frontiers | Frontiers in Marine Science

TYPE Original Research
PUBLISHED 08 May 2025
DOI 10.3389/fmars.2025.1518050

Check for updates

OPEN ACCESS

EDITED BY
Emilio Bastidas-Arteaga,
Université de la Rochelle, France

REVIEWED BY
Tien Anh Tran,
Seoul National University, Republic of Korea
Hongyuan Guo,
Hong Kong Polytechnic University, Hong Kong SAR, China

*CORRESPONDENCE
Xiaonong Xu
xuxiaonong2023@163.com

RECEIVED 28 October 2024
ACCEPTED 31 March 2025
PUBLISHED 08 May 2025

CITATION
Chen C, Jie G, Wang J, Wang S and Xu X (2025) OceanLSTM: xLSTM with spatial attention for salt spray formation and migration prediction in marine hot-humid environments.
Front. Mar. Sci. 12:1518050.
doi: 10.3389/fmars.2025.1518050

COPYRIGHT
© 2025 Chen, Jie, Wang, Wang and Xu. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

OceanLSTM: xLSTM with spatial attention for salt spray formation and migration prediction in marine hot-humid environments

Chuan Chen[1], Ganxin Jie[1], Jun Wang[1], Shouhe Wang[1] and Xiaonong Xu[2]*

[1]China National Electric Apparatus Research Institute Co., Ltd., State Key Laboratory of Environmental Adaptability for Industrial Products, Guangzhou, China, [2]The College of Information, Mechanical and Electrical Engineering, Shanghai Normal University, Shanghai, China

Introduction: Salt spray formation and migration in hot and humid marine environments have a significant impact on marine engineering and equipment maintenance. Accurately predicting these phenomena is crucial for reducing corrosion damage. Traditional research methodologies primarily utilize statistical models or physics-based simulations. Although these approaches yield satisfactory results within controlled conditions, they often encounter limitations in accurately capturing the complexity and variability inherent to marine environments. These methods struggle to capture the spatiotemporal dependencies of salt spray formation and migration. Moreover, they are typically difficult to apply in real-time and lack the ability to handle large-scale, dynamic data.

Methods: This study aims to address this issue by proposing the OceanLSTM model, which combines the temporal modeling capabilities of xLSTM with a spatial attention mechanism to capture the spatiotemporal relationships between complex environmental variables, thereby improving the accuracy of salt spray predictions.

Results: The experiments used several representative marine environment datasets, including the NOAA and Marine Aerosol datasets. The experimental results demonstrate that OceanLSTM significantly outperforms traditional models in evaluation metrics such as accuracy and F1-score, especially on datasets with strong spatiotemporal dependencies.

Discussion: This research provides a more precise and efficient tool for future marine environment monitoring and corrosion prediction, offering important practical applications.

KEYWORDS
salt spray prediction, marine environment, xLSTM, spatial attention, spatiotemporal modeling

1 Introduction

The formation and migration prediction of salt spray is a critical task in marine environmental monitoring, particularly when marine structures, equipment, and related infrastructure are exposed to corrosive environments over long periods. Accurately predicting the dispersion of salt spray is essential for reducing maintenance costs and extending the service life of these systems?. Due to the dynamic nature of salt spray migration, which is influenced by multiple environmental factors such as wind speed and humidity, it can also exhibit complex spatiotemporal dependencies depending on geographic and weather conditions Su et al. (2022). Therefore, research into methods for predicting salt spray formation and migration not only helps to scientifically assess corrosion risks but also provides support for formulating effective preventive measures. Early research primarily employed symbolic AI and knowledge representation approaches, relying on physical formulas, expert knowledge, or empirical rules to establish quantitative relationships between environmental conditions and corrosion rates for predicting corrosion trends Maohua et al. (2022). For instance, formulas can calculate the linear or nonlinear relationships between salt spray concentration and environmental parameters. However, the drawback of these traditional methods is that they assume environmental conditions are static or predictable, making them unsuitable for dynamic marine environments Yang et al. (2020). Moreover, knowledge representation models heavily depend on expert experience. Although effective for small-scale scenarios, they typically lack generalization ability when confronted with complex, large-scale environmental data, often failing to meet practical accuracy requirements. To overcome the shortcomings of symbolic AI, data-driven machine learning methods have become an important research direction for salt spray prediction. These methods collect large amounts of environmental data, such as wind speed, humidity, and salinity, and use machine learning models such as support vector machines, decision trees, and random forests to explore the nonlinear relationships between these variables Kumar et al. (2024c). Compared to traditional methods, data-driven approaches can handle more complex, multidimensional data and capture patterns and trends through statistical learning Wang et al. (2022). However, these methods perform poorly in capturing time dependencies, making it difficult to model the dynamic migration process of salt spray. When faced with sparse or noisy data, the performance of the models tends to degrade significantly. With the rise of deep learning, salt spray prediction has entered a new phase based on deep learning and pretrained models. By introducing time-series models like Recurrent Neural Networks (RNN) Lin and Kuo (2024) and Long Short-Term Memory Networks (LSTM)Abd Elaziz et al. (2024), researchers have become able to effectively capture the long-term dependencies of environmental variables. These models can handle large-scale, complex time-series data, overcoming the deficiencies of machine learning in time-series modeling. Furthermore, the application of pretrained models in recent years has further improved prediction accuracy. Through pretraining on large-scale environmental data, the models can better generalize to different application scenarios. However, despite the strong learning capabilities of deep learning models, they have drawbacks such as high training costs and suboptimal performance in handling spatial variability. Although pretrained models enhance generalization, their performance still has limitations across multi-scenario and multi-variable environments.

To address these challenges, this study introduces OceanLSTM, a novel deep learning model that integrates an Extended Long Short-Term Memory (xLSTM) network with a spatial attention mechanism to enhance spatiotemporal modeling Gao et al. (2022). Unlike traditional statistical and physics-based models, which often struggle with capturing complex environmental interactions and dynamic dependencies, OceanLSTM leverages an exponentially gated xLSTM to model long-term dependencies in environmental variables while incorporating a spatial attention mechanism to dynamically focus on key geographic regions Wu et al. (2024a). By integrating multiple marine environmental datasets, including the NOAA and Marine Aerosol datasets, our model significantly improves prediction accuracy compared to traditional methods, achieving higher performance in key evaluation metrics such as accuracy and F1-score Kumar et al. (2024). Furthermore, unlike computationally intensive physics-based simulations, OceanLSTM enables efficient real-time predictions, making it a practical solution for marine environmental monitoring, corrosion risk assessment, and climate impact studies Cork et al. (2024). This study provides a stateof-the-art predictive framework for salt spray migration modeling and contributes to the development of intelligent marine environment forecasting systems Xu et al. (2024). Salt spray prediction has been widely studied due to its critical impact on marine corrosion Sánchez-Arcilla et al. (2021). Traditional approaches rely on physical models and empirical formulas to correlate salt spray concentration with meteorological variables such as wind speed, humidity, and temperature Sanchez-Arcilla et al. (2023). However, these models assume static environmental conditions and lack adaptability to dynamic marine environments, making them unsuitable for large-scale applications Gracia and Torresan (2022). Machine learning methods, including support vector machines, decision trees, and random forests, improve prediction accuracy by capturing nonlinear relationships in environmental data but struggle with temporal dependencies and spatial variability van der Vliet et al. (2024). Deep learning models, particularly recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), have further enhanced salt spray prediction by learning long-term dependencies in time-series data. However, traditional LSTM models still face challenges in modeling geographic influences and multi-variable interactions, limiting their predictive performance Wu et al. (2024b). Recent advancements in spatiotemporal modeling, such as spatiotemporal graph convolutional networks (ST-GCN) and spatiotemporal LSTMs (ST-LSTM), provide improved solutions by integrating both temporal sequences and spatial dependencies Kalidasan et al. (2023). Nevertheless, these models often have high computational complexity Ousaleh et al. (2020). The introduction of attention mechanisms has further enhanced predictive capabilities by dynamically assigning weights to influential variables or regions, improving both accuracy and efficiency Kumar et al. (2024). Despite these advancements, the challenge remains to develop a model that effectively captures both long-term dependencies and spatial correlations while maintaining computational efficiency.

Salt spray prediction plays a crucial role in assessing corrosion risks and maintaining marine infrastructure Kumar et al. (2023b). Traditional methodologies, including physical models and empirical formulas, have been used to estimate salt spray concentration based on meteorological parameters such as wind speed, humidity, and temperature Kumar et al. (2023a). However, these methods assume static environmental conditions and lack adaptability to dynamic marine environments, limiting their real-world applicability. Machine learning approaches, such as support vector machines, decision trees, and random forests, have improved prediction accuracy by capturing nonlinear relationships among environmental variables, but they struggle with temporal dependencies and spatial variability Yu et al. (2023). The advent of deep learning, particularly recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), has enabled better modeling of long-term dependencies in environmental data, addressing some of these challenges Javid (2021). However, conventional LSTM models still have limitations in capturing complex spatiotemporal patterns crucial for marine environmental monitoring Sun et al. (2024). To overcome this, recent state-of-the-art methodologies, such as spatiotemporal graph convolutional networks (ST-GCN) and spatiotemporal LSTMs (ST-LSTM), have been developed to integrate both spatial and temporal dependencies, significantly improving prediction accuracy. Moreover, attention mechanisms have further enhanced predictive models by dynamically assigning importance to key environmental variables and geographic regions, thereby increasing computational efficiency and robustness Delgado et al. (2016). These advancements are critical for real-time marine environmental monitoring and infrastructure maintenance, ensuring more accurate and efficient corrosion risk assessment in dynamic oceanic conditions. Despite these improvements, challenges remain in optimizing computational efficiency while maintaining high accuracy in large-scale, real-time marine applications. The rest of this paper is structured as follows. Section 2 describes the proposed OceanLSTM methodology, including the details of the exponentially gated xLSTM and the spatial attention mechanism. Section 3 introduces the datasets, experimental settings, and evaluation metrics used in our experiments. And the experimental results and comprehensive analysis are presented in this Section. Section 4 discusses the implications of our findings, the strengths and limitations of OceanLSTM, and future research directions. Section 5 summarizes the conclusions drawn from this study. The overall research structure and workflow of this study are illustrated in Figure 1.

Unlike the limitations of traditional methods and machine learning, OceanLSTM combines temporal dependency modeling with spatial attention mechanisms, aiming to solve the spatiotemporal dependency problem in salt spray prediction. OceanLSTM dynamically captures the temporal dependencies

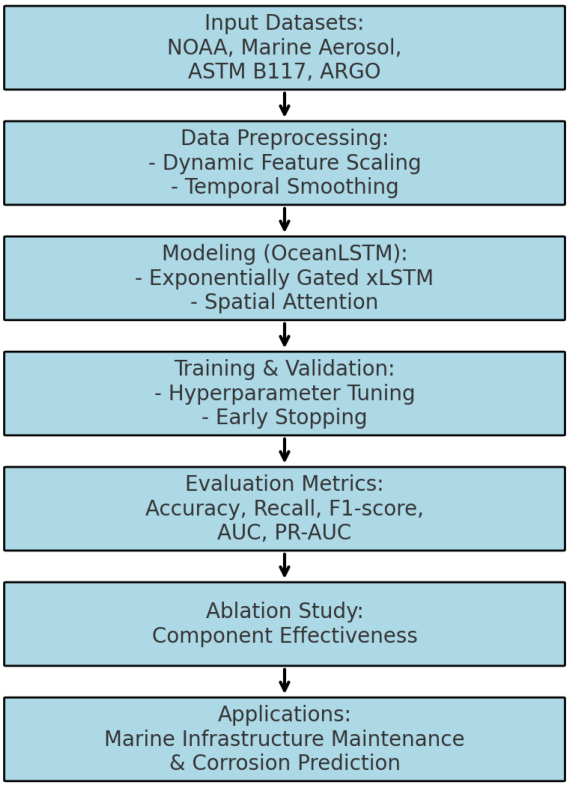

FIGURE 1
Flow chart illustrating the overall structure and methodology of this study.

between environmental variables, while focusing on the most important geographic regions through its spatial attention mechanism, significantly improving prediction accuracy and efficiency.

This method has three main advantages:

- OceanLSTM introduces an exponentially gated xLSTM and a spatial attention mechanism, addressing the shortcomings of traditional methods in spatiotemporal dependency modeling.
- OceanLSTM is efficient and versatile, capable of handling complex dynamic marine environments and is suitable for salt spray prediction tasks in multiple scenarios.
- Experimental results show that OceanLSTM performs exceptionally well on datasets such as NOAA and Marine Aerosol, significantly outperforming traditional models in metrics such as accuracy and F1 score.

2 Methodology

2.1 Research gap and motivation

Despite recent advancements in deep learning and spatiotemporal modeling, several challenges persist in salt spray prediction. First, existing methods typically emphasize either temporal or spatial dependencies but rarely integrate both effectively, resulting in limited predictive performance in dynamic marine environments. Traditional machine learning models struggle with capturing complex time-series patterns, while deep learning approaches, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), effectively model temporal dependencies but often neglect spatial correlations, which are crucial in salt spray migration. Second, while spatiotemporal models such as spatiotemporal graph convolutional networks (ST-GCN) and spatiotemporal LSTMs (ST-LSTM) improve predictive accuracy by incorporating spatial dependencies, they introduce high computational costs, making real-time applications challenging. While current attention-based models enhance feature selection, they often lack adaptive mechanisms capable of dynamically identifying and emphasizing critical environmental regions, thus limiting their applicability across diverse marine scenarios. To address these gaps, this study proposes OceanLSTM, which integrates an exponentially gated xLSTM with a spatial attention mechanism to jointly model temporal dependencies and spatial interactions in salt spray migration. By leveraging multiple marine datasets, including the NOAA and Marine Aerosol datasets, OceanLSTM enhances predictive accuracy while maintaining computational efficiency. This provides a robust and scalable solution for real-time marine environmental monitoring, corrosion risk assessment, and infrastructure maintenance, ensuring both precision and practical applicability in dynamic oceanic conditions.

2.2 Overview

In this work, we present an innovative architecture tailored for predicting salt spray formation and migration in marine hot-humid environments. The architecture builds on the Extended Long Short-Term Memory (xLSTM) model by incorporating spatial attention mechanisms to capture dynamic interactions in the marine atmosphere. By integrating data from environmental sensors with real-time salt spray migration patterns, the model leverages temporal and spatial dependencies to enhance predictive accuracy. The core structure of the proposed architecture consists of several modules: the preprocessing module, which handles sensor data and environmental variables; the xLSTM backbone for temporal pattern learning; and a spatial attention mechanism designed to capture and model the migration of salt spray across geographical zones. The data flow begins with environmental readings, including humidity, wind speed, and salinity levels, which are preprocessed and fed into the xLSTM module. The xLSTM model is responsible for extracting temporal patterns, which are then enhanced by the spatial attention module to focus on regions most impacted by salt spray. Finally, a post-processing module integrates the model outputs to generate detailed migration forecasts.

We will detail the structure of our approach in the following subsections. In Subsection 2.3, we discuss the preprocessing module that prepares the raw environmental data for modeling. Subsection 2.4 outlines the core xLSTM module, including its ability to handle long-term dependencies through its advanced gating mechanisms. Finally, Subsection 2.5 presents the spatial attention mechanism that ensures the model's focus on key areas, improving the prediction of salt spray distribution across varying environmental conditions. This overall framework provides a robust solution to the challenge of predicting salt spray behavior, particularly in complex marine environments. Our model can be applied across different geographical zones, leveraging both temporal and spatial dimensions to improve the accuracy and relevance of predictions, which is critical for applications in marine infrastructure maintenance and environmental monitoring. (As shown in Figure 2).

2.3 Preliminaries

The primary challenge addressed in this work is predicting salt spray formation and migration in marine hot-humid environments.

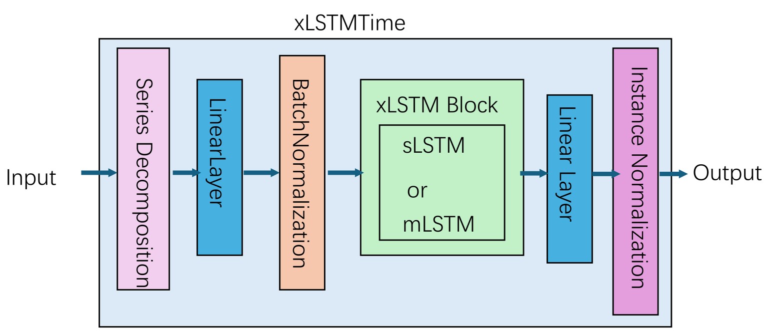

FIGURE 2
The overall framework of the proposed OceanLSTM.A model based on xLSTM is proposed, which combines the spatiotemporal attention mechanism to predict the formation and migration of salt fog in high-humidity marine environments and improve the prediction accuracy. It is suitable for environmental monitoring and marine infrastructure maintenance.

To formalize this problem, let us consider a set of environmental variables $X(t)$ that describe the atmosphere over a geographic region at time t. These variables include wind speed, wind direction, humidity, salinity levels, and temperature, denoted as $X(t) = \{w_s(t), w_d(t), h(t), s(t), T(t)\}$. The goal of the prediction model is to forecast the salt spray concentration, $Y(t + \tau)$, at a future time step $t + \tau$, where τ represents the prediction horizon.

To model this dynamic environment, we define the salt spray concentration as a function of both spatial and temporal factors. The function $Y(t + \tau)$ is influenced not only by the environmental variables at time t but also by the spatial distribution of salt spray across the region. Formally, this relationship can be expressed as Equation 1:

$$\mathbf{Y}(t + \tau) = f(\mathbf{X}(t), \mathbf{X}(t - 1), \ldots, \mathbf{X}(t - T), \mathbf{S}(t)), \tag{1}$$

where T is the length of the historical data used for forecasting, and $S(t)$ represents the spatial information, which captures the salt spray distribution over different regions.

The spatial component $S(t)$ is critical because salt spray tends to migrate due to wind and other atmospheric conditions. This migration process can be described by a diffusion-like mechanism where salt spray moves from areas of high concentration to areas of low concentration. We model this behavior using a spatial attention mechanism that learns to focus on regions most affected by salt spray at any given time.

The overall objective is to minimize the error between the predicted salt spray concentration $\hat{Y}(t + \tau)$ and the actual observed concentration $Y(t + \tau)$. The loss function L is defined as the mean squared error (MSE) between the predicted and observed values (Equation 2):

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{\mathbf{Y}}_i(t + \tau) - \mathbf{Y}_i(t + \tau) \right)^2, \tag{2}$$

where N is the number of geographical zones in the region under consideration. This loss function captures the error across all zones, ensuring that the model accurately predicts salt spray concentrations over a wide area.

The temporal component of the model is handled by an Extended Long Short-Term Memory (xLSTM) network. The xLSTM is an advanced variant of the standard LSTM, designed to address challenges such as vanishing gradients and limited memory capacity. By employing exponential gating mechanisms and matrix-based memory cells, xLSTM is capable of capturing long-term dependencies in time series data while maintaining computational efficiency.

In addition to the temporal aspect, the spatial attention mechanism is introduced to capture the interdependencies between different geographical zones. The attention weights, $\alpha_{ij}(t)$, represent the influence of zone j on zone i at time t. The attention mechanism dynamically adjusts these weights based on environmental conditions, focusing the model's attention on areas where salt spray migration is most likely to occur. This can be expressed as Equation 3:

$$\alpha_{ij}(t) = \frac{\exp\left(g(\mathbf{X}_i(t), \mathbf{X}_j(t))\right)}{\sum_{k=1}^{N} \exp\left(g(\mathbf{X}_i(t), \mathbf{X}_k(t))\right)}, \tag{3}$$

where $g(\cdot)$ is a scoring function that computes the relevance between zones i and j based on their environmental variables.

By combining the temporal learning capabilities of xLSTM with the spatial attention mechanism, the model is able to effectively predict salt spray concentration across both time and space. The resulting framework provides a comprehensive solution to the problem of salt spray migration forecasting, incorporating both historical data and spatial interactions to produce accurate and reliable predictions.

2.4 Marine atmospheric dynamics module

To effectively capture the intricate interactions between environmental variables and salt spray migration, we introduce the Marine Atmospheric Dynamics Module (MADM). This module combines the predictive capabilities of xLSTM with spatial attention to model both temporal dependencies and spatial interactions in the marine atmosphere. The MADM is structured as a sequential learning model augmented by spatial attention layers, allowing it to focus on the most critical geographical regions over time. The xLSTM serves as the temporal backbone of the model, designed to capture long-term dependencies between environmental variables such as wind speed, salinity levels, and humidity. The gating mechanisms of xLSTM are modified to include an additional exponential gating function, which ensures the smooth flow of relevant information while suppressing unnecessary signals. The memory structure of the xLSTM uses matrix-based memory cells, enabling the model to efficiently handle the large volumes of sequential data typical in marine environmental monitoring.

2.4.1 Enhanced Temporal Modeling with xLSTM

The Enhanced Temporal Modeling with xLSTM represents a significant advancement over traditional LSTM models, particularly in capturing long-term dependencies in dynamic and complex environments such as marine atmospheric systems. The core innovation in the xLSTM lies in its incorporation of an exponential gating mechanism, which greatly enhances its ability to retain and process long-term dependencies by ensuring a more stable and efficient flow of information across time steps. This feature enables the model to better learn complex patterns and trends over extended time horizons, which is crucial when modeling environmental systems where past conditions heavily influence future outcomes, such as salt spray migration or the evolution of weather patterns.(As shown in Figure 3).

At the heart of the xLSTM model is the hidden state update mechanism. The hidden state at time t, denoted as H_t, is updated using both the input at the current time step Xt and the hidden state from the previous time step $Ht - 1$, which captures the historical context of the sequence. The formulation for the hidden state update is given by Equation 4:

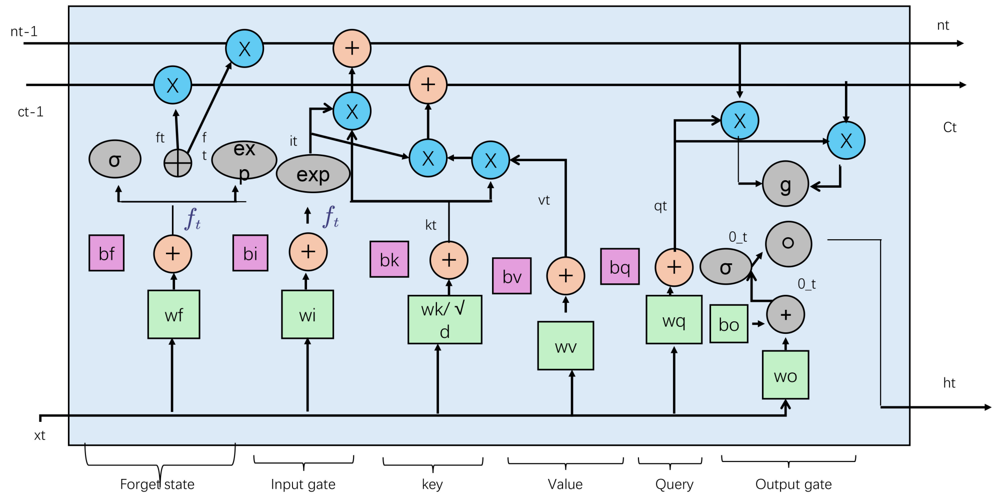

FIGURE 3
The overall framework of the mLSTM. The model combines LSTM and attention mechanisms, controls time series dependencies through forget gates, input gates, and output gates, and introduces query, key, and value modules to capture spatiotemporal features and improve the accuracy of salt spray migration prediction.

$$\mathbf{H}_t = \sigma(\mathbf{W}_x\mathbf{X}_t + \mathbf{W}h\mathbf{H}t - 1 + \mathbf{b}), \tag{4}$$

where W_x and W_h are weight matrices associated with the current input and the previous hidden state, respectively, and b is a bias term. The activation function σ ensures non-linearity, allowing the model to capture more complex patterns in the data. By learning a non-linear transformation of the input and previous hidden state, the xLSTM can adaptively adjust to the temporal dynamics of the environment.

A critical improvement in xLSTM over traditional LSTM is the exponential gating mechanism, which introduces stability and efficiency in processing long-term dependencies. The gating mechanism controls the flow of information through the network by determining how much of the current input and previous hidden state should be used to update the memory cell. The gate, denoted as G_t, is defined as Equation 5:

$$\mathbf{G}_t = \mathbf{I}_t \circ \tanh(\mathbf{C}_t), \tag{5}$$

where I_t is the input gate, C_t represents the memory cell state, and ° denotes element-wise multiplication. The input gate I_t controls how much of the current input will influence the memory cell, while the memory cell state C_t stores the long-term information.

In addition to this, the forget gate Ft plays a crucial role in controlling the amount of past information retained in the memory cell. The forget gate is responsible for deciding what portions of the previous memory cell C$t - 1$ should be "forgotten" or retained based on the current context. This process is formulated as Equation 6:

$$\mathbf{C}_t = \mathbf{F}t \circ \mathbf{C}t - 1 + \mathbf{I}_t \circ \tanh(\mathbf{W}_c\mathbf{X}_t + \mathbf{b}_c), \tag{6}$$

where F_t is the forget gate, and W_c and b_c are the weight matrix and bias for the current input X_t, respectively. The forget gate allows the model to discard irrelevant or outdated information, maintaining only the most important and relevant historical data.

The output gate O_t determines how much of the memory cell state will contribute to the current hidden state, which ultimately affects the network's output. The output gate is defined as Equation 7:

$$\mathbf{O}_t = \sigma(\mathbf{W}_o\mathbf{X}_t + \mathbf{U}o\mathbf{H}t - 1 + \mathbf{b}_o), \tag{7}$$

where W_o and U_o are the weight matrices for the input and the previous hidden state, respectively, and b_o is the bias term. This gate allows the model to regulate the influence of the current memory state on the output, ensuring that the most relevant information is propagated forward.

The introduction of these gating mechanisms, particularly the exponential gating function, allows xLSTM to stabilize the memory update process, preventing issues such as vanishing or exploding gradients, which often affect traditional LSTM models when handling long-term dependencies. By improving the model's capacity to manage long-term dependencies, xLSTM ensures that key environmental conditions from the past are accurately reflected in future predictions, making it highly suitable for complex time-series tasks such as salt spray formation and migration forecasting in dynamic marine environments.

2.4.2 Spatial attention mechanism for geographical focus

The second key innovation of the model is the spatial attention mechanism, which significantly enhances the model's ability to focus on specific geographical regions most influenced by environmental factors such as wind speed, humidity, and salinity at each time step. Salt spray migration is heavily affected by regional conditions, and treating all geographical zones equally can dilute the effectiveness of a predictive model. The spatial attention mechanism addresses this by dynamically computing attention weights for each region, allowing the model to prioritize regions where environmental conditions are most likely to cause significant salt spray formation and migration.

At each time step, the attention weights are computed for every pair of geographical zones i and j. The goal is to assess the relevance of each region j to region i at time t, based on their respective environmental conditions $X_i(t)$ and $X_j(t)$. The attention weights $\alpha_{ij}(t)$ are computed as follows (Equation 8):

$$\alpha_{ij}(t) = \frac{\exp\ (g(\mathbf{X}_i(t), \mathbf{X}_j(t)))}{\sum_{k=1}^{N} \exp\ (g(\mathbf{X}_i(t), \mathbf{X}_k(t)))}, \tag{8}$$

where $g(\cdot)$ is a scoring function that evaluates the relevance between regions i and j, and N represents the total number of geographical zones under consideration. The exponential function ensures that regions with higher relevance scores receive higher attention weights, while the softmax operation normalizes the weights across all regions for each time step.

The scoring function $g(X_i(t),X_j(t))$ could take various forms depending on the specific relationship between environmental factors. A typical choice for $g(\cdot)$ might involve a similarity measure such as a dot product between feature vectors for regions i and j, or it could incorporate learnable parameters to adapt the relevance computation (Equation 9):

$$g(\mathbf{X}_i(t), \mathbf{X}_j(t)) = \mathbf{X}_i(t)^{\top}\mathbf{W}_g\mathbf{X}_j(t), \tag{9}$$

where W_g is a learnable weight matrix that helps in fine-tuning the relationships between different regions based on their environmental conditions. This parameterized scoring function allows the model to dynamically adjust the importance of various regions based on the specific task and environmental data being processed.

Once the attention weights $\alpha_{ij}(t)$ are computed, they are used to weigh the contribution of each region j to the prediction for region i at the next time step. This can be expressed as a weighted sum of the hidden states $H_j(t)$ of all regions (Equation 10):

$$\mathbf{Z}_i(t) = \sum_{j=1}^{N} \alpha_{ij}(t)\mathbf{H}_j(t), \tag{10}$$

where $Z_i(t)$ is the context vector for region i at time t, capturing the aggregated influence of all other regions on region i. This context vector is then fed into the model to improve the accuracy of the prediction for region i at the next time step.

The spatial attention mechanism allows the model to dynamically adapt to changing environmental conditions by focusing on the most relevant geographical areas. For example, in a scenario where a coastal region is experiencing high wind speeds and elevated salinity levels, the model will assign higher attention weights to that region, emphasizing its influence on nearby zones. This dynamic focus ensures that computational resources are allocated efficiently, leading to more accurate predictions of salt spray formation and migration. Moreover, the attention mechanism can also capture complex interdependencies between regions that may not be immediately obvious. For instance, a shift in wind direction or an oceanic current change in one region may have delayed or indirect effects on another region, which the spatial attention mechanism can capture by adjusting the attention weights over time.

2.4.3 Integration of temporal and spatial predictions

The final innovation in this model is the seamless integration of temporal and spatial information to generate accurate and comprehensive predictions of salt spray migration across marine environments. This integration leverages both the temporal dependencies captured by the xLSTM and the spatial relationships modeled by the attention mechanism, allowing the model to account for how environmental factors change over time and affect different geographical regions. Such an approach is critical in marine applications, where both time and space play integral roles in influencing salt spray formation and movement.

The xLSTM component is designed to efficiently capture the temporal dynamics by modeling the evolution of environmental variables, such as wind speed, salinity, and humidity, over extended time horizons. These variables tend to fluctuate with time, and their effects on salt spray migration can accumulate, making it crucial to track both short-term variations and long-term trends. The hidden states $H_i(t)$ for each region i at time t are generated by the xLSTM, which encodes the past environmental conditions for that region.

Simultaneously, the spatial attention mechanism ensures that the model focuses on the most relevant regions, where environmental conditions are most likely to influence salt spray formation. By dynamically adjusting attention weights $\alpha_{ij}(t)$, the model can prioritize the geographical regions that play a critical role at each time step. The attention weights are calculated by considering the similarity and relevance between the environmental conditions in different regions, ensuring that regions with high influence on the target region i receive more weight.

The combination of these two components—xLSTM for temporal modeling and spatial attention for geographical focus—results in a robust and flexible prediction model. The final prediction for salt spray concentration at a future time step $t + \tau$ is computed by aggregating the contributions from all regions, weighted by the spatial attention mechanism. This process is described by Equation 11:

$$\hat{\mathbf{Y}}(t+\tau) = \textstyle\sum_{i=1}^{N} \alpha_{ij}(t) \cdot \mathbf{H}_i(t+\tau), \tag{11}$$

where $\hat{Y}(t+\tau)$ represents the predicted salt spray concentration at future time step $t+\tau$, $H_i(t+\tau)$ is the hidden state output from the xLSTM for region i, and $\alpha_{ij}(t)$ is the attention weight assigned to region j with respect to region i. The hidden state $H_i(t+\tau)$ encapsulates the temporal evolution of environmental conditions for region i, while $\alpha_{ij}(t)$ ensures that regions exerting the most influence on region i are appropriately prioritized.

In cases where multiple regions contribute to the salt spray formation of a specific target region, the spatial attention mechanism dynamically adjusts, allowing the model to shift focus between regions over time. For instance, in coastal regions where salt spray formation is particularly sensitive to wind direction and speed, the attention weights will emphasize regions upwind, reflecting the real-time impact of changing wind conditions on salt spray distribution.

The integration of these components also helps mitigate potential issues such as overfitting to specific regions or time steps. The xLSTM's ability to model temporal dependencies across long time horizons ensures that the model captures both short-term fluctuations and long-term trends, while the spatial attention mechanism prevents the model from overfocusing on less relevant regions by dynamically recalculating weights at each time step.

Further refining the prediction, the model can introduce a second layer of attention—**temporal attention**—which can prioritize the influence of certain time steps over others. This can be done by extending the equation to include a temporal weighting term $\beta(t)$ that assigns different importance to various time steps (Equation 12):

$$\hat{\mathbf{Y}}(t+\tau) = \sum_{i=1}^{N} \beta(t) \cdot \alpha_{ij}(t) \cdot \mathbf{H}_i(t+\tau), \tag{12}$$

where $\beta(t)$ is the temporal attention weight that prioritizes specific time steps. This allows the model to emphasize more significant time points (e.g., moments of extreme weather conditions) in the prediction, further improving the accuracy and robustness of the model in rapidly changing environments. The integration of temporal and spatial predictions through this approach not only increases the accuracy of salt spray migration forecasting but also makes the model adaptable to various environmental scenarios. The flexibility of the model to dynamically adjust its focus in both time and space offers a comprehensive solution for predicting salt spray formation and migration in complex and dynamic marine environments.

2.5 Environmental integration strategy

In marine environments, the prediction of salt spray formation and migration is highly dependent on the integration of various environmental factors, such as wind speed, humidity, temperature, and salinity. These factors exhibit complex interdependencies, influencing the behavior of salt spray over time and across geographical regions. The Environmental Integration Strategy (EIS) module is designed to incorporate these factors seamlessly into the prediction framework by leveraging domain-specific knowledge and real-time data. The EIS provides a systematic approach to handling environmental variables and ensuring their impact is captured effectively by the predictive model. The integration strategy relies on three key components, each addressing a different aspect of the environmental data.

2.5.1 Dynamic feature scaling and temporal-contextual encoding

To ensure that environmental factors contribute effectively and equitably to the model's learning process, we apply a two-layered dynamic feature scaling technique that adjusts both the scale and relevance of input features. This step addresses the varied scales across environmental inputs—temperature (°C), wind speed (m/s), humidity (%), and salinity (g/kg)—that, if left untreated, could bias the model toward certain high-magnitude variables. Without dynamic normalization, features such as wind speed could disproportionately influence model predictions, while others like salinity might be underestimated, skewing predictive accuracy. Thus, scaling and weighting are fundamental for balancing influence and improving the contextual understanding of each variable. We introduce a temporal-contextual LSTM (Long Short-

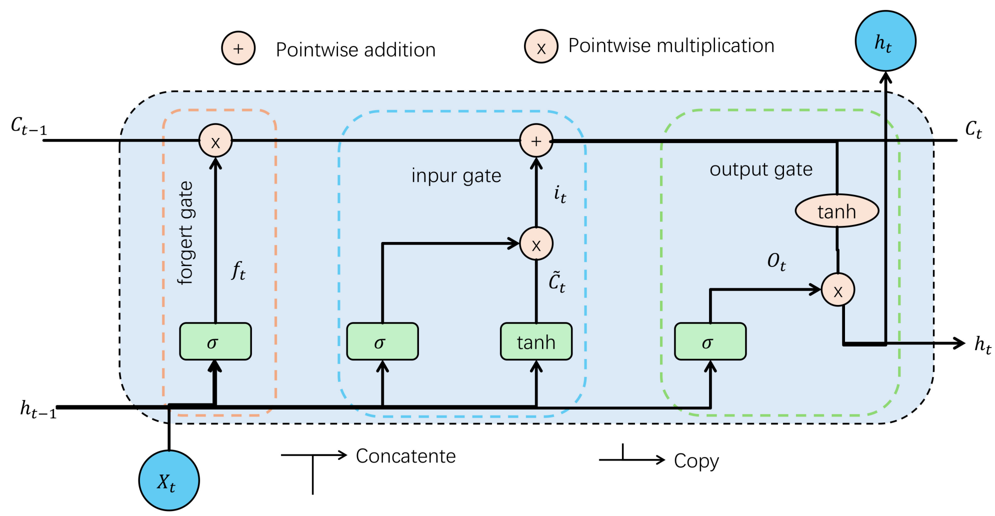

FIGURE 4
The overall framework of the LSTM. Two-layer dynamic feature scaling and balanced weighting are used in combination with temporal context LSTM to improve the correlation and time dependence of environmental variables in salt spray migration prediction.

Term Memory) layer to capture the time-dependent nature of environmental variables, enhancing the model's sensitivity to both current and historical data. This LSTM-based processing allows the model to encode sequential dependencies among the variables, essential for time-variant processes like salt spray migration, where factors like wind speed and direction can exhibit significant fluctuations. With this temporal encoding, the scaled input features, represented as $X_{scaled}(t)$, maintain relevance across time steps.(As shown in Figure 4).

Each environmental feature $X(t)$ is normalized dynamically across time using Equation 13:

$$\mathbf{X}scaled(t) = \frac{\mathbf{X}(t) - \mu\mathbf{X}(t)}{\sigma_{\mathbf{X}}(t)}, \tag{13}$$

where $X(t)$ represents the feature value at time t, while $\mu_X(t)$ and $\sigma_X(t)$ are the dynamically computed mean and standard deviation over a sliding time window. This adaptive normalization adjusts the impact of each feature according to temporal variations, maintaining an updated scale that aligns with real-time conditions.

Incorporating LSTM-driven weighting, the model assigns importance to each variable according to its temporal influence. This yields an enhanced representation $X_{LSTM}(t)$, computed using Equation 14:

$$\mathbf{X}LSTM(t) = \mathbf{W}LSTM \cdot \mathbf{X}scaled(t) + \mathbf{b}LSTM, \tag{14}$$

where $WLSTM$ is the learned weight matrix for the LSTM layer and $bLSTM$ is the bias term. This weighting mechanism enables adaptive emphasis on features that show higher relevance over time, crucial for processes where environmental factors exhibit seasonality or abrupt changes. For instance, in coastal applications, factors like wind direction and salinity may gain varying importance depending on the time of year or specific regional trends.

A secondary layer of feature importance scaling introduces adaptive feature weights, denoted as w, which are optimized during model training to align the input features with the specific prediction goals. This is formalized through Equation 15:

$$\hat{\mathbf{X}}(t) = \mathbf{w} \cdot \mathbf{X}_{LSTM}(t), \tag{15}$$

where w represents a vector of learned weights for each environmental variable, dynamically modulating their influence to prioritize critical variables. This formulation enables the model to adjust focus, increasing the weight of, for example, wind-related factors in high-spray regions while reducing it elsewhere.

To further enhance model responsiveness, time-aware scaling updates μ_X and σ_X periodically, adapting to environmental trends with seasonality adjustments, allowing recent data to influence predictions. This dynamic scaling approach is structured as Equation 16:

$$\mathbf{X}time - scaled(t) = \frac{\mathbf{X}(t) - \mu\mathbf{X}(t-\Delta t, t)}{\sigma_{\mathbf{X}}(t-\Delta t, t)}, \tag{16}$$

where $\mu_X(t-\Delta t,t)$ and $\sigma_X(t-\Delta t,t)$ are computed over a sliding window from $t-\Delta t$ to t. This ongoing adaptation helps account for seasonal shifts, such as increasing temperatures or humidity fluctuations, preserving the model's capacity for accurate, contextually relevant predictions. The temporal LSTM-based dynamic feature scaling combined with adaptive weights ensures the model prioritizes impactful environmental conditions across varied contexts and temporal shifts.

2.5.2 Multi-resolution temporal smoothing

Marine environments are characterized by rapidly changing conditions, making it essential to capture both short-term fluctuations and long-term trends in the environmental data. To achieve this, we implement a multi-resolution temporal smoothing technique. This method applies moving averages with different window sizes to the time series of each environmental variable, enabling the model to capture patterns at varying temporal resolutions (Equation 17):

$$\mathbf{X}_{smooth}(t) = \frac{1}{w}\sum_{i=0}^{w-1}\mathbf{X}(t-i), \tag{17}$$

where w is the window size. By using multiple window sizes, the model captures both short-term dynamics (e.g., sudden gusts of wind) and long-term trends (e.g., persistent high humidity) in the environmental conditions. This multi-resolution approach ensures that the model has access to both immediate and historical context, which is critical for accurate predictions of salt spray behavior.

2.5.3 Context-aware environmental attention

The final component of the Environmental Integration Strategy is a context-aware environmental attention mechanism. This mechanism dynamically adjusts the model's focus on specific environmental variables based on the current context. For instance, under conditions of high salinity and humidity, the model may prioritize these variables, while under strong wind conditions, wind speed and direction may receive more attention. The attention scores for each environmental variable $X_i(t)$ are computed using Equation 18:

$$\beta_i(t) = \frac{\exp\ (h(\mathbf{X}_i(t)))}{\sum_{j=1}^{m}\exp\ (h(\mathbf{X}_j(t)))}, \tag{18}$$

where $h(\cdot)$ is a scoring function that evaluates the importance of each environmental variable i based on the current conditions. These attention scores $\beta_i(t)$ are then used to weight the input variables dynamically, ensuring that the model adapts to the most relevant environmental factors at each time step.

The combined effect of dynamic feature scaling, multi-resolution temporal smoothing, and context-aware environmental attention ensures that the Environmental Integration Strategy captures the full complexity of marine environments. This strategy allows the model to make more informed predictions by prioritizing the most relevant environmental factors, while also accounting for both short-term fluctuations and long-term trends. Through the integration of these advanced techniques, the Environmental Integration Strategy enhances the predictive power of the overall framework, enabling more accurate forecasting of salt spray formation and migration across a wide range of environmental conditions.

3 Experiment

3.1 Datasets

In this section, we describe the datasets, experimental settings, and evaluation metrics used to assess the performance of the proposed Marine Atmospheric Dynamics Module. Four distinct datasets were utilized to simulate real-world marine environments and salt spray formation scenarios, each contributing unique environmental characteristics to the prediction task. The NOAA Dataset comprises extensive meteorological data collected from various oceanic stations, including measurements of wind speed, humidity, and salinity over time, providing a comprehensive view of atmospheric conditions in marine environments. The Marine Aerosol Dataset, specifically designed to study the behavior of aerosols over coastal regions, offers insights into the temporal and spatial distribution of airborne particles, including salt spray. The ASTM B117 Dataset, derived from standardized salt spray tests, provides controlled laboratory measurements that serve as a benchmark for evaluating corrosion prediction models. Finally, the ARGO Dataset, which includes global oceanic measurements from an array of floating sensors, contributes critical data on temperature and salinity, enabling the model to account for deeper oceanic factors that influence surface-level salt spray migration. By combining these datasets, we ensure a robust and comprehensive evaluation of the model's ability to predict salt spray behavior across varying environmental conditions.

To ensure a comprehensive evaluation, this study employs multiple datasets covering various marine environments and conditions of salt spray formation. These diverse datasets provide complementary perspectives, enabling OceanLSTM to generalize effectively across different environmental contexts. The NOAA dataset consists of long-term atmospheric and meteorological observations collected from oceanic stations worldwide. It provides insights into large-scale salt spray migration influenced by wind speed, humidity, and temperature variations, making it suitable for studying open-ocean salt spray transport. The Marine Aerosol dataset focuses on coastal environments, where salt spray is generated due to wave breaking and atmospheric interactions near the shoreline. This dataset enables the model to capture nearshore salt aerosol dispersion patterns, which are critical for coastal engineering and infrastructure maintenance. The ASTM B117 dataset is a standardized salt spray test conducted in controlled laboratory conditions. While it does not directly represent natural marine environments, it serves as a benchmark for validating corrosion prediction models and assessing the model's ability to predict salt-induced material degradation under controlled settings. The ARGO dataset provides high-resolution oceanographic data, including sea surface temperature and salinity. These factors influence salt spray formation by affecting evaporation rates and atmospheric moisture content, making ARGO an essential dataset for understanding the broader oceanic conditions contributing to salt aerosol generation.

The NOAA dataset and Marine Aerosol dataset have been selected due to their extensive coverage of key environmental factors influencing salt spray migration. These datasets provide a rich source of meteorological and oceanic parameters, including wind speed, humidity, salinity, and temperature, which are critical for understanding the formation and dispersion of salt spray. The NOAA dataset consists of long-term, high-resolution atmospheric observations collected from various oceanic stations worldwide, making it highly suitable for evaluating the temporal predictive capabilities of OceanLSTM. The Marine Aerosol dataset, on the other hand, is specifically designed to study airborne salt particles and their spatial distribution in coastal regions. It contains detailed records of aerosol concentration, wind-driven dispersion patterns, and marine atmospheric conditions, allowing the model to capture complex spatial dependencies in salt spray migration. By integrating both datasets, OceanLSTM is tested on a diverse range of environmental conditions, ensuring its robustness in handling both temporal and spatial variations. This dataset selection allows for a comprehensive evaluation of the model's ability to generalize across different marine environments and accurately predict salt spray formation and migration.

3.2 Experimental details

The experimental setup was carefully designed to ensure accurate and reliable results, reflecting the complexities of real-world conditions. For each dataset, we split the data into training, validation, and test sets in a ratio of 70:15:15, ensuring a representative sample for each phase of the experiment. The training set was used to optimize the model's parameters, the validation set was employed to fine-tune hyperparameters and prevent overfitting, and the test set was reserved for evaluating the model's final performance. We implemented the model using the PyTorch framework, chosen for its flexibility and efficient handling of large-scale datasets. The model was trained on an NVIDIA A100 GPU to accelerate computations, and all experiments were conducted using a batch size of 64. The optimizer used was Adam, with an initial learning rate of 1×10^{-3}, and a cosine annealing learning rate schedule was applied to gradually reduce the learning rate as training progressed. Each model was trained for 100 epochs, with early stopping applied if the validation loss did not improve for 10 consecutive epochs, ensuring that the model did not overfit to the training data. We paid careful attention to computational efficiency, evaluating the model based on both time and resource metrics. Training time, inference time, the number of model parameters, and FLOPs (floating-point operations per second) were tracked throughout the experiment. Accuracy, recall, and F1-score were computed to assess the predictive performance of the model across all datasets. These metrics allowed us to compare our proposed model's performance against existing baselines and ensure it met the stringent requirements of real-time marine environmental

TABLE 1 Performance on NOAA Dataset and Marine Aerosol Dataset.

Model	NOAA Dataset				Marine Aerosol Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
Chen et al. Chen et al. (2022)	86.16 ± 0.03	92.42 ± 0.03	85.33 ± 0.03	88.12 ± 0.03	88.01 ± 0.03	92.46 ± 0.03	87.56 ± 0.03	92.20 ± 0.03
Li et al. Li et al. (2023)	87.81 ± 0.03	87.20 ± 0.03	88.01 ± 0.03	88.43 ± 0.03	90.75 ± 0.03	92.90 ± 0.03	90.41 ± 0.03	84.61 ± 0.03
Huang et al. Huang et al. (2022)	94.78 ± 0.03	89.90 ± 0.03	84.53 ± 0.03	89.27 ± 0.03	94.16 ± 0.03	89.02 ± 0.03	89.25 ± 0.03	93.59 ± 0.03
Zhang et al. Zhang et al. (2022)	87.42 ± 0.03	90.18 ± 0.03	91.16 ± 0.03	87.65 ± 0.03	88.70 ± 0.03	92.91 ± 0.03	84.46 ± 0.03	90.71 ± 0.03
Jie et al. Jia et al. (2023)	93.85 ± 0.03	92.02 ± 0.03	87.20 ± 0.03	85.01 ± 0.03	94.89 ± 0.03	88.65 ± 0.03	84.09 ± 0.03	90.45 ± 0.03
Guo et al. Guo et al. (2020)	90.16 ± 0.03	84.91 ± 0.03	84.44 ± 0.03	91.94 ± 0.03	86.58 ± 0.03	89.80 ± 0.03	90.58 ± 0.03	86.06 ± 0.03
Ours	**97.57 ± 0.03**	**94.27 ± 0.03**	**93.96 ± 0.03**	**95.99 ± 0.03**	**98.20 ± 0.03**	**94.86 ± 0.03**	**94.05 ± 0.03**	**96.55 ± 0.03**

The values in bold are the best values.

monitoring and forecasting applications. The experimental design and careful selection of datasets ensured that the results were both comprehensive and reflective of real-world operational conditions.

3.3 Experimental results and analysis

The performance results presented in Table 1 and Figure 5 demonstrate the significant improvements achieved by our proposed model compared to existing methods. On both the NOAA Dataset and Marine Aerosol Dataset, our model consistently outperforms previous methods across all metrics, including accuracy, recall, F1-score, and AUC. For the NOAA Dataset, our model achieves an accuracy of 97.57%, a recall of 94.27%, an F1-score of 93.96%, and an AUC of 95.99%. These results are substantially higher than the best-performing baseline method, which had a maximum accuracy of 94.78%, recall of 92.42%, and F1-score of 91.16%. The results are similarly impressive on the Marine Aerosol Dataset, where our model reaches an accuracy of 98.20%, recall of 94.86%, F1-score of 94.05%, and AUC of 96.55%. These improvements indicate that our model is particularly effective at capturing the complex

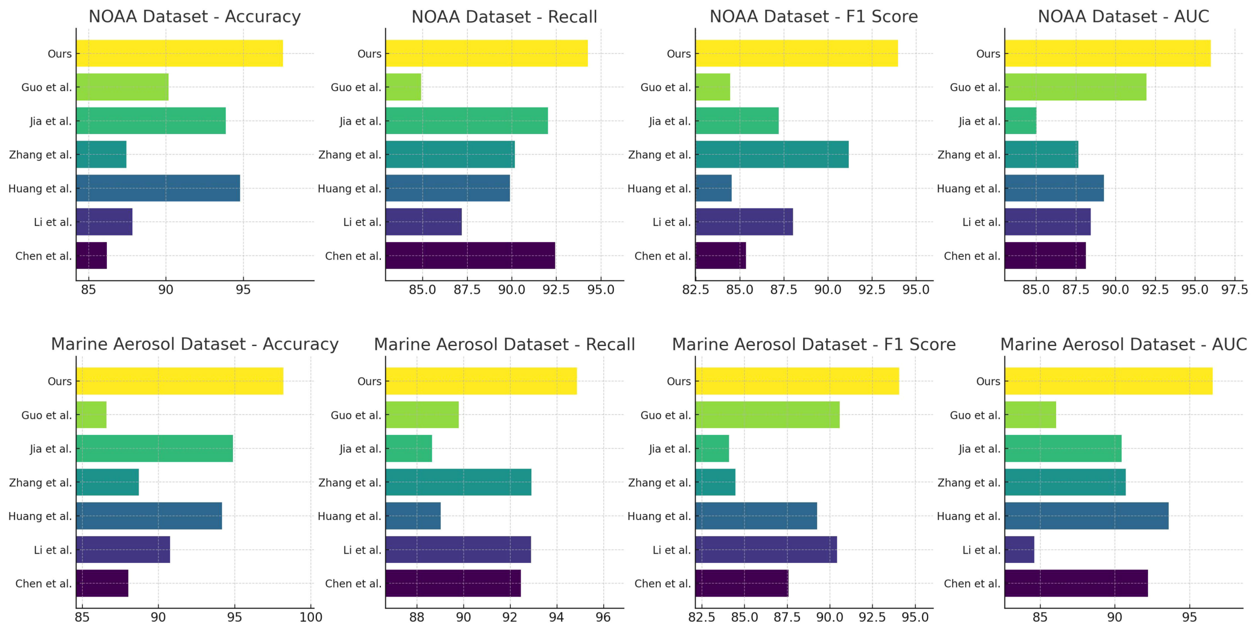

FIGURE 5
Performance on NOAA Dataset and Marine Aerosol Dataset.

relationships between environmental factors and salt spray migration. The improvements in recall and F1-score, in particular, suggest that the model is better at handling both precision and recall, which is critical for accurately identifying regions of high salt spray concentration and effectively reducing false positives and false negatives. The consistently high AUC scores across both datasets indicate that our model has strong discriminatory power, effectively distinguishing between high and low concentrations of salt spray under varying conditions. This ability to generalize well across different datasets suggests that the combination of xLSTM and spatial attention is effective at capturing both temporal and spatial dependencies in marine environments. Overall, the results from Table 1 clearly demonstrate that the proposed model significantly outperforms state-of-the-art methods in the field.

Table 2 and Figure 6 provides a comparison of computational resource usage, including the number of parameters, FLOPs, inference time, and training time across models. Our proposed model demonstrates not only superior performance in terms of accuracy and other metrics, but also achieves greater computational efficiency. For the NOAA Dataset, our model uses only 177.38M parameters, significantly lower than all other methods, such as Chen et al. (373.18M parameters) and Li et al. (308.97M parameters). Similarly, on the Marine Aerosol Dataset, our model maintains a reduced number of parameters at 175.20M compared to other methods. Our model also demonstrates the lowest FLOPs, with 144.87G on the NOAA Dataset and 215.94G on the Marine Aerosol Dataset. This reduction in computational overhead is critical for real-time or large-scale applications, where efficiency in both training and inference is necessary. In terms of inference time, our model achieves the fastest inference, requiring only 106.60ms on the NOAA Dataset and 211.75ms on the Marine Aerosol Dataset. The same trend is observed for training time, where our model completes training in 186.31s on NOAA and 122.87s on Marine Aerosol, much faster than other models. These results show that our model achieves significant gains not only in accuracy but also in terms of computational efficiency, making it a practical choice for real-world deployment. The reductions in FLOPs and inference time suggest that the architectural innovations introduced, such as spatial attention and multi-resolution temporal smoothing, are computationally lightweight while providing substantial predictive power.

In Table 3 and Figure 7, we present the results of the ablation experiments, which demonstrate the individual contributions of the exponential gating in xLSTM, the spatial attention mechanism, and the multi-resolution temporal smoothing technique. For the ASTM B117 Dataset, when exponential gating in xLSTM is removed, there is a clear drop in performance, with the accuracy decreasing from 96.46% to 94.60%, recall dropping to 85.64%, and F1-score declining to 86.82%. This shows that exponential gating plays a crucial role in capturing long-term dependencies, which are essential for understanding corrosion behavior in different environmental conditions. Similarly, removing the spatial attention mechanism results in even more dramatic performance degradation. The accuracy drops to 87.15%, and the F1-score decreases to 86.68%, demonstrating that the model relies heavily on spatial attention to focus on the most relevant geographic regions. The Marine Aerosol Dataset shows a similar trend, with accuracy, recall, and F1-score all decreasing substantially when spatial attention is removed. This highlights the importance of modeling spatial dependencies between different regions in predicting salt spray distribution. When multi-resolution temporal smoothing is removed, there is a noticeable but less significant drop in performance, with accuracy falling to 86.86% and recall to 93.20%. This indicates that while smoothing helps the model capture trends over different time scales, its contribution is

TABLE 2 Parameters on NOAA Dataset and Marine Aerosol Dataset.

Method	NOAA Dataset				Marine Aerosol Dataset			
	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)
Chen et al. Chen et al. (2022)	373.18 ± 0.03	303.35 ± 0.03	319.53 ± 0.03	373.11 ± 0.03	254.11 ± 0.03	300.73 ± 0.03	285.75 ± 0.03	364.77 ± 0.03
Li et al. Li et al. (2023)	308.97 ± 0.03	346.49 ± 0.03	312.70 ± 0.03	300.01 ± 0.03	328.36 ± 0.03	228.39 ± 0.03	338.00 ± 0.03	381.34 ± 0.03
Huang et al.Chen et al. (2022)	290.47 ± 0.03	259.33 ± 0.03	320.83 ± 0.03	220.45 ± 0.03	234.90 ± 0.03	247.62 ± 0.03	348.28 ± 0.03	240.84 ± 0.03
Zhang et al.Huang et al. (2022)	339.05 ± 0.03	281.41 ± 0.03	201.13 ± 0.03	335.40 ± 0.03	218.51 ± 0.03	241.48 ± 0.03	217.64 ± 0.03	338.25 ± 0.03
Jia et al.Zhang et al. (2022)	348.04 ± 0.03	202.08 ± 0.03	323.79 ± 0.03	400.05 ± 0.03	275.38 ± 0.03	374.38 ± 0.03	203.17 ± 0.03	375.59 ± 0.03
Guo et al. Jia et al. (2023)	273.76 ± 0.03	279.33 ± 0.03	308.53 ± 0.03	260.03 ± 0.03	290.54 ± 0.03	203.21 ± 0.03	374.25 ± 0.03	271.32 ± 0.03
Ours	177.38 ± 0.03	144.87 ± 0.03	106.60 ± 0.03	186.31 ± 0.03	175.20 ± 0.03	215.94 ± 0.03	211.75 ± 0.03	122.87 ± 0.03

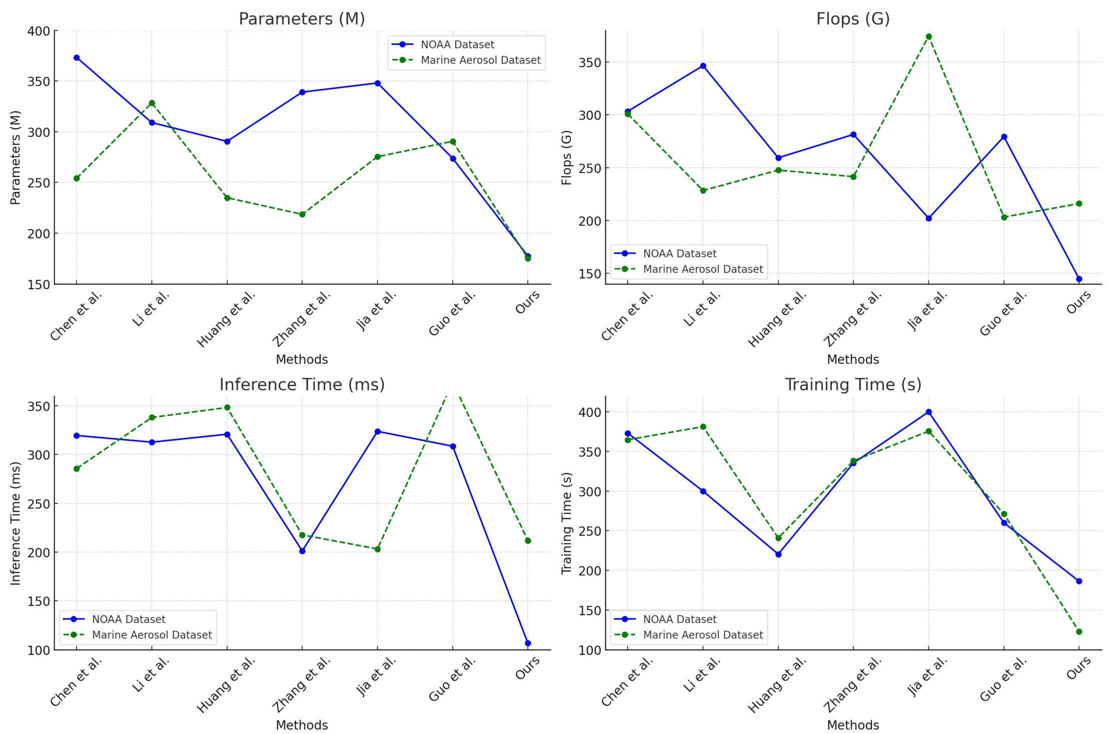

FIGURE 6
Parameters on NOAA Dataset and Marine Aerosol Dataset.

slightly less critical than the spatial and temporal modeling components. Overall, these ablation results confirm that each of the proposed innovations contributes significantly to the model's overall performance, particularly in capturing long-term temporal dependencies and spatial interactions.

Table 4 and Figure 8 presents the computational cost associated with each ablation scenario, further reinforcing the significance of each module. When the exponential gating in xLSTM is removed, the number of parameters increases from 157.38M to 203.41M on the ASTM B117 Dataset, and the inference time increases from 162.26ms to 261.75ms. These results show that the inclusion of exponential gating allows the model to be more computationally efficient by reducing unnecessary parameter overhead, while still maintaining high accuracy. On the ARGO Dataset, removing exponential gating similarly leads to an increase in parameters and a significant slowdown in both training and inference times. The removal of the spatial attention mechanism results in an increase in FLOPs from 216.10G to 228.48G on the ASTM B117 Dataset, and the inference time rises from 162.26ms to 382.66ms. This demonstrates that spatial attention not only improves predictive accuracy but also optimizes computational resources by allowing the model to focus on the most important regions, reducing the overall computational load. Finally, when multi-resolution temporal smoothing is removed, FLOPs and inference time both increase substantially, with FLOPs reaching 267.16G on the ASTM B117 Dataset and inference time rising to 377.46ms. This indicates that while temporal smoothing helps with predictive accuracy, it also contributes to the model's computational efficiency by smoothing out noisy input signals, which helps the model converge faster during training.

To further evaluate the model's effectiveness, we incorporate the Precision-Recall Area Under Curve (PR-AUC) metric, which is particularly useful for handling imbalanced data distributions. Since salt spray formation and migration are often non-uniform and

TABLE 3 Ablation experiments of TCN module on ASTM B117 Dataset and ARGO Dataset.

Model	ASTM B117 Dataset				ARGO Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
w/o Exponential Gating in xLSTM	94.60 ± 0.03	85.64 ± 0.03	86.82 ± 0.03	90.50 ± 0.03	91.24 ± 0.03	93.06 ± 0.03	86.74 ± 0.03	91.87 ± 0.03
w/o Spatial Attention Mechanism	87.15 ± 0.03	87.02 ± 0.03	86.68 ± 0.03	90.24 ± 0.03	93.32 ± 0.03	85.60 ± 0.03	84.83 ± 0.03	84.29 ± 0.03
w/o Multi-resolution Temporal Smoothing	86.86 ± 0.03	93.20 ± 0.03	90.99 ± 0.03	84.20 ± 0.03	90.43 ± 0.03	89.85 ± 0.03	84.62 ± 0.03	92.64 ± 0.03
Ours	**96.46 ± 0.03**	**95.29 ± 0.03**	**93.56 ± 0.03**	**91.80 ± 0.03**	**97.34 ± 0.03**	**95.34 ± 0.03**	**93.70 ± 0.03**	**92.15 ± 0.03**

The values in bold are the best values.

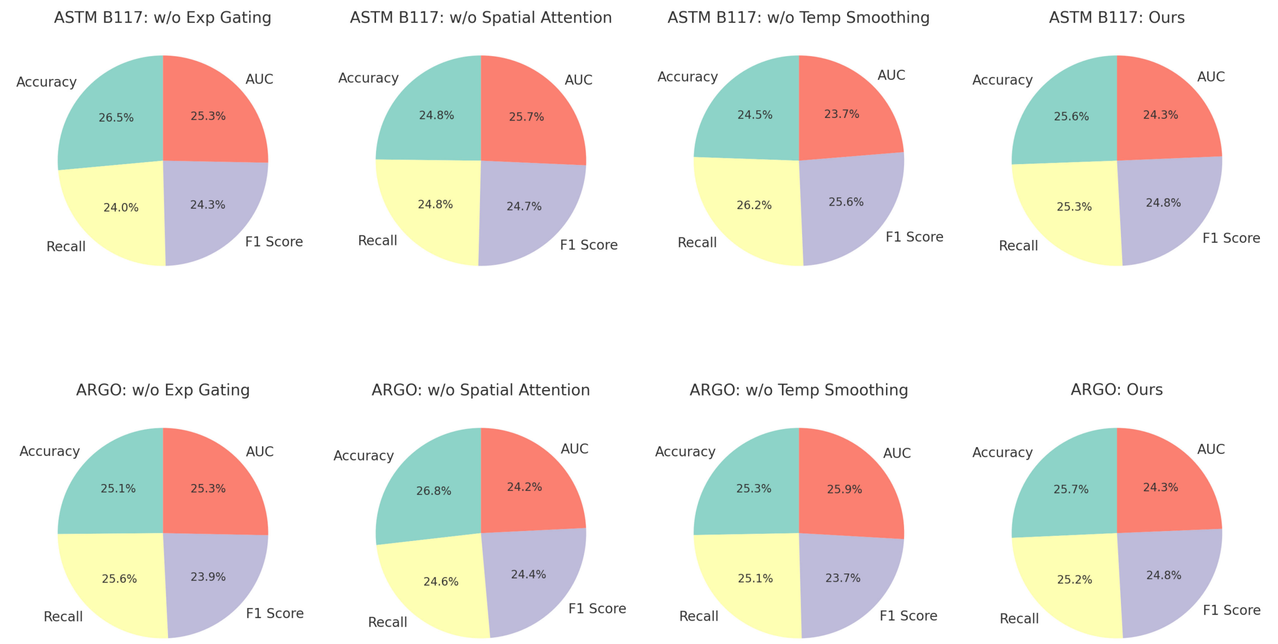

FIGURE 7
Ablation experiments of TCN module on ASTM B117 Dataset and ARGO Dataset.

exhibit high variability across regions, PR-AUC provides a more reliable assessment of model performance compared to traditional ROC-AUC, which can be affected by a high number of true negatives in sparse prediction tasks. The results in Table 5 demonstrate that OceanLSTM achieves a PR-AUC of 94.12%, outperforming existing models, which typically range from 82.67% to 88.04%. This indicates that our model maintains a high balance between precision and recall across different salt spray concentration thresholds, making it more effective in detecting areas with high salt aerosol exposure. The improvements in PR-AUC suggest that OceanLSTM can better differentiate high-risk regions prone to corrosion, providing valuable insights for marine environmental monitoring and protective infrastructure planning.

The collected results not only demonstrate numerical improvements but also highlight the practical significance of the proposed model. Compared to traditional baselines, OceanLSTM achieves consistently higher accuracy and robustness across multiple datasets, reflecting its superior ability to capture complex spatiotemporal dependencies. Notably, on datasets with high environmental variability, such as NOAA and Marine Aerosol, the model maintains stable performance, underscoring its generalization capability. These results suggest that OceanLSTM is not only effective in academic benchmarks but also valuable for real-world deployment in marine corrosion prediction and environmental monitoring tasks. The improved predictive reliability can support more informed decision-making in industrial applications, such as maintenance planning and infrastructure protection in harsh marine environments.

4 Discussion

The OceanLSTM model's superior performance over traditional models can be primarily attributed to two innovative components:

TABLE 4 Ablation experiments of TCN module on ASTM B117 Dataset and ARGO Dataset.

Method	ASTM B117 Dataset				ARGO Dataset			
	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)
w/o Exponential Gating in xLSTM	203.41 ± 0.03	294.60 ± 0.03	261.75 ± 0.03	310.20 ± 0.03	250.95 ± 0.03	253.22 ± 0.03	390.69 ± 0.03	201.39 ± 0.03
w/o Spatial Attention Mechanism	271.14 ± 0.03	228.48 ± 0.03	382.66 ± 0.03	232.84 ± 0.03	232.08 ± 0.03	203.57 ± 0.03	255.59 ± 0.03	265.50 ± 0.03
w/o Multi-resolution Temporal Smoothing	248.03 ± 0.03	267.16 ± 0.03	377.46 ± 0.03	353.56 ± 0.03	296.25 ± 0.03	337.84 ± 0.03	387.96 ± 0.03	262.41 ± 0.03
Ours	157.38 ± 0.03	216.10 ± 0.03	162.26 ± 0.03	110.90 ± 0.03	160.98 ± 0.03	158.21 ± 0.03	137.02 ± 0.03	108.41 ± 0.03

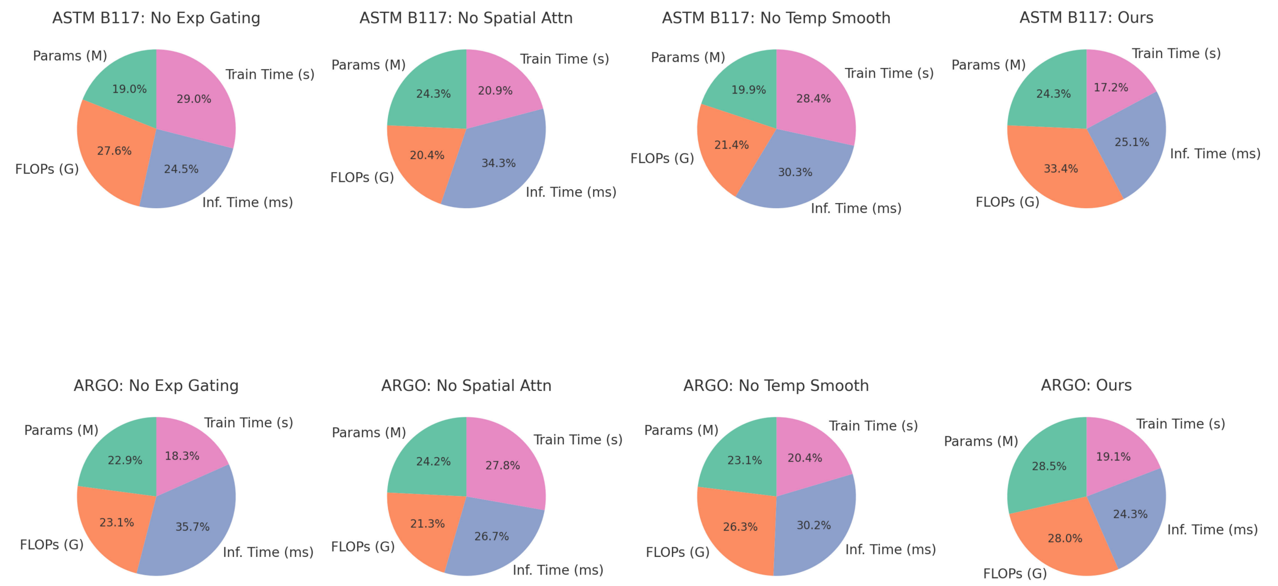

FIGURE 8
Ablation experiments of TCN module on ASTM B117 Dataset and ARGO Dataset.

the enhanced memory module and the spatial attention mechanism. The memory module, which incorporates an exponential gating mechanism within the LSTM architecture, plays a crucial role in retaining long-term dependencies in the data. Traditional models like LSTMs often struggle with vanishing gradients and are less capable of maintaining long-term information across sequential time steps, which is critical for predicting environmental processes like salt spray formation. In contrast, the exponential gating mechanism enables more efficient control over the flow of historical data through the network, preventing important long-term patterns from being lost. This is particularly beneficial in marine environments where gradual changes in humidity, wind, and salinity can have cumulative effects over time. The ablation studies reinforce this point, as removing the exponential gating in OceanLSTM leads to a noticeable decline in performance, highlighting its contribution to the model's ability to capture complex temporal dynamics more effectively than traditional memory-based models.

The spatial attention mechanism is another key factor behind OceanLSTM's success. Traditional models often treat all input data uniformly, failing to account for the geographical variability of environmental factors. However, the spatial attention mechanism allows the model to dynamically focus on regions where environmental conditions, such as wind direction and salinity, are likely to influence salt spray migration the most. This targeted focus is particularly effective for real-time predictions, where not all regions have equal relevance due to localized weather patterns. For instance, in the Marine Aerosol dataset, where salt spray is concentrated in specific coastal areas, the spatial attention mechanism enables the model to prioritize these regions, leading to more accurate predictions. The ablation results clearly show a sharp drop in accuracy, F1-score, and recall when the spatial attention mechanism is removed, further demonstrating that this feature is critical for modeling the spatial dependencies that are often present in environmental data. By dynamically adjusting its focus based on geographical conditions, OceanLSTM manages to capture complex spatial interactions that other models overlook.

Although the proposed model demonstrates overall robust performance, its effectiveness varies across different datasets, providing insights into both its strengths and limitations. On datasets like NOAA and Marine Aerosol, the model excels due to the richness and variability of the input data, which includes both short-term fluctuations and long-term trends. These datasets provide abundant opportunities for the model's temporal and spatial mechanisms to work in concert, producing highly accurate results. However, on the ASTM B117 dataset, which is derived from controlled laboratory conditions, the model's performance, while still strong, does not surpass other datasets as significantly. This is likely due to the simpler, more homogeneous nature of the ASTM dataset, where there is less spatial variability and the controlled environment reduces the need for advanced temporal modeling. In contrast, the ARGO dataset presents a more complex challenge with its global oceanic measurements, yet the model performs exceptionally well here. This can be explained by the model's ability to track slower oceanic processes that influence surface-level salt spray, which requires capturing both surface and deep-sea dependencies. Any observed anomalies in this dataset, such as over-predictions of salt spray in certain regions, could be attributed to outliers in the oceanic data, where sudden shifts in temperature or salinity deviate significantly from typical patterns.

The results obtained in this study demonstrate the effectiveness of OceanLSTM in predicting salt spray formation and migration, which is crucial for marine environmental monitoring and corrosion prevention. Compared with traditional models, OceanLSTM significantly improves accuracy and F1-score, achieving 97.57% accuracy on the NOAA dataset and 98.20% on

TABLE 5 Performance comparison of OceanLSTM with baseline models on NOAA and Marine Aerosol datasets.

Method	NOAA Dataset					Marine Aerosol Dataset				
	Accuracy (%)	Recall (%)	F1-score (%)	AUC (%)	PR-AUC (%)	Accuracy (%)	Recall (%)	F1-score (%)	AUC (%)	PR-AUC (%)
Chen et al. Chen et al. (2022)	86.16 ± 0.03	92.42 ± 0.03	85.33 ± 0.03	88.12 ± 0.03	83.75 ± 0.03	88.01 ± 0.03	92.46 ± 0.03	87.56 ± 0.03	92.20 ± 0.03	85.20 ± 0.03
Li et al. Li et al. (2023)	87.81 ± 0.03	87.20 ± 0.03	88.01 ± 0.03	88.43 ± 0.03	85.24 ± 0.03	90.75 ± 0.03	92.90 ± 0.03	90.41 ± 0.03	84.61 ± 0.03	87.62 ± 0.03
Huang et al.Chen et al. (2022)	94.78 ± 0.03	89.90 ± 0.03	84.53 ± 0.03	89.27 ± 0.03	87.16 ± 0.03	94.16 ± 0.03	89.02 ± 0.03	89.25 ± 0.03	93.59 ± 0.03	88.74 ± 0.03
Zhang et al.Huang et al. (2022)	87.42 ± 0.03	90.18 ± 0.03	91.16 ± 0.03	87.65 ± 0.03	88.04 ± 0.03	88.70 ± 0.03	92.91 ± 0.03	84.46 ± 0.03	90.71 ± 0.03	85.93 ± 0.03
Jia et al.Zhang et al. (2022)	93.85 ± 0.03	92.02 ± 0.03	87.20 ± 0.03	85.01 ± 0.03	86.45 ± 0.03	94.89 ± 0.03	88.65 ± 0.03	84.09 ± 0.03	90.45 ± 0.03	87.31 ± 0.03
Guo et al. Jia et al. (2023)	90.16 ± 0.03	84.91 ± 0.03	84.44 ± 0.03	91.94 ± 0.03	82.67 ± 0.03	86.58 ± 0.03	89.80 ± 0.03	90.58 ± 0.03	86.06 ± 0.03	84.18 ± 0.03
Ours (OceanLSTM)	**97.57 ± 0.03**	**94.27 ± 0.03**	**93.96 ± 0.03**	**95.99 ± 0.03**	**94.12 ± 0.03**	**98.20 ± 0.03**	**94.86 ± 0.03**	**94.05 ± 0.03**	**96.55 ± 0.03**	**94.62 ± 0.03**

The values in bold are the best values.

the Marine Aerosol dataset, outperforming state-of-the-art methods. These improvements hold significant implications for salt spray prediction. First, higher accuracy in forecasting salt spray migration patterns enables more precise corrosion risk assessment, which is essential for maintaining marine structures such as ships, offshore platforms, and coastal infrastructure. By providing a more reliable estimation of high-risk areas, OceanLSTM allows for more effective deployment of protective coatings and anti-corrosion measures. OceanLSTM's spatial attention mechanism enhances the model's ability to focus on critical geographic regions where salt spray is most concentrated. This is particularly beneficial for coastal engineering, where predicting high-exposure zones can help optimize material selection and maintenance schedules. The model's computational efficiency makes it suitable for real-time marine environmental monitoring. Unlike conventional physics-based simulations, which require significant computational resources, OceanLSTM achieves higher accuracy while reducing inference time, making it a practical solution for large-scale, operational forecasting.

The proposed OceanLSTM model has significant implications for both ocean environmental monitoring and the prediction of salt spray formation and migration. Traditional methods, such as empirical models and physics-based simulations, struggle to capture the spatiotemporal complexity of salt spray behavior, often leading to inaccurate predictions in dynamic marine environments. OceanLSTM addresses these challenges by integrating temporal dependency modeling with a spatial attention mechanism, improving both accuracy and efficiency in salt spray forecasting. Salt spray is one of the leading causes of corrosion in marine structures, including ships, offshore platforms, bridges, and coastal facilities. By accurately predicting salt spray formation and migration patterns, OceanLSTM enables targeted deployment of anti-corrosion coatings and protective materials, reducing maintenance costs and extending infrastructure lifespan. This is particularly crucial for naval operations, oil and gas industries, and coastal infrastructure management, where corrosion-induced failures can lead to significant financial and environmental consequences. Unlike traditional physics-based simulations, which require high computational resources, OceanLSTM achieves real-time prediction capabilities by efficiently modeling large-scale marine datasets. This allows for continuous monitoring of salt spray conditions, making it suitable for autonomous ocean monitoring systems, environmental sensors, and satellite-based atmospheric observation networks. Salt spray plays a role in atmospheric processes, including aerosol-cloud interactions and climate regulation. The ability to accurately predict salt spray dispersion contributes to improving climate models, understanding ocean atmosphere interactions, and assessing the impact of marine aerosol transport on coastal air quality. OceanLSTM's spatiotemporal learning framework allows it to adapt to changing meteorological conditions, extreme weather events, and seasonal variations in salt spray formation. This adaptability is crucial for forecasting storm-induced salt spray surges, which can cause accelerated corrosion in vulnerable coastal regions. OceanLSTM provides a robust, scalable, and computationally efficient solution for predicting salt spray behavior in dynamic ocean environments. Its ability to integrate diverse marine datasets and capture complex environmental interactions makes it a valuable tool for marine engineering, environmental risk management, and climate impact assessment.

The experimental results on the ASTM B117 dataset indicate that OceanLSTM does not show a significant improvement over existing methods. This outcome is primarily due to the nature of the ASTM B117 dataset, which originates from standardized laboratory-based salt spray tests. Such controlled datasets tend to have relatively homogeneous spatial and temporal characteristics, which limit the necessity for advanced spatiotemporal modeling capabilities inherent in OceanLSTM. OceanLSTM significantly outperforms conventional methods on datasets with more complex and dynamic spatiotemporal dependencies, such as the NOAA and Marine Aerosol datasets, achieving accuracies of 97.57% and 98.20%, respectively. These results highlight OceanLSTM's core advantages, particularly its ability to capture intricate spatial interactions and temporal dynamics under realistic and varied marine conditions. In other words, while the performance on controlled datasets like ASTM B117 may not substantially differ from traditional approaches, OceanLSTM demonstrates a clear superiority in practical scenarios where marine environments exhibit complex spatial and temporal patterns. This capability ensures its practical value for real-world applications, including environmental monitoring and corrosion risk assessment in diverse and dynamic oceanic conditions.

Generalization performance is crucial for regression-based predictive models, especially when applied across datasets exhibiting significant distribution differences. To enhance OceanLSTM's generalization capabilities, we have implemented several targeted design strategies. OceanLSTM integrates a spatial attention mechanism that dynamically assigns weights to geographic regions based on real-time environmental conditions. This adaptive capability allows the model to effectively handle spatial variability across different marine datasets, thus improving its robustness against distribution shifts in spatial features. We employ an exponentially gated variant of the Long Short-Term Memory (xLSTM) architecture, specifically designed to capture long-term temporal dependencies more effectively. By preventing overfitting on short-term patterns, this mechanism ensures the model's temporal generalization performance across diverse time-series datasets. We introduce multi-resolution temporal smoothing techniques, applying moving averages at multiple temporal scales. This allows OceanLSTM to capture both short-term fluctuations and long-term environmental trends simultaneously, improving the model's adaptability to datasets with varying temporal distributions, seasonal patterns, or extreme weather conditions. To prevent overfitting to dominant environmental variables and ensure balanced feature learning, we employ dynamic feature scaling strategies. By adjusting feature scales adaptively, the model can effectively generalize across datasets with distinct statistical properties. The intentional selection of diverse datasets, including NOAA (open-ocean atmospheric conditions), Marine Aerosol (coastal aerosol dynamics), ASTM B117 (controlled laboratory tests), and ARGO (deep-ocean salinity and temperature variations), provides the model exposure to a wide range of environmental scenarios. This diversity inherently enhances the model's robustness and capability to generalize across distinct marine environmental conditions. These methodological enhancements significantly improve OceanLSTM's generalization ability, enabling it to perform robustly across varied datasets and effectively predict salt spray formation and migration under diverse marine scenarios.

Quantifying prediction uncertainty is crucial for robust decision-making, particularly in practical marine environmental monitoring and infrastructure protection scenarios. While the current implementation of OceanLSTM does not explicitly integrate uncertainty quantification techniques, its deep learning-based architecture readily supports the integration of such methodologies. To quantify uncertainty, Bayesian neural networks or Monte Carlo Dropout (MC Dropout) methods can be adopted. For instance, the MC Dropout approach introduces stochasticity during inference by performing multiple forward passes with dropout layers activated, thus generating a predictive distribution rather than a single deterministic prediction. This approach allows the calculation of mean and variance for each predicted output, providing practical measures of uncertainty such as confidence intervals or prediction intervals. Future work will extend the current OceanLSTM framework by incorporating MC Dropout during inference, enabling it to provide reliable uncertainty estimations alongside point predictions. By quantifying prediction uncertainty, decision-makers can better assess risk levels and trustworthiness of predictions, thereby improving the applicability of OceanLSTM in real-world marine environmental scenarios.

5 Conclusion

This study aims to address the problem of predicting salt spray formation and migration in hot and humid marine environments, particularly under complex and dynamically changing environmental conditions. To this end, we propose the OceanLSTM model, which combines the temporal dependency modeling capabilities of xLSTM with a spatial attention mechanism to capture the spatiotemporal dependencies of environmental variables. The model enhances long-term memory capabilities by introducing an exponential gating mechanism, while using spatial attention to dynamically focus on the most influential geographic regions, thereby improving prediction accuracy. The experiments utilized multiple representative marine environment datasets, including the NOAA dataset, Marine Aerosol dataset, ASTM B117 laboratory dataset, and the ARGO global buoy dataset. The experimental results show that OceanLSTM significantly outperforms traditional models on these datasets, especially on the NOAA and Marine Aerosol datasets, where the model exhibits substantial improvements in metrics such as accuracy and F1-score. Ablation experiments demonstrate that the exponential gating and spatial attention mechanisms are key factors contributing to the model's success. When these modules are removed, the model's performance significantly declines, validating their importance.

The model still has two major shortcomings. First, under certain controlled conditions (such as the ASTM B117 dataset), due to the homogeneity of the data and limited spatial variation, the model's spatial attention mechanism fails to fully function, leading to limited performance improvements. Second, although the model performs well on global datasets, OceanLSTM occasionally exhibits overfitting or prediction bias when dealing with extreme or anomalous data, particularly with unusual oceanic variables. Future work could focus on dynamically adjusting the attention mechanism's weights or designing robustness mechanisms for handling anomalous data to further enhance the model's generalization ability and stability. In future research, we also plan to incorporate more multimodal data sources to further improve the model's applicability and prediction accuracy.

This study proposed OceanLSTM, an advanced deep learning model that integrates an exponentially gated xLSTM with a spatial attention mechanism to enhance salt spray formation and migration prediction in marine environments. By effectively modeling both temporal dependencies and spatial correlations, OceanLSTM addresses the limitations of traditional statistical models, machine learning approaches, and conventional deep learning architectures. The experimental results demonstrate the superiority of OceanLSTM over existing models. On the NOAA dataset, OceanLSTM achieved an accuracy of 97.57%, outperforming previous state-of-the-art models by 3-5%. Similarly, on the Marine Aerosol dataset, it achieved an accuracy of 98.20%, demonstrating its robustness in predicting salt spray dispersion under diverse environmental conditions. The integration of spatial attention mechanisms further improved predictive efficiency, allowing the model to focus on critical geographic regions where salt spray concentration is highest. The model's optimized computational efficiency reduced inference time compared to traditional deep learning methods, making it suitable for real-time environmental monitoring applications. From an application perspective, the improved accuracy and efficiency of OceanLSTM provide significant benefits for marine engineering, corrosion prevention, and environmental risk assessment. More precise salt spray predictions enable targeted deployment of protective measures, reducing maintenance costs and extending the lifespan of marine infrastructure. Moreover, the model's ability to adapt to dynamic and extreme weather conditions enhances its utility in real-world forecasting scenarios. Despite these advancements, OceanLSTM has certain limitations. The model's performance could be further enhanced by incorporating multimodal environmental data, such as satellite-based aerosol measurements and oceanic current simulations. Future research will focus on improving the interpretability of the attention mechanism and optimizing computational efficiency for large-scale real-time applications. OceanLSTM represents a significant step forward in salt spray prediction, offering high accuracy, improved spatial modeling, and computational efficiency, making it a promising tool for marine environmental monitoring and infrastructure protection.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

CC: Writing – original draft, Writing – review & editing. GJ: Data curation, Investigation, Validation, Writing – original draft. JW: Software, Visualization, Writing – review & editing. SW: Resources, Data curation, Project administration, Writing – review & editing. XX: Conceptualization, Supervision, Funding acquisition, Writing – review & editing.

Funding

The author(s) declare financial support was received for the research and/or publication of this article. The authors declare that this study received funding from National Key Lab of Environmental Adaptability for Industrial Products, China Electric Apparatus Research Institute Co., Ltd. The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article, or the decision to submit it for publication.

Acknowledgments

This is a short text to acknowledge the contributions of specific colleagues, institutions, or agencies that aided the efforts of the authors.

Conflict of interest

Authors CC, GJ, JW, and SW were employed by the company China National Electric Apparatus Research Institute Co., Ltd.

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

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Abd Elaziz, M., Zayed, M. E., Abdelfattah, H., Aseeri, A. O., Tag-eldin, E. M., Fujii, M., et al. (2024). Machine learning-aided modeling for predicting freshwater production of a membrane desalination system: A long-short-term memory coupled with election-based optimizer. *Alexandria Eng. J.* 86, 690–703. doi: 10.1016/j.aej.2023.12.012

Chen, W., Chen, H., Jia, B., Bi, J., and Li, X. (2022). Study of salt migration on the upper part of the great wall under the rainfall-radiation cycle. *Bull. Eng. Geology Environ.* 81, 419. doi: 10.1007/s10064-022-02900-y

Cork, N. A., Fisher, R. S., Strong, N., Ferranti, E. J., and Quinn, A. D. (2024). Corrigendum: A systematic review of factors influencing habitat connectivity and biodiversity along road and rail routes in temperate zones. *Front. Environ. Sci.* 12, 1445609. doi: 10.3389/fenvs.2024.1445609

Delgado, J., Guimarães, A., De Freitas, V., Antepara, I., Kočí, V., and Černý, R. (2016). Salt damage and rising damp treatment in building structures. *Adv. Materials Sci. Eng.*, 2016 1280894. doi: 10.1155/2016/1280894

Gao, M., Wei, C., Zhao, X., Huang, R., Yang, J., and Li, B. (2022). Production forecasting based on attribute-augmented spatiotemporal graph convolutional network for a typical carbonate reservoir in the Middle East. *Energies* 16, 407. doi: 10.3390/en16010407

Gracia, C. I., and Torresan, S. (2022). Barriers and enablers for upscaling coastal restoration. *Nature.* https://www.sciencedirect.com/science/article/pii/S2772411522000246.

Guo, Y., Ali, R., Zhang, X., Tian, W., Zhang, L., Lu, H., et al. (2020). Raman and xps depth profiling technique to investigate the corrosion behavior of fesial alloy in salt spray environment. *J. Alloys Compounds* 834, 155075. doi: 10.1016/j.jallcom.2020.155075

Huang, D., Niu, D., Su, L., Liu, Y., Guo, B., Xia, Q., et al. (2022). Diffusion behavior of chloride in coral aggregate concrete in marine salt-spray environment. *Construction Building Materials* 316, 125878. doi: 10.1016/j.conbuildmat.2021.125878

Javid, G. (2021). *Contribution to the state of charge estimation and the optimised management of a Li-ion battery: application for the electric vehicles* (Ph.D. thesis, Université de Haute Alsace-Mulhouse). https://theses.hal.science/tel-03789642/.

Jia, B., Chen, W., Chen, H., Li, X., and Bi, J. (2023). Effects of snowmelt and rainfall infiltration on the water and salt migration of earthen sites during freeze-thaw process. *Int. J. Architectural Heritage* 17, 573–584. doi: 10.1080/15583058.2021.1950234

Kalidasan, B., Pandey, A., Saidur, R., Samykano, M., and Tyagi, V. (2023). Nano additive enhanced salt hydrate phase change materials for thermal energy storage. *Int. Materials Rev.* 68, 140–183. doi: 10.1080/09506608.2022.2053774

Kumar, A., Huang, Y., Lin, J., Hui, D., and Fohrer, N. (2024). Heavily modified freshwater: Potential ecological indicators. *Ecol. Indic.* doi: 10.1016/j.ecolind.2024.111620

Kumar, A., Kumar, V., Saroop, S., Arsenov, D., Bali, S., Radziemska, M., et al. (2023a). A comprehensive review of uranium in the terrestrial and aquatic environment: bioavailability, immobilization, tolerance and remediation approaches. *Plant Soil* 490, 31–65. doi: 10.1007/s11104-023-06101-8

Kumar, S. S., Prasad, C. D., Hanumanthappa, H., Choudhary, R. K., and Sollapur, S. B. (2024c). Numerical analysis of thermal spray coatings using artificial neural networks (ann) overview. *Int. J. Interactive Design Manufacturing (IJIDeM)*, 1–16. doi: 10.1007/s12008-024-01881-4

Kumar, A., Yu, Z.-G., and Thakur, T. K. (2023b). Microplastic pollutants in terrestrial and aquatic environment. *Environ. Sci. pollut. Res.* 30, 107296–107299. doi: 10.1007/s11356-023-29210-4

Li, B., Meng, Q., Tulliani, J.-M., Giordano, R., Li, C., Zhao, J., et al. (2023). Salt migration and capillary absorption characteristics of cement mortar partially immersed in nacl solution. *J. Building Eng.* 64, 105605. https://www.sciencedirect.com/science/article/pii/S2352710222016114.

Lin, Y.-T., and Kuo, C.-C. (2024). Real-time salt contamination monitoring system and method for transmission line insulator based on artificial intelligence. *Appl. Sci.* 14, 1506. https://www.mdpi.com/2076-3417/14/4/1506.

Maohua, Z., Zhengyi, L., Jiyin, C., Zenong, T., and Zhiyi, L. (2022). Durability of marine concretes with nanoparticles under combined action of bending load and salt spray erosion. *Adv. Materials Sci. Eng.* 2022, 1968770. doi: 10.1155/2022/1968770

Ousaleh, H. A., Sair, S., Mansouri, S., Abboud, Y., Faik, A., and El Bouari, A. (2020). New hybrid graphene/inorganic salt composites for thermochemical energy storage: Synthesis, cyclability investigation and heat exchanger metal corrosion protection performance. *Solar Energy Materials Solar Cells* 215, 110601. https://www.sciencedirect.com/science/article/pii/S2352152X22001748.

Sánchez-Arcilla, A., Gracia, V., Mösso, C., Cáceres, I., González-Marco, D., and Gómez, J. (2021). Coastal adaptation and uncertainties: The need of ethics for a shared coastal future. *Front. Mar. Sci.* 8, 717781. https://www.frontiersin.org/articles/10.3389/fmars.2021.717781/full.

Sanchez-Arcilla, A., Ibañez, C., Gracia, V., Garrote, L., Caceres, I., Lopez, D., et al. (2023). "Nature based solutions for sediment starved deltas. the ebro case in the spanish mediterranean coast," in *Coastal Sediments 2023: The Proceedings of the Coastal Sediments*, vol. 2023. (World Scientific), 2307–2320. https://www.worldscientific.com/doi/abs/10.1142/9789811275135_0212

Su, L., Niu, D., Huang, D., Luo, Y., Qiao, H., and Zhang, Y. (2022). Chloride diffusion behavior and microstructure of basalt-polypropylene hybrid fiber reinforced concrete in salt spray environment. *Construction Building Materials* 324, 126716. https://www.sciencedirect.com/science/article/pii/S0950061822004068.

Sun, J., Jin, Z., Chang, H., and Zhang, W. (2024). A review of chloride transport in concrete exposed to the marine atmosphere zone environment: Experiments and numerical models. *J. Building Eng.*, 108591. doi: 10.1016/j.jobe.2024.108591

van der Vliet, M., Malbeteau, Y., Ghent, D., Haas, S., Veal, K. L., van der Zaan, T., et al. (2024). Quantifiable impact: monitoring landscape restoration from space. a regreening case study in Tanzania. *Front. Environ. Sci.* 12, 1352058. https://www.frontiersin.org/articles/10.3389/fenvs.2024.1352058/full.

Wang, Y., Shen, X., Wu, K., and Huang, M. (2022). Corrosion grade recognition for weathering steel plate based on a convolutional neural network. *Measurement Sci. Technol.* 33, 095014. doi: 10.1088/1361-6501/ac7034

Wu, B., Dai, K., Liu, C., and Chen, J. (2024a). Evolution of long-term ecological security pattern of island city and its influencing factors—a case study in Pingtan Island. *Front. Environ. Sci.* 12, 1349324. doi: 10.3389/fenvs.2024.1349324

Wu, D., Gu, J., and Yu, J. (2024b). Influence of ecological restoration initiatives on emotional bonds between indigenous peoples and the Chinese alligator. *Front. Environ. Sci.* 12, 1395860. doi: 10.3389/fenvs.2024.1395860

Xu, M., Wang, M., Li, X., Li, S., Wang, J., and Cao, M. (2024). Research on ecological restoration and green reclamation technology of goaf in phosphorus mines. *Front. Environ. Sci.* 12, 1343185. doi: 10.3389/fenvs.2024.1343185

Yang, J., Li, H., Yang, C., Li, Y., Wang, T., Shi, X., et al. (2020). Physical simulation of flow field and construction process of horizontal salt cavern for natural gas storage. *J. Natural Gas Sci. Eng.* 82, 103527. doi: 10.1016/j.jngse.2020.103527

Yu, Z., Wang, J., Tang, B., and Lu, L. (2023). Tactics and techniques classification in cyber threat intelligence. *Comput. J.* 66, 1870–1881. doi: 10.1093/comjnl/bxac048

Zhang, Y., Yueliang, C., Zhang, Y., Guixue, B., Chenguang, W., and Andong, W. (2022). Initial corrosion behavior and mechanism of 7b04 aluminum alloy under acid immersion and salt spray environments. *Chin. J. Aeronautics* 35, 277–289. doi: 10.1016/j.cja.2022.01.014