TYPE Editorial
PUBLISHED 05 October 2023
DOI 10.3389/fmars.2023.1296334

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EDITED AND REVIEWED BY
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RECEIVED 18 September 2023
ACCEPTED 29 September 2023
PUBLISHED 05 October 2023

CITATION
He J, Du Z and Xiao X (2023) Editorial: Spatiotemporal modeling and analysis in marine science. *Front. Mar. Sci.* 10:1296334. doi: 10.3389/fmars.2023.1296334

Editorial: Spatiotemporal modeling and analysis in marine science

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KEYWORDS

spatiotemporal, modeling, marine science, machine learning, time-frequency

Editorial on the Research Topic
Spatiotemporal modeling and analysis in marine science

Recent advancements in monitoring technologies have ushered in an era characterized by an explosion of spatiotemporal data across diverse fields, notably within global oceans. This surge of data, sourced from satellites, unmanned aerial vehicles, buoys, and unmanned underwater vehicles, poses challenges in extracting meaningful insights and bridging the gap between raw data and scientific understanding (Frankel and Reid, 2008; Wu et al., 2020). Data-driven spatiotemporal modeling and analysis present potential solutions, offering avenues to uncover inherent features within the data, delineate characteristics of natural phenomena, refine general knowledge or theories, and bolster the management and conservation of oceans. Consequently, based on these spatiotemporal, spatial or temporal data, specific methodologies are tailored and employed for analysis. For instance, prevalent machine learning and deep learning techniques excel in modeling the nonlinear and non-stationary aspects of spatiotemporal, spatial, or temporal data (Ham et al., 2019; Reichstein et al., 2019; Runge et al., 2019; Callaghan et al., 2021). Geostatistical methods adeptly capture spatial or spatiotemporal correlations within such data (He and Kolovos, 2018; He and Christakos, 2021; Wu et al., 2021). Additionally, time-frequency methods decompose temporal data into distinct series for nuanced variation detection (Cazelles et al., 2008; Xiao et al., 2019). Cutting-edge frameworks, such as those integrating geostatistical and machine learning methods, have been proposed to more accurately reflect the natural phenomena (Du et al., 2021). The primary objective of this Research Topic is to furnish a platform for scholars to disseminate novel methodologies or insights within the spatiotemporal context of marine or coastal regions.

Chen et al. posited that integrating artificial intelligence (AI) technology with extensive datasets from ocean observations can significantly address challenges in advancing marine science or theory, especially in the intermediate ocean depths ranging from approximately 100 to 1,000 meters. In their review titled "Deep Blue AI for Knowledge Discovery of Intermediate Ocean," they synthesized findings from satellite remote sensing at around 100 meters deep and *in situ* observations at approximately 1,000 meters. Additionally, they discussed three distinct AI methodologies: associative statistical, physically informed, and mathematically driven neural networks. The application of these methodologies was reviewed in context, covering areas such as the 3-D identification and trajectory prediction of oceanic eddies, the vertical reconstruction of Ekman drift, internal wave forecasting, and subsurface chlorophyll maxima prediction.

Wang et al. centered their research on predicting typhoon activity to bolster decision-making aimed at mitigating associated risks. A pivotal challenge in modeling arose when selecting the optimal number of historical satellite images for future predictions. Using too few images might not offer adequate information on typhoon trajectories, while an excessive number could diminish the size of the training dataset. To address this, the team devised a feature enhancement module paired with a channel attention module. This combination was designed to amplify the intrinsic characteristics of typhoons and determine the appropriate number of images for subsequent modeling. The spatiotemporal attributes of typhoons were then modeled using a symmetrical encode-decode module comprising convolutional long short-term memory networks (ConvLSTM). Furthermore, a multi-scale strategy was implemented to curtail information loss during the ConvLSTM process. In their quest to design the optimal structure for the Enhanced Multi-Scale Deep Neural Network (EMSN), the team explored multi-scale components, channel attention modules, and spatiotemporal capture units. By adjusting various parameters within these modules, they assessed the accuracy of typhoon predictions. Notably, the EMSN outperformed both the MSCIP satellite image predictor and the conventional U-net.

While hyperspectral remote sensing data are limited and costly, Hu et al. investigated the potential of reconstructing hyperspectral images using economical RGB images, a development that could enhance marine observations. By replacing the standard convolution kernel with atrous convolution and incorporating a multi-scale atrous convolution residual block, the image's multi-scale spatial features were more effectively extracted by integrating images across different scales into a multi-scale feature layer without increasing computational costs. The introduced Multi-Scale Atrous Convolution Residual Network (MACRN) comprises three segments: low-level feature extraction, high-level feature extraction, and feature transformation. MACRN's efficacy was evaluated using clean and real-world datasets and benchmarked against exsiting algorithms like HSCNN-R, HSCNN-D, HRNet, AWAN, and MST++.

Li devoted significant effort to applying the greedy strategy for mode identification with significantly crossed frequencies and overlapped component separation. Consequently, the Spatio-Temporal Nonconvex Penalty Adaptive Chirp Mode Decomposition (STNP-ACMD) algorithm was proposed. It addresses the limitations of traditional algorithms, such as ACMD and Variational Mode Decomposition (VMD), which primarily prioritize channel-wise processing without accommodating the coupled nature and spatio-temporal characteristics. The STNP-ACMD employs a recursive mode extraction approach to segregate overlapped components or crossed intrinsic functions and accentuates the spatio-temporal relationship within the coupled nature by refining the spatial and temporal matrices. Comparative analysis, using both numerical and real-world case studies, demonstrated that STNP-ACMD surpassed the Ensemble Empirical Mode Decomposition and VMD.

Chiu et al. leveraged the spatial correlation traits found within observed data to estimate blue carbon (BC) stocks in marsh soils. A Bayesian linear mixed-effects model was devised to assimilate auxiliary information from variables such as marsh type, soil category, soil depth, and marsh site. This model assumed that site effects adhered to the intrinsic conditional autoregressive (ICAR) spatial dependence. By incorporating the ICAR marsh site effects, an inherent spatial clustering of sites became discernible, a pattern not reflected in the primary auxiliary predictors. Notably, the ICAR model produced a narrower confidence interval for the marsh site effects' coefficient compared to its non-ICAR counterpart, highlighting the spatial correlation of BC stock and underscoring the importance of including these characteristics in BC assessment models.

Author contributions

JH: Funding acquisition, Writing – original draft, Writing – review & editing. ZD: Writing – review & editing. XX: Writing – review & editing.

Funding

This work is supported by National Natural Science Foundation of China (Nos. 42301374 and 42171398), the Major Program of Natural Science Foundation of Zhejiang for Creative Research Group (Grant No. LDT23D06024D06) and Science Foundation of Donghai Laboratory (Grant No. 2022KF01012).

Acknowledgments

We thank Dr. Dongxiao Zhang for his help on handling one manuscript submitted to this Research Topic. We also thank all authors of the articles published in this Research Topic for their significant contributions and the reviewers for their valuable comments. We appreciate the kindly help and supports from Rui Fernandes, Ronan Conlon, Alice Lickley, Joshua Chew, Minea Kaartinen, Francesco Rossetti, and Emily Keynton.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

Publisher's note

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