STDM models on ST ocean data. To the best of our knowledge, a comprehensive survey of existing studies remains missing in the literature, which hinders not only computer scientists from identifying the research issues in ocean data mining but also ocean scientists to apply advanced STDM techniques. In this paper, we provide a comprehensive survey of existing STDM studies for ocean science. Concretely, we first review the widely-used ST ocean datasets and highlight their unique characteristics. Then, typical ST ocean data quality enhancement techniques are discussed. Next, we classify existing STDM studies for ocean science into four types of tasks, i.e., prediction, event detection, pattern mining, and anomaly detection, and elaborate the techniques for these tasks. Finally, promising research opportunities are discussed. This survey can help scientists from both computer science and ocean science better understand the fundamental concepts, key techniques, and open challenges of STDM for ocean science.

CCS Concepts: • **Information systems** → **Spatial-temporal Data Mining**; • **Applied computing** → *Environmental sciences*.

Additional Key Words and Phrases: spatial-temporal data, ocean science, data mining, machine learning.

ACM Reference Format:

Hanchen Yang, Jiannong Cao, Wengen Li, Shuyu Wang, Hui Li, Jihong Guan, and Shuigeng Zhou. x. Spatial-Temporal Data Mining for Ocean Science: Data, Methodologies and Opportunities. *J. ACM* x, x, Article x (x x), 47 pages. <https://doi.org/XXXXXX.XXXXXXX>

^{*}Corresponding Author

Authors' addresses: **Hanchen Yang**, neoyang@tongji.edu.cn, Tongji University, The Hong Kong Polytechnic University, 4800 Caoan Rd, Jiading Qu, Shanghai Shi, China, 200092; **Jiannong Cao**, jiannong.cao@polyu.edu.hk, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China; **Wengen Li**, lwengen@tongji.edu.cn, Tongji University, 4800 Caoan Rd, Jiading Qu, Shanghai Shi, China, 200092; **Shuyu Wang**, tj_sywang@tongji.edu.cn, Tongji University, 4800 Caoan Rd, Jiading Qu, Shanghai Shi, China, 200092; **Hui Li**, 2230760@tongji.edu.cn, Tongji University, 4800 Caoan Rd, Jiading Qu, Shanghai Shi, China, 200092; **Jihong Guan**, jhguan@tongji.edu.cn, Tongji University, 4800 Caoan Rd, Jiading Qu, Shanghai Shi, China, 200092; **Shuigeng Zhou**, sgzhou@fudan.edu.cn, Fudan University, 4800 Caoan Rd, YangPu Qu, Shanghai Shi, China, 200092.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© x Association for Computing Machinery.

0004-5411/x/x-ARTx \$15.00

<https://doi.org/XXXXXX.XXXXXXX>

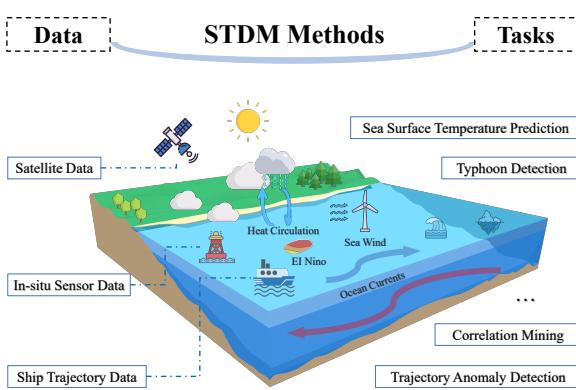


Fig. 1. The illustration of STDM for ocean science, which utilizes various STDM methods to discover unknown but potentially useful patterns from different ocean data sources for a number of data mining tasks.

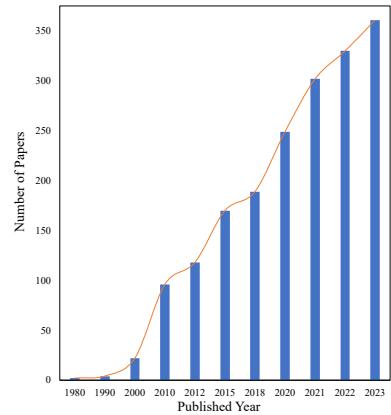


Fig. 2. 1980-2023 publications of STDM studies for ocean science (Results from Web of Science with query keywords: [Spatial-temporal & ocean] or [Spatiotemporal & ocean]).

1 INTRODUCTION

Ocean, covering more than two-thirds of the earth, plays an important role in various applications (e.g., climate forecasting and ocean transportation [149]), and is critical to human survival and sustainable development. Many real-world events and phenomena (e.g., El Niño and typhoons) occurring in ocean generally not only are associated with spatial locations but also change over time. Thus, the collected ocean data for monitoring these events and phenomena are typically spatial-temporal (ST) data in nature and require specific spatial-temporal data mining (STDM) techniques to conduct data analysis. As shown in Fig. 1, STDM for ocean science aims to uncover the ST patterns and correlations from various ST ocean data, helps us better understand the ocean system, and provides valuable support for various real-world applications. For example, accurate prediction of sea surface temperature (SST) is of great significance in weather forecasting, El Niño event detection, and disaster warning, and could also benefit aquaculture and agriculture [8].

The past decades have witnessed ever-increasing ST ocean data and lots of research on STDM for ocean science, which lays the solid foundation for addressing various oceanic issues in the data-driven paradigm. With the rapid development of data sensing technologies, numerous ocean observation sensors of different types have been deployed on various platforms, including space remote satellites, automatic buoys, and vessels all over the world, producing large amounts of ST ocean data. To be more specific, an estimate puts the size of ST ocean data in 2030 at 350 Petabytes (1 PB = 1,000 TB), and this number is predicted to grow exponentially [169]. With such huge amounts of ST ocean data, an increasing number of studies on STDM for ocean science have been conducted. According to incomplete statistics of the related publications from 1980 to 2023 on Web of Science, as shown in Fig. 2, ocean STDM receives increasing attention over time, and the increasing trend in the last three years is especially obvious. This trend indicates that STDM for ocean science has become a hot research topic in recent years.

Though STDM for ocean science is a vibrant interdisciplinary field, there are still some obstacles that hinder its development and applications.

First, there is a lack of review on available ST ocean datasets and their unique data characteristics. In the past decades, ST ocean datasets collected from different sources have been released

Table 1. A summary of the related surveys on STDM.

Year	Ref.	Contribution	Scope				
			Data	Data Quality	ST Prediction	Event Detection	Pattern Mining
2014	[52]	Overview the STDM methods and give some case studies of climate data.			✓	✓	✓
2015	[197]	Provide a complexity comparison of typical STDM methods.				✓	✓
2019	[228]	Summarize the latest deep learning methods in STDM.			✓		
2020	[114]	Overview the GAN-based models for ST data completion.		✓			
2021	[73]	Overview the ST methods for SST prediction.	✓		✓		
2022	[244]	Summarize the current research methodologies and the challenges of STDM in ocean domain.	✓		✓	✓	✓
2022	[196]	Overview of the latest STDM methods for multiple fields.			✓	✓	✓
2022	[74]	Summarize some challenging issues and open problems of multiple STDM directions.			✓	✓	✓
2023	[39]	Overview the latest large foundation model in weather and climate, mainly focus on time series and text data.	✓		✓		
Ours		A survey of STDM methods for ocean science: multi-source datasets with unique characteristics, data quality enhancement methods, advanced models in various tasks, and future directions.	✓	✓	✓	✓	✓

by various producers, e.g., National Oceanic and Atmospheric Administration (NOAA), National Aeronautics and Space Administration (NASA), and European Centre for Medium-Range Weather Forecasts (ECMWF). However, these datasets have diverse data collection protocols, sensors, and technologies, leading to diversity in data resolution, coverage, and quality. Currently, there is no systematic review of these data to facilitate researchers to choose appropriate datasets for studying different problems and tasks of ocean science. Moreover, ST ocean data has some unique characteristics, e.g., diverse regionality, high sparsity, inherent uncertainty, and deep ST dependencies, which are also not well investigated. For example, due to the large-scale coverage of the ocean on Earth, there exists diverse regionality in different areas. The collected ST ocean data in the Arctic Ocean may have opposite seasonality patterns from the data near the equator, which is difficult to model in a unified system. According to [137], the extreme weather in remote regions (e.g., the Antarctica Ocean) makes it difficult to deploy the in-situ sensors to collect data, and the heavy cloud in some periods may cause more than 80% of satellite data to be lost, which are two main reasons for the data sparsity problem. The sensors' stability and transmission loss may both cause uncertainty in ocean data. In addition, the complex and unknown ocean circulation, as well as teleconnection between different regions in the ocean [134], may bring deep and hidden ST dependencies in the data. Ignoring these unique data characteristics could lead to low accuracy and bad interpretability of the STDM methods for ocean science. Therefore, from the data perspective, analyzing the widely-used ST ocean datasets and identifying their unique data characteristics is necessary.

Second, although there are already some surveys on STDM, a systematic and comprehensive review dedicated to the application of STDM in ocean science is currently absent from the literature. Table 1 summarizes and compares the related surveys of STDM in terms of contribution and scope. To provide a clear comparison, we put different oceanic STDM tasks into four types, i.e., ST prediction, event detection, pattern mining, and anomaly detection, which will be discussed in detail in Section 4. Concretely, Faghous et al. [52] reviewed the STDM methods and conducted several case studies in the climate domain. Ki et al. [197] provided an introduction to typical STDM methods from the perspective of computational complexity. Wang et al. [228] surveyed recent

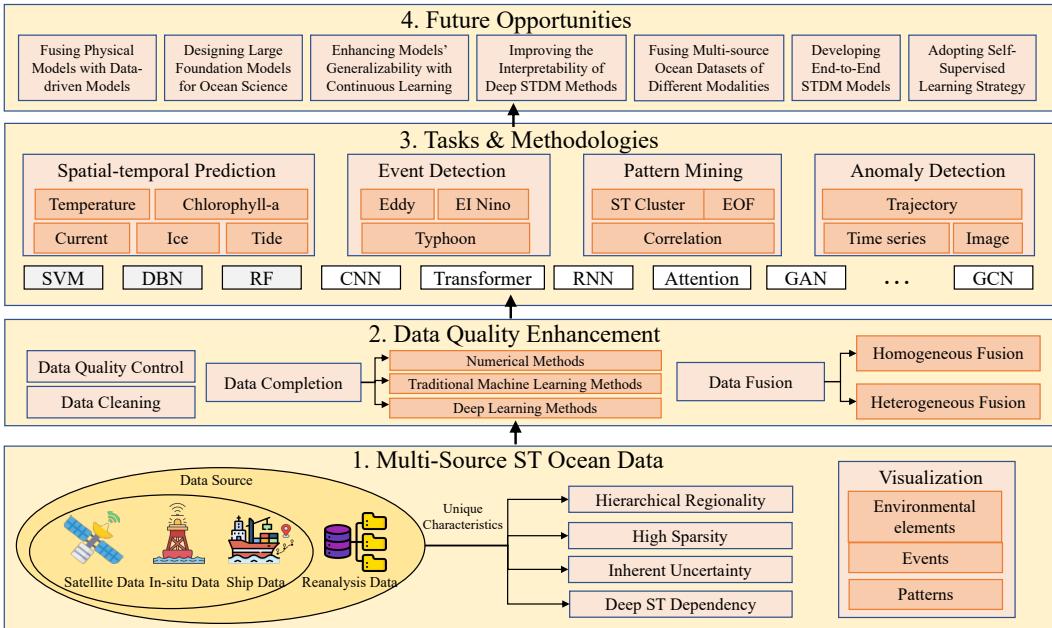


Fig. 3. The content and organization of this survey.

studies on deep learning techniques for STDM. Kim et al. [114] summarized the data completion methods for improving the quality of ST data for downstream applications. Haghbin et al. [73] reviewed the datasets and different types of methods for sea surface temperature (SST) prediction. Wu et al. [244] classified the STDM methods for the ocean into statistic methods and machine learning methods and gave case studies on some STDM tasks in the ocean. Sharma et al. [196] analyzed the typical problems of STDM, with emphasis on the tasks of prediction and clustering for ST data. Handi et al. [74] summarized some challenging issues in STDM, e.g., dynamic ST dependencies and poor data quality. Chen et al. [39] overview the latest large foundation model for weather and climate data, especially on text data and time-series data. Although these studies above give some introduction to some STDM methods related to ocean, there does not exist a survey that covers all the key components of STDM for ocean science, including available ST datasets, data processing methods to enhance data quality, STDM methods for various tasks, and future directions.

Third, STDM for ocean science is a typical multi-disciplinary research field where rapidly evolving computer science meets conventional ocean science. The development of STDM for ocean science will not only help computer scientists identify new research issues but also assist ocean science researchers in applying advanced STDM methods to solve their problems, which could benefit various oceanic applications. However, the existing and ever-arising challenges and opportunities of STDM for ocean science have not been well studied. For example, most existing methods only directly apply STDM methods to addressing ocean issues with large amounts of ST ocean data, ignoring the underlying physical laws of the ocean, which usually lack robustness and interpretability [73, 244]. Thus, to further promote the development of STDM for ocean science, it is urgent to systematically and comprehensively summarize the related STDM studies for ocean science,

and discuss their advantages and disadvantages to help researchers both in computer science and ocean science areas identify potential directions for further exploration.

Keep these in mind, in this paper, as shown in Fig. 3, we provide a comprehensive survey to systematically summarize the available ST ocean datasets, data quality enhancement methods, and STDM techniques for solving various ocean issues and highlight the arising challenges. In summary, the contributions of this survey are fourfold as follows:

- **Summarizing the wide-used and accessible ocean datasets.** We review different categories of ST ocean data, including satellite data, in-situ data, ship data, and reanalysis data, and present the popular datasets that are widely used from multiple dimensions (e.g., spatial resolution, temporal coverage, and related studies). In addition, we identify the unique data characteristics of ST ocean data and discuss typical data visualization methods.
- **Reviewing the quality enhancement methods for ST ocean data.** We analyze the fundamental but necessarily important data quality enhancement methods, including data cleaning, data completion, data fusion, and data transforming for ST ocean data, and provide the corresponding representative models.
- **Classifying the advanced STDM methods of typical ocean tasks.** This survey provides a comprehensive overview of the recent advances in STDM techniques for ocean science, and subsumes the main tasks into four types, i.e., ST prediction, event detection, pattern mining, and anomaly detection. For each type of these tasks, we provide a detailed review of the corresponding STDM techniques.
- **Pinpointing the existing challenges and future directions.** We also identify the open problems that have not been well solved and provide some promising research directions in the future, which could help researchers in both computer science and ocean science identify new research topics and promote the development of smart ocean.

The rest of this survey is organized as follows: Table 2 defines the abbreviations used in this survey to facilitate understanding. Section 2 presents different categories of ST ocean datasets, identifies their unique characteristics, and provides typical ST ocean data visualization methods. Section 3 summarizes the techniques for improving the quality of ST ocean data, including data cleaning, data completion, data fusion, and data transforming. Section 4 classifies typical STDM tasks for ocean science into four types and presents a gallery of the technologies for each task. Section 5 discusses the existing challenges and suggests future potential directions. We finally conclude this survey in Section 6.

2 DATA SOURCES, UNIQUE CHARACTERISTICS AND VISUALIZATION

In this section, as shown in Table 3, we first summarize four categories of ST ocean data, i.e., satellite data, in-situ data, ship data, and reanalysis data, according to the data sources, and present the representative datasets with their basic information, including temporal periods, spatial resolution, spatial coverage, temporal resolution, and accessible storage. After that, we identify four unique data characteristics of ST ocean data, enabling researchers to understand the critical difficulties in applying STDM techniques to solving ocean issues. Finally, the widely used visualization methods for ST ocean data are discussed.

2.1 Multi-source ST Ocean Data

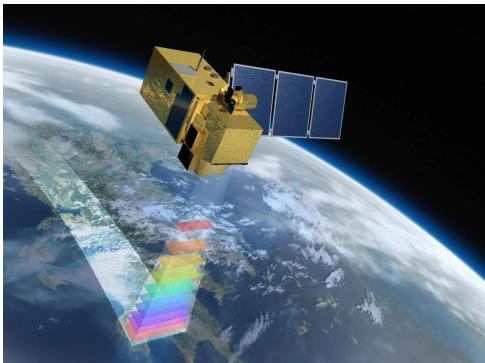
Typically, existing ST ocean data covers various ocean factors such as temperature, chlorophyll-a, ocean current, sea ice, and tide. The majority of these data are collected by various measurement devices (e.g., satellite sensors, in-situ sensors, and ship sensors) or from the outputs of reanalysis systems (e.g., ECMWF reanalysis system and NOAA reanalysis system). According to the data

Table 2. List of Abbreviations.

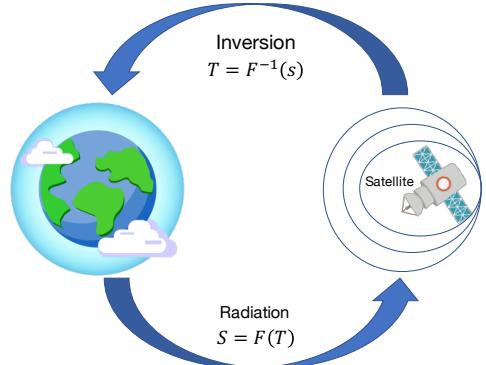
Abbreviation	Full Name
AVHRR	Advanced Very-High-Resolution Radiometer
Argo	Array for Real-time Geostrophic Oceanography
Chl-a	Chlorophyll a
OISST	Optimum Interpolation Sea Surface Temperature
El Niño	El Niño-Southern Oscillation Phenomenon
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
ECMWF	European Centre for Medium-Range Weather Forecasts
ST	Spatial-Temporal
STDM	Spatial-Temporal Data Mining
SST	Sea Surface Temperature
SSS	Sea Surface Salinity

Table 3. Comparison of different categories of ST ocean data.

Category	Spatial coverage	Temporal coverage	Spatial resolution	Temporal resolution	Quality	Timeliness
Satellite data	global	long	low	days	medium	low
In-situ data	local	short	high	hours	medium	high
Ship data	local	short	high	minutes	low	medium
Reanalysis data	global	long	low	days	high	low



(a) The collection of original satellite data.



(b) The inversion process of satellite data.

Fig. 4. Satellite data collection and inversion. (a) Satellite data collection with different bands [2]; (b) Data inversion to process the original satellite data.

sources, ST ocean data can be divided into four categories, including satellite data, in-situ sensor data, ship data, and reanalysis data. Table 3 briefly summarizes the advantages and disadvantages of the four categories of ST ocean data. The satellite data and reanalysis data usually have wide spatial coverage and a long-term observation period but have low timeliness to obtain the original data. The ship data and in-situ sensor data have better timeliness but lower data quality due to the data sparsity issue. In this section, we will introduce the typical and commonly used ST ocean datasets of the four data categories and summarize their features in Table 4.

Table 4. Public datasets and their features.

Category	Name	Period	Spatial Resolution	Coverage	Temporal Resolution	Citation	Type	Source
Satellite Data	MODIS	2000-present	0.011x0.041	Global	8 days	[95, 118, 119]	Sea surface temperature, ocean color, sea surface salinity	https://modis.gsfc.nasa.gov/
		2002-present	1 km x 1 km	Global	daily	[216]		
		2002-present	0.083 x 0.083°	Global	monthly	[111]		
	AVHRR	1979-present	1.1 km x 1.1 km	Global	daily	[85, 118]	Sea surface temperature, ocean color	https://www.euemedsat.info/archiv/
	Sentinel-3	2016-present	1.2 km x 1.2 km	Global	5 days	[23, 24, 57, 94, 136, 139, 252]	Sea surface temperature, ocean color	https://sentinel-copernicus.eu/web/sentinel/
	GOCI	2010-2021	0.5 km x 0.5 km	Korean sea	hourly	[141, 171, 209, 262]	Sea surface chlorophyll-ocean color	https://oceancolor.gsfc.nasa.gov/data/goci/
	CZCS	1978-1986	0.825 km x 0.825 km	Global	8 days	[155]	Sea surface chlorophyll-l	https://oceancolor.gsfc.nasa.gov/data/CZCS/
	OCM-2	2009-present	1-4 km x 1-4 km	Global	2 days	[180]	Ocean color	https://oceancolor.gsfc.nasa.gov/OCM-2/
	SeaWiFS	1997-2010	1-4 km x 1-4 km	Global	daily	[135, 237]	Ocean color	https://oceancolor.gsfc.nasa.gov/SeaWiFS/
	Argo	1996-present	Trajectories of about 14,000 floats	Global	1-10 days	[15, 20, 33, 247, 253]	sea surface temperature, sea surface salinity	https://argo.ucsd.edu/
In-situ data	GC-BGC	2021-present	Trajectories of about 500 floats	Global	10 days	[28, 90, 199, 251]	Sea O ₂ , sea Ph	https://www.go-bgc.org/
	SOCCOM	2004-present	Trajectories of about 200 floats	Antarctic Ocean	10 days	[31, 105]	Ocean carbon	https://seacomprinetone.edu/
	AIS	2016 to 2018	Trajectories of about 750,000 vessels	Global	30 seconds - 1 day	[26, 51, 62, 92]	Trajectory anomalies, ship tracking	https://www.vntsdata.com/
	VMS	April, 2020	Trajectories of about 70,000 vessels	Global	30 seconds - 1 day	[195, 206]	Trajectory anomalies	https://marinecadastre.gov/
Reanalysis Data	OISST	1979-present	0.25x0.25°	Global	daily	[99, 249, 270, 279]	Sea surface temperature	https://www.noaa.gov/
	ERAI	1950-present	4°x4°	Global	12 hour	[124, 142, 154, 265]	Sea surface temperature	https://www.ecmwf.int/
	CMEMS Level 3 SLA	2004-present	0.125x0.125°	Global	daily	[65]	Sea level anomalies	https://marine.copernicus.eu/
	CMEMS	1993-2020	0.25x0.25°	Global	daily	[14]	Sea surface height anomaly	https://marine.copernicus.eu/
	HadISST4	1961-1990	5x5°	Global	monthly	[193]	Air/Marine temperature anomalies	https://www.metoffice.gov.uk/
	COBE SST	1891 to present	1x1°	Global	monthly	[42, 81, 212]	Sea surface temperature	https://psl.noaa.gov/data/
	CMAP Precipitation	1979-present	2.5x2.5°	Global	monthly	[47, 115, 135]	Penman global gridded precipitation means.	https://psl.noaa.gov/data/
	WOD	1772 to 2017	1x1°	Global	daily	[88]	Sea temperature, salinity, oxygen	https://www.noaa.noaa.gov/products/world-ocean-database
	Extreme-ERAS	1975-2018	0.25x0.25°	Global	daily	[106]	sea temperature	https://www.ecmwif.int/
	ClimateNet	1996-2010	1x1°	Global	daily	[177]	tropical cyclones	https://www.noaa.noaa.gov/products
OSCAR	1993-present	1-4 km x 1-4 km	Global	daily	[215, 220]	Ocean Current	https://www.noaa.noaa.gov/products/global-ocean-currents-database	
	GOCD	1993-2013	1-4 km x 1-4 km	Global	daily	[25, 27]	Ocean Current	https://www.noaa.noaa.gov/products/global-ocean-currents-database

2.1.1 Satellite Data. Satellite data, also named remote sensing data, became available in the late 1960s and are a source of high-quality data for monitoring the ocean. The view from space allows ocean factors (e.g., SST and sea surface chlorophyll-a) to be measured globally, especially in remote regions where it is not convenient to deploy sensors. Additionally, satellites can ensure large spatial coverage and frequent observation, even in extreme weather conditions. During the past decade, much progress has been made in ocean monitoring using satellites, and the quality of satellite instruments and the accuracy of inversion algorithms have improved considerably, making satellite observations be widely used in various ocean tasks, e.g., sea ice prediction [264] and typhoon detection [188].

As shown in Fig. 4(a), satellite data collection is to detect the thermal energy emitted by the earth's surface using spaceborne microwave or infrared radiometers [103]. The surface radiation is modified in its passage through the atmosphere to the radiometer by a bunch of processes, e.g., atmospheric absorption, emission, and scattering. Thus, with appropriate data inversion, we can obtain valid estimates of various ocean factors. The general satellite data inversion process is shown in Fig. 4(b), where S denotes the radiation signal emitted by the ocean surface, and T is the target data obtained by the data inversion function F . The data inversion function F is generally non-linear; its inverse function is F^{-1} . Through the data inversion algorithms [198, 265], the radiation signal can be transferred to ST time series data of various ocean factors, e.g., SST and sea surface chlorophyll-a.

Many countries have launched satellites for various ocean applications and we introduce the wide-used satellite data as below.

- **MODIS:** The Moderate Resolution Imaging Spectroradiometer (MODIS) is a key instrument onboard the Earth Observing System (EOS) Terra and Aqua platforms, and designed to monitor the atmosphere, ocean, and land surface. MODIS has a viewing swath width of 2,330 km and views the entire surface of the Earth every two days. It measures 36 spectral bands between 0.405 and 14.385 μm , and acquires data at three spatial resolutions, i.e., 0.25km, 0.5km, and 1km.
- **AVHRR:** The Advanced Very High-Resolution Radiometer (AVHRR) multi-purpose imaging instrument is used for monitoring global cloud cover, sea surface temperature, ice, snow, and vegetation cover characteristics. AVHRR provides four-to-six-band multispectral data from the NOAA polar-orbiting satellite series. AVHRR provides continuous global coverage since June 1979 and its spatial resolution is 1.1 km.
- **Sentinel-3:** Sentinel-3 is a dedicated Copernicus satellite mission delivering a variety of high-quality ocean and atmosphere measurements. The main objective of the mission is to collect parameters such as sea surface topography, sea surface temperature, and ocean surface color. It provides two-day global coverage optical data with two satellites and altimetry measurements for sea and land applications with real-time data products delivered in less than three hours. The spatial resolution of Sentinel-3 is 1.2 km.
- **GOCI:** Geostationary Ocean Color Imager (GOCI) is the first ocean color sensor launched to monitor ocean color around the Korean Peninsula. GOCI has a large temporal coverage and a revisit time of around one hour. The spatial resolution of GOCI is about 0.5 km.
- **CZCS:** The Coastal Zone Color Scanner (CZCS) is a multi-channel scanning radiometer aboard the ocean remote sensing satellite Nimbus 7. CZCS could map chlorophyll concentration, sediment distribution, salinity, ocean currents, and the temperature of coastal waters. CZCS measures reflect solar energy in six channels at a spatial resolution of 0.8 km.
- **SeaWiFS:** Sea-viewing Wide Field-of-view Sensor (SeaWiFS) is loaded on the OrbView-2 satellite launched by NASA in 1997. SeaWiFS aims to obtain accurate ocean color data

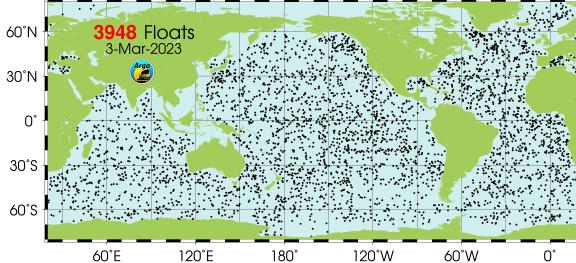


Fig. 5. The global distribution of Argo sensors in 2023 [4].

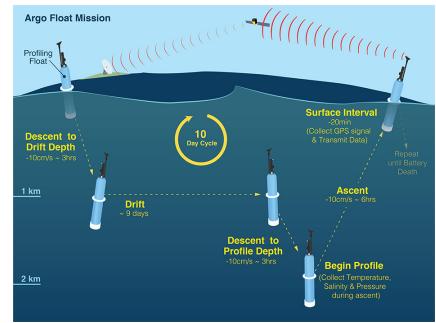


Fig. 6. The workflow of Argo sensors [5].

for the global ocean and makes this data readily available to researchers. SeaWiFS has six watercolor bands with a bandwidth of 20nm, i.e., 412nm, 443nm, 490nm, 510nm, 555nm, and 670nm. Compared with CZCS, the performance indicators of this sensor have been greatly improved, such as more reasonable band settings, higher signal-to-noise ratio, and richer band information. SeaWiFS has two spatial resolutions, i.e., 1.1 km and 4.5 km, and its temporal resolution is daily or once every two days.

2.1.2 In-situ Sensor Data. In-situ sensor data refers to the data collected where the instrument is physically located. It is a traditional but important way to collect data for ocean factors and has a long history since the 1600s [52]. In the past few decades, numerous in-situ sensors of different types, e.g., buoy sensors, underwater sensors, and station sensors, have been deployed all over the world. However, considering the wide spatial coverage of the ocean, in-situ sensor data are still sparse in space and time since they are only available when and where the sensors are physically located. In addition, due to the data privacy issue, only a small portion of in-situ sensor data is available to the public. We introduce the three available and widely used in-situ sensor datasets, i.e., Argo, Go-BGC, and SOCCOM, as below.

- **Argo:** Array for Real-time Geostrophic Oceanography (Argo) is an international program that uses profiling floats to observe temperature, salinity, currents, and other factors in the ocean. It has been in operation since the early 2000s and provides real-time data for studying climate and oceanography. Fig. 5 shows the global distribution of 3948 sensors from the Argo program [4]. As shown in Fig. 6, the Argo float mission is a 10-day cycle, and Argo sensors drift at a depth of 1000 meters (the so-called parking depth) and measure the conductivity, the temperature, etc., as it moves back up to the ocean surface. Once the float is on the surface, it will communicate with a satellite and send its location and collected data to them, then continue its mission (around 4-5 years).
- **GO-BGC:** The Global Ocean Biogeochemistry (GO-BGC) Array is a project to build a global network of chemical and biological sensors on profiling floats. The network monitors biogeochemical cycles and ocean health, including the elemental cycles of carbon, oxygen, and nitrogen through all seasons of the year.
- **SOCCOM:** The Southern Ocean Carbon and Climate Observations and Modeling project (SOCCOM) is a multi-institutional program focusing on unlocking the mysteries of the Antica Ocean, exploring the influence of carbon, nutrients, oxygen, and other factors on global climate.

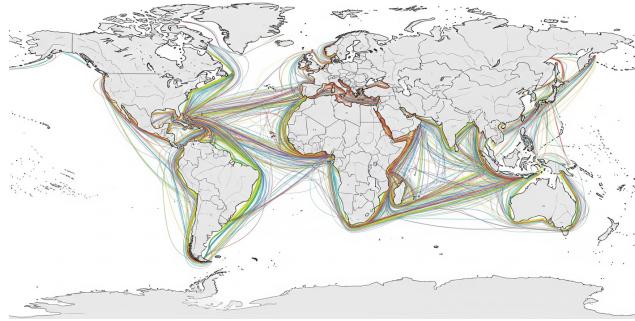


Fig. 7. The visualization of ship trajectories in the Automatic Identification System (AIS).

2.1.3 Ship Data. Ship data is collected by ships and vessels for directly observing the ocean factors, collecting biology samples, and investigating the ocean [206]. Ships can collect marine data at different locations along their trajectories. Here, we introduce two common tracking systems that record the information of ships.

- **AIS:** Automatic identification system (AIS) is an operation tracking system that provides ships' information such as the type of ship, location, and speed. Fig. 7 visualizes several AIS trajectories of ships. AIS was used by the U.S. Coast Guard in 2009 for the first time to monitor and transmit the locations of huge vessels. According to the International Maritime Organization (IMO), the goals of developing AIS are to help recognize ships, assist in target tracking, enhance the safety of marine traffic, and make the flow of vessel traffic smooth. Since 2004, installing AIS transponders for vessels over 300 tons of weight is mandatory in the International Convention for Safety of Life at Sea (SOLAS) guideline.
- **VMS:** Vessel Monitoring System (VMS) is a form of satellite tracking using transmitters on board fishing vessels. It tracks vessels in a similar way to AIS but is restricted to government regulators or other fisheries authorities. All European Union, Faroese, and Norwegian vessels that exceed 12 meters in length must be fitted with VMS units. VMS collects the locations, times, and oceanic features along the trajectories of vessels.

2.1.4 Reanalysis Data. It is important to have complete observations of the ocean system in both spatial and temporal dimensions. However, the observations discussed above are usually unevenly distributed. Even in satellite data, the observations cannot provide a complete recording of the state of the ocean system across the globe at a given point in time. Reanalysis data is the most completed data, which fills the gaps in the observational records through the simulation models or the physic models [279]. Reanalysis datasets are often globally complete and consistent in time. They are among the most-used datasets in ocean, especially in various data-driven ocean applications. We introduce the four widely-used reanalysis datasets as follows:

- **OISST:** NOAA's Optimum Interpolation Sea Surface Temperature (OISST, also known as Reynolds' SST) is a series of global reanalysis products, including the weekly OISST data and daily OISST data. OISST generates smoothed and complete ocean observation data by conducting interpolating and extrapolating operations based on a combination of ocean temperature observations from satellites and in-situ platforms (e.g., ships and buoys). The input data is first mapped to specific regular grids since they are usually irregularly distributed in space. Then, statistical methods, e.g., optimum interpolation (OI) [91], are applied to fill in the missing values.

- **ClimateNet**: is an open and expert-labeled dataset designed for high-precision analyses of extreme weather events. It focuses on capturing tropical cyclones and atmospheric rivers in high-resolution climate model outputs.
- **ERA5**: ECMWF Reanalysis Atmosphere V5 (ERA5) is published by ECMWF for monitoring the global climate, which provides hourly data with estimates of uncertainty for the parameters of atmospheric, land-surface, and ocean. ERA5 provides atmospheric parameters on 37 pressure levels, sea surface temperature, sea wave height, etc.
- **Extreme-ERA5**: is a subset from ERA5 to evaluate the prediction capability of data-driven models under extreme weather conditions. It comprises various extreme weather events defined by climate variables exceeding localized thresholds (e.g., heatwaves and cold breaks due to sea level temperature anomalies).
- **OSCAR**: Ocean Surface Current Analyses Real-time (OSCAR) is a global surface current database provided by NASA. OSCAR data are calculated based on satellite-sensed sea surface height gradients, ocean vector winds, and sea surface temperature gradients using a simplified physical model. Daily averaged surface currents are provided on a global 0.25 x 0.25-degree grid over an assumed well-mixed top 30 meters of the ocean from 1993 to the present.
- **GOCD**: The Global Ocean Current Database (GOCD) is a typical reanalysis data that integrates ocean current data from a wide variety of methods, resolutions and formats into a single universal format. Daily averaged surface currents are provided on a global 0.25 x 0.25-degree grid of the temporal coverage from 1962 to 2013.

2.2 Unique Data Characteristics

Compared with typical ST data (e.g., traffic flow data and epidemic outbreak data), ST ocean data not only contains ST dependencies between adjacent locations but also has a lot of complex and unique characteristics. Here, we summarize four unique characteristics of ST ocean data, as shown below.

Diverse Regionality. In general, the ocean can be divided into a lot of regions in different ways. For example, one general partition is based on the climate zones to divide the ocean into various regions, such as tropical zones and frigid zones. On the one hand, each region has a diverse pattern from the others. As shown in Fig. 8(a), the collected ocean data in the same region usually have similar patterns, but the data from different regions may have opposite patterns [173, 257]. On the other hand, when learning the ST correlations in ocean, it is of high importance to capture the ST correlations between regions since the ocean is a unified system. Moreover, due to the ocean current and atmospheric circulation, the correlations between regions are not static but dynamically changing over time. The dynamic nature of these correlations complicates the task to effectively learn and generalize across the varied features of all ocean regions. Therefore, adaptive learning approaches tailored to specific regional characteristics are necessary to accurately analyze ocean data and enhance the predictive performance of STDM models, ultimately leading to a more comprehensive understanding of marine ecosystems and environment changes.

High Sparsity. Sparsity is an important characteristic of ST ocean data. In-situ data and ship data are usually collected in a sparse and uneven distribution in both space and time, which leads to high sparsity in observation data for certain periods and some ocean areas. Satellite data may be highly missed due to the cloud covering the scanning cycle of satellites, and the sensors' stability and transmission loss. For example, according to [137], the missing rate of MODIS satellite data could be higher than 80% in some periods. Moreover, as illustrated in Fig. 8(b), the Chl-a data from both of the Yangtze River, China, on March 16, 2022, and the South China Sea on November 27, 2023, exhibit high sparsity, with a missing rate exceeding 50%. The high data sparsity issue hinders the ability of STDM approaches to identify and understand important oceanic patterns and trends,

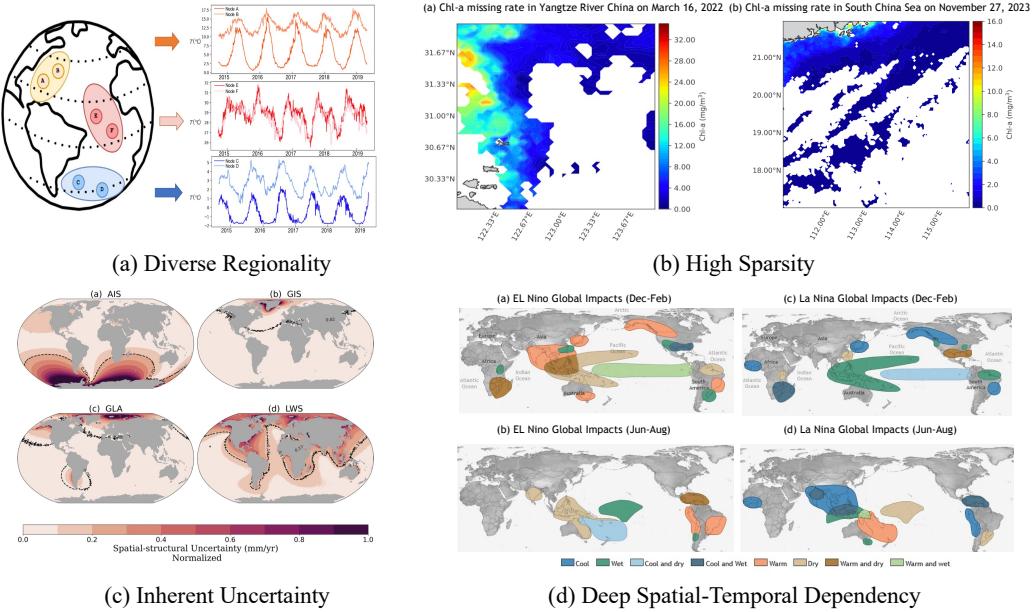
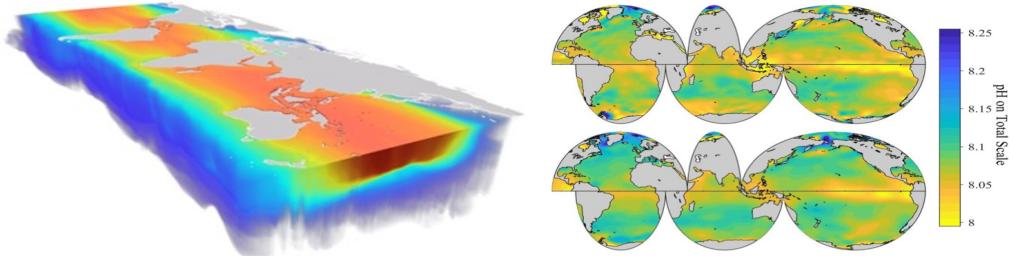


Fig. 8. The illustration of the four unique characteristics of ST ocean data. (a) shows that the SST data collected from different regions may have diverse patterns [257]. (b) shows that the Chl-a data collected in two different locations suffer from high data missing problems [230]. (c) provides the spatial uncertainty on four different datasets [29]. (d) illustrates the spatial-temporal dependency across different seasons of two well-known phenomena, i.e., El Nino and La Nina [96].

which leads to unreliable analyzing results. Thus, how to address the sparsity issue in ST ocean data is an important yet challenging task for developing STDM methods for ocean science.

Inherent Uncertainty. Another characteristic of ST ocean data is the inherent uncertainty due to the instability of the data collection process, which may cause the collected data to contain noise and deviate from real values. Concretely, the uncertainty in ST ocean data stems from the fact that many ocean datasets have biases in sampling and measurement. For instance, uncertainty might occur because a particular thermometer is miscalibrated or poorly sited. However, data producers seldom provide uncertain information about data. For example, one may have access to three different SST datasets: one reanalysis dataset at $2.5^\circ \times 2.5^\circ$ spatial resolution, another dataset at $0.75^\circ \times 0.75^\circ$ spatial resolution, and a satellite dataset at $0.25^\circ \times 0.25^\circ$ spatial resolution. As shown in Fig. 8(c), there are four different datasets to monitor the sea-level changes. For the spatial-structural uncertainty, four datasets have different biases and uncertainties [29] at different locations. Since each dataset has its own biases, effectively fusing these datasets to obtain the correct information is a challenging issue.

Deep Spatial-temporal Dependency. With the wide spatial coverage of the global ocean and long-term temporal recording, ST ocean data have more complex and deeper ST dependencies than typical ST data. Concretely, from the spatial view, the wide spatial coverage brings complicated ST dependencies between different ocean locations. For example, as illustrated in Fig. 8(d), two well-known phenomena, i.e., El Nino and La Nina, occurring in the equatorial Pacific Ocean, have been proven to cause intense storms and extreme temperatures in many regions far away from the Pacific Ocean via the tropical tropospheric and atmospheric bridge mechanism [96, 259]. From



(a) The visualization of global SST at different depths.

(b) The visualization of global surface ocean pH.

Fig. 9. The visualizations of ocean environmental elements: (a) The global SST at different depths [6], and (b) the global surface ocean pH from two different analysis projects [101].

the temporal view, the temporal dependency of these two phenomena is complicated and dynamic across different seasons, which requires STDM methods to have the capability to model such dynamics. Moreover, the spatial and temporal dependencies are often intertwined and influence the interactions between various ocean factors across different regions. Thus, modeling and capturing such intricate dependencies are crucial for understanding ocean dynamics.

2.3 Data Visualization

Visualization of ocean data is important for scientists and engineers to understand various ocean phenomena and discover their underlying complex and dynamic patterns. Since interactive visual analysis integrates the experts' knowledge into the design of models and algorithms [133], it allows us to interactively explore, analyze, and assess data at different spatial-temporal scales to gain insights into the data. We introduce three typical types of visualization methods for ST ocean data as below.

- **Ocean environmental elements visualization.** Ocean environmental elements are a number of basic physical properties that affect the ocean ecosystem, including scalar data (e.g., temperature and salinity) and flow fields (e.g., trajectories and ocean currents). 2D plots (e.g., points, lines, surfaces, particles, and glyphs) and 3D volume rendering are widely used methods for the visualization of these ocean environmental elements. For example, Fig. 9 visualizes the global SST at different depths and the distribution of global surface ocean pH. Currently, with the rapid development of hardware technology, the GPU-based hybrid graphics visualization approach is popular [133]. Su et al. [208] developed an ocean data visualization system that supports line contouring, volume rendering, and dynamic simulation of the sea current field. The system employs GPU-based rendering to visualize scalar or flow fields efficiently and is used to monitor the changing processes of ocean environmental elements. Liu and Chen [144] also developed a framework for interactive visual analysis of heterogeneous marine data. Ocean environmental elements visualization could help us well understand the inherent operating processes of the ocean system.
- **Ocean event visualization.** The interaction between various ocean environmental elements constitutes a variety of ocean events. For instance, ocean eddies, ocean fronts, typhoons, and El Niño are common events occurring in the ocean, which often last for several days to several months. Each event has different characters and needs special algorithms for visualization. Various methods have been proposed to visualize these events. For example, Fig. 10 visualizes the trajectory of typhoon Hato in 2017. George et al. [66] proposed a framework for the

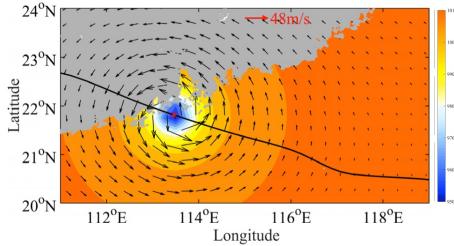


Fig. 10. The visualization of typhoon Hato at 04:00 UTC on 23 August 2017, where the black line shows the path of Hato [48].

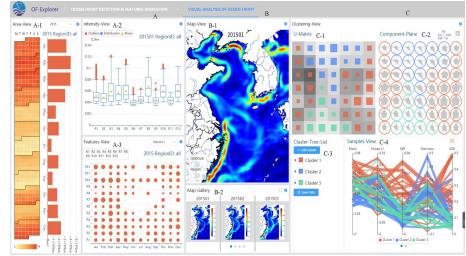


Fig. 11. The interface of OFExplorer, a visualization tool for exploring and discovering SST characteristics and patterns [248].

visual analysis of the sea level rise event and provided multiple visual analytic tools for interactive hydrodynamic flux calculation on spatial-temporal and multivariate data. Holl et al. [84] developed an interactive visualization system for sea surface height data to support interactive exploration and analysis of the spatial distribution and the temporal evolution of ocean eddies. In general, the spatial and temporal scales of ocean events are often different, which requires event visualization methods to be adaptable to changeable scales [123].

- **Ocean pattern visualization.** Ocean patterns are related to complex ocean processes, which are hidden in the spatial and temporal variability of ocean data. ST pattern visualization is used for understanding the evolution characteristics of the ocean environmental elements (e.g., temperature and salinity) or phenomena (e.g., eddies and fronts) over time to detect trends, periodicity, and other important factors. For example, Xie et al. [248] developed the visualization tool OFExplorer, as shown in Fig. 11, to discover the changing patterns of SST. Another ocean pattern visualization approach integrates the changes of ocean environmental elements in both time and space into a 3D volume rendering [184] by reducing the feature dimension through slicing, averaging, and aggregation operations or using PCA-like methods [189, 202].

3 DATA QUALITY ENHANCEMENT

High data quality is of great significance to ensure that the results of STDM are reliable, accurate, and complete [114]. However, in practice, it is difficult to get high-quality ST ocean data for various reasons, such as limited spatial and temporal coverage, failures of data collection devices, and data loss during transmission. Meanwhile, the diversity of the data sources also affects the quality of ST ocean data. To address the data quality issue, a number of studies have been conducted on data quality enhancement, which makes ST ocean data more suitable for specific applications. In this section, we first overview the typical data quality control methods and then summarize the three foundational data processing operations, i.e., data cleaning, data completion, and data fusion, and the corresponding techniques to improve the quality of ST ocean data. In addition, we introduce the data transforming process, which transforms the data representation to meet the specific requirements of STDM tasks.

3.1 Data Quality Control

Conducting spatio-temporal data mining over erroneous data could lead to invalid conclusions. Conversely, rejecting extreme but valid data may result in missing important events [45]. Therefore, the goal of data quality control is to minimize or eliminate incorrect data, enabling better decision-making. Five commonly-used metrics for data quality are listed as follows:

- **Data Range Checks:** Verify that the data values fall within expected ranges [98]. For example, sea surface temperature should be within the range of -2°C to 35°C.
- **Physic Consistency Checks:** Ensure that related data points are consistent with each other by Physics law [125]. For instance, with both sea surface salinity and temperature data, we can check their consistency with known physical and oceanographic laws.
- **Temporal Consistency:** Check for temporal consistency in time-series data and ensure that there are no sudden, unexplained jumps or drops in the data by utilizing the sliding windows.
- **Spatial Consistency:** For spatial data, ensure that the values are consistent across neighboring regions. Sudden changes in values across small spatial distances may indicate errors.
- **Cross-Validation:** Cross-validate the data with other reliable sources or datasets to ensure its accuracy.

3.2 Data Cleaning

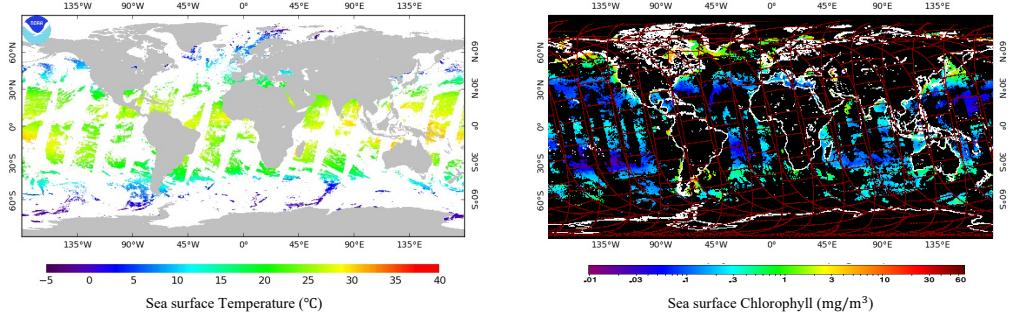
Data cleaning aims to remove incorrectly formatted data, which may result in inaccurate analysis and unreliable results. Data cleaning requires a good understanding of the real distributions and statistical implications of the original data. Existing methods, e.g., **statistical analysis methods**, **proximity measurement methods** and **density-based clustering methods**, for data cleaning usually use constraints, rules, and patterns to detect and remove the outliers in data [278]. Statistical analysis methods usually detect outliers that do not follow the given data distributions or regression equations. Proximity measurement methods first define a proximity measure between data points and then identify those abnormal data points that are far away from the other data points. Density-based clustering methods often detect data outliers by comparing their local density with the neighboring data points and are suitable for non-uniformly distributed data. For ST ocean data, we could utilize the above methods to remove the incorrectly formatted data points to improve data quality for downstream STDM tasks.

3.3 Data Completion

The issue of data missing or sparsity is very common in ST ocean data due to the influence of various inevitable factors such as cloud occlusion, bad weather, and sensor failure. If missing values are not well treated, the data analysis results may be unreliable and inaccurate, leading to bias in further applications. As shown in Fig. 12(a) and Fig. 12(b), due to the cloud occlusion, both AVHRR data and MODIS data have many missing values. According to Fig. 12(c), the monthly missing rate of MODIS data in the Northern South China Sea is often between 20% and 50%, and the missing rate of SST even reaches 60% in 2012, let alone the daily data missing rates. Apparently, compared with typical ST data such as traffic data and crowd volume data, the missing rate in ocean data is extremely high, making it difficult to conduct data analysis and restricting the development of real-world applications (e.g., weather forecasting and typhoon detection). Therefore, data completion is regarded as a necessary step in ST ocean data quality enhancement and a variety of data completion methods have been proposed. In this section, we briefly introduce the problem definition of data completion and the related techniques.

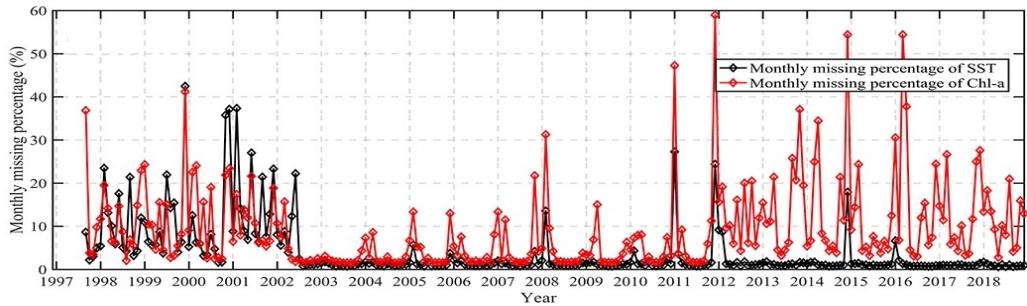
As shown in Fig. 13, we use matrix $X = (X_1, \dots, X_j, \dots, X_T) \in \mathbb{R}^{N \times T}$ to represent the time-series of recorded ocean data for N nodes (e.g., grid ocean regions and sensor locations) at T timestamps, where X_j represents the observation values for all nodes at timestamp τ_j , and $x_{i,j}$ is the observation value of node v_i at timestamp τ_j . In addition, a masked matrix $M = (M_1, \dots, M_j, \dots, M_T) \in \mathbb{R}^{N \times T}$ is introduced for X , where each entry $m_{i,j} = 0$ if the entry $x_{i,j} \in X$ is missing, otherwise $m_{i,j} = 1$.

Given the incomplete data matrix X and its masked matrix M , the data completion problem aims to fill the missing values in X and ensure that the filled values are close to the real values, i.e.,



(a) The spatial distribution of SST records from AVHRR satellite data on 3 October 2021, where the white areas have no data, and the gray areas are lands [1].

(b) The spatial distribution of Chl-a records from MODIS satellite data on 3 October 2021, where the black areas have no data [3].



(c) The monthly missing percentages of SST and Chl-a in the area of Northern South China Sea from 1997 to 2018 [150].

Fig. 12. Distributions and missing rates of global SST and Chl-a data. (a) / (b) The spatial distribution of SST / Chl-a records from AVHRR / MODIS satellite data on 3 October 2021, and (c) the monthly average missing rates of SST and Chl-a in the Northern South China Sea from 1997 to 2018.

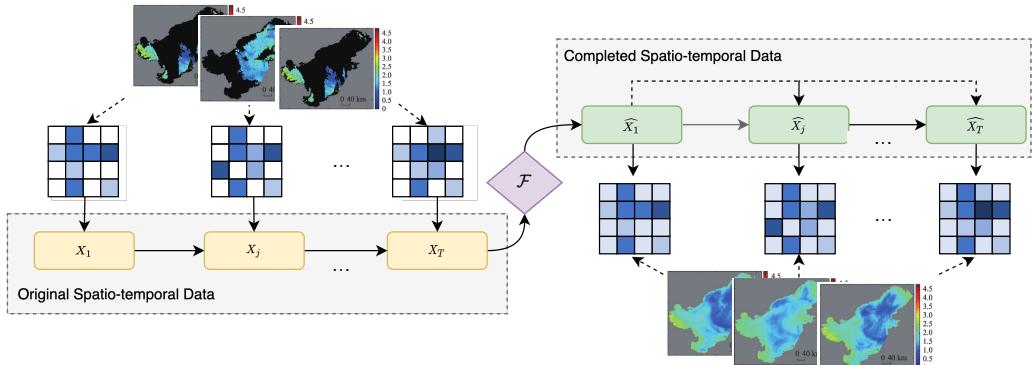


Fig. 13. The general framework of ST data completion, where the input is incomplete ST data, the output is completed data, and \mathcal{F} could be various data completion algorithms.

Table 5. Major existing methods of ocean data completion.

Category	Strengths	Weaknesses	Model	Year	Approach
Numerical methods	Need a small amount of data, simple, fast, flexible, and adaptable.	Cannot model non-linear data, depend on a correct domain knowledge.	OI [91] Kriging [168] DINEOF [11] STGF [277]	1987 1990 2005 2024	min-variance linear combination of nearby data Empirical Orthogonal Function (EOF) averaging neighbors' data
Traditional machine learning based methods	Can model dynamic, non-linear, and noisy data, easy to set up, self-adaptable, self-organizing, and error tolerant.	Have a high computational cost and tend to overfit when applied to long-term data.	ANN [176] RF [38] KNN [89] SVR [160] MF [140]	2008 2019 2021 2021 2022	artificial neural network a multitude of decision trees averaging k-nearest neighbors calculating the best model to fit points matrix decomposition
Deep learning methods	Extract deep features from the data, can work with noisy data, captures temporal dependencies over variable periods of time, high accuracy.	High complexity, high computational cost, need to be tuned carefully lack of interpretability	CNN [218] GAN [170] STA-GAN [231] GCN [137] U-Net [261] Transformer [71]	2021 2021 2022 2023 2023 2024	convolutional neural network generative adversarial network generative adversarial network graph completion network attention network transformer network

$$\widehat{X} = \mathcal{F}_{\theta}\{X, M\}, \quad (1)$$

$$\widetilde{X} = X + \widehat{X} \odot (O - M), \quad (2)$$

where \widehat{X} is the generated data matrix by data completion model function \mathcal{F} , θ denotes all the learnable parameters in the model, O is a matrix whose entries are all ones, and \odot denotes Hadamard product. Finally, we can get the completed data \widetilde{X} .

Existing ST data completion methods can be roughly divided into three categories, i.e., numerical methods, traditional machine learning-based methods, and deep learning methods. And the summarization and comparison of these methods are in Table 5.

3.3.1 Numerical methods. Numerical methods learn the linear correlations from past observations and the domain knowledge (e.g., physical laws of the ocean) to achieve data completion. History average (HA) only uses the average of past data to fill in the missing values, which is too simple to learn the non-linear relationships. To simulate the true data distribution, the Optimal Interpolation (OI) method [91] uses the min-variance to obtain the ideal unbiased approximation of missing data and is widely used to build cloud-free SST products by fusing data from multiple platforms, such as satellite data, in-situ data, and ship data. For example, the OI method is employed in the NOAA OISST products [91] and the blended foundation SST products [85]. In addition, the OI method is popular for analyzing daily SST by fusing the AVHRR satellite data and the Tropical Rainfall Measuring Mission Microwave Imager products. Distance-based data completion methods fill the missing data with the average of the data within a certain physical distance and are also popular in the early ages. For example, Kriging and IDW [21] have been proposed to achieve SST data completion based on the spatial relevance of original data. DINEOF is widely used to complete Chl-a data, SST data, ocean wind data, and multivariate ocean factors [70, 256].

In practice, numerical methods are simple, flexible, and widely used for filling in missing values in various ocean data products. However, they cannot well learn the complex nonlinear relationships in ocean data, and some methods are highly dependent on expert knowledge to set the values of parameters, which is not sufficient to achieve accurate ST data completion.

3.3.2 Traditional machine learning-based methods. Traditional machine learning-based methods aim to utilize historical ocean data to train machine learning models to simulate data distributions for data completion. For example, Chen et al. [38] used RF to improve the completion of Chl-a data with two external factors, i.e., the Ocean Color Index and the Rayleigh-corrected Reflectivity. Distance-based method K-Nearest Neighbors (KNN) and kernel-based SVR method have also been adopted to fill missing values of ocean data based on distance measurement [89, 160]. Artificial

Neural Network (ANN) is applied for the completion of SST data in the Mediterranean [176]. Jouini et al. [106] proposed the Self-Organizing Map (SOM) network to complete Chl-a data under heavy cloud coverage by integrating SST and sea surface height (SSH).

In sum, traditional machine learning-based methods are easy to set up and have the ability to model the dynamic, non-linear, and noisy features of ST ocean data. However, they have a high computational cost, tend to overfit when applied to long-term data, and cannot well capture the complex ST dependencies in ocean data.

3.3.3 Deep learning-based methods. To capture the complex ST dependencies, deep learning-based data completion methods have been introduced to improve the quality of sparse ST ocean data. For example, Jean-Marie [218] achieved the completion of SST data using a neural network (NN) and proved that the NN is superior to the OI and EOF methods. Zhao et al. [274] proposed an LSTM-based method to fill the missing values of wave height data. Chen et al. [40] proposed the FTC-LSTM method that combines Fourier Transform Convolution (FTC) and LSTM to simultaneously capture global spatial features and global temporal features of Chl-a for data imputation. Ye et al. [261] proposed an attention U-Net model for reconstructing MODIS data and introduced attention gates to learn the most important features of missing data. Barth et al. [17] proposed the Data-Interpolating Convolutional Auto-Encoder (DINCAE 1.0) for the completion of Chl-a data. Han et al. [79] extended DINCAE 1.0 by introducing SST data. Furthermore, Yan et al. [254] proposed the DINCAE-BME method for reconstructing Chl-a data and utilized Bayesian Maximum Entropy (BME) to integrate multiple types of information. Then, DINCAE 2.0 was proposed to handle multivariate data, including SST, Chl-a, and wind speed, for reconstructing MODIS-Terra SST and altimetry observations [18]. Wang et al. [231] proposed the STA-GAN model, which demonstrates strong performance in satellite data completion. This model utilizes the ST attention mechanism of Graph Attention Networks (GAT) to learn short-term temporal dependencies and dynamic spatial dependencies and incorporates Generative Adversarial Networks (GAN) to capture the original distribution of satellite data. Considering the limited observational information from highly sparse remote sensing data, Wang et al. [229] further proposed the S2-STI method, which incorporates external data such as SST and Photosynthetically Active Radiation (PAR) to enhance the accuracy of Chl-a data imputation. Specifically, this method generates ST embedding representations for the external data to enrich the information about Chl-a data and develops a GAN-based Data Imputation (GDI) module to reconstruct the distribution of Chl-a data.

Deep learning-based data completion algorithms achieve high accuracy in ST ocean data completion and can capture dynamic dependencies over time. However, they still have some weaknesses. First, they are of high complexity, and the training and tuning processes are time-consuming. Besides, they are treated as "black boxes" and have low interpretability. Therefore, it is still worth exploring to reduce the time complexity of deep ST ocean data completion methods and enhance interpretability.

3.4 Data Fusion

For many STDM tasks, e.g., climate forecasting and typhoon tracking, multi-source ocean data collected by various producers, e.g., NOAA, NASA, and ECMWF, are required to obtain comprehensive knowledge. These different datasets usually have diverse data collecting standards, equipment, and technologies, leading to different ST resolutions, different ST coverage, and different data quality. For example, in-situ observations can provide precise information about the ocean at specific locations, but they have issues of sparsity, uneven distribution, and low resolution. Meanwhile, satellite data can provide continuous observation of the ocean over a wide area and for long periods but is unable to obtain fine-grained information at the location level. Therefore, combining the benefits of

multi-source observation data to build high-quality ST ocean datasets is an essential yet challenging problem. Specifically, for STDM in ocean, data fusion is integrating multiple data sources to obtain more comprehensive and consistent information about the ocean. Existing methods for fusing multi-source ST ocean data can be roughly classified into two categories, i.e., homogeneous data fusion methods and heterogeneous data fusion methods.

3.4.1 Homogeneous data fusion methods. Homogeneous data fusion aims to combine the datasets from the same source into a comprehensive dataset to improve the data quality. At early ages, the most common way to fuse homogeneous data is to utilize their statistical characteristics (e.g., local mean matching, regression analysis, and statistical region merging). However, it is difficult to fuse the observation records of two datasets from the same source with different spatial and temporal scales. To solve this problem, Nguyen et al. [164] presented the spatial data fusion methodology based on the spatial-random-effects model, where the spatial distribution is learned based on the data of different temporal scales within the same region. Kang et al. [151] proposed the Dynamic Fused Gaussian Process (DFGP) to combine a low-rank representation with a general covariance matrix with a dynamic-statistical approach to fuse the satellite data from different sensors. Jung et al. [107] utilized RF to fuse two satellite datasets to provide high-quality SST data. Raizer et al. [178] introduced a digital wavelet transform method to combine information in both spatial and temporal domains across two satellite datasets. More recently, Hou et al. [87] proposed a spatial-temporal ocean data fusion model based on ConvLSTM to fuse multi-source data to predict SST.

3.4.2 Heterogeneous data fusion methods. Heterogeneous data fusion aims to combine data from different data sources, thus providing more comprehensive information than the dataset from a single source. Due to the variety in form and content across spatial and temporal scales, it is much more difficult to fuse heterogeneous data than homogeneous data. Chen et al. [7] developed a Bayesian inference model to fuse in-situ and satellite data for accurate chlorophyll-a estimation. Han et al. [78] introduced a CNN-based fusion algorithm to combine satellite image data with time-series data. Wang et al. [226] proposed an ODF-net to fuse in-situ observations, satellite observations, and reanalysis data using a self-training attention mechanism for short-term SST prediction.

In conclusion, fusing multi-source data can enhance data consistency and quality and improve the accuracy of STDM tasks for ocean science. However, existing methods for fusing ST ocean data usually rely heavily on prior statistical knowledge of linear principles, normal distributions, and error covariances. In addition, these methods are often tailored for specific datasets and tasks, and there are no unified data fusion frameworks that can fuse various ST ocean data sources. These limitations are still open issues that need further exploration.

3.5 Data Transforming

In practice, different ocean application scenarios correspond to different categories of STDM tasks and problem formulations, and different STDM tasks usually have different requirements for the formats of input data. Therefore, the original data from multiple sources cannot be directly used for various STDM tasks. An important process before putting data into STDM models is to transform the data to meet the specific requirements of the data mining task. As shown in Fig. 14, we provide a clear mapping from different data sources to different data instances (i.e., ST points, Trajectories, Time series, and ST raster) and four types of tasks (cf. Section 4 for the details). For example, an ST point refers to a tuple containing spatial and temporal information as well as ocean features (e.g., temperature and chlorophyll-a), which can be obtained by in-situ sensors and ship sensors. Then, a series of ST points collected at different locations can be utilized for detecting various events (e.g., El Niño and typhoon). A trajectory, usually collected by a sailing ship or moving sensor, consists of

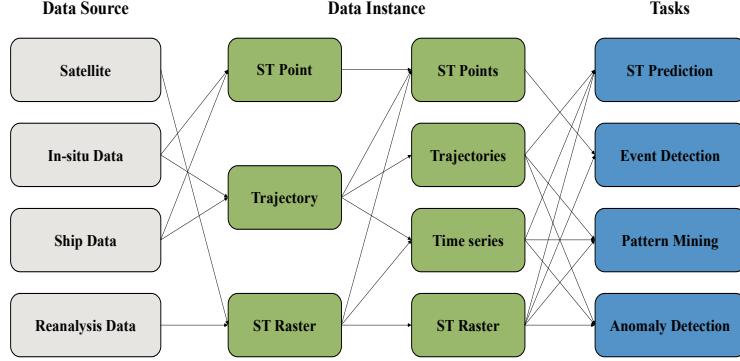


Fig. 14. A mapping from the data sources to the data instances and the four types of ocean STDM tasks.

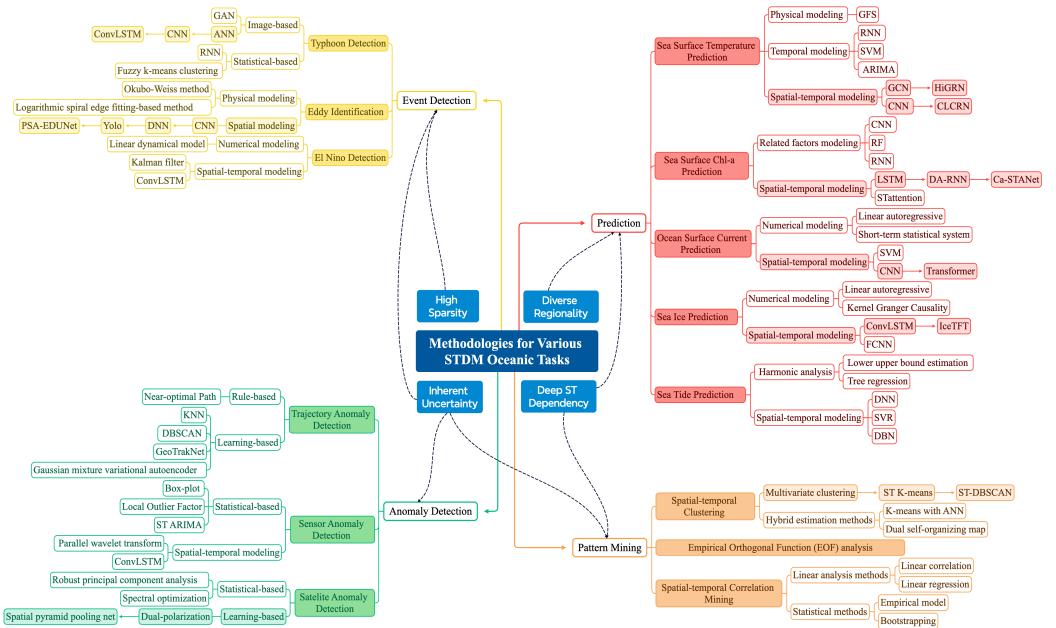


Fig. 15. The taxonomy of methodologies of different ocean STDM tasks.

the continuous measurements of an ST feature over a set of moving reference points in space and time and can be utilized in ship anomaly detection, as well as pattern mining tasks. ST raster data refers to the measurement of a continuous or discrete ST field recorded at fixed locations in space and at fixed points in time, which is usually collected by the satellite sensors and obtained from the outputs of reanalysis models. ST raster data is an important data format for STDM tasks and also can be transformed into other data instances (e.g., ST points and time series) for different tasks.

4 TASKS & METHODOLOGIES

To provide a clear overview of the STDM techniques for ocean science, we classify the STDM tasks into four typical categories, i.e., prediction, event detection, pattern mining, and anomaly

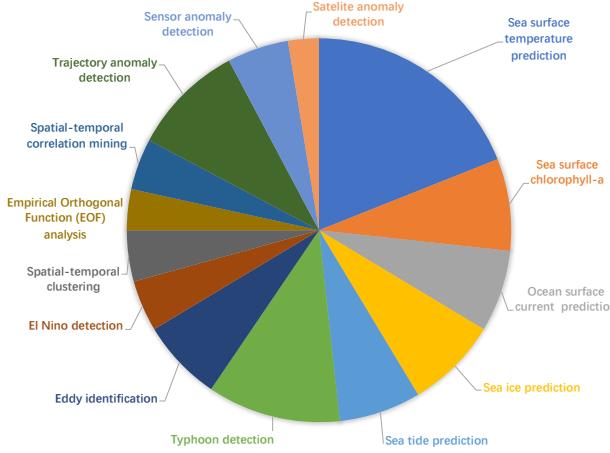


Fig. 16. The distribution of publications of various ocean STDM tasks (data from the Web of Science).

Table 6. Representative studies for the ocean STDM tasks.

Task Categories	Tasks	Related studies
Spatial-temporal Prediction	Sea surface temperature prediction	[183],[207],[8],[238],[269]
	Sea surface chlorophyll-a prediction	[243],[267],[260],[246],[86],[270],[210], . . . [73],[7],[118],[63]
	Ocean surface current prediction	[256],[174]
	Sea ice prediction	[146],[181],[266],[82],[263],[126],[235],[95], [61],[16],[191],[72],[182],[192],[97],[214],[272], [264],[224],[223],[175],[43],[143],[143],[276]
	Sea tide prediction	[190],[109],[110],[68],[167],[258],[185],[194].
Spatial-temporal Event Detection	Typhoon detection	[113],[255],[148],[116],[10], [37],[118],[188],[67].
	Eddy identification	[239],[32],[200],[158],[127],[147],[50].
	El Niño detection & prediction	[64],[30],[213],[233],[117].
Spatial-temporal Pattern Mining	Spatial-temporal clustering	[83],[240],[69],[93],[7]
	Empirical Orthogonal Function (EOF) analysis	[44],[162].
	Spatial-temporal correlation mining	[41]
Spatial-temporal Anomaly Detection	Trajectory anomaly detection	[204],[242],[76],[58],[13],[186],[187],[60],[128], [204],[163],[128].
	Sensor anomaly detection	[152],[12],[112].
	Satelite anomaly detection	[153],[77],[53].

detection, based on the problem formulation. We then introduce the typical downstream applications and representative methods for each category of tasks. Fig. 15 illustrates the overall taxonomy of representative methodologies of different ocean STDM tasks and highlights the most crucial characteristics (c.f. Section 2.2) that need to be addressed for each category of tasks. For instance, capturing diverse regional variations and deep ST dependencies is highly important for ST prediction tasks in the ocean. In addition, Fig. 16 presents the distribution of published research papers on these tasks (data from the Web of Science), among which SST prediction and typhoon detection are the most popular. Table 6 further overviews the representative studies for each category of STDM tasks, and Table 7 summarizes the representative methods by comparing their complexity, spatial-temporal modeling techniques, and enhancing modules.

Table 7. The comparison of representative STDM methods in ocean science.

Task Categories	Methods	Complexity	Spatial modeling	Temporal modeling	Enhancing modules
Spatial-temporal Prediction	ConvLSTM [246, 263]	Low	CNN	LSTM	
	DA-RNN [235]	Low	Attention	LSTM	
	TransLSTM [97]	Low	Transformer	LSTM	
	CLCRN [138]	Medium	Conditional local convolution	LSTM	
	HIGRN [257]	High	GRU	RNN+Attention	Regional clustering
	ECM-HMSTM [63]	High	hybrid multiscale U-Net	LSTM	Error correction
Spatial-temporal Event Detection	ConvLSTM [37, 116]	Low	CNN	LSTM	
	FCRNN [10]	Low	MLP	RNN	
	ConvLSTM-EMD [233]	Medium	CNN	RNN	Empirical Mode Decomposition
	GAN [188]	High	DNN	Generator	Physical models
	Data-Attention-Yolo [234]	High	Attention	Yolo	
	PSA-EDUNet [275]	Medium	U-Net	Pyramid Split Attention	
Spatial-temporal Pattern Mining	HEK [69]	Low	K-means clustering	ANN	
	DSOM [157]	Low	Attention	Self-Organizing Map	
	LR [41]	Low	55	Linear Regression	
Spatial-temporal Anomaly Detection	Cluster [53]	Low	KNN	SVM	
	GMVAE [250]	Medium	55	Variational Autoencoder	Dynamic Time Warping
	GeoTrakNet [163]	Low	55	Variational RNN	Gaussian approximation
	RPCA [203]	Low	55	Low-rank Decomposition	
	SPPN [227]	Medium	Spatial Pyramid Pooling	Multivariate Gaussian Distribution	

4.1 Spatial-temporal Prediction

Spatial-temporal prediction is an important STDM task for ocean science that predicts the future changes of various ocean factors, e.g., temperature, chlorophyll-a, and ice concentration. ST prediction aims to understand the regularity of historical observations to predict future observations. The key challenge in ST prediction is that ocean factors have complex spatial and temporal dependencies. For example, events occurring in a region may affect other regions far away (spatially and temporally). For ST prediction in the ocean, we overview the experiments setting for ST prediction and five representative tasks, i.e., sea surface temperature prediction, sea surface chlorophyll-a prediction, ocean surface current prediction, sea surface chlorophyll-a prediction, and sea tide prediction.

4.1.1 Experiments settings. Given the time series $X = \{X_0, X_1, \dots, X_t\}$, we have $X_{:t} = \{x_{1,t}, x_{2,t}, \dots, x_{N,t}\} \in \mathbb{R}^{N \times d}$ that records d -dimension data at N locations at time t , where d represents the dimension of observed factors. Then, ST prediction aims to seek a function \mathcal{F} to predict the features in upcoming τ time steps based on the data of the last T time steps, i.e.,

$$\{\hat{X}_{t+1}, \hat{X}_{t+2}, \dots, \hat{X}_{t+\tau}\} = \mathcal{F}_{\theta}\{X_{:t-T+1}, X_{:t-T}, \dots, X_{:t}\} \quad (3)$$

where θ denotes the learnable parameters in function \mathcal{F} . Commonly used metrics for evaluating ST prediction include Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), both measuring the average errors of the prediction values and ground-truth values. Mean Absolute Percentage Error (MAPE) is also frequently used to provide a normalized measure of prediction accuracy. Additionally, the correlation coefficient (R) is used to assess the strength and direction of the linear relationship between observed and predicted values. These metrics collectively provide a comprehensive assessment of ST prediction models' performance in capturing the spatial and temporal dynamics in ocean data.

4.1.2 Sea surface temperature prediction. Sea surface temperature (SST) is one critical parameter for monitoring global climate change, and accurate SST prediction is important to weather forecasting, disaster warning, and ocean environment protection. The major challenge in predicting SST is that SST has dynamic patterns changing over time, long-term temporal dependencies, and complex spatial dependencies. SST prediction has been studied for decades, and existing methods for SST prediction can be roughly grouped into three categories, i.e., physical models [183, 207], temporal methods [8, 267], and spatial-temporal methods [86, 138, 260, 270].

Physical models combine the laws of physics, e.g., Newton's laws of motion, the law of conservation of energy, and the seawater equation of state, to predict SST. For instance, the Global Forecast System (GFS) [183] conducts SST prediction by combining the Navier-Stokes equation, solar radiation function, and ocean latent heat circulation equation to simulate the changes of SST. Although physical models have been widely used in the past decades, they require a good understanding of the underlying changing mechanism of SST to choose the determining factors of physical functions. However, the changing mechanism of SST is complicated, making it difficult to use only the factors of explicit equations to capture SST patterns.

Temporal methods, as a widely used type of SST prediction methods, formulate SST prediction as a time series prediction problem that can be solved by various temporal models, e.g., vector autoregressive models, hidden Markov models (HMM), support vector machines (SVM) model, and some temporal deep learning methods [8, 138, 260, 267]. For example, Aguilar et al. [243] introduced warm water volume as an additional feature to enhance SST prediction with an SVM model. Generally speaking, these are linear models that use a window of past information to predict the SST records in the future. Although these methods can predict the trend of SST to a certain extent, they ignore the long-term dependencies, leading to low overall prediction accuracy. Zhang et al. [267] employed a fully connected LSTM to predict future SST in Bohai, where the LSTM structure models SST sequences and the fully connected structure produces the prediction results. These temporal methods mainly focus on extracting the temporal features of SST and cannot well capture the spatial correlations among the SST time series.

Spatial-temporal prediction methods combine typical deep learning methods such as CNN, RNN, and GCN to capture the ST dependencies in ocean data. Xiao et al. [246] employed the ConvLSTM model for SST prediction by using CNN to extract the spatial information of gridded SST and LSTM to capture the temporal dependencies of SST. Hou et al. [86] proposed a dilated convolutional model to obtain long-term dependencies of SST series, and the model achieves better prediction performance than ConvLSTM. To learn the complicated non-adjacent connections among SST series, researchers also model the spatial correlations of SST time series with GCN. As shown in Fig. 17, CLCRN [138] utilizes a GCN-based method to establish local spaces for modeling the dependencies of the spatial neighbors and predicting future SST. Zhang et al. [270] developed the memory GCN to build a distance-based adjacency matrix to represent the spatial correlations of SST series at different locations. To capture regional correlations, Yang et al. [257] proposed the HiGRN to capture the hierarchical relationship between regions for global SST prediction. Gao et al. [63] proposed a hybrid multi-scale spatial-temporal model combined with the error correction map to predict SST.

Spatial-temporal prediction methods have been widely used to capture the ST dependencies in SST and achieve good performance. However, most of them focus on capturing the static dependencies in SST, ignoring the dynamic ST dependencies and the combination with the physic models, which is still worth exploring in the future.

4.1.3 Sea surface chlorophyll-a prediction. Predicting the sea surface chlorophyll-a (Chl-a) concentration could facilitate the monitoring and early warning of harmful algal bloom events that have serious impacts on marine fisheries. For Chl-a prediction, the major difficulty is to model the seasonality and the related factors affecting Chl-a. To discover the related factors, Liu et al. [146] used the absolute principal components score (APCS) method to simulate the effects of multiple chemical variables on Chl-a in Lake Qilu. However, these statistical methods are of low prediction accuracy. In recent years, various machine learning methods (e.g., SVM, decision trees (DT), RF, feed-forward neural network (FFNN), and regression models) are widely used for Chl-a prediction [266]. For example, an FFNN model [181] was used to forecast the Chl-a concentration seven days in advance

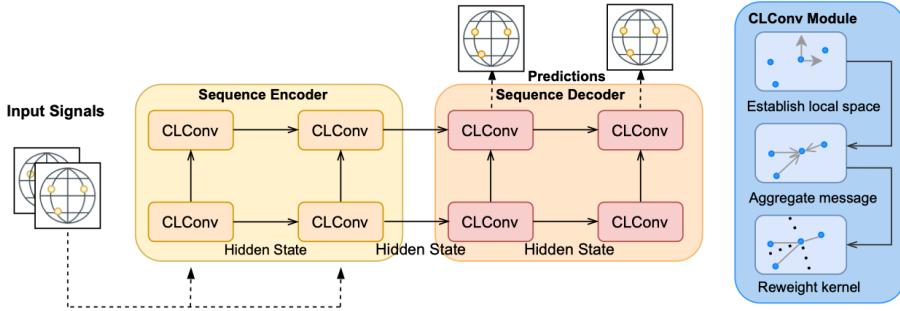


Fig. 17. The framework of the CLCRN model, which is implemented based on the Sequence to Sequence architecture with the encoder fed with previously observed data and the decoder generating the predictions [138].

in Lake Kasumigaura of Japan. Hill et al. [82] used a CNN to predict Chl-a concentrations in the Gulf of Mexico region. Moreover, Yossof et al. [263] adapted an LSTM model and a CNN model to predict the harmful algal blooms on the western coast of Sabah.

4.1.4 Ocean surface current prediction. Ocean surface current refers to the large-scale, regular, and stable flows of water on the surface of ocean in a certain direction. Accurate prediction of ocean currents can not only assist shipping, fishery, and tourism to produce economic benefits, but also play an important role in many marine tasks such as vessel path planning and Autonomous Underwater Vehicles (AUS) controlling. The major challenge in ocean surface current prediction is to model the dynamics of slow and large-scale currents. Earlier studies on ocean current prediction mostly used numerical modeling methods and linear statistical models. For instance, physical methods could derive currents from sea surface height using established physical equations [201]. Frolov et al. [61] developed a statistical model that utilizes linear autoregressive techniques to predict ocean surface currents. Barrick et al. [16] introduced a short-term statistical system to forecast ocean surface currents in Northern Norway using only a few hours of prior data. Despite their effectiveness, both physical and statistical methods require significant processing costs and parameters manually determined by domain experts.

With the advancement of machine learning, non-parametric prediction methods are increasingly being adopted for ocean current forecasting. Various machine learning algorithms, such as Gaussian Processes, SVM, Genetic Algorithms, and ANN, have been employed to enhance the accuracy of current prediction [72, 182, 191, 272]. For instance, Sarkar et al. [192] developed an ANN model incorporating fully connected layers alongside recurrent LSTM layers to predict tidal currents in specific regions. To capture the dynamic ST dependencies of ocean currents, Alexandre et al. [97] introduced a Transformer model integrated with LSTM to leverage real-time in-situ data for current prediction. Similarly, Nathachai et al. [214] proposed an ST model that capitalizes on distinct domain characteristics by employing a CNN to capture spatial properties and a Gated Recurrent Unit (GRU) to capture temporal dynamics.

Although existing studies can capture the ST features in ocean surface current data and achieve good prediction performance, the large-scale spatial dependencies and the correlations with other related factors (e.g., wind flow and the ocean tides) are still not well considered, which affects the prediction accuracy of ocean surface currents.

4.1.5 Sea ice prediction. Sea ice prediction is a crucial task in monitoring and preventing global warming and also plays an important role in coastal port traffic and vessel path planning. For the study of sea ice, the data from satellites are often the main or even the only data source because it is difficult to obtain in-situ sea ice observation data due to extreme weather. According to [161], the ever-increasing melting speed has made it more difficult to make accurate sea ice prediction. Consequently, utilizing the limited data to predict future sea ice data is a challenging issue.

Traditional machine learning methods, e.g., BP network, ANN, and linear regression, are widely used for sea ice prediction. For example, Li et al. [130] developed a sea ice-intensive degree-day prediction method that combines kernel Granger Causality analysis (KGC) and SVM to predict sea ice. However, these machine learning methods cannot well capture the ST dependencies in sea ice data, which leads to low prediction accuracy. To directly capture the spatial dependencies, Wang et al. [224] introduced a CNN-based approach that utilizes satellite image data to estimate sea ice during melting seasons. Wang et al. [223] proposed a fully connected CNN (FCNN) model to predict sea ice along Canada's east coast. To capture temporal dependencies, Petrou et al. [175] employed ConvLSTM for short-term sea ice prediction. To identify the impactful factors on sea ice, Mu et al. [161] proposed an interpretable long-term prediction model (IceTFT) that fuses multiple atmospheric and oceanic variables, and utilizes the temporal fusion transformer and multi-head attention mechanism to automatically adjust the weights of predictors and filter spuriously correlated variables.

Most existing studies on sea ice prediction are purely data-driven methods [143, 276]. However, it has been proven that combining physical knowledge with machine learning is an effective way to achieve accurate sea ice prediction. How to combine the physical mechanisms of sea ice with data-driven methods is a challenging issue for achieving accurate sea ice prediction.

4.1.6 Sea tide prediction. Tides are periodic fluctuations of the ocean surface and are caused by the gravitational pull of the sun and moon. Tidal energy generated by the fluctuation of tidal water level is a vital renewable energy source. For a long time, tide prediction has provided safety guarantees for port operations, shipping traffic, and coastal protection, and also provides essential support for offshore aquaculture and the prevention of natural disasters [280].

In the early ages, the most commonly used technique to predict sea tides was harmonic analysis, which forecasts the tidal variations with historical observations. However, harmonic analysis suffers from the fact that the parameters are numerous, some of which have a very long return period, thus costing a lot of time. Currently, the widely used methods for tidal prediction are also based on machine learning. For example, Sarkar et al. [190] used the BP algorithm, cascade correlation algorithm, and conjugate gradient algorithm to predict the tides continuously. Kavousi-Fard et al. [109] proposed a probabilistic method that uses Lower Upper bound Estimation (LUBE) to model the uncertainties of tidal current prediction in the Bay of Fundy, NS, Canada. Granata et al. [68, 167] used tree regression, RF, and multilayer perceptron to predict the tide level of Venice based on satellite data.

The high sparsity and large spatial resolution of satellite data present significant challenges in developing a high-quality unified sea tide prediction model. To address this issue, Yang et al. [258] combined satellite data and tide gauge data to estimate tidal sea levels using a Deep Belief Network (DBN). Riazi et al. [185] developed a DNN that incorporates tidal generating forces along with geological and biological factors for tidal level prediction. Despite these advancements, the deep correlations inherent in sea tide data remain unexplored by current methods.

4.2 Spatial-temporal Event Detection

In ocean science, an ST event usually means that there are significant and persistent changes happening at a particular time and location, such as typhoons, eddies, and other extreme ocean phenomena. Monitoring and detecting these events can provide early warning to prevent severe damage to personal safety and social safety. In recent years, extreme ocean events become more and more frequent under the circumstance of global warming. Therefore, accurate detection of ST events in ocean is important. Specifically, in this section, we give a brief overview of the detection of typical ST ocean events, including typhoon, eddy, and El Niño event.

4.2.1 Experiments settings. Event detection often uses both real-world and simulation data to ensure a comprehensive evaluation of detection methods' effectiveness and robustness. Thus, cross-validation techniques are employed to provide a robust and unbiased assessment of the model's performance. In addition to cross-validation, real-world scenario testing is crucial for evaluating the system's performance under diverse conditions. This includes testing the system in various seasonal and geographic conditions to ensure its reliability and effectiveness across different environments. Commonly used metrics for event detection include Accuracy, Precision, Recall, and F1 score, which can assess the model's ability to correctly identify events. MAE and RMSE are used to measure the accuracy of continuous variables such as wind speed and tidal heights. Confusion Matrix is also commonly used to provide detailed statistics of true positives, false positives, true negatives, and false negatives. Additionally, sensitivity analysis could test the model under various hypothetical scenarios to evaluate its response to different types of events.

4.2.2 Typhoon detection. A typhoon refers to a large storm system that has a circular or spiral system of violent winds and typically has hundreds of kilometers in diameter. Typhoons often occur in the tropical ocean and are usually accompanied by strong winds, heavy rain, and storm surges. Typhoon detection is of high importance to provide early warnings for disaster management in coastal areas. Typhoons usually move rapidly and are affected by multiple environmental parameters, e.g., SST, cloud cover, atmospheric pressure, and wind speed. To detect a typhoon, it is crucial to capture the extreme changes of these factors at a particular time and location. Typhoon detection has been studied for decades, and existing methods can be roughly grouped into two categories, statistical-based methods and image-based methods, according to the type of data.

For the statistical-based methods, typhoon-related atmospheric and oceanic factors (e.g., SST and wind speed) and tide-gauge data are collected for the detection of typhoons. For example, Sophie et al. [67] combined the NOAA unifying tropical cyclone data with the ERA reanalysis wind field data to construct a fusion neural network for typhoon path prediction. To predict the typhoon formation process and intensity, Chen et al. [37] combined CNN and LSTM to learn the spatio-temporal relationship among typhoon-related atmospheric and oceanic variables. To combine more factors, Alemany et al. [10] established a fully connected RNN with a lot of oceanic factors, i.e., typhoon center location, wind speed, and central pressure at 6-hour intervals from NOAA. Moreover, many researchers formulate typhoon detection as an ST clustering problem, which can not only discover the typhoon but also localize central typhoon cyclones. Kim et al. [113] evaluated the performance of three clustering methods, i.e., K-means clusterin, Fuzzy C-means clustering (FCM), and hierarchical clustering, for typhoon detection. The results indicated that FCM outperformed the others in terms of clustering efficiency and fitting degree, highlighting its effectiveness in handling the inherent uncertainty in typhoon data. Yang et al. [255] employed a mixed regression clustering algorithm alongside the mass moment method for analyzing typhoon cyclone trajectories and accurately identified the typhoon tracks in the South China Sea.

With the development of computer vision and the increasing amount of satellite image data, CNN-based methods are widely used to discover typhoons. Kovordanyi et al. [118] established a multi-layer ANN to predict the movement of cyclones based on the AVHRR images from NOAA. Ruttgers et al. [188] proposed a GAN-based detection method and discovered that integrating reanalysis data from physical models with satellite image data significantly improved the detection performance. Kim et al. [116] introduced a ConvLSTM-based model to capture both spatial and temporal dynamics for detecting typhoon tracks and predicting future trajectories. Considering that typhoons are relatively rare weather phenomena and the proportion of positive and negative samples is seriously unbalanced, Zhao et al. [273] proposed a CNN-based detection method with data enhancement technology, such as shearing, rotation, and gray-level transformation, to generate new samples for better typhoon events detection.

The state-of-the-art typhoon detection methods can already achieve quite good detection performance. However, achieving real-time typhoon detection is still a challenging problem due to the high complexity of detection methods and the complex dynamics in the development of typhoons.

4.2.3 Ocean eddy identification. An eddy is a circular current of water. Ocean eddies play an important role in ocean energy transfer and nutrient distribution. Accurately identifying the variation of ocean eddies is the key to understanding the oceanic flow and ocean circulation system [239]. It is challenging to autonomously detect eddies since they are not static objects but a distortion evolving through a continuous field. Images obtained from satellite sensors have a large spatial resolution and a wide swath of observation, which makes them effective sources for gaining comprehensive and detailed information to detect ocean eddies. Existing methods for ocean eddy identification can be roughly grouped into two categories, i.e., physical-based methods and data-driven methods.

The physical-based methods describe and detect the eddies with their physical information. The Okubo-Weiss method [239] is the most popular statical and physical procedure to discover the patterns of eddies, and it also has good interpretability. Chelton et al. [32] tracked and analyzed global eddy variability using sixteen years of unified sea surface height data, which allows for a comprehensive understanding of eddy dynamics on a global scale. Yang et al. [158] proposed a logarithmic spiral edge fitting-based method to extract eddy information, such as the center position, diameter, and edge size, from satellite images. These methods are dependent on the physical parameters, geometrics, and handcrafted features related to eddies. However, eddies are highly dynamic, and the underlying physical processes are too complex to be described using physical models with predetermined parameters.

Instead of extracting factors based on expert knowledge, data-driven models can learn high-level eddy features automatically from data. For example, Du et al. [50] utilized a spatial pyramid model and an SVM classifier method to recognize the eddies in satellite image data. As shown in Fig. 18, Wang et al. [234] proposed the object detection method using the Data-Attention-Yolo to process the satellite data on eddy identification. To better capture the spatial pyramid correlations, Zhao et al. [275] developed the pyramid split attention (PSA) eddy detection U-Net model (PSA-EDUNet) that targets oceanic eddy identification from ocean remote sensing imagery. These data-driven methods utilizing satellite data are proven to be effective for eddy detection. However, due to the limited resolution of satellite data, existing methods can only discover eddies with a large diameter but lack the ability to detect eddies with a diameter smaller than 50 km.

4.2.4 El Niño detection. El Niño is an irregularly periodic variation in winds and SST over the tropical Eastern Pacific Ocean, and it can cause extreme weather events, e.g., floods and droughts, around the world. An El Niño event can be identified if the absolute value of the 3-month mean of SST in the Niño 3.4 region (5°S - 5°N , 170°E - 120°W) reaches or exceeds 0.5°C and lasts for at least

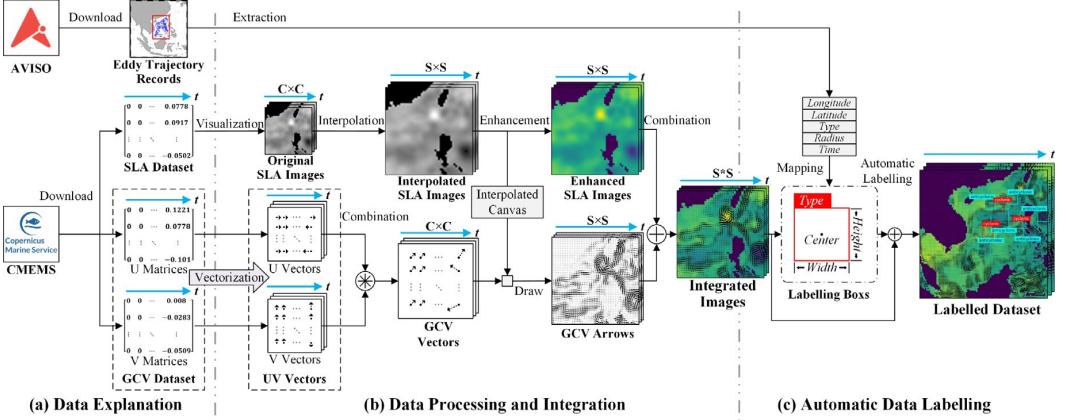


Fig. 18. The framework of data-attention-YOLO for eddy identification method, where (a) the two input datasets, (b) the data processing and integration process, and (c) automatic data labeling that is designed to transform the original eddy data to the labeled integrated data [234].

5 months. In general, El Niño event has mutual influence with many other regions across the world. Therefore, the biggest challenge for El Niño detection is to capture the complex ST dependencies of the SST in different regions within a large spatial coverage.

Most early El Niño detection models use physical laws and mathematical equations to deduce the results from the complicated interaction between the atmosphere and ocean [117]. However, these methods need domain knowledge and require a lot of factor setting of functions. To address this issue, many researchers use data mining methods for El Niño detection, which do not involve physical equations and achieve better performance than the physical methods [30, 213]. For example, Cane et al. [30] proposed a linear dynamical model to identify the El Niño event one year ahead.

Recently, deep learning methods have been introduced to achieve long-term (e.g., more than one year) prediction and detection of El Niño events. For instance, Wang et al. [233] combined the ConvLSTM Encoder-Decoder model with the Empirical Mode Decomposition (EMD) technique to achieve El Niño prediction three years in advance. This hybrid approach integrates spatial-temporal modeling with signal decomposition to enhance prediction accuracy. Besides, Gao et al. [64] proposed a new inflation scheme based on a local ensemble transform Kalman filter to improve the long-term prediction of El Niño events. Though these methods provide valuable suggestions on whether El Niño events will occur, it is still difficult to accurately detect the onset of an El Niño event because a series of reactions together lead to the El Niño events.

4.3 Spatial-temporal Pattern Mining

ST patterns mining is a fundamental STDM task to discover the hidden, potentially useful, and unknown associations and correlations in ocean data, which is of great importance for various applications, such as finding circulation regimes, identifying extreme-causing weather patterns and evaluating the effects of climate changes. In this section, we review some notable ST pattern mining approaches, including clustering, EOF analysis, and correlation mining, in the ocean.

4.3.1 Experiments settings. Many statistical analyses and data-driven methods have been proposed to uncover the associations and correlations among ST ocean data. Common evaluation metrics include classification metrics (e.g., accuracy, precision, recall, and F1 score) and regression metrics (e.g., MSE, RMSE, and MAE). For clustering tasks, evaluation metrics such as the silhouette score,

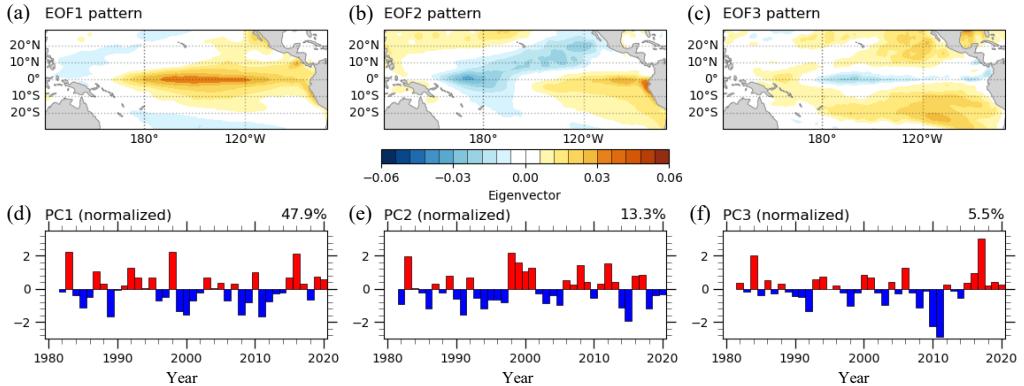


Fig. 19. Spatial distributions (a,b,c) and time series (d,e,f) of the SST anomalies of the first three modes by EOF decomposition in the North Pacific Ocean from 1982 to 2020.

purity, and entropy are often employed. Beyond these quantitative metrics, collaboration with domain experts is also essential to validate the findings based on existing oceanic knowledge and environmental implications to ensure credibility.

4.3.2 Spatial-temporal clustering. Clustering is one key data analysis task in data mining that aims to group data samples with high similarity into the same class. In general, each data sample to be classified is defined as an input vector, and the clustering result is determined by calculating the similarity between the input vector and the clustered vectors. If the similarity reaches a certain value, the input vector is divided into the corresponding classes. Compared with linear regression analysis, clustering methods (e.g., hierarchical clustering, k-means clustering, and self-organizing maps clustering) are able to reveal unknown and hidden patterns without prior knowledge from domain experts.

In the early stages, hierarchical clustering methods were utilized to discover the spatial patterns of ocean circulation in the northern hemisphere [159]. Hoffman et al. [83] developed a quantitative statistical clustering technique termed Multivariate Spatio-Temporal Clustering (MSTC), which can discover regions with similar environmental characteristics, e.g., the dry high-altitude weather of North American and Asian winters, and the warming weather in Antarctica and western Greenland. White et al. [240] employed the k-means method to generate climate and vegetation clusters, which are then used to infer phenological responses to climate changes. Gu et al. [69] introduced a hybrid estimation method that combines the k-means clustering algorithm with an ANN model to reveal the seasonal variation patterns of sea surface temperature (SST) and salinity in the Indian Ocean. Moreover, Rafael et al. [157] applied the dual Self-Organizing Map (SOM) method to analyze ocean salinity and current data from 1993 to 2012 and uncovered the ocean circulation and its variability patterns, revealing recurrent circulation patterns during different seasons.

Although there are already some studies on ST clustering, the physical meaning and significance of the generated clusters are often debatable. Moreover, there are no guarantees to find meaningful ST patterns because of the high spatial and temporal variability in ocean data. Therefore, developing an effective ST clustering method to produce clustering patterns with physical meanings is still a big challenge for ocean science.

4.3.3 Empirical Orthogonal Function analysis. One of the most fundamental tools in ST pattern finding is Empirical Orthogonal Function (EOF) analysis. EOF is synonymous with the eigenvectors in the traditional eigenvalue decomposition of a covariance matrix [80]. According to Cressie and Wikle [44], EOF analysis is simply principle component analysis (PCA) in the discrete case. In the continuous case, EOF is a Karhunen-Loeve (KL) expansion.

EOF analysis has been traditionally used to identify a low-dimensional subspace that best explains the ST variance of ocean data. In order to better understand the spatial distribution characteristics of the SST in the North Pacific, the EOF method [102] is used to analyze the variability of SST during 1980-2020, and three spatial distributions with large variance contribution were obtained, as shown in Fig. 19. By identifying the dominant spatial structures and their evolution over time, we can discover clear ST patterns. For instance, Harika and Virendra [162] utilized the EOF method to identify three broad divisions of the ocean region—western, central, and eastern-based on seasonal ice mass gain or loss from satellite data. In sum, EOF is a powerful analysis method that has been widely used in ocean science. However, the existing versions of EOF are slightly out of date, and there is a need to develop new EOF-based methods to take full advantage of the large amount of ST ocean data and the advanced STDM techniques.

4.3.4 Spatial-temporal correlation mining. Correlation mining in ocean aims to analyze the relationship between ocean variables, e.g., understanding ocean-atmosphere interaction, studying the effects of climate change, and finding the hidden correlations of teleconnection patterns. Various methods, including linear analysis methods and statistical decomposition methods, have been proposed for ST correlation mining in ocean. For example, Chen et al. [41] used linear regression to explore the correlations between different oceanic regions and the fire activities in the Amazon, which demonstrates the interconnectedness of oceanic and terrestrial systems. Furthermore, Liu et al. [145] used linear analysis to reveal a significant correlation between forest resources and SST in the western-north Pacific Ocean area, indicating the influence of oceanic conditions on terrestrial ecosystems. In practice, finding the underlying correlation in the ocean is of high interest to us, but it is still a difficult task that requires prior oceanic knowledge and tons of experiments.

4.4 Spatial-temporal Anomaly Detection

Anomalies refer to the sets of observations that deviate from expected behaviors as compared with other observations. ST anomaly detection in ocean domain is an important task used in a wide variety of ocean applications. For example, trajectory anomaly detection can be used to detect whether a ship is currently undertaking a voyage that may cause an accident or whether it has changed its route to avoid bad weather conditions. In this section, we summarize three typical ST anomaly detection tasks, i.e., trajectory anomaly detection, sensor time-series anomaly detection, and satellite image anomaly detection, for STDM in ocean.

4.4.1 Experiments settings. For ST anomaly detection in ocean, the data are collected from various sources such as satellites, sensors, and buoys. Experimental settings thus differ according to the data types. In general, for ST anomaly detection, we usually use clustering methods and probabilistic methods for trajectory data, RNN-based models for time-series data, and CNNs for image data. Commonly used metrics include precision, recall, F1-score, and ROC curves. Detected anomalies are typically analyzed and visualized using heatmaps and time-series plots to provide detailed insights. Specifically, a unique challenge with trajectory data is the lack of labeled data, resulting in most studies relying on case studies to validate model performance.

4.4.2 Trajectory anomaly detection. During the voyage of the ship, various abnormal situations may be encountered, such as equipment failure, rocking and collision, and illegal activities. It is

of high significance to implement effective trajectory anomaly detection, which enables timely detection and notification of abnormal events, and helps quickly take measures to protect property safety and people safety. With over 1,490,776 ships tracking worldwide [242], it is difficult and time-consuming to manually find anomalies. Therefore, automatically analyzing the trajectory data to quickly and accurately detect anomalies is of high necessity. To this end, many trajectory anomaly detection methods have been proposed, and these methods can be roughly divided into two categories, i.e., rule-based methods and learning-based methods. These methods primarily focus on identifying abnormal behaviors in the trajectories of ships by analyzing spatiotemporal characteristics such as position, speed, and direction.

Concretely, rule-based methods use a set of rules for anomaly detection, which requires a good understanding of the anomalies [204]. For example, Soleimani et al. [204] proposed a near-optimal path method to detect ship trajectory anomalies and provided reasonable explanations for the detected anomalies. Kontopoulos et al. [122] introduced a real-time system for detecting AIS switch-offs as a typical anomaly, in which vessels turn off their transponders to conceal their locations. However, in practice, it is difficult to design a complete set of rules to cover various trajectory anomalies. Moreover, rule-based methods are often time-consuming and labor-intensive, limiting their applications.

For learning-based methods, many researchers utilize stochastic methods and machine learning methods, e.g., the classification model [53], gaussian process [186], gaussian mixture model [13], density estimation model [187], and Bayesian network [60], to achieve trajectory anomaly detection. For example, Fahn et al. [53] proposed a typical classification method based on SVM and KNN to classify ship trajectories for detecting the abnormal ones. However, classification-based detection methods require manually labeling the trajectories and are prone to the risk of overfitting [75]. To solve this problem, Han et al. [76] introduced the density-based clustering method DBSCAN to learn the distribution of trajectories without labeling. Xie et al. [250] developed the Gaussian Mixture Variational Autoencoder (GMVAE) using an unsupervised classification method and achieved a high detection rate (91.26%). Martha et al. [58] combined autoregressive and cluster analysis to detect anomalies in maritime navigation trajectories. To further capture the hidden and deep correlations, Duong et al. [163] proposed GeoTrakNet to utilize neural networks to learn the probability representation of AIS trajectories for detecting trajectory anomalies. Fig. 20 visualizes the results of three typical trajectory anomaly detection methods on the same dataset, where the GeoTrakNet achieves the best performance. Kexin et al. [129] proposed an adaptive vessel trajectory anomaly detection model based on transfer learning and transformer architecture, which introduces multiple attention modules to mine the dynamic dependencies between data points in the trajectory sequence. David et al. [172] proposed a context information extraction process over Automatic Identification System (AIS) real-world ship data, building a system with the capability to extract representative points of a trajectory cluster. Furthermore, Venskus et al. [217] proposed a maritime automated identification system using a self-organizing map to detect ship anomalies.

Although there exist many methods for ship trajectory anomaly detection in ocean, an objective and fair comparison between these methods is hardly possible due to closed evaluation datasets and missing ground truth for anomalies. Therefore, it is worthwhile to further explore unsupervised or semi-supervised trajectory anomaly detection methods based on the large volume of unlabeled trajectory data and limited labeled data.

4.4.3 Sensor time-series anomaly detection. Sensor time-series anomaly detection focuses on analyzing the time-series data, e.g., temperature, salinity, and current speed, collected by ocean sensors to identify abnormal variations in environmental conditions. Many in-situ sensors are usually located in harsh environmental conditions and transmit the collected data across networks. Hence,

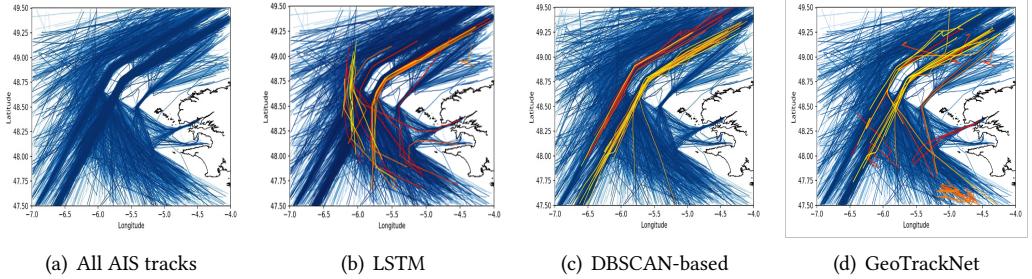


Fig. 20. The visualization of AIS trajectories and the corresponding detection results of three trajectory anomaly detection methods [163] from January 1 to March 31, 2017, where blue color indicates normal trajectories and the other colors indicate the detected abnormal trajectories.

the collected data usually contain a series of outliers and anomalies. Detecting these outliers and anomalies is important for improving the quality and reliability of the ST ocean datasets. To this end, the major difficulty is to differentiate the true anomaly rather than the regular fluctuation, which requires a good understanding of the corresponding environmental circumstances. Researchers have developed many automated statistical and machine-learning methods to jointly use spatial and temporal information for detecting sensor time-series anomalies. For example, Anbaro [12] used an ST ARIMA model to define the coherent ST neighborhoods and then detected the outliers, which have their values significantly different from the mean of nearby ST neighborhoods. To analyze the anomaly from the typical statistics, Kumars [152] utilized three typical outlier detection algorithms, i.e., Box-plot, Local Distance-based Outlier Factor, and Local Outlier Factor, to detect the outliers in wave height time-series records. Recently, Chen et al. [36] proposed an outlier detection method based on the neighborhood rough residual network to detect outliers in IoT-Enabled Maritime Transportation Systems.

4.4.4 Satellite image anomaly detection. Satellite image anomalies refer to defective remote sensing images that may contain abnormal color, color cast, and unknown objects. Satellite image anomaly detection has a broad application, e.g., ship invading detection and extreme cloud detection. Detecting image anomalies is more difficult than detecting the anomalies in trajectory data and time series data because visual features are more difficult to capture than numerical features. Marino et al. [153] proposed an incoherent dual-polarization detector to identify the anomaly of small icebergs in satellite images. Han et al. [77] proposed a spectral anomaly detection method based on dictionary optimization with sparse and low-rank constraints, where the error matrix that cannot be fully expressed by the optimized spectral dictionary is defined as an anomaly. Christopher et al. [203] developed a Robust Principal Component Analysis (RPCA) approach to distinguish clouds and other transient anomalies in satellite images.

Recently, various CNN-based methods have been applied for satellite image anomaly detection due to their high capability in analyzing image data and achieved promising detection results [222, 227]. For example, Wang et al. [227] proposed a spatial pyramid pooling network with the multivariate Gaussian distribution to detect ships by regarding a ship as an abnormal ocean area. However, most existing satellite image anomaly detection methods still rely on labeled images with manual expert annotations and cannot take full advantage of the large amount of unlabeled satellite image data.

5 FUTURE OPPORTUNITIES

The progress in STDM for ocean science has imposed significant impacts on various ocean applications, as discussed above. However, there are still some open issues that require continuous efforts from both computer science and ocean science. In this section, we highlight multiple promising research directions for further advancing the STDM techniques in ocean science.

5.1 Designing large foundation models for ocean science

Recently, the large foundation models (e.g., BERT [46], GPT [59], and ViT [179]) have received tremendous popularity in computer science and surpassed many state-of-the-art machine learning models by pre-training on big datasets and fine-tuning for different downstream tasks [55]. In ocean science, large ST ocean datasets of wide spatial coverage have been collected for various oceanic tasks, which lays the solid foundation for designing unified large models. Many latest methods (e.g., ClimaX [165], Fuxi [35], Pangu-Weather [22], and Fengwu [34]) are trained with a large amount of ocean data, and can accurately predict the future results [232]. For example, the Pangu-Weather forecasting model is trained on 39-year global weather datasets and achieves great performance on different downstream forecasting tasks such as medium-range weather forecasting and extreme weather forecasting. Ideally, large foundation models should be trained on multi-source ST ocean datasets to capture the underlying patterns and regularity among different data sources and produce more accurate analysis results for various tasks. Unfortunately, these are still under-explored in existing studies. Therefore, designing large foundation models in the domain of ocean science presents excellent opportunities to incorporate various tasks and diverse data sources, ultimately improving the results of various STDM tasks.

5.2 Fusing physical models with data-driven models

Over the past centuries, numerous physical models (e.g., ocean calculation models, numerical ocean models, and physical oceanography models [205]) have been developed and play a crucial role in addressing various oceanic applications. They employ a series of functions and theories to simulate physical processes within the ocean, such as ocean circulation and heat transfer. These methods perform well on many oceanic tasks but rely on the factors determined by expert knowledge. With the advancements in data science, data-driven models, which do not require extensive expert inputs, have gained attention for their ability to capture hidden information by utilizing historical data for training [228]. Some recent studies find that it is reasonable and feasible to combine physical models with data-driven methods [219]. To this end, physics-aware AI, physics-informed machine learning, and physics-guided machine learning [9, 108] have been introduced. These methods combine the advantages of physics models and data-driven models and can provide more robust and accurate results in many fields, such as robotics, civil engineering, and finance. Specifically for ocean science, the physical-guided models can achieve high physical consistency and reduce the uncertainty of results. Taking the SST prediction as an example, Arka et al. [100] integrate traditional physical laws (e.g., temperature density and energy conservation) and recurrent graph networks to predict SST. However, the studies on Physical-guided STDM in the ocean are limited, and most of them are focused on the prediction of ocean factors (e.g., temperature, ice, and salinity [156, 245]). Multiple obstacles still exist in fusing physical models with data-driven models., e.g., the difference in data formats, problem definitions, and model structures. Therefore, designing a general paradigm to fuse physical models with data-driven models is an interesting and promising research direction.

5.3 Enhancing the models' generalizability with continuous learning

Lots of STDM models operate on the assumption of independent and identically distributed (IID) training and test data [221]. Despite showing promising results, STDM should be substantially improved through continuous learning to perform good generalization ability on various unseen scenarios. Continual learning [225], also referred to lifelong or incremental learning, is the process of updating a model over time as new data emerges. Given the ever-evolving nature of ocean patterns, continuous learning is particularly beneficial. It enables models to adapt to new changes and enhances their predictive accuracy and robustness. However, the implementation of continuous learning in models poses some challenges. First, models undergoing learning can experience a phenomenon known as "catastrophic forgetting" where a model may forget previously learned patterns after being updated with new data. Balancing the maintenance of model stability while still allowing it to learn from new data poses a significant challenge. Second, the computational power and storage capacity of a device inherently limit on-device machine learning. Deploying and updating large climate models on devices with limited resources could be difficult. Techniques for model compression, efficient computation, and selective model updating are essential to make on-device adaptation of models feasible. Despite these obstacles, continuous learning presents a promising avenue for enhancing the performance and generalizability of STDM models.

5.4 Improving the interpretability of deep STDM methods

Many STDM approaches are based on deep-learning models, e.g., CNN, RNN, and Transformer, and achieve good performance on various tasks. However, these approaches are typically regarded as black boxes with poor interpretability [54, 121]. The interpretability of STDM methods means the ability to present and explain the model behaviors in understandable forms to humans, which enables users to easily make reasonable and convincing decisions [49, 104]. For ocean science, it is of high importance to build a connection between the STDM results and the underlying physics to provide valuable advice for various ocean applications, e.g., the warning of extreme weather conditions. Although attention mechanisms have been used in some previous STDM studies for ocean science to increase the model interpretability (e.g., periodicity and local spatial dependency), developing more interpretable STDM methods to reveal the natural laws of the ocean remains an open problem [120, 271].

5.5 Fusing multi-source ocean datasets of different modalities

As discussed in Section 2, the ocean data used in STDM tasks usually has multiple sources, including satellite data, in-situ data, ship data, and reanalysis data, and these datasets are often in different modalities. Fusing multi-source datasets can obtain comprehensive information to help STDM models perform better than single datasets. Although there are already some studies on data fusion (cf. Section 3.4), there are still many challenges in fusing multi-source datasets. First, most existing ocean STDM methods focus on fusing different data sources for the same ocean factor (e.g., SST) in single tasks (e.g., SST prediction) and cannot combine the observations of multiple factors (e.g., SST, ocean current, and Chl-a) for multiple tasks (e.g., SST prediction, current prediction, and Chl-a prediction) at the same time. Second, it is difficult to handle the heterogeneity in spatial and temporal resolutions for different datasets, e.g., image satellite data, gridded reanalysis data, and ST points data. Recently, some researchers have used transfer learning and meta-learning to fuse different ocean data sources and introduce the pre-trained models in computer vision and urban computing [241] to capture the features of multi-modal ocean datasets. However, the challenges mentioned above are still not well addressed and require deeper investigation in the future.

5.6 Developing end-to-end STDM models

Currently, many STDM methods for ocean science require the input ST ocean data to be complete and of high quality. To meet such requirements, data cleaning, data completion, and data fusion are conducted over the original ST ocean data. However, these processes are time-consuming and may lead to the loss of some crucial data information. For example, in the SST prediction task, the missing rate of SST records retrieved from the satellite data may be higher than 80% for some periods and locations due to the cloud coverage [137]. Existing methods for SST prediction usually utilize data completion methods (e.g., history average, optimal interpolation, and GAN-based networks) to fill in the missing values before conducting the prediction. However, these methods ignore the sparse distribution of original data and the reasons behind the sparsity (e.g., typhoons and heavy rainfall), which may seriously influence the prediction accuracy. Therefore, developing end-to-end STDM models to learn knowledge and patterns directly from the original sparse ST ocean data is also a promising research direction.

5.7 Adopting self-supervised learning strategy

Self-supervised learning [56, 131, 236] is an effective direction of machine learning where models learn knowledge from the data itself, eliminating the need for manual labeling. This approach emerged from the need to utilize the vast amounts of unlabeled data available in various fields. Nowadays, self-supervised methods [19, 132, 211] are increasingly being utilized in ocean science to enhance data analysis and prediction capabilities. They leverage vast amounts of unlabeled ocean data, such as satellite data, in-situ data, and ship data, to learn patterns and features without the need for extensive manual labeling. For example, automated anomaly detection of ships using self-supervised learning models can facilitate early warning systems by identifying unusual patterns in ocean conditions and detecting anomalies in ship trajectories. However, self-supervised learning in ocean science still encounters several challenges. First, data quality and availability can be inconsistent, thus impacting model accuracy. Second, the complexity of ocean systems makes it difficult to learn the intricate correlations and dynamic patterns in ST ocean data without labels. It is thus necessary to develop more robust and general self-supervised methods based on the large volume of ST ocean data.

6 CONCLUSION

The increasing numbers of satellites, buoys, and other ocean observation facilities have generated a flood of ST ocean data, which makes it possible to develop STDM methods for various ocean applications, e.g., weather forecasting and typhoon detection. The past decades have witnessed the rapid development of STDM techniques for ocean science, which enable us to uncover the underlying ST dependencies within ocean data for solving the challenging problems in ocean science. This survey provides a comprehensive overview of the existing STDM studies for ocean science, including the available ST ocean datasets and their unique characteristics, data visualization tools, data quality enhancement methods, and the methodologies for different categories of STDM tasks. In addition, some promising research opportunities for future research are also pinpointed. We hope that this survey can help computer scientists identify important research issues in ocean, and inspire researchers in ocean science to apply advanced STDM techniques to a variety of ocean applications.

ACKNOWLEDGMENTS

This work was supported in part by the National Natural Science Foundation of China (No. 62202336, No. 62172300, No. 62372326) and the Fundamental Research Funds for the Central Universities (No.

2024-4-YB-03), Hong Kong RGC Theme-based Research Scheme (T22-502/18-R), HK RGC Research Impact Fund (R5006-23), and the Research Institute for Artificial Intelligence of Things, The Hong Kong Polytechnic University.

REFERENCES

- [1] 2021. AVHRR. https://www.class.noaa.gov/data_available/avhrr/index.htm, Last accessed on 2021-10-03.
- [2] 2021. Copernicus Sentinel-2. <https://sentinel.esa.int/web/success-stories/-/how-can-copernicus-sentinel-2-aid-in-water-mapping-using-artificial-intelligence>, Last accessed on 2021-7-28.
- [3] 2021. MODIS. <https://modis.gsfc.nasa.gov/gallery/>, Last accessed on 2021-10-03.
- [4] 2022. Argo Floats to Improve Our Knowledge of the Ocean. <https://www.euro-argo.eu/Outreach/Educational-material/Discover-Argo-floats>, Last accessed on 2022-5-12.
- [5] 2023. Argo Program. <https://globalocean.noaa.gov/research/argo-program/>, Last accessed on 2023-1-2.
- [6] 2024. ArcGIS Pro. <https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview/>, Last accessed on 2024-8-11.
- [7] Tri Dev Acharya, Kyung Wan Yoo, and Dong Ha Lee. 2017. GIS-based Spatio-temporal Analysis of Marine Accidents Database in the Coastal Zone of Korea. *Journal of Coastal Research* 79, sp1 (2017), 114 – 118.
- [8] Silvestre Aguilar-Martinez and William W. Hsieh. 2009. Forecasts of Tropical Pacific Sea Surface Temperatures by Neural Networks and Support Vector Regression. *International Journal of Oceanography* (2009), 1–13.
- [9] Muhammad Aurangzeb Ahmad and Şenel Özönder. 2020. Physics inspired models in artificial intelligence. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 3535–3536.
- [10] Sheila Alemany, Jonathan Beltran, Adrian Perez, and Sam Ganzfried. 2019. Predicting hurricane trajectories using a recurrent neural network. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 468–475.
- [11] Aïda Alvera-Azcárate, Alexander Barth, Michel Rixen, and Jean-Marie Beckers. 2005. Reconstruction of incomplete oceanographic data sets using empirical orthogonal functions: application to the Adriatic Sea surface temperature. *Ocean Modelling* 9, 4 (2005), 325–346.
- [12] Tao Cheng Berk Anbaroğlu. 2009. Spatio-temporal outlier detection in environmental data. *Spatial and Temporal Reasoning for Ambient Intelligence Systems* (2009), 1–10.
- [13] Mathias Anneken, Yvonne Fischer, and Jürgen Beyerer. 2015. Evaluation and comparison of anomaly detection algorithms in annotated datasets from the maritime domain. In *2015 SAI Intelligent Systems Conference (IntelliSys)*. IEEE, 169–178.
- [14] Lotfi Aouf, Danièle Hauser, Celine Tison, and Bertrand Chapron. 2018. On the Assimilation of Multi-Source of Directional Wave Spectra from Sentinel-1A and 1B, and CFOSAT in the Wave Model MFWAM: Toward an Operational Use in CMEMS-MFC. In *2018 IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2018, Valencia, Spain, July 22–27, 2018*. IEEE, 5663–5666.
- [15] Christopher J. Banks, Christine Gommenginger, Meric Srokosz, and Helen M. Snaith. 2012. Validating SMOS Ocean Surface Salinity in the Atlantic With Argo and Operational Ocean Model Data. *IEEE Trans. Geosci. Remote. Sens.* 50, 5-1 (2012), 1688–1702.
- [16] Donald Barrick, Vicente Fernandez, Maria I Ferrer, Chad Whelan, and Øyvind Breivik. 2012. A short-term predictive system for surface currents from a rapidly deployed coastal HF radar network. *Ocean Dynamics* 62 (2012), 725–740.
- [17] Alexander Barth, Aida Alvera-Azcárate, Matjaz Licer, and Jean-Marie Beckers. 2020. DINCAE 1.0: A Convolutional Neural Network with Error Estimates to Reconstruct Sea Surface Temperature Satellite Observations. *Geoscientific Model Development* 13, 3 (2020), 1609–1622.
- [18] Alexander Barth, Aida Alvera-Azcárate, Charles Troupin, and Jean-Marie Beckers. 2022. DINCAE 2.0: multivariate convolutional neural network with error estimates to reconstruct sea surface temperature satellite and altimetry observations. *Geoscientific Model Development* 15, 5 (2022), 2183–2196.
- [19] Pierre Bernabé, Arnaud Gotlieb, Bruno Legeard, Dusica Marijan, Frank Olaf Sem-Jacobsen, and Helge Spieker. 2023. Detecting Intentional AIS Shutdown in Open Sea Maritime Surveillance Using Self-Supervised Deep Learning. *IEEE Transactions on Intelligent Transportation Systems* (2023).
- [20] Tata V. S. Udaya Bhaskar and Chiranjivi Jayaram. 2015. Evaluation of Aquarius Sea Surface Salinity With Argo Sea Surface Salinity in the Tropical Indian Ocean. *IEEE Geosci. Remote. Sens. Lett.* 12, 6 (2015), 1292–1296.
- [21] Shrutipli Bhattacharjee, Pabitra Mitra, and Soumya K. Ghosh. 2014. Spatial Interpolation to Predict Missing Attributes in GIS Using Semantic Kriging. *IEEE Transactions on Geoscience and Remote Sensing* 52, 8 (2014), 4771–4780.
- [22] Kaifeng Bi, Lingxi Xie, Hengheng Zhang, Xin Chen, Xiaotao Gu, and Qi Tian. 2023. Accurate medium-range global weather forecasting with 3D neural networks. *Nature* (2023), 1–6.
- [23] Nguyen An Binh, Pham Viet Hoa, Giang Thi Phuong Thao, Ho Dinh Duan, and Phan Minh Thu. 2022. Evaluation of Chlorophyll-a estimation using Sentinel 3 based on various algorithms in southern coastal Vietnam. *Int. J. Appl. Earth Obs. Geoinformation* 112 (2022), 102951.

[24] François Boy, Jean-François Crétaux, Malik Boussaroque, and Céline Tison. 2022. Improving Sentinel-3 SAR Mode Processing Over Lake Using Numerical Simulations. *IEEE Trans. Geosci. Remote. Sens.* 60 (2022), 1–18.

[25] T Boyer and L Sun. 2016. Global Ocean Currents Database. *American Geophysical Union* 2016 (2016), OD14A–2400.

[26] Bruno Brandoli, Alessandra Raffaetà, Marta Simeoni, Pedram Adibi, Fateha Khanam Bappee, Fabio Pranovi, Giulia Rovinelli, Elisabetta Russo, Claudio Silvestri, Amilcar Soares, and Stan Matwin. 2022. From multiple aspect trajectories to predictive analysis: a case study on fishing vessels in the Northern Adriatic sea. *GeoInformatica* 26, 4 (2022), 551–579.

[27] Bruno Buongiorno Nardelli. 2020. A multi-year time series of observation-based 3D horizontal and vertical quasi-geostrophic global ocean currents. *Earth System Science Data* 12, 3 (2020), 1711–1723.

[28] Wen-Yu Cai, Zi-Qiang Liu, and Mei-Yan Zhang. 2019. Trajectory Clustering Based Oceanic Anomaly Detection Using Argo Profile Floats. In *Communications and Networking - 14th EAI International Conference, ChinaCom 2019, Shanghai, China, November 29 - December 1, 2019, Proceedings, Part I (Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, Vol. 312)*. Springer, 498–508.

[29] Carolina ML Camargo, Riccardo EM Riva, Tim HJ Hermans, and Aimée BA Slangen. 2022. Trends and uncertainties of mass-driven sea-level change in the satellite altimetry era. *Earth System Dynamics* 13, 3 (2022), 1351–1375.

[30] Mark A Cane, Stephen E Zebiak, and Sean C Dolan. 1986. Experimental forecasts of EL Nino. *Nature* 321, 6073 (1986), 827–832.

[31] Paul Chamberlain, Bruce Cornuelle, Lynne D. Talley, Kevin Speer, Cathrine Hancock, and Stephen Riser. 2023. Acoustic Float Tracking with the Kalman Smoother. *Journal of Atmospheric and Oceanic Technology* 40, 1 (2023), 15–35.

[32] Dudley B. Chelton, Michael G. Schlax, and Roger M. Samelson. 2011. Global observations of nonlinear mesoscale eddies. *Progress in Oceanography* 91, 2 (2011), 167–216.

[33] Jianqiang Chen, Xun Gong, Xinyu Guo, Xiaogang Xing, Keyu Lu, Huiwang Gao, and Xiang Gong. 2022. Improved Perceptron of Subsurface Chlorophyll Maxima by a Deep Neural Network: A Case Study with BGC-Argo Float Data in the Northwestern Pacific Ocean. *Remote. Sens.* 14, 3 (2022), 632.

[34] Kang Chen, Tao Han, Junchao Gong, Lei Bai, Fenghua Ling, Jing-Jia Luo, Xi Chen, Leiming Ma, Tianming Zhang, Rui Su, Yuanzheng Ci, Bin Li, Xiaokang Yang, and Wanli Ouyang. 2023. FengWu: Pushing the Skillful Global Medium-range Weather Forecast beyond 10 Days Lead. *arXiv:2304.02948* [cs.AI]

[35] Lei Chen, Xiaohui Zhong, Feng Zhang, Yuan Cheng, Yinghui Xu, Yuan Qi, and Hao Li. 2023. FuXi: A cascade machine learning forecasting system for 15-day global weather forecast. *npj Climate and Atmospheric Science* 6, 1 (2023), 190.

[36] Qiong Chen, Liangru Xie, Lirong Zeng, Sining Jiang, Weiping Ding, Xiaomeng Huang, and Hao Wang. 2023. Neighborhood rough residual network-based outlier detection method in IoT-enabled maritime transportation systems. *IEEE Transactions on Intelligent Transportation Systems* (2023).

[37] Rui Chen, Xiang Wang, Weimin Zhang, Xiaoyu Zhu, Aiping Li, and Chao Yang. 2019. A hybrid CNN-LSTM model for typhoon formation forecasting. *GeoInformatica* 23 (2019), 375–396.

[38] Shuangling Chen, Chuanmin Hu, Brian B. Barnes, Yuyuan Xie, Gong Lin, and Zhongfeng Qiu. 2019. Improving Ocean Color Data Coverage through Machine Learning. *Remote Sensing of Environment* 222 (2019), 286–302.

[39] Shengchao Chen, Guodong Long, Jing Jiang, Dikai Liu, and Chengqi Zhang. 2023. Foundation models for weather and climate data understanding: A comprehensive survey. *arXiv preprint arXiv:2312.03014* (2023).

[40] Siyu Chen and Jun Zhao. 2024. Enhanced Reconstruction of Satellite-derived Monthly Chlorophyll a concentration with Fourier Transform Convolutional-LSTM. *IEEE Transactions on Geoscience and Remote Sensing* (2024).

[41] Yang Chen, James T. Randerson, Douglas C. Morton, Ruth S. DeFries, G. James Collatz, Prasad S. Kasibhatla, Louis Giglio, Yufang Jin, and Miriam E. Marlier. 2011. Forecasting Fire Season Severity in South America Using Sea Surface Temperature Anomalies. *Science* 334, 6057 (2011), 787–791.

[42] Zhumomin Chen, Young-Oh Kwon, Ke Chen, Paula Fratantoni, Glen Gawarkiewicz, and Terrence M Joyce. 2020. Long-term SST variability on the Northwest Atlantic continental shelf and slope. *Geophysical Research Letters* 47, 1 (2020), e2019GL085455.

[43] Junhwa Chi and Hyun-choel Kim. 2017. Prediction of arctic sea ice concentration using a fully data driven deep neural network. *Remote Sensing* 9, 12 (2017), 1305.

[44] Noel Cressie and Christopher K Wikle. 2015. *Statistics for spatio-temporal data*. John Wiley & Sons.

[45] James A Cummings. 2011. Ocean data quality control. *Operational oceanography in the 21st Century* (2011), 91–121.

[46] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).

[47] Zizhen Dong, Ruowen Yang, Jie Cao, and Lin Wang. 2023. Effect of Anthropogenic Forcing on Increased Winter Precipitation in Southeast Asia from 1979 to 2014. *Frontiers in Environmental Science* 10 (2023), 2723.

[48] Mei Du, Yijun Hou, Po Hu, and Kai Wang. 2020. Effects of typhoon paths on storm surge and coastal inundation in the Pearl River Estuary, China. *Remote Sensing* 12, 11 (2020), 1851.

[49] Mengnan Du, Ninghao Liu, and Xia Hu. 2019. Techniques for interpretable machine learning. *Commun. ACM* 63, 1 (2019), 68–77.

[50] Yanling Du, Wei Song, Qi He, Dongmei Huang, Antonio Liotta, and Chen Su. 2019. Deep learning with multi-scale feature fusion in remote sensing for automatic oceanic eddy detection. *Information Fusion* 49 (2019), 89–99.

[51] Christopher D. Elvidge, Tilottama Ghosh, Feng-Chi Hsu, and Mikhail N. Zhizhin. 2022. VIIRS Monitoring and Reporting on Lit Fishing Vessel Detections in Southeast Asia. In *IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2022, Kuala Lumpur, Malaysia, July 17-22, 2022*. IEEE, 4779–4782.

[52] James H. Faghmous and Vipin Kumar. 2014. Spatio-Temporal Data Mining for Climate Data: Advances, Challenges, and Opportunities. In *Data Mining and Knowledge Discovery for Big Data*. Vol. 1. Springer Berlin Heidelberg, Berlin, Heidelberg, 83–116.

[53] C Fahn, Jer Ling, M Yeh, P Huang, and M Wu. 2019. Abnormal maritime activity detection in satellite image sequences using trajectory features. *International Journal of Future Computer and Communication* 8, 1 (2019), 29–33.

[54] Feng-Lei Fan, Jinjun Xiong, Mengzhou Li, and Ge Wang. 2021. On interpretability of artificial neural networks: A survey. *IEEE Transactions on Radiation and Plasma Medical Sciences* 5, 6 (2021), 741–760.

[55] Liancheng Fang, Aiwei Liu, Hengrui Zhang, Henry Peng Zou, Weizhi Zhang, and Philip S Yu. 2025. Tabgen-icl: Residual-aware in-context example selection for tabular data generation. *arXiv preprint arXiv:2502.16414* (2025).

[56] Ziquan Fang, Yuntao Du, Lu Chen, Yujia Hu, Yunjun Gao, and Gang Chen. 2021. E 2 dtc: An end to end deep trajectory clustering framework via self-training. In *2021 IEEE 37th International Conference on Data Engineering (ICDE)*. IEEE, 696–707.

[57] Rubén Fernández-Beltran, Damian Ibañez, Jian Kang, and Filiberto Pla. 2022. Time-Resolved Sentinel-3 Vegetation Indices Via Inter-Sensor 3-D Convolutional Regression Networks. *IEEE Geosci. Remote. Sens. Lett.* 19 (2022), 1–5.

[58] Martha Dais Ferreira, Jessica NA Campbell, and Stan Matwin. 2022. A novel machine learning approach to analyzing geospatial vessel patterns using AIS data. *GIScience & Remote Sensing* 59, 1 (2022), 1473–1490.

[59] Luciano Floridi and Massimo Chiriatti. 2020. GPT-3: Its nature, scope, limits, and consequences. *Minds and Machines* 30 (2020), 681–694.

[60] Nicola Forti, Leonardo M Millefiori, Paolo Braca, and Peter Willett. 2021. Bayesian filtering for dynamic anomaly detection and tracking. *IEEE Trans. Aerospace Electron. Systems* 58, 3 (2021), 1528–1544.

[61] Sergey Frolov, Jeffrey Paduan, Michael Cook, and James Bellingham. 2012. Improved statistical prediction of surface currents based on historic HF-radar observations. *Ocean Dynamics* 62 (2012), 1111–1122.

[62] M. M. Galotto-Tébar, A. Pomares-Padilla, I. A. Czerwinski, and J. C. Gutiérrez-Estrada. 2022. Is the vessel fishing? Discrimination of fishing activity with low-cost intelligent mobile devices through traditional and heuristic approaches. *Expert Syst. Appl.* 200 (2022), 117091.

[63] Gui Gao, Bingxiu Yao, Zhiyuan Li, Dingfeng Duan, and Xi Zhang. 2024. Forecasting of Sea Surface Temperature in Eastern Tropical Pacific by A Hybrid Multi-Scale Spatial-Temporal Model Combining Error Correction Map. *IEEE Transactions on Geoscience and Remote Sensing* (2024).

[64] Yanqiu Gao, Youmin Tang, Xunshu Song, and Zheqi Shen. 2021. Parameter Estimation Based on a Local Ensemble Transform Kalman Filter Applied to El Niño–Southern Oscillation Ensemble Prediction. *Remote Sensing* 13, 19 (2021), 3923.

[65] Augustine-Moses Gaavwase Gbagir and Alfred Colpaert. 2020. Assessing the Trend of the Trophic State of Lake Ladoga Based on Multi-Year (1997–2019) CMEMS GlobColour-Merged CHL-OC5 Satellite Observations. *Sensors* 20, 23 (2020), 6881.

[66] Richard L. S. F. George, Peter E. Robins, Alan G. Davies, Panagiotis D. Ritsos, and Jonathan C. Roberts. 2014. Interactive Visual Analytics of Hydrodynamic Flux for the Coastal Zone. *Environmental Earth Sciences* 72, 10 (2014), 3753–3766.

[67] Sophie Giffard-Roisin, Mo Yang, Guillaume Charpiat, Balázs Kégl, and Claire Monteleoni. 2018. Fused deep learning for hurricane track forecast from reanalysis data. In *Climate Informatics Workshop Proceedings 2018*.

[68] Francesco Granata and Fabio Di Nunno. 2021. Artificial Intelligence models for prediction of the tide level in Venice. *Stochastic Environmental Research and Risk Assessment* 35, 12 (2021), 2537–2548.

[69] Chen Gu, Jifeng Qi, Yizhi Zhao, Wenming Yin, and Shanliang Zhu. 2022. Estimation of the Mixed Layer Depth in the Indian Ocean from Surface Parameters: A Clustering-Neural Network Method. *Sensors* 22, 15 (2022), 5600.

[70] Junting Guo, Jingfang Lu, Yuming Zhang, Chen Zhou, Shufang Zhang, Daosheng Wang, and Xianqing Lv. 2022. Variability of Chlorophyll-a and Secchi Disk Depth (1997–2019) in the Bohai Sea Based on Monthly Cloud-Free Satellite Data Reconstructions. *Remote Sensing* 14, 3 (2022), 639.

[71] Shuai Guo, Menglei Xia, Huanqun Xue, Shuang Wang, and Chao Liu. 2024. OceanCrowd: Vessel trajectory data-based participant selection for mobile crowd sensing in ocean observation. *IEEE Transactions on Sustainable Computing* (2024).

[72] Yang Guozhen, Wang Haifeng, Qian Hui, and Fang Jianming. 2017. Tidal current short-term prediction based on support vector regression. In *IOP Conference Series: Materials Science and Engineering*, Vol. 199. IOP Publishing, 012024.

[73] Masoud Haghbin, Ahmad Sharafati, Davide Motta, Nadhir Al-Ansari, and Mohamadreza Hosseiniyan Moghadam Noghani. 2021. Applications of Soft Computing Models for Predicting Sea Surface Temperature: A Comprehensive Review and Assessment. *Progress in Earth and Planetary Science* 8, 1 (2021), 4.

[74] Ali Hamdi, Khaled Shaban, Abdelkarim Erradi, Amr Mohamed, Shakila Khan Rumi, and Flora D Salim. 2022. Spatiotemporal data mining: a survey on challenges and open problems. *Artificial Intelligence Review* (2022), 1–48.

[75] X Han, C Armenakis, and M Jadidi. 2020. DBSCAN optimization for improving marine trajectory clustering and anomaly detection. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences* 43 (2020).

[76] Xuyang Han, Costas Armenakis, and Mojgan Jadidi. 2021. Modeling vessel behaviours by clustering ais data using optimized dbscan. *Sustainability* 13, 15 (2021), 8162.

[77] Xiaolin Han, Huan Zhang, and Weidong Sun. 2021. Spectral anomaly detection based on dictionary learning for sea surfaces. *IEEE Geoscience and Remote Sensing Letters* 19 (2021), 1–5.

[78] Yanling Han, Yekun Liu, Zhonghua Hong, Yun Zhang, Shuhu Yang, and Jing Wang. 2021. Sea ice image classification based on heterogeneous data fusion and deep learning. *Remote Sensing* 13, 4 (2021), 592.

[79] Zhaohui Han, Yijun He, Guoqiang Liu, and William Perrie. 2020. Application of dincae to reconstruct the gaps in chlorophyll-a satellite observations in the south china sea and west philippine sea. *Remote Sensing* 12, 3 (2020), 480.

[80] Abdel Hannachi, Ian T Jolliffe, and David B Stephenson. 2007. Empirical orthogonal functions and related techniques in atmospheric science: A review. *International Journal of Climatology: A Journal of the Royal Meteorological Society* 27, 9 (2007), 1119–1152.

[81] Zeke Hausfather, Kevin Cowtan, David C Clarke, Peter Jacobs, Mark Richardson, and Robert Rohde. 2017. Assessing recent warming using instrumentally homogeneous sea surface temperature records. *Science advances* 3, 1 (2017), e1601207.

[82] Paul R. Hill, Anurag Kumar, Marouane Temimi, and David R. Bull. 2020. HABNet: Machine Learning, Remote Sensing-Based Detection of Harmful Algal Blooms. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13 (2020), 3229–3239.

[83] Forrest M Hoffman, William W Hargrove Jr, David J Erickson III, and Robert J Oglesby. 2005. Using clustered climate regimes to analyze and compare predictions from fully coupled general circulation models. *Earth Interactions* 9, 10 (2005), 1–27.

[84] Thomas Holtt, Ahmed Magdy, Peng Zhan, Guoning Chen, Ganesh Gopalakrishnan, Ibrahim Hoteit, Charles D. Hansen, and Markus Hadwiger. 2014. Ovis: A Framework for Visual Analysis of Ocean Forecast Ensembles. *IEEE Transactions on Visualization and Computer Graphics* 20, 8 (2014), 1114–1126.

[85] Kohtaro Hosoda and Futoki Sakaida. 2016. Global Daily High-Resolution Satellite-Based Foundation Sea Surface Temperature Dataset: Development and Validation against Two Definitions of Foundation SST. *Remote Sensing* 8, 11 (2016), 962.

[86] Siyun Hou, Wengen Li, Tianying Liu, Shuigeng Zhou, Jihong Guan, Rufu Qin, and Zhenfeng Wang. 2021. D2CL: A Dense Dilated Convolutional LSTM Model for Sea Surface Temperature Prediction. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* (2021), 12514–12523.

[87] Siyun Hou, Wengen Li, Tianying Liu, Shuigeng Zhou, Jihong Guan, Rufu Qin, and Zhenfeng Wang. 2022. MUST: A Multi-source Spatio-Temporal data fusion Model for short-term sea surface temperature prediction. *Ocean Engineering* 259 (2022), 111932.

[88] Pang-chi Hsu, Tim Li, and Bin Wang. 2011. Trends in global monsoon area and precipitation over the past 30 years. *Geophysical Research Letters* 38, 8 (2011).

[89] Chuanmin Hu, Lian Feng, and Qi Guan. 2021. A Machine Learning Approach to Estimate Surface Chlorophyll *a* Concentrations in Global Oceans From Satellite Measurements. *IEEE Transactions on Geoscience and Remote Sensing* 59, 6 (2021), 4590–4607.

[90] Qiwei Hu, Xiaoyan Chen, Yan Bai, Xianqiang He, Teng Li, and Delu Pan. 2023. Reconstruction of 3-D Ocean Chlorophyll *a* Structure in the Northern Indian Ocean Using Satellite and BGC-Argo Data. *IEEE Trans. Geosci. Remote Sens.* 61 (2023), 1–13.

[91] Boyin Huang, Chunying Liu, Viva Banzon, Eric Freeman, Garrett Graham, Bill Hankins, Tom Smith, and Huai-Min Zhang. 2021. Improvements of the Daily Optimum Interpolation Sea Surface Temperature (DOISST) Version 2.1. *Journal of Climate* 34, 8 (2021), 2923–2939.

[92] Jie Huang, Fengwei Zhu, Zejun Huang, Jian Wan, and Yongjian Ren. 2021. Research on Real-Time Anomaly Detection of Fishing Vessels in a Marine Edge Computing Environment. *Mob. Inf. Syst.* 2021 (2021), 5598988:1–5598988:15.

[93] Mingfeng Huang, Kuan Zhang, Zhiwen Zeng, Tian Wang, and Yuxin Liu. 2020. An AUV-Assisted Data Gathering Scheme Based on Clustering and Matrix Completion for Smart Ocean. *IEEE Internet of Things Journal* 7, 10 (2020), 9904–9918.

[94] Manuel Huber, Craig Donlon, and Montserrat Pinol Sole. 2023. Global Surface Water Density Masks to Refine Sentinel 3 Data Acquisitions. *IEEE Geosci. Remote. Sens. Lett.* 20 (2023), 1–5.

[95] Khalid A Hussein, Khameis Al Abdouli, Dawit T Ghebreyesus, Pakorn Petchprayoon, Naeema Al Hosani, and Hatim O. Sharif. 2021. Spatiotemporal variability of chlorophyll-a and sea surface temperature, and their relationship with bathymetry over the coasts of UAE. *Remote Sensing* 13, 13 (2021), 2447.

[96] Toshichika Izumi, Jing-Jia Luo, Andrew J Challinor, Gen Sakurai, Masayuki Yokozawa, Hirofumi Sakuma, Molly E Brown, and Toshio Yamagata. 2014. Impacts of El Niño Southern Oscillation on the global yields of major crops. *Nature communications* 5, 1 (2014), 3712.

[97] Alexandre Immas, Ninh Do, and Mohammad-Reza Alam. 2021. Real-time in situ prediction of ocean currents. *Ocean Engineering* 228 (2021), 108922.

[98] Bruce Ingleby and Matt Huddleston. 2007. Quality control of ocean temperature and salinity profiles—Historical and real-time data. *Journal of Marine systems* 65, 1-4 (2007), 158–175.

[99] Mohammad Jahanbakht, Wei Xiang, and Mostafa Rahimi Azghadi. 2022. Sea Surface Temperature Forecasting With Ensemble of Stacked Deep Neural Networks. *IEEE Geosci. Remote. Sens. Lett.* 19 (2022), 1–5.

[100] Xiaowei Jia, Jacob Zwart, Jeffrey Sadler, Alison Appling, Samantha Oliver, Steven Markstrom, Jared Willard, Shaoming Xu, Michael Steinbach, Jordan Read, et al. 2021. Physics-guided recurrent graph model for predicting flow and temperature in river networks. In *Proceedings of the 2021 SIAM International Conference on Data Mining (SDM)*. SIAM, 612–620.

[101] Li-Qing Jiang, Brendan R Carter, Richard A Feely, Siv K Lauvset, and Are Olsen. 2019. Surface ocean pH and buffer capacity: past, present and future. *Scientific reports* 9, 1 (2019), 18624.

[102] Ning Jiang and Congwen Zhu. 2018. Asymmetric Changes of ENSO Diversity Modulated by the Cold Tongue Mode Under Recent Global Warming. *Geophysical Research Letters* 45 (10 2018).

[103] Juan C Jiménez-Muñoz and José A Sobrino. 2003. A generalized single-channel method for retrieving land surface temperature from remote sensing data. *Journal of geophysical research: atmospheres* 108, D22 (2003).

[104] Chang Jin, Han Peng, Hanchen Yang, Wengen Li, and Jihong Guan. 2023. On Evaluating the Predictability of Sea Surface Temperature Using Entropy. *Remote Sensing* 15, 8 (2023), 1956.

[105] Kenneth S. Johnson, Matthew R. Mazloff, Mariana B. Bif, Yuichiro Takeshita, Hans W. Jannasch, Tanya L. Maurer, Joshua N. Plant, Ariane Verdy, Peter M. Walz, Stephen C. Riser, and Lynne D. Talley. 2022. Carbon to Nitrogen Uptake Ratios Observed Across the Southern Ocean by the SOCCOM Profiling Float Array. *Journal of Geophysical Research: Oceans* 127, 9 (2022), e2022JC018859.

[106] Manel Jouini, Marina Lévy, Michel Crépon, and Sylvie Thiria. 2013. Reconstruction of Satellite Chlorophyll Images under Heavy Cloud Coverage Using a Neural Classification Method. *Remote Sensing of Environment* 131 (2013), 232–246.

[107] Sihun Jung, Cheolhee Yoo, and Jungho Im. 2022. High-resolution seamless daily sea surface temperature based on satellite data fusion and machine learning over Kuroshio Extension. *Remote Sensing* 14, 3 (2022), 575.

[108] George Em Karniadakis, Ioannis G Kevrekidis, Lu Lu, Paris Perdikaris, Sifan Wang, and Liu Yang. 2021. Physics-informed machine learning. *Nature Reviews Physics* 3, 6 (2021), 422–440.

[109] Abdollah Kavousi-Fard. 2016. Modeling uncertainty in tidal current forecast using prediction interval-based SVR. *IEEE Transactions on Sustainable Energy* 8, 2 (2016), 708–715.

[110] Abdollah Kavousi-Fard and Wencong Su. 2017. A Combined Prognostic Model Based on Machine Learning for Tidal Current Prediction. *IEEE Transactions on Geoscience and Remote Sensing* 55, 6 (2017), 3108–3114.

[111] Katherine A Kilpatrick, Guillermo Podestá, Elizabeth Williams, Susan Walsh, and Peter J Minnett. 2019. Alternating decision trees for cloud masking in MODIS and VIIRS NASA sea surface temperature products. *Journal of atmospheric and oceanic technology* 36, 3 (2019), 387–407.

[112] Hyeon-Jae Kim, Dong-Hoon Kim, Chaewook Lim, Yongtak Shin, Sang-Chul Lee, Youngjin Choi, and Seung-Buhm Woo. 2021. An outlier detection using autoencoder for ocean observation data. *Journal of Korean Society of Coastal and Ocean Engineers* 33, 6 (2021), 265–274.

[113] Hyeong-Seog Kim, Joo-Hong Kim, Chang-Hoi Ho, and Pao-Shin Chu. 2011. Pattern classification of typhoon tracks using the fuzzy c-means clustering method. *Journal of Climate* 24, 2 (2011), 488–508.

[114] Jaeyoon Kim, Donghyun Tae, and Junhee Seok. 2020. A survey of missing data imputation using generative adversarial networks. In *2020 International conference on artificial intelligence in information and communication (ICAIIIC)*. IEEE, 454–456.

[115] Kwang-Yul Kim, Jinwon Kim, Kyung-On Boo, Sungbo Shim, and Youngmi Kim. 2019. Intercomparison of precipitation datasets for summer precipitation characteristics over East Asia. *Climate Dynamics* 52, 5-6 (2019), 3005–3022.

[116] Sookkyung Kim, Hyojin Kim, Joonseok Lee, Sangwoong Yoon, Samira Ebrahimi Kahou, Karthik Kashinath, and Mr Prabhat. 2019. Deep-hurricane-tracker: Tracking and forecasting extreme climate events. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 1761–1769.

[117] Ben P Kirtman. 2003. The COLA anomaly coupled model: Ensemble ENSO prediction. *Monthly weather review* 131, 10 (2003), 2324–2341.

[118] Prabhat K Koner. 2019. Daytime sea surface temperature retrieval using short-wave infrared channel (s). In *Remote Sensing of the Ocean, Sea Ice, Coastal Waters, and Large Water Regions 2019*, Vol. 11150. SPIE, 232–244.

[119] Prabhat K. Koner. 2020. A transformative approach to enhance the parameter information from microwave and infrared remote sensing measurements. *Big Earth Data* 4, 3 (2020), 322–347.

[120] Lingbai Kong, Wengen Li, Hanchen Yang, Yichao Zhang, Jihong Guan, and Shuigeng Zhou. 2024. CausalFormer: An Interpretable Transformer for Temporal Causal Discovery. *IEEE Transactions on Knowledge & Data Engineering* 01 (2024), 1–14.

[121] Lingbai Kong, Hanchen Yang, Wengen Li, Jihong Guan, and Shuigeng Zhou. 2024. Traffexplainer: A Framework towards GNN-based Interpretable Traffic Prediction. *IEEE Transactions on Artificial Intelligence* (2024).

[122] Ioannis Kontopoulos, Konstantinos Chatzikokolakis, Dimitris Zisis, Konstantinos Tserpes, and Giannis Spiliopoulos. 2020. Real-time maritime anomaly detection: detecting intentional AIS switch-off. *International Journal of Big Data Intelligence* 7, 2 (2020), 85–96.

[123] Patrick Köthur, Mike Sips, Andrea Unger, Julian Kuhlmann, and Doris Dransch. 2014. Interactive visual summaries for detection and assessment of spatiotemporal patterns in geospatial time series. *Information Visualization* 13, 3 (2014), 283–298.

[124] Olesia Kuchinskaia, Ilia Bryukhanov, Maxim Penzin, Evgeny Ni, Anton Doroshkevich, Vadim Kostyukhin, Ignatii Samokhvalov, Konstantin Pustovalov, Iurii Bordulev, Valentina Bryukhanova, Alexander Stykon, Nikolay Kirillov, and Ivan Zhivotenyuk. 2023. ERA5 Reanalysis for the Data Interpretation on Polarization Laser Sensing of High-Level Clouds. *Remote. Sens.* 15, 1 (2023), 109.

[125] Siv K Lauvset and Toste Tanhua. 2015. A toolbox for secondary quality control on ocean chemistry and hydrographic data. *Limnology and Oceanography: Methods* 13, 11 (2015), 601–608.

[126] Sangmok Lee and Donghyun Lee. 2018. Improved prediction of harmful algal blooms in four Major South Korea's Rivers using deep learning models. *International journal of environmental research and public health* 15, 7 (2018), 1322.

[127] Redouane Lguensat, Miao Sun, Ronan Fablet, Pierre Tandeo, Evan Mason, and Ge Chen. 2018. EddyNet: A Deep Neural Network For Pixel-Wise Classification of Oceanic Eddies. In *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*. 1764–1767.

[128] Hui Li, Wengen Li, Shuyu Wang, Hanchen Yang, Jihong Guan, and Yichao Zhang. 2024. STAD: Ship trajectory anomaly detection in ocean with dynamic pattern clustering. *Ocean Engineering* 313 (2024), 119530.

[129] Kexin Li, Jian Guo, Ranchong Li, Yujun Wang, Zongming Li, Kun Miu, and Hui Chen. 2023. The Abnormal Detection Method of Ship Trajectory with Adaptive Transformer Model Based on Migration Learning. In *International Conference on Spatial Data and Intelligence*. Springer, 204–220.

[130] Ming Li, Ren Zhang, and Kefeng Liu. 2021. Machine Learning Incorporated With Causal Analysis for Short-Term Prediction of Sea Ice. *Frontiers in Marine Science* 8 (2021), 649378.

[131] Tianyi Li, Lu Chen, Christian S Jensen, Torben Bach Pedersen, Yunjun Gao, and Jilin Hu. 2022. Evolutionary clustering of moving objects. In *2022 IEEE 38th International Conference on Data Engineering (ICDE)*. IEEE, 2399–2411.

[132] Tao Li, Wei Jin, Randi Fu, and Caifen He. 2022. Daytime sea fog monitoring using multimodal self-supervised learning with band attention mechanism. *Neural Computing and Applications* 34, 23 (2022), 21205–21222.

[133] Wenqing Li, Ge Chen, Qianqian Kong, Zhenzhen Wang, and Chengcheng Qian. 2011. A VR-Ocean System for Interactive Geospatial Analysis and 4D Visualization of the Marine Environment around Antarctica. *Computers & Geosciences* 37, 11 (2011), 1743–1751.

[134] Xichen Li, Wenju Cai, Gerald A Meehl, Dake Chen, Xiaojun Yuan, Marilyn Raphael, David M Holland, Qinghua Ding, Ryan L Fogt, Bradley R Markle, et al. 2021. Tropical teleconnection impacts on Antarctic climate changes. *Nature Reviews Earth & Environment* 2, 10 (2021), 680–698.

[135] Xiaofan Li, Guoqing Zhai, Shouting Gao, and Xinyong Shen. 2015. Decadal trends of global precipitation in the recent 30 years. *Atmospheric Science Letters* 16, 1 (2015), 22–26.

[136] Ting Lian, Xiaozhou Xin, Zhiqing Peng, Fugen Li, Hailong Zhang, Shanshan Yu, and Huiyuan Liu. 2022. Estimating Evapotranspiration over Heterogeneous Surface with Sentinel-2 and Sentinel-3 Data: A Case Study in Heihe River Basin. *Remote. Sens.* 14, 6 (2022), 1349.

[137] Zheng Lian, Lan Chen, Licai Sun, Bin Liu, and Jianhua Tao. 2023. GCNet: Graph Completion Network for Incomplete Multimodal Learning in Conversation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2023).

[138] Haitao Lin, Zhangyang Gao, Yongjie Xu, Lirong Wu, Ling Li, and Stan Z Li. 2022. Conditional local convolution for spatio-temporal meteorological forecasting. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 36. 7470–7478.

[139] Huizeng Liu, Xianqiang He, Qingquan Li, Xianjun Hu, Joji Ishizaka, Susanne Kratzer, Chao Yang, Tiezhu Shi, Shuibo Hu, Qiming Zhou, and Guofeng Wu. 2022. Evaluation of Ocean Color Atmospheric Correction Methods for Sentinel-3

OLCI Using Global Automatic In Situ Observations. *IEEE Trans. Geosci. Remote. Sens.* 60 (2022), 1–19.

[140] Hanlin Liu and Linchao Li. 2022. Missing Data Imputation in GNSS Monitoring Time Series Using Temporal and Spatial Hankel Matrix Factorization. *Remote Sensing* 14, 6 (2022), 1500.

[141] Jianfei Liu, William J. Emery, Xiongbin Wu, Miao Li, Chuan Li, and Lan Zhang. 2017. Computing Ocean Surface Currents From GOCE Ocean Color Satellite Imagery. *IEEE Trans. Geosci. Remote. Sens.* 55, 12 (2017), 7113–7125.

[142] Qinghua Liu, Qiming Zeng, and Zhiliang Zhang. 2023. Evaluation of InSAR Tropospheric Correction by Using Efficient WRF Simulation with ERA5 for Initialization. *Remote. Sens.* 15, 1 (2023), 273.

[143] Quanhong Liu, Ren Zhang, Yangjun Wang, Hengqian Yan, and Mei Hong. 2021. Daily prediction of the arctic sea ice concentration using reanalysis data based on a convolutional lstm network. *Journal of Marine Science and Engineering* 9, 3 (2021), 330.

[144] Shuai Liu, Ge Chen, Shifeng Yao, Fenglin Tian, and Wei Liu. 2017. A Framework for Interactive Visual Analysis of Heterogeneous Marine Data in an Integrated Problem Solving Environment. *Computers & Geosciences* 104 (2017), 20–28.

[145] Xiaohong Liu, Wenling An, Kerstin Treydte, Xuemei Shao, Steven Leavitt, Shugui Hou, Tuo Chen, Weizhen Sun, and Dahe Qin. 2012. Tree-ring $\delta^{18}\text{O}$ in southwestern China linked to variations in regional cloud cover and tropical sea surface temperature. *Chemical Geology* 291 (2012), 104–115.

[146] Yong Liu, Huaicheng Guo, and Pingjian Yang. 2010. Exploring the influence of lake water chemistry on chlorophyll a: A multivariate statistical model analysis. *Ecological Modelling* 221, 4 (2010), 681–688.

[147] Josue Lopez, Stewart Santos, Clement Atzberger, and Deni Torres. 2018. Convolutional Neural Networks for Semantic Segmentation of Multispectral Remote Sensing Images. In *2018 IEEE 10th Latin-American Conference on Communications (LATINCOM)*. 1–5.

[148] Thomas Loridan, Ryan P Crompton, and Eugene Dubossarsky. 2017. A machine learning approach to modeling tropical cyclone wind field uncertainty. *Monthly Weather Review* 145, 8 (2017), 3203–3221.

[149] Ranran Lou, Zhihan Lv, and Mohsen Guizani. 2023. Wave Height Prediction Suitable for Maritime Transportation Based on Green Ocean of Things. *IEEE Trans. Artif. Intell.* 4, 2 (2023), 328–337.

[150] Chunlei Ma, Jun Zhao, Bin Ai, and Shaqie Sun. 2021. Two-Decade Variability of Sea Surface Temperature and Chlorophyll-a in the Northern South China Sea as Revealed by Reconstructed Cloud-Free Satellite Data. *IEEE Transactions on Geoscience and Remote Sensing* 59, 11 (2021), 9033–9046.

[151] Pulong Ma and Emily L Kang. 2020. Spatio-Temporal data fusion for massive sea surface temperature data from MODIS and AMSR-E instruments. *Environmetrics* 31, 2 (2020), e2594.

[152] Kumars Mahmoodi and Hassan Ghassemi. 2018. Outlier Detection in Ocean Wave Measurements by Using Unsupervised Data Mining Methods. *Polish Maritime Research* 25, 1 (2018), 44–50.

[153] Armando Marino, Wolfgang Dierking, and Christine Wesche. 2016. A depolarization ratio anomaly detector to identify icebergs in sea ice using dual-polarization SAR images. *IEEE Transactions on Geoscience and Remote Sensing* 54, 9 (2016), 5602–5615.

[154] Barry McNicholl, Yee Hui Lee, Abraham G. Campbell, and Soumyabrata Dev. 2022. Evaluating the Reliability of Air Temperature From ERA5 Reanalysis Data. *IEEE Geosci. Remote. Sens. Lett.* 19 (2022), 1–5.

[155] Frédéric Mélin, Paolo Colandrea, Pieter De Vis, and Samuel E. Hunt. 2022. Sensitivity of Ocean Color Atmospheric Correction to Uncertainties in Ancillary Data: A Global Analysis With SeaWiFS Data. *IEEE Trans. Geosci. Remote. Sens.* 60 (2022), 1–18.

[156] Yuxin Meng, Eric Rigall, Xueen Chen, Feng Gao, Junyu Dong, and Sheng Chen. 2021. Physics-guided generative adversarial networks for sea subsurface temperature prediction. *IEEE transactions on neural networks and learning systems* 34, 7 (2021), 3357–3370.

[157] Rafael Meza-Padilla, Cecilia Enriquez, Yonggang Liu, and Christian M. Appendini. 2019. Ocean Circulation in the Western Gulf of Mexico Using Self-Organizing Maps. *Journal of Geophysical Research: Oceans* 124, 6 (2019), 4152–4167.

[158] Yang Min and Zhong Jin-song. 2013. A method based on logarithmic spiral edge fitting for information extraction of eddy in the SAR image. *Journal of Radars* 2, 2 (2013), 226–233.

[159] Kingtse Mo and Michael Ghil. 1988. Cluster analysis of multiple planetary flow regimes. *Journal of Geophysical Research: Atmospheres* 93, D9 (1988), 10927–10952.

[160] Hamid Mohebzadeh, Esmaeil Mokari, Prasad Daggupati, and Asim Biswas. 2021. A Machine Learning Approach for Spatiotemporal Imputation of MODIS Chlorophyll-a. *International Journal of Remote Sensing* 42, 19 (2021), 7381–7404.

[161] Bin Mu, Xiaodan Luo, Shijin Yuan, and Xi Liang. 2023. IcetFT v 1.0: 0: Interpretable Long-Term Prediction of Arctic Sea Ice Extent with Deep Learning. *Geoscientific Model Development Discussions* (2023), 1–28.

[162] Harika Munagapati and Virendra M. Tiwari. 2021. Spatio-Temporal Patterns of Mass Changes in Himalayan Glaciated Region from EOF Analyses of GRACE Data. *Remote Sensing* 13, 2 (2021).

[163] Duong Nguyen, Rodolphe Vadaine, Guillaume Hajduch, René Garello, and Ronan Fablet. 2021. GeoTrackNet A maritime anomaly detector using probabilistic neural network representation of AIS tracks and a contrario detection.

IEEE Transactions on Intelligent Transportation Systems 23, 6 (2021), 5655–5667.

[164] Hai Nguyen, Noel Cressie, and Amy Braverman. 2012. Spatial statistical data fusion for remote sensing applications. *J. Amer. Statist. Assoc.* 107, 499 (2012), 1004–1018.

[165] Tung Nguyen, Johannes Brandstetter, Ashish Kapoor, Jayesh K Gupta, and Aditya Grover. 2023. ClimaX: A foundation model for weather and climate. *arXiv preprint arXiv:2301.10343* (2023).

[166] Tung Nguyen, Jason Jewik, Hritik Bansal, Prakhar Sharma, and Aditya Grover. 2024. Climatelearn: Benchmarking machine learning for weather and climate modeling. *Advances in Neural Information Processing Systems* 36 (2024).

[167] Onuwa Okwuashi and Christopher Ndehedehe. 2017. Tide modelling using support vector machine regression. *Journal of Spatial Science* 62, 1 (2017), 29–46.

[168] Margaret A Oliver and Richard Webster. 1990. Kriging: a method of interpolation for geographical information systems. *International Journal of Geographical Information System* 4, 3 (1990), 313–332.

[169] Jonathan T Overpeck, Gerald A Meehl, Sandrine Bony, and David R Easterling. 2011. Climate data challenges in the 21st century. *science* 331, 6018 (2011), 700–702.

[170] Yang Pan, Mingwu Jin, Shunrong Zhang, and Yue Deng. 2021. TEC Map Completion Through a Deep Learning Model: SNP-GAN. *Space Weather* 19, 11 (2021), e2021SW002810.

[171] Ji-Eun Park and Kyung-Ae Park. 2021. Application of Deep Learning for Speckle Removal in GOCI Chlorophyll-a Concentration Images (2012–2017). *Remote. Sens.* 13, 4 (2021), 585.

[172] David Sánchez Pedroche, Jesús García Herrero, and José Manuel Molina López. 2024. Context learning from a ship trajectory cluster for anomaly detection. *Neurocomputing* 563 (2024), 126920.

[173] Han Peng, Wengen Li, Chang Jin, Hanchen Yang, and Jihong Guan. 2023. MuSTC: A Multi-Stage Spatio–Temporal Clustering Method for Uncovering the Regionality of Global SST. *Atmosphere* 14, 9 (2023), 1358.

[174] Han Peng, Wengen Li, Chang Jin, Yichao Zhang, Jihong Guan, Hanchen Yang, and Shuigeng Zhou. 2025. Cross-Region Graph Convolutional Network with Periodicity Shift Adaptation for Wide-area SST Prediction. *ACM Transactions on Intelligent Systems and Technology* (2025).

[175] Zisis I Petrou and YingLi Tian. 2017. Prediction of sea ice motion with recurrent neural networks. In *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. IEEE, 5422–5425.

[176] E. Pisoni, F. Pastor, and M. Volta. 2008. Artificial Neural Networks to Reconstruct Incomplete Satellite Data: Application to the Mediterranean Sea Surface Temperature. *Nonlinear Processes in Geophysics* 15, 1 (2008), 61–70.

[177] Prabhat, Karthik Kashinath, Mayur Mudigonda, Sol Kim, Lukas Kapp-Schwoerer, Andre Graubner, Ege Karaismailoglu, Leo von Kleist, Thorsten Kurth, Annette Greiner, et al. 2020. ClimateNet: An expert-labelled open dataset and Deep Learning architecture for enabling high-precision analyses of extreme weather. *Geoscientific Model Development Discussions* 2020 (2020), 1–28.

[178] Victor Raizer. 2013. Multisensor data fusion for advanced ocean remote sensing studies. In *2013 IEEE International Geoscience and Remote Sensing Symposium-IGARSS*. IEEE, 1622–1625.

[179] René Ranftl, Alexey Bochkovskiy, and Vladlen Koltun. 2021. Vision transformers for dense prediction. In *Proceedings of the IEEE/CVF international conference on computer vision*. 12179–12188.

[180] N. Srinivasa Rao, M. M. Ali, M. V. Rao, and I. V. Ramana. 2005. Estimation of ship velocities from MODIS and OCM. *IEEE Geosci. Remote. Sens. Lett.* 2, 4 (2005), 437–439.

[181] Friedrich Recknagel, Jason Bobbin, Peter Whigham, and Hugh Wilson. 2002. Comparative application of artificial neural networks and genetic algorithms for multivariate time-series modelling of algal blooms in freshwater lakes. *Journal of Hydroinformatics* 4, 2 (03 2002), 125–133.

[182] P.G. Remya, Raj Kumar, and Sujit Basu. 2012. Forecasting tidal currents from tidal levels using genetic algorithm. *Ocean Engineering* 40 (2012), 62–68.

[183] Carlos Alberto Repelli and Paulo Nobre. 2004. Statistical prediction of sea-surface temperature over the tropical Atlantic. *International Journal of Climatology: A Journal of the Royal Meteorological Society* 24, 1 (2004), 45–55.

[184] Bernd Resch, Ralf Wohlfahrt, and Christoph Wosniok. 2014. Web-Based 4D Visualization of Marine Geo-Data Using WebGL. *Cartography and Geographic Information Science* 41, 3 (2014), 235–247.

[185] Amin Riazi. 2020. Accurate tide level estimation: A deep learning approach. *Ocean Engineering* 198 (2020), 107013.

[186] H Rong, AP Teixeira, and C Guedes Soares. 2019. Ship trajectory uncertainty prediction based on a Gaussian Process model. *Ocean Engineering* 182 (2019), 499–511.

[187] H Rong, AP Teixeira, and C Guedes Soares. 2020. Data mining approach to shipping route characterization and anomaly detection based on AIS data. *Ocean Engineering* 198 (2020), 106936.

[188] Mario Ruttgers, Sangseung Lee, and Donghyun You. 2018. Typhoon track prediction using satellite images in a Generative Adversarial Network. *arXiv preprint arXiv:1808.05382* (2018).

[189] Dominik Sacha, Leishi Zhang, Michael Sedlmair, John A. Lee, Jaakkko Peltonen, Daniel Weiskopf, Stephen C. North, and Daniel A. Keim. 2017. Visual Interaction with Dimensionality Reduction: A Structured Literature Analysis. *IEEE Transactions on Visualization and Computer Graphics* 23, 1 (2017), 241–250.

[190] Dripta Sarkar, Michael Osborne, and Thomas Adcock. 2016. A Machine Learning Approach to the Prediction of Tidal Currents.. In *The 26th International Ocean and Polar Engineering Conference*. OnePetro.

[191] Dripta Sarkar, Michael A. Osborne, and Thomas A.A. Adcock. 2018. Prediction of tidal currents using Bayesian machine learning. *Ocean Engineering* 158 (2018), 221–231.

[192] Dripta Sarkar, Michael A. Osborne, and Thomas A. A. Adcock. 2019. Spatiotemporal Prediction of Tidal Currents Using Gaussian Processes. *Journal of Geophysical Research: Oceans* 124, 4 (2019), 2697–2715.

[193] Andrew P Schurer, K Cowtan, E Hawkins, Michael E Mann, Vivian Scott, and SFB Tett. 2018. Interpretations of the Paris climate target. *Nature Geoscience* 11, 4 (2018), 220–221.

[194] Ali Shahabi and Navid Tahvildari. 2024. A deep-learning model for rapid spatiotemporal prediction of coastal water levels. *Coastal Engineering* 190 (2024), 104504.

[195] Amir Yaghoubi Shahir, Mohammad A. Tayebi, Uwe Glässer, Tilemachos Charalampous, Zahra Zohrevand, and Hans Wehn. 2019. Mining Vessel Trajectories for Illegal Fishing Detection. In *2019 IEEE International Conference on Big Data (IEEE BigData), Los Angeles, CA, USA, December 9-12, 2019*. IEEE, 1917–1927.

[196] Arun Sharma, Zhe Jiang, and Shashi Shekhar. 2022. Spatiotemporal Data Mining: A Survey. arXiv:2206.12753

[197] Shashi Shekhar, Zhe Jiang, Reem Ali, Emre Eftelioglu, Xun Tang, Venkata Gunturi, and Xun Zhou. 2015. Spatiotemporal Data Mining: A Computational Perspective. *ISPRS International Journal of Geo-Information* 4, 4 (2015), 2306–2338.

[198] Tianyang Shi, Zhengxia Zou, Zhenwei Shi, Jialan Chu, Jianhua Zhao, Ning Gao, Ning Zhang, and Xinzhong Zhu. 2018. Mudflat aquaculture labeling for infrared remote sensing images via a scanning convolutional network. *Infrared Physics Technology* 94 (2018), 16–22.

[199] Chan Shu, Peng Xiu, Xiaogang Xing, Guoqiang Qiu, Wentao Ma, Robert J. W. Brewin, and Stefano Ciavatta. 2022. Biogeochemical Model Optimization by Using Satellite-Derived Phytoplankton Functional Type Data and BGC-Argo Observations in the Northern South China Sea. *Remote. Sens.* 14, 5 (2022), 1297.

[200] Sijing Shu, Ji Yang, Chuanxun Yang, Hongda Hu, Wenlong Jing, Yiqiang Hu, and Yong Li. 2021. Performance Analysis of Ocean Eddy Detection and Identification by L-Band Compact Polarimetric Synthetic Aperture Radar. *Remote Sensing* 13, 23 (2021).

[201] Anirban Sinha and Ryan Abernathay. 2021. Estimating Ocean Surface Currents With Machine Learning. *Frontiers in Marine Science* 8 (2021).

[202] Mike Sips, Patrick Kothur, Andrea Unger, Hans-Christian Hege, and Doris Dransch. 2012. A Visual Analytics Approach to Multiscale Exploration of Environmental Time Series. *IEEE Transactions on Visualization and Computer Graphics* 18, 12 (2012), 2899–2907.

[203] Christopher Small and Daniel Sousa. 2024. Robust Cloud Suppression and Anomaly Detection in Time-Lapse Thermography. *Remote Sensing* 16, 2 (2024), 255.

[204] Behrouz Haji Soleimani, Erico N De Souza, Casey Hilliard, and Stan Matwin. 2015. Anomaly detection in maritime data based on geometrical analysis of trajectories. In *2015 18th International Conference on Information Fusion (Fusion)*. IEEE, 1100–1105.

[205] Robert H Stewart. 2008. *Introduction to physical oceanography*. Robert H. Stewart.

[206] S. Storm-Furru and Stefan Bruckner. 2020. VA-TRAC: Geospatial Trajectory Analysis for Monitoring, Identification, and Verification in Fishing Vessel Operations. *Comput. Graph. Forum* 39, 3 (2020), 101–114.

[207] Andrea Storto, Simona Masina, and Antonio Navarra. 2016. Evaluation of the CMCC Eddy-permitting Global Ocean Physical Reanalysis System (C-GLORS, 1982–2012) and Its Assimilation Components. *Quarterly Journal of the Royal Meteorological Society* 142, 695 (2016), 738–758.

[208] Tianyun Su, Zhu Cao, Zhihan Lv, Chang Liu, and Xinfang Li. 2016. Multi-Dimensional Visualization of Large-Scale Marine Hydrological Environmental Data. *Advances in Engineering Software* 95 (2016), 7–15.

[209] Deyong Sun, Xiaoping Su, Zhongfeng Qiu, Shengqiang Wang, Zhihua Mao, and Yijun He. 2019. Remote Sensing Estimation of Sea Surface Salinity from GOCI Measurements in the Southern Yellow Sea. *Remote. Sens.* 11, 7 (2019), 775.

[210] Yongjiao Sun, Xin Yao, Xin Bi, Xuechun Huang, Xiangguo Zhao, and Baiyou Qiao. 2021. Time-Series Graph Network for Sea Surface Temperature Prediction. *Big Data Research* (2021), 100237.

[211] Yifeng Sun, Yaochi Zhao, Zhuhua Hu, Wei Wu, Jingwen Xia, and Yizhen Wang. 2024. SSRLM: A self-supervised representation learning method for identifying one ship with multi-MMSI codes. *Ocean Engineering* 312 (2024), 119186.

[212] Chaoli Tang, Dewei Hao, Yuanyuan Wei, Fengmei Zhao, Han Lin, and Xin Wu. 2022. Analysis of Influencing Factors of SST in Tropical West Indian Ocean Based on COBE Satellite Data. *Journal of Marine Science and Engineering* 10, 8 (2022), 1057.

[213] Youmin Tang, Rong-Hua Zhang, Ting Liu, Wansuo Duan, Dejian Yang, Fei Zheng, Hongli Ren, Tao Lian, Chuan Gao, Dake Chen, et al. 2018. Progress in ENSO prediction and predictability study. *National Science Review* 5, 6 (2018), 826–839.

[214] Nathachai Thongniran, Peerapon Vateekul, Kulsawasd Jitkajornwanich, Siam Lawawirojwong, and Panu Srestasathiern. 2019. Spatio-Temporal Deep Learning for Ocean Current Prediction Based on HF Radar Data. In *2019 16th International Joint Conference on Computer Science and Software Engineering (JCSSE)*. 254–259.

[215] Mary-Louise Timmermans and John Marshall. 2020. Understanding Arctic Ocean circulation: A review of ocean dynamics in a changing climate. *Journal of Geophysical Research: Oceans* 125, 4 (2020), e2018JC014378.

[216] Jorge Vazquez-Cuervo, Jose Gomez-Valdes, Marouan Bouali, Luis E Miranda, Tom Van der Stocken, Wenqing Tang, and Chelle Gentemann. 2019. Using saildrones to validate satellite-derived sea surface salinity and sea surface temperature along the California/Baja Coast. *Remote Sensing* 11, 17 (2019), 1964.

[217] Julius Venskus, Povilas Treigys, Jolita Bernatavičienė, Gintautas Tamulevičius, and Viktor Medvedev. 2019. Real-time maritime traffic anomaly detection based on sensors and history data embedding. *Sensors* 19, 17 (2019), 3782.

[218] Jean-Marie Vient, Frederic Jourdin, Ronan Fablet, Baptiste Mengual, Ludivine Lafosse, and Christophe Delacourt. 2021. Data-Driven Interpolation of Sea Surface Suspended Concentrations Derived from Ocean Colour Remote Sensing Data. *Remote Sensing* 13, 17 (2021), 3537.

[219] Laura Von Rueden, Sebastian Mayer, Katharina Beckh, Bogdan Georgiev, Sven Giesselbach, Raoul Heese, Birgit Kirsch, Julius Pfrommer, Annika Pick, Rajkumar Ramamurthy, et al. 2021. Informed Machine Learning—A taxonomy and survey of integrating prior knowledge into learning systems. *IEEE Transactions on Knowledge and Data Engineering* 35, 1 (2021), 614–633.

[220] Guihua Wang, Lingwei Wu, Wei Mei, and Shang-Ping Xie. 2022. Ocean currents show global intensification of weak tropical cyclones. *Nature* 611, 7936 (2022), 496–500.

[221] Haoyu Wang, Shinen Hu, and Xiaofeng Li. 2023. An Interpretable Deep Learning ENSO Forecasting Model. *Ocean-Land-Atmosphere Research* 2 (2023), 0012.

[222] Haibo Wang, Wenyong Yu, Jiangbin You, Ruolin Ma, Weilin Wang, and Bo Li. 2021. A Unified Framework for Anomaly Detection of Satellite Images Based on Well-Designed Features and an Artificial Neural Network. *Remote Sensing* 13, 8 (2021).

[223] Lei Wang, K Andrea Scott, David A Clausi, and Yan Xu. 2017. Ice concentration estimation in the gulf of St. Lawrence using fully convolutional neural network. In *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. IEEE, 4991–4994.

[224] Lei Wang, K Andrea Scott, Linlin Xu, and David A Clausi. 2016. Sea ice concentration estimation during melt from dual-pol SAR scenes using deep convolutional neural networks: A case study. *IEEE Transactions on Geoscience and Remote Sensing* 54, 8 (2016), 4524–4533.

[225] Liyuan Wang, Xingxing Zhang, Hang Su, and Jun Zhu. 2023. A comprehensive survey of continual learning: Theory, method and application. *arXiv preprint arXiv:2302.00487* (2023).

[226] Mingqing Wang, Danni Wang, Yanfei Xiang, Yishuang Liang, Ruixue Xia, Jinkun Yang, Fanghua Xu, and Xiaomeng Huang. 2023. Fusion of ocean data from multiple sources using deep learning: Utilizing sea temperature as an example. *Frontiers in Marine Science* 10 (2023), 1112065.

[227] Nan Wang, Bo Li, Qizhi Xu, and Yonghua Wang. 2018. Automatic ship detection in optical remote sensing images based on anomaly detection and SPP-PCANet. *Remote Sensing* 11, 1 (2018), 47.

[228] Senzhang Wang, Jiannong Cao, and Philip S. Yu. 2022. Deep Learning for Spatio-Temporal Data Mining: A Survey. *IEEE Transactions on Knowledge and Data Engineering* 34, 8 (2022), 3681–3700.

[229] Shuyu Wang, Wengen Li, Jihong Guan, Xiwei Liu, Yichao Zhang, and Shuigeng Zhou. 2024. Self-Supervised Spatio-Temporal Imputation Model for Highly Sparse Chl-a Data via Fusing Multi-source Satellite Data. *IEEE Transactions on Geoscience and Remote Sensing* (2024).

[230] Shuyu Wang, Wengen Li, Jihong Guan, Xiwei Liu, Yichao Zhang, and Shuigeng Zhou. 2024. Self-Supervised Spatiotemporal Imputation Model for Highly Sparse Chl-a Data via Fusing Multisource Satellite Data. *IEEE Transactions on Geoscience and Remote Sensing* 62 (2024), 1–16.

[231] Shuyu Wang, Wengen Li, Siyun Hou, Jihong Guan, and Jiamin Yao. 2022. STA-GAN: A Spatio-Temporal Attention Generative Adversarial Network for Missing Value Imputation in Satellite Data. *Remote Sensing* 15, 1 (2022), 88.

[232] Shuyu Wang, Wengen Li, Hanchen Yang, Jihong Guan, Xiwei Liu, Yichao Zhang, Rufu Qin, and Shuigeng Zhou. 2025. Llm4hrs: Llm-based spatio-temporal imputation model for highly-sparse remote sensing data. *IEEE Transactions on Geoscience and Remote Sensing* (2025).

[233] Si Wang, Lin Mu, and Darong Liu. 2021. A hybrid approach for El Niño prediction based on Empirical Mode Decomposition and convolutional LSTM Encoder-Decoder. *Computers & Geosciences* 149 (2021), 104695.

[234] Xinning Wang, Xuegong Wang, Chong Li, Yuben Zhao, and Peng Ren. 2022. Data-attention-YOLO (DAY): A comprehensive framework for mesoscale eddy identification. *Pattern Recognition* 131 (2022), 108870.

[235] Xiaofan Wang and Lingyu Xu. 2020. Unsteady multi-element time series analysis and prediction based on spatial-temporal attention and error forecast fusion. *Future Internet* 12, 2 (2020), 34.

[236] Yi Wang, Conrad M Albrecht, Nassim Ait Ali Braham, Lichao Mou, and Xiao Xiang Zhu. 2022. Self-supervised learning in remote sensing: A review. *IEEE Geoscience and Remote Sensing Magazine* 10, 4 (2022), 213–247.

[237] Yueqi Wang, Zhiqiang Gao, and Dongyan Liu. 2019. Multivariate DINEOF Reconstruction for Creating Long-Term Cloud-Free Chlorophyll-a Data Records From SeaWiFS and MODIS: A Case Study in Bohai and Yellow Seas, China. *IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens.* 12, 5 (2019), 1383–1395.

[238] Zhuo Wang, Cuixian Lu, Yuxin Zheng, Yini Tan, Xuanzhen Zhang, Quanfei Wang, Xiaohong Zhang, and Jens Wickert. 2025. STG-DNN: A Spatio-temporal Graph Deep Neural Network for GNSS-R Ocean Wind Speed Retrieval. *IEEE Transactions on Geoscience and Remote Sensing* (2025).

[239] John Weiss. 1991. The dynamics of enstrophy transfer in two-dimensional hydrodynamics. *Physica D: Nonlinear Phenomena* 48, 2 (1991), 273–294.

[240] Michael A White, Forrest Hoffman, William W Hargrove, and Ramakrishna R Nemani. 2005. A global framework for monitoring phenological responses to climate change. *Geophysical Research Letters* 32, 4 (2005).

[241] Jared D. Willard, Jordan S. Read, Alison P. Appling, Samantha K. Oliver, Xiaowei Jia, and Vipin Kumar. 2021. Predicting Water Temperature Dynamics of Unmonitored Lakes With Meta-Transfer Learning. *Water Resources Research* 57, 7 (2021), e2021WR029579.

[242] Konrad Wolsing, Linus Roeper, Jan Bauer, and Klaus Wehrle. 2022. Anomaly detection in maritime AIS tracks: A review of recent approaches. *Journal of Marine Science and Engineering* 10, 1 (2022), 112.

[243] Aiming Wu, William W. Hsieh, and Benyang Tang. 2006. Neural network forecasts of the tropical Pacific sea surface temperatures. *Neural Networks* 19, 2 (2006), 145–154. Earth Sciences and Environmental Applications of Computational Intelligence.

[244] Song Wu, Xiaoyong Li, Wei Dong, Senzhang Wang, Xiaojiang Zhang, and Zichen Xu. 2022. Multi-Source and Heterogeneous Marine Hydrometeorology Spatio-Temporal Data Analysis with Machine Learning: A Survey. *World Wide Web* (2022).

[245] Song Wu, Xiaojiang Zhang, Senliang Bao, Wei Dong, Senzhang Wang, and Xiaoyong Li. 2023. Predicting Ocean Temperature in High-Frequency Internal Wave Area with Physics-Guided Deep Learning: A Case Study from the South China Sea. *Journal of Marine Science and Engineering* 11, 9 (2023), 1728.

[246] Changjiang Xiao, Nengcheng Chen, Chuli Hu, Ke Wang, Zewei Xu, Yaping Cai, Lei Xu, Zeqiang Chen, and Jianya Gong. 2019. A Spatiotemporal Deep Learning Model for Sea Surface Temperature Field Prediction Using Time-Series Satellite Data. *Environmental Modelling & Software* 120 (2019), 104502.

[247] Changjiang Xiao, Xiaohua Tong, Dandan Li, Xiaojian Chen, Qiquan Yang, Xiong Xv, Hui Lin, and Min Huang. 2022. Prediction of long lead monthly three-dimensional ocean temperature using time series gridded Argo data and a deep learning method. *Int. J. Appl. Earth Obs. Geoinformation* 112 (2022), 102971.

[248] Cui Xie, Jian Song, and Junyu Dong. 2022. OFExplorer: multi-facetted visual analysis of ocean front. *Journal of Visualization* (2022), 1–12.

[249] Jiang Xie, Jiaming Ouyang, Jiyuan Zhang, Baogang Jin, Suixiang Shi, and Lingyu Xu. 2022. An Evolving Sea Surface Temperature Predicting Method Based on Multidimensional Spatiotemporal Influences. *IEEE Geosci. Remote. Sens. Lett.* 19 (2022), 1–5.

[250] Lei Xie, Tao Guo, Jiliang Chang, Chengpeng Wan, Xinyuan Hu, Yang Yang, and Changkui Ou. 2023. A Novel Model for Ship Trajectory Anomaly Detection Based on Gaussian Mixture Variational Autoencoder. *IEEE Transactions on Vehicular Technology* (2023), 1–10.

[251] Xiaogang Xing, Emmanuel S. Boss, Jie Zhang, and Fei Chai. 2020. Evaluation of Ocean Color Remote Sensing Algorithms for Diffuse Attenuation Coefficients and Optical Depths with Data Collected on BGC-Argo Floats. *Remote. Sens.* 12, 15 (2020), 2367.

[252] Jiafei Xu and Zhizhao Liu. 2022. The First Validation of Sentinel-3 OLCI Integrated Water Vapor Products Using Reference GPS Data in Mainland China. *IEEE Trans. Geosci. Remote. Sens.* 60 (2022), 1–17.

[253] Cunjin Xue, Tianyu Zhang, Yangfeng Xu, and Fenzhen Su. 2022. An ocean current-oriented graph-based model for representing Argo trajectories. *Comput. Geosci.* 166 (2022), 105143.

[254] Xiting Yan, Zekun Gao, Yutong Jiang, Junyu He, Junjie Yin, and Jiaping Wu. 2023. Application of Synthetic DINCAE-BME Spatiotemporal Interpolation Framework to Reconstruct Chlorophyll-a from Satellite Observations in the Arabian Sea. *Journal of Marine Science and Engineering* 11, 4 (2023), 743.

[255] Feng Yang, Guofeng Wu, Yunyan Du, and Xiangwei Zhao. 2017. Trajectory data mining via cluster analyses for tropical cyclones that affect the South China Sea. *ISPRS International Journal of Geo-Information* 6, 7 (2017), 210.

[256] Hanchen Yang, Yuwei Chen, Jiannong Cao, Wengen Li, Yu Yang, Shuyu Wang, Jihong Guan, Rufu Qin, and Shuigeng Zhou. 2024. UniOcean: A Unified Framework for Predicting Multiple Ocean Factors of Varying Temporal Scales. *IEEE Transactions on Geoscience and Remote Sensing* (2024).

[257] Hanchen Yang, Wengen Li, Siyun Hou, Jihong Guan, and Shuigeng Zhou. 2023. HiGRN: A Hierarchical Graph Recurrent Network for Global Sea Surface Temperature Prediction. *ACM Trans. Intell. Syst. Technol.* 14, 4, Article 73

(jul 2023), 19 pages.

[258] Lianjun Yang, Taoyong Jin, Xianwen Gao, Hanjiang Wen, Tilo Schöne, Mingyu Xiao, and Hailan Huang. 2021. Sea level fusion of satellite altimetry and tide gauge data by deep learning in the mediterranean sea. *Remote Sensing* 13, 5 (2021), 908.

[259] Song Yang, Zhenning Li, Jin-Yi Yu, Xiaoming Hu, Wenjie Dong, and Shan He. 2018. El Niño–Southern Oscillation and its impact in the changing climate. *National Science Review* 5, 6 (2018), 840–857.

[260] Yuting Yang, Junyu Dong, Xin Sun, Estanislau Lima, Quanquan Mu, and Xinhua Wang. 2018. A CFCC-LSTM Model for Sea Surface Temperature Prediction. *IEEE Geoscience and Remote Sensing Letters* 2 (2018), 207–211.

[261] Haibin Ye, Shilin Tang, Chaoyu Yang, and Chuqun Chen. 2023. Reconstruction of Daily MODIS/Aqua Chlorophyll-a Concentration in Turbid Estuarine Waters Based on Attention U-NET. *Remote Sensing* 15, 3 (2023), 546.

[262] Jong-Min Yeom, Seungtaek Jeong, Jong-Sung Ha, Kwon-Ho Lee, Chang-Suk Lee, and Seonyoung Park. 2022. Estimation of the Hourly Aerosol Optical Depth From GOCEI Geostationary Satellite Data: Deep Neural Network, Machine Learning, and Physical Models. *IEEE Trans. Geosci. Remote. Sens.* 60 (2022), 1–12.

[263] Fatin Nadiah Yussof, Normah Maan, and Mohd Nadzri Md Reba. 2021. LSTM Networks to Improve the Prediction of Harmful Algal Blooms in the West Coast of Sabah. *International Journal of Environmental Research and Public Health* 18, 14 (2021).

[264] Natalia Zakhvatkina, Vladimir Smirnov, and Irina Bychkova. 2019. Satellite SAR data-based sea ice classification: An overview. *Geosciences* 9, 4 (2019), 152.

[265] Chun-gui Zhang, Yong Ren, Yi-yong Cai, Y Zeng, and X Zhang. 2009. Study on local monitoring model for SST in Taiwan strait based on MODIS data. *J. Trop. Meteorol* 25 (2009), 73–81.

[266] Feng Zhang, Yuanyuan Wang, Minjie Cao, Xiaoxiao Sun, Zhenhong Du, Renyi Liu, and Xinyue Ye. 2016. Deep-Learning-Based Approach for Prediction of Algal Blooms. *Sustainability* 8, 10 (2016).

[267] Qin Zhang, Hui Wang, Junyu Dong, Guoqiang Zhong, and Xin Sun. 2017. Prediction of Sea Surface Temperature Using Long Short-Term Memory. *IEEE Geoscience and Remote Sensing Letters* 14, 10 (2017), 1745–1749.

[268] Rui Zhang, Qingshan Liu, Renlong Hang, and Guangcan Liu. 2022. Predicting Tropical Cyclogenesis Using a Deep Learning Method From Gridded Satellite and ERA5 Reanalysis Data in the Western North Pacific Basin. *IEEE Trans. Geosci. Remote. Sens.* 60 (2022), 1–10.

[269] Tao Zhang, Pengfei Lin, Hailong Liu, Pengfei Wang, Ya Wang, Kai Xu, Weipeng Zheng, Yiwen Li, Jinrong Jiang, Lian Zhao, et al. 2025. A Coupled Transformer-CNN Network: Advancing Sea Surface Temperature Forecast Accuracy. *IEEE Transactions on Geoscience and Remote Sensing* (2025).

[270] Xiaoyu Zhang, Yongqing Li, Alejandro C. Frery, and Peng Ren. 2022. Sea Surface Temperature Prediction With Memory Graph Convolutional Networks. *IEEE Geoscience and Remote Sensing Letters* 19 (2022), 1–5.

[271] Yu Zhang, Peter Tiňo, Aleš Leonardis, and Ke Tang. 2021. A survey on neural network interpretability. *IEEE Transactions on Emerging Topics in Computational Intelligence* 5, 5 (2021), 726–742.

[272] Zeguo Zhang and Jianchuan Yin. 2024. Spatial-temporal Offshore Current Field Forecasting Using Residual-learning Based Purely CNN Methodology with Attention Mechanism. *Applied Artificial Intelligence* 38, 1 (2024), 2323827.

[273] Liling Zhao, Yifei Chen, and Victor S Sheng. 2020. A real-time typhoon eye detection method based on deep learning for meteorological information forensics. *Journal of Real-Time Image Processing* 17, 1 (2020), 95–102.

[274] Lingxiao Zhao, Zhiyang Li, Junsheng Zhang, and Bin Teng. 2023. An Integrated Complete Ensemble Empirical Mode Decomposition with Adaptive Noise to Optimize LSTM for Significant Wave Height Forecasting. *Journal of Marine Science and Engineering* 11, 2 (2023), 435.

[275] Nan Zhao, Baoxiang Huang, Jie Yang, Milena Radenkovic, and Ge Chen. 2023. Oceanic Eddy Identification Using Pyramid Split Attention U-Net With Remote Sensing Imagery. *IEEE Geoscience and Remote Sensing Letters* 20 (2023), 1–5.

[276] Qingyu Zheng, Ru Wang, Guijun Han, Wei Li, Xuan Wang, Qi Shao, Xiaobo Wu, Lige Cao, Gongfu Zhou, and Song Hu. 2024. A Spatio-Temporal Multiscale Deep Learning Model for Subseasonal Prediction of Arctic Sea Ice. *IEEE Transactions on Geoscience and Remote Sensing* (2024).

[277] Gaoxiang Zhou, Ming Liu, Linlin Xu, and Liangzhi Li. 2024. A gap-filling method for satellite-derived chlorophyll-a time series based on neighborhood spatiotemporal information. *International Journal of Applied Earth Observation and Geoinformation* 128 (2024), 103724.

[278] Huchen Zhou, Mohan Li, and Zhaoquan Gu. 2020. Knowledge fusion and spatiotemporal data cleaning: A review. In *2020 IEEE Fifth International Conference on Data Science in Cyberspace (DSC)*. IEEE, 295–301.

[279] Yanan Zhu, Yuanlong Li, Fan Wang, and Mingkun Lv. 2022. Weak Mesoscale Variability in the Optimum Interpolation Sea Surface Temperature (OISST)-AVHRR-Only Version 2 Data before 2007. *Remote. Sens.* 14, 2 (2022), 409.

[280] Wenxiao Zhuge, Guoxiang Wu, Bingchen Liang, Zhiming Yuan, Peng Zheng, Jinghua Wang, and Luming Shi. 2024. A statistical method to quantify the tide-surge interaction effects with application in probabilistic prediction of extreme storm tides along the northern coasts of the South China Sea. *Ocean Engineering* 298 (2024), 117151.