Spatiotemporal Analysis of River Health Using Remote Sensing and Machine Learning Approaches

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Abstract: Disclosing the spatiotemporal (ST) fluctuations of nutrients in coastal waters is essential for comprehending and assessing the coastal environment, consequently offering practical recommendations for aquatic restoration. This study introduced a Machine Learning (ML) that integrates ST data, facilitating the establishment of quantitative connections between determined external variables and extensive satellite imagery, while reducing estimation errors exceeding 40% compared to traditional ML models lacking ST integration. The ST patterns of Dissolved Inorganic Nitrogen (DIN) and Dissolved Inorganic Phosphorus (DIP) throughout 45000 km² of the Sea were acquired on an 8-day interval. The ST variations illustrated the water quality trends, revealing fluctuations of two critical nutrients in harbors affected by complex anthropogenic impacts, typical waterways with multiple river components, and open oceans with significant fisheries. Despite a 25% and 20% reduction in DIN and DIP concentrations over nine years, the inshore ocean's water condition has not improved, particularly during fall and winter. The research conducted a quantitative analysis of the primary causes of water degradation and offered scientific recommendations for focused surveillance and regional cooperation in governance.

Keywords: Spatiotemporal Analysis; River Health; Remote Sensing; Machine Learning.

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I. Introduction

Geospatial techniques have recently been extensively used for the spatiotemporal (ST) surveillance of ecological phenomena, particularly in assessing lake water quality indicators Batina & Krtalić (2024). This use is primarily facilitated by high spatial and temporal resolution information. This element has consistently faced challenges owing to the absence of suitable sensors. Intermediate resolution detectors, distinguished by frequent revisit intervals and good radiometric decision, have been employed; their spatial accuracy is inadequate for detecting tiny lakes. Numerous studies have used Landsat information; however, these satellites are constrained by their return frequency for continuous monitoring Hemati et al. (2021).

The emergence of sensors with enhanced spatial, spectral, and temporal resolution, including Latitude and Sentinel-2, has facilitated the collection and modeling of water quality from satellite orbits. Research was done to track turbidity and Colored Dissolved Organic Materials (CDOM) using pictures of lakes within two river systems An et al. (2023). The findings indicated that, although constrained by spectrum and radiological resolution, these pictures are an effective and valuable instrument to track water quality in small lakes (<1 km2). Research was done in Estonia to assess Multi-Spectral Imaging (MSI) data Cao et al. (2021) for measuring several lake water quality indicators, including chlorophyll a (Chl-a), surface dye, CDOM, and Dissolved-Organic-Carbon (DOC). Field data of various characteristics were juxtaposed with the band proportion methods generated from Sentinel-2.

II. Proposed ML-based ST Analysis

Considering the factors above, the research aimed to develop an ST Machine Learning (ML) algorithm to accurately estimate Dissolved Inorganic Nitrogen (DIN) and Dissolved Inorganic Phosphorus (DIP) with remote sensing (RS) reflection and field measurement information in the extensive coastlines of a representative area Kim et al. (2022); Zhu et al. (2024). The primary advancements are delineated in Fig. 1. An ML approach integrating ST findings into a designed Deep Belief Network (DBN) Sohn (2021) has been suggested to derive the sequential variations of nutrients in the research area from extensive records of nutrient reports and corresponding daily searches over the 2010-2018 period. A thorough study was performed to comprehend the ST trends of nutrients according to yearly, seasonal, monthly, and 8-day average spatial dispersion.

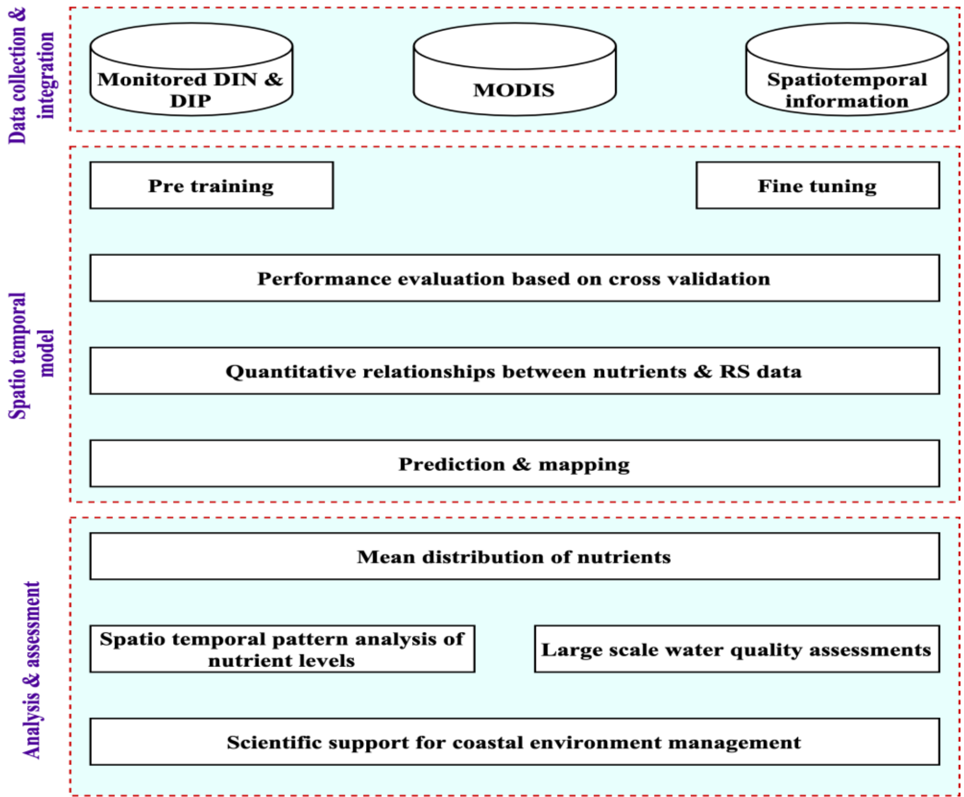

Figure 1: Architecture of the Proposed Model

2.1. Measurement of Nitrogen and Phosphorus

The Marine Management and Prediction Center gathered the in situ nutrient information Zhu et al. (2024). The sample, measurements, and evaluation complied with the Requirements for Oceanographic Research. The quantity of yearly surveillance stations rose consistently from 95 to 330. In 2019, the average annual readings for DIN and DIP revealed elevated levels mostly in waterways, where DIN and DIP levels above 1.10 and 0.06 mg/L, correspondingly. In the last decade, the number of measurements and stations has risen, making it crucial to utilize measurements to get constant variations of DIN and DIP at an appropriate scale to assess the water's condition along the coastline thoroughly.

2.2. Acquisitions and Data Processing

The ground-based reflectance information for channels 1-7 of Aqua has been prepared and downloaded employing Google Earth Engines, utilizing its robust parallel processing capabilities. The daily searches of groups 1-6 were retrieved by correlating them with the ST records (individual pixels at 600 m granularity and a morning frame) of the observed DIN and DIP information. The research inspected the matching database using the verification band to preserve pixels. It was determined that the information quality of spectrum 6 was significantly worse than that of the remaining spectrum, leading to its exclusion from the studies. Thereafter, the 1 km precision cloud condition band was used to filter out cloud-free recordings.

2.3. ST ML System

This work sought to integrate ST data into the DBN model, a conventional ML approach, to address the intricate non-linearity and ST variation in nutrient forecasting within a large-scale maritime environment. The DBN consisted of layered Restricted-Boltzmann-Machines (RBMs) and Back-Propagating (BP) tier.

An RBM consists of visual (v) and concealed (h) units, with connectivity among both levels. During the development of the RBM, each concealed unit is assigned a value of 1 or 0 based on whether its likelihood exceeds a uniformly dispersed randomized integer. In contrast, every visible unit corresponds directly to its likelihood.

This work developed an illustration of the ST DBN for calculating nutrient levels, paralleling the approach of the geo-intelligent DBN. The input parameters had two components: the surface reflectance data and ST variables. ST data is further categorized into temporal and spatial components, due to the significant regional variability of coastal fertilizers and the correlation between water depth and proximity to the shore, which indicates anthropogenic impact. The geographical coordinates and depth data were employed as spatial variables. The coastline condition fluctuates throughout the period and displays periodic fluctuations across many levels.

III. Results

Figure 2 illustrates that in the absence of combined ST data, the MLR exhibited the worst performance, demonstrating considerable non-linearity in the connection between micronutrients and satellite information within the coastline setting. The DBN attained markedly superior R* compared to Message Passing Neural Network (MPNN) and General Regression Neural Network (GRNN) for variables in both sample-oriented and site-oriented groups. The discovery that the DBN with a more intricate structure exhibited higher results indicates that the simulation of coastline fertilizers is difficult, necessitating advanced smart systems.

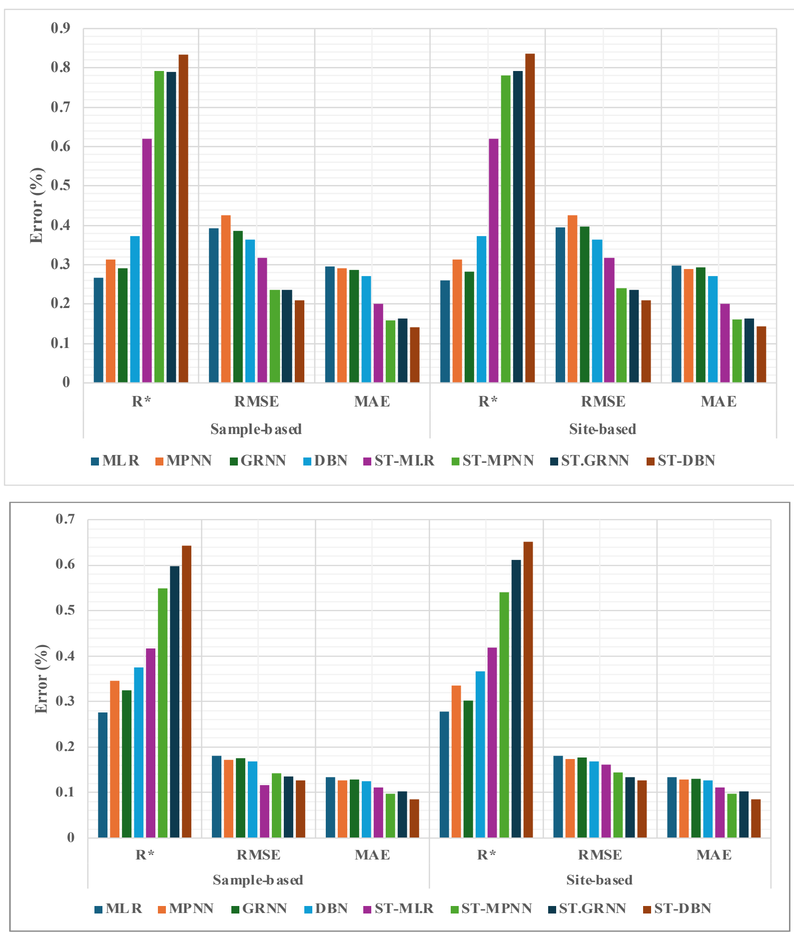

Figure 2: DIN and DIP Analysis

Despite the DBN enhancing the efficacy of conventional models (MPNN and GRNN), the results remained inadequate. The primary issue is likely that the reflection cannot adequately represent the ST fluctuations in water quality metrics. The initial algorithms' accuracy was enhanced with ST data integration, indicating that the ST-integrated ML approach substantially benefits nutrient prediction.

Among these algorithms, the STDBN design had superior performance, while the STGRNN and STMPNN showed worse performance, with the STMLR design being the least effective. This arrangement was congruent with the design of the first models. The STMLR surpassed the non-ST-oriented DBN by including ST data, achieving sample-oriented CV R^2 coefficients of 0.631 and 0.428 for DINs and DIPs. This indicated that the minerals are closely linked to ST features. The STMPNN and STGRNN demonstrated significantly higher accuracy than the STMLR by more effectively modeling the non-linear interactions among nourishment and predictions. The STDBN provided a more accurate characterization of the predicted connection, benefiting from layer-by-layer pre-training, compared to the STMPNN and STGRNN. The STDBN system achieved the maximum accuracy, with sample-based cross-validation R' and Root Mean Squared Error (RMSE) readings of 0.824 and 0.231 mg/L for DIN, and 0.635 and 0.0152 mg/L for DIP, respectively. The STDBN system has decreased the estimation errors (i.e., RMSE and Mean Absolute Errors (MAE)) of DIN and DIP by over 45% compared to the non-ST-integrated DBN system. The findings indicated that STDBN had commendable spatial forecasting ability. The findings demonstrate that the STDBN method is an efficient and reliable method for estimating coastal fertilizers.

IV. Conclusion

This work created an ML model that integrates spatial and temporal information to quantify the correlations between nutrient density and satellite information in a typical anthropogenically affected coastline region. The elucidated nutrient concentrations and extensive understanding of water quality might facilitate the enhancement of the coastline ecosystem.

Given the intricate non-linearity and ST variation in the satellite imagery recovery of coastline calories, the technique retrieved ST information from the input database. It included it for an optimal DBN. Compared to methods without ST data, the STDBN decreased prediction errors by a minimum of 40%, showing that DINs and DIPs concentrations are reliably calculated by ST-integrated modeling. The concentrations of DINs and DIPs dropped by 25% and 20% over 8 years, exhibiting a steady fall in spatial observation. The water condition did not enhance considerably, as the decreased DIN content remained substantially over the crucial threshold of the most detrimental level.

The provincial governance should enhance runoff, speed, and DIN content monitoring in the river delta by deploying fixed buoys and using real-time satellite information more extensively. It is essential to strengthen the regulation of DIN input during the fall and winter months while prioritizing collaboration with the environmental administration agencies of the Delta.

The STDBN offers a novel remote sensing approach and a suitable evaluation technique for investigating ST water and nutrient quality variations across extensive coastal regions. However, additional uses in diverse aquatic conditions are required to validate its usefulness and durability in the future. This research enhanced the effectiveness of extensive data collecting and preparation to leverage capabilities fully in the future. It is anticipated that more storage-efficient techniques, such as conducting every test on a server located in the cloud, would be developed.

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