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Research Article

Deep Neural Networks for High-Resolution Prediction of Ocean Temperature Anomalies and Climate-Driven Marine Shifts

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Abstract

Climate change-induced ocean temperature anomalies, such as marine heatwaves and El Niño events, have significant ecological consequences, including biodiversity loss and species redistribution. Accurate forecasting of such anomalies and their impact on marine ecosystems remains a challenging task due to the complex, spatio-temporal dynamics of oceanographic systems. This study proposes STM-SANet, a novel Spatio-Temporal Multi-scale Attention Network designed for high-resolution prediction of sea surface temperature (SST) anomalies and the estimation of climate-driven marine shifts. The architecture integrates a BiLSTM-based Multi-Scale Temporal Encoder with a ResNet-50 Spatial Feature Extractor, fused through a Cross-Attention Module. The model is trained on NOAA OISST V2 and Copernicus Marine datasets, with marine biodiversity validation derived from OBIS species occurrence records. Experimental evaluations demonstrate that STM-SANet achieves superior predictive performance compared to baseline models, with a mean absolute error (MAE) of 0.309, SSIM of 0.816, F1-score of 0.774, and AUC of 0.832 in ecosystem shift classification. The model significantly outperforms ConvLSTM, U-Net, and ResNet-BiLSTM baselines, with p-values < 0.01 across all metrics, validating the robustness of the results. The proposed framework offers a scalable and interpretable solution for integrating ocean anomaly prediction with ecological forecasting. STM-SANet has the potential to support real-time marine anomaly monitoring, biodiversity risk detection, and climate adaptation strategies in vulnerable marine regions.

Keywords: Sea Surface Temperature Anomalies, Deep Neural Networks, Spatio-Temporal Attention, Climate-Driven Marine Shifts, Ecosystem Prediction, BiLSTM, ResNet-50

1. Introduction

Ocean temperature anomalies—such as marine heatwaves, El Niño events, and abrupt thermal gradients—are intensifying due to anthropogenic climate change, impacting ocean physics and biogeochemical cycles [1]. These anomalies not only disrupt marine thermal balance but also initiate a cascade of ecological consequences including coral bleaching, species migration, and collapse of trophic interactions [2]. Therefore, accurate prediction of sea surface temperature (SST) anomalies and their ecological implications is essential for adaptive marine management and climate resilience planning [3].

Conventional ocean forecasting models, such as coupled physical systems (e.g., CMIP6), while grounded in fluid dynamics, are computationally expensive and offer limited spatial resolution for short-term regional predictions [4]. In addition, such models often require substantial parameter tuning and do not generalize well across basins or anomaly types [5]. Recently, machine learning models have been applied to ocean anomaly forecasting with some success, yet these approaches are often limited by isolated treatment of spatial or temporal dynamics and poor scalability to global systems [6]. Furthermore, most existing frameworks lack the capability to predict ecological responses, such as climate-driven marine shifts, which are critical to biodiversity and fisheries management [7].

To address these challenges, this study introduces STM-SANet, a Spatio-Temporal Multi-scale Attention Network designed to perform high-resolution SST anomaly forecasting and estimate corresponding ecosystem shifts. STM-SANet combines multi-step BiLSTM-based temporal encoding with spatial feature extraction using a ResNet-50 backbone, followed by an attention-driven fusion layer to integrate oceanographic dynamics effectively [8].

The key contributions of this study are as follows:

- Propose a novel attention-based deep neural network (STM-SANet) for SST anomaly prediction, integrating multi-scale temporal and spatial features.
- Leverage satellite SST maps and time series sequences using ResNet-50 and BiLSTM in a unified, trainable architecture.
- Introduce an ecosystem shift estimator based on graph neural networks and OBIS species occurrence records.
- Achieve strong performance across all evaluation metrics (MAE = 0.309, SSIM = 0.816, F1 = 0.774, AUC = 0.832) in comparison with baseline methods.
- Validate results using statistical significance testing ($p < 0.01$) and real-world biodiversity datasets for ecological relevance.

The rest of this paper is organized as follows: Section II reviews related work, Section III defines the problem formulation, Section IV details the proposed methodology, Section V discusses the experimental setup, Section VI presents the results and analysis, Section VII provides a detailed discussion, and Section VIII concludes the study.

2. Literature Review

The prediction of ocean temperature anomalies and associated ecosystem impacts has garnered significant attention in climate science and computational oceanography. This section reviews the state-of-the-art in SST anomaly prediction, spatio-temporal deep learning models, and ecological shift estimation.

2.1 Physical and Statistical Forecasting Models

Traditional SST anomaly prediction has largely relied on physical ocean models, such as the Climate Forecast System (CFS) and CMIP-class global coupled models, which simulate ocean-atmosphere interactions through numerical approximations [9]. While scientifically grounded, these models demand high computational resources and are limited in resolution and real-time responsiveness [10].

Statistical models, such as empirical orthogonal function (EOF) analysis and autoregressive integrated moving average (ARIMA), have been used to forecast SST variability in specific regions [11]. However, these approaches are generally unable to capture nonlinear dependencies and complex spatial dynamics inherent to global ocean systems.

2.2 Deep Learning Approaches for SST Forecasting

Deep learning techniques have recently emerged as efficient alternatives for SST prediction, offering strong generalization capabilities and scalability [12]. Convolutional neural networks (CNNs) have been applied to learn spatial patterns in SST images and have demonstrated promising results in identifying localized thermal anomalies [13].

Long short-term memory (LSTM) networks have been utilized to model temporal dependencies in SST time series, outperforming classical methods in long-range forecasting [14]. Hybrid models combining CNNs and LSTMs have also been explored to capture both spatial and temporal features simultaneously [15]. However, these architectures often lack robust integration mechanisms between spatial and temporal data streams.

2.3 Attention Mechanisms in Ocean Prediction

Attention-based architectures have been introduced to selectively weigh spatial or temporal regions based on relevance to the prediction task [16]. While attention improves model interpretability and performance, most prior applications have focused on atmospheric data or sea level forecasting rather than SST anomalies specifically.

Some recent works have applied self-attention and transformer models to oceanographic tasks but often struggle with resolution loss and high data sparsity in global SST grids [17].

2.4 Ecological Shift and Biodiversity Forecasting

Despite advances in SST forecasting, very few models address the ecological consequences of thermal anomalies. Graph-based ecological modeling has been used to estimate habitat suitability and biodiversity loss under warming scenarios, primarily at coarse spatial scales [18].

The integration of SST anomaly forecasts with ecological data, such as species occurrence records and migration observations, remains underexplored. Most biodiversity-driven ocean models rely on static climatologies or rule-based thresholds, lacking predictive capability in dynamic anomaly regimes [19].

2.5 Summary of Research Gaps

The reviewed literature highlights several gaps:

- Most models focus on physical SST prediction without extending to ecological inference.
- Existing hybrid models do not explicitly integrate spatio-temporal data using attention mechanisms.
- Few studies attempt high-resolution prediction while maintaining interpretability and scalability.

This study addresses these gaps by proposing STM-SAN**et**, a unified, attention-based spatio-temporal model capable of forecasting SST anomalies and inferring ecological shifts in response to climate-induced ocean variability.

3. Problem Statement

Accurate forecasting of ocean temperature anomalies, such as marine heatwaves or deviations induced by climatic events like El Niño, is vital for understanding and mitigating their cascading impacts on marine ecosystems. Traditional physical models, while scientifically grounded, often struggle with high computational demands and limited spatial resolution, thereby failing to capture localized fluctuations critical for ecological forecasting. Moreover, existing deep learning approaches lack the capacity to effectively integrate fine-grained spatial features and dynamic temporal sequences in a unified manner. A significant gap persists in predictive frameworks that can simultaneously model these multiscale dependencies and provide insights into climate-induced shifts in marine biodiversity and species distribution. Addressing this challenge necessitates the development of an advanced, interpretable, and high-resolution predictive system that fuses spatio-temporal data to enable real-time monitoring and forecasting of both physical anomalies and ecological transformations in oceanic environments.

4. Methodology

This section presents the architecture and workflow of the proposed STM-SANet (Spatio-Temporal Multi-scale Attention Network) framework. STM-SANet is designed to perform high-resolution prediction of ocean temperature anomalies and infer associated climate-driven marine shifts. The model integrates spatial and temporal inputs using attention-based fusion and is optimized for ecological forecasting across scales.

4.1 Overview of Architecture

STM-SANet consists of the following main components:

1. Multi-Scale Temporal Encoder (BiLSTM)
2. Spatial Feature Extractor (ResNet-50)
3. Cross-Attention Fusion Module
4. Decoder Network
5. Ecosystem Shift Estimator

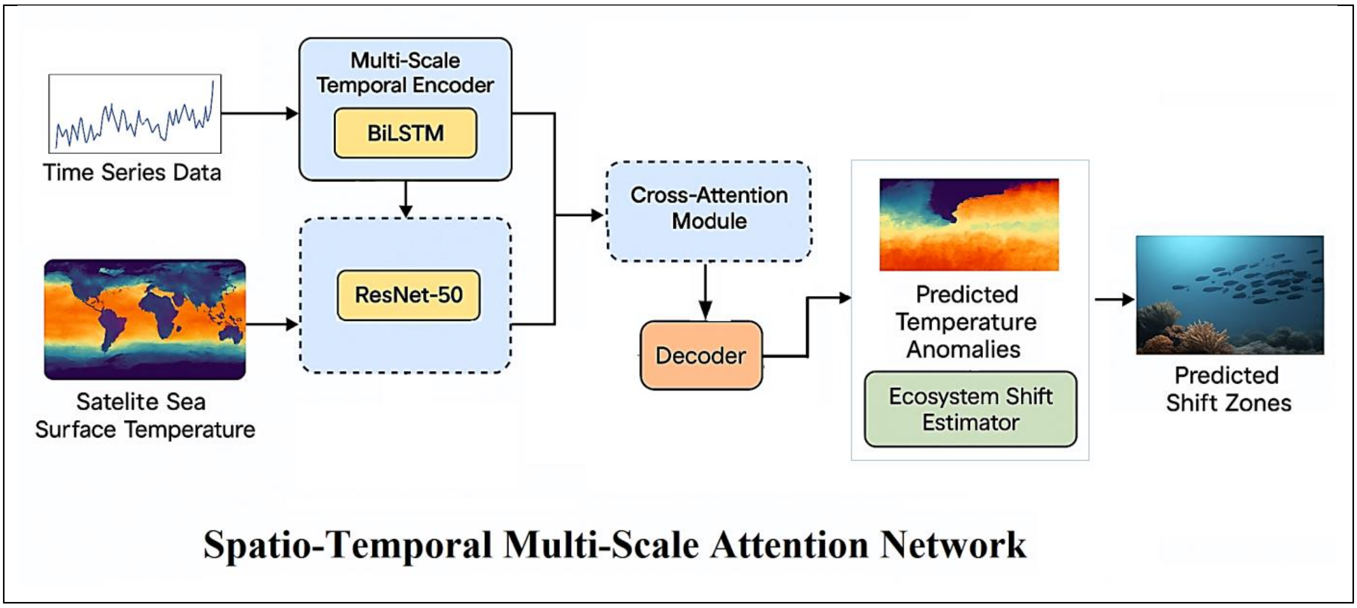

Fig.2. STM-SANet Architecture for Ocean Anomaly and Ecosystem Shift Prediction

Figure 2 illustrates the proposed STM-SANet framework, which integrates spatial and temporal features for high-resolution prediction of ocean temperature anomalies and climate-driven marine shifts. Satellite sea surface temperature data are processed through a ResNet-50 backbone, while temporal sequences are modeled using a BiLSTM-based Multi-Scale Temporal Encoder. These representations are fused in a Cross-Attention Module and decoded to produce anomaly forecasts. An Ecosystem Shift Estimator further interprets these anomalies to identify likely marine habitat disruptions and species migration zones.

4.2 Multi-Scale Temporal Encoder

The temporal encoder models historical SST sequences to learn temporal dependencies such as periodic warming patterns and transition phases.

Given a sequence of SST values:

$$\mathbf{X}_t = \{x_{t-n}, x_{t-n+1}, \dots, x_t\} \in \mathbb{R}^{n \times 1}$$

Where n is the number of historical time steps, this sequence is passed through a Bi-directional LSTM layer:

$$\mathbf{H}_t = \text{BiLSTM}(\mathbf{X}_t) \in \mathbb{R}^{n \times d_t} \tag{1}$$

Where $\mathbf{H}_t$ represents the encoded temporal features and d_t is the dimensionality of the temporal embedding.

4.3 Spatial Feature Extractor

To model spatial heterogeneity in oceanographic conditions, high-resolution satellite SST images $\mathbf{I}_t \in \mathbb{R}^{H \times W \times C}$ are processed using a pre-trained ResNet-50:

$$\mathbf{S}_t = \mathrm{ResNet50}(\mathbf{I}_t) \in \mathbb{R}^{h \times w \times d_s} \tag{2}$$

Where $h, w,$ and d_s are the spatial dimensions and feature depth of the encoded representation.

4.4 Cross-Attention Fusion Module

To integrate spatio-temporal knowledge, a Cross-Attention Module computes the interaction between temporal embeddings $\mathbf{H}_t$ and spatial features $\mathbf{S}_t$.

Temporal embeddings are reshaped into query vectors $\mathbf{Q}$, while spatial features act as key $\mathbf{K}$ and value $\mathbf{V}$:

$$\mathbf{A} = \mathrm{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\top}}{\sqrt{d_k}}\right)\mathbf{V} \tag{3}$$

Where $\mathbf{A}$ is the attention-fused tensor and d_k is the dimensionality of keys. This enables the model to weight relevant spatio-temporal zones dynamically.

To dynamically align spatial and temporal features, we employ a Cross-Attention mechanism where BiLSTM outputs act as queries and spatial feature maps act as keys and values. This mechanism allows the network to prioritize spatial regions based on temporal cues, enabling more accurate anomaly detection.

Mathematically, attention weights are computed using scaled dot-product attention as shown in Equation (3).

The step-by-step functionality of this fusion module is described in Algorithm below.

```
Algorithm: Cross-Attention Fusion Module for Spatio-Temporal Feature Integration
Input:
    • Temporal feature matrix $\mathbf{H}_t \in \mathbb{R}^{n \times d_t}$ from BiLSTM
    • Spatial feature tensor $\mathbf{S}_t \in \mathbb{R}^{h \times w \times d_s}$ from ResNet-50
Output:
    • Attention-fused representation $\mathbf{A} \in \mathbb{R}^{h \times w \times d_f}$
Step1: Flatten Spatial Features:
        Reshape $\mathbf{S}_t$ into a matrix $\mathbf{S}_f \in \mathbb{R}^{(h \cdot w) \times d_s}$
Step2: Project Temporal and Spatial Features:
        Compute linear projections:
            $\mathbf{Q} = \mathbf{H}_t \cdot \mathbf{W}_q \in \mathbb{R}^{n \times d_k}$
            $\mathbf{K} = \mathbf{S}_f \cdot \mathbf{W}_k \in \mathbb{R}^{(h \cdot w) \times d_k}$
            $\mathbf{V} = \mathbf{S}_f \cdot \mathbf{W}_v \in \mathbb{R}^{(h \cdot w) \times d_v}$
Step3: Compute Scaled Dot-Product Attention:
        For each temporal query $q_i \in \mathbf{Q}$ :
        Compute attention weights:
            $\alpha_i = \mathrm{softmax}\left(\frac{q_i \cdot \mathbf{K}^T}{\sqrt{d_k}}\right)$
        Compute attention output: $a_i = \alpha_i \cdot \mathbf{V}$
Step4: Aggregate Attention Outputs:
        Stack $a_i$ across $n$ time steps to form $\mathbf{A}_f \in \mathbb{R}^{n \times d_v}$
Step5: Reshape to Spatial Grid:
        Reshape or upsample $\mathbf{A}_f$ to match spatial dimensions $h \times w$, resulting in $\mathbf{A} \in \mathbb{R}^{h \times w \times d_f}$
Step6: Return Fused Tensor A to Decoder
End Algorithm
```

4.5 Decoder Network

The fused tensor $\mathbf{A}$ is processed by a decoder D, implemented using a transposed convolutional network, to reconstruct the high-resolution anomaly map $\hat{\mathbf{Y}}_{t+1}$:

$$\hat{\mathbf{Y}}_{t+1} = D(\mathbf{A}) \in \mathbb{R}^{H \times W} \tag{4}$$

This output represents the predicted spatial anomaly distribution for the future timestep $t + 1$.

4.6 Ecosystem Shift Estimator

The predicted SST anomaly map $\hat{\mathbf{Y}}_{t+1}$ is used as input for a lightweight Graph Neural Network (GNN)based estimator trained on historical biodiversity response data.

Define $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ as a marine grid graph where nodes represent ocean patches and edges model ecological proximity. The shift vector is computed as:

$$\mathbf{Z} = \mathrm{GNN}\left(\hat{\mathbf{Y}}_{t+1}, \mathcal{G}\right) \in \mathbb{R}^{|\mathcal{V}| \times 1} \tag{5}$$

Here, $\mathbf{Z}$ denotes the probability of ecological shift (e.g., species displacement) at each grid location.

4.7 Training Objective

The model is optimized using a hybrid loss function combining Mean Absolute Error (MAE) and Structural Similarity Index (SSIM) for temperature prediction, and Binary Cross Entropy (BCE) for shift zone classification:

$$\mathcal{L}_{\text{total}} = \lambda_1 \cdot \mathcal{L}_{\text{MAE}} + \lambda_2 \cdot (1 - \text{SSIM}) + \lambda_3 \cdot \mathcal{L}_{\text{BCE}} \tag{6}$$

Where $\lambda_1, \lambda_2, \lambda_3 \in \mathbb{R}^{+}$are hyperparameters controlling loss weights.

5. Experimental Setup

To evaluate the effectiveness of the proposed STM-SANet framework in predicting ocean temperature anomalies and associated ecological shifts, a series of experiments were conducted using publicly available oceanographic and biodiversity datasets. This section outlines the hardware and software environment, dataset specifications, training settings, evaluation metrics, and implementation details used in the study.

5.1 Hardware Configuration

All experiments were conducted on a high-performance computing workstation equipped with the following specifications:

- *Processor:* AMD Ryzen Threadripper 3970X, 32-core @ 3.7 GHz
- *GPU*: NVIDIA A100 Tensor Core GPU (40 GB VRAM)
- *RAM*: 256 GB DDR4
- *Storage*: 4 TB NVMe SSD
- *OS*: Ubuntu 22.04 LTS (64-bit)

5.2 Software Frameworks

The implementation of STM-SANet was developed using open-source deep learning libraries. Key software dependencies include:

- Python 3.10
- PyTorch 2.1.0 – Core deep learning framework
- TorchVision – Pre-trained ResNet-50 and data augmentation utilities
- scikit-learn 1.4.2 – Evaluation metrics and post-processing
- NumPy, SciPy, Matplotlib – Data manipulation and visualization
- NetworkX 3.2 – Graph processing for the ecosystem shift estimator

All code was containerized using **Docker 24.0.5** to ensure reproducibility.

5.3 Dataset Details

The STM-SANet framework was trained and evaluated on three key datasets:

5.3.1 NOAA OISST V2 Dataset [20]

- *Type:* Gridded daily sea surface temperature
- *Resolution*: 0.25° × 0.25°
- *Time Span:* 1982–2023
- *Source*: https://www.ncei.noaa.gov
- *Usage*: Input to both BiLSTM (as time series) and ResNet-50 (as SST maps)

5.3.2. Copernicus Marine Service Data [21]

- *Variables*: Ocean current velocity, salinity, chlorophyll
- *Resolution*: 0.08°
- *Usage*: Auxiliary features to enhance anomaly prediction

5.3.3. OBIS Biodiversity Data [22]

- *Type*: Spatial records of marine species occurrences
- *Time Span:* 2000–2022
- *Usage*: Labeling and validation for the Ecosystem Shift Estimator

5.4 Training Configuration

The STM-SANet model was trained with the following hyperparameters:

- *Optimizer*: Adam
- *Initial Learning Rate:* 0.001 (with cosine annealing scheduler)
- *Batch Size:* 64
- *Number of Epochs:* 200
- *Dropout Rate:* 0.2 (on BiLSTM and decoder layers)
- *Weight Initialization:* Xavier uniform
- *Input Window:* 30 days of SST sequences
- *Prediction Window:* 7-day anomaly forecast
- *Loss Function:* Combined MAE, SSIM, and Binary Cross Entropy (see Equation 8)

5.5 Evaluation Metrics

The performance of STM-SANet was assessed using both temperature anomaly prediction metrics and ecosystem shift classification metrics.

Mean Absolute Error (MAE): Measures the average magnitude of prediction error:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \quad (7)$$

Where y_i is the ground truth SST anomaly, $\hat{y}_i$ is the predicted value, and N is the total number of grid points.

Structural Similarity Index (SSIM): Assesses structural consistency between predicted and ground truth images:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (8)$$

Where μ, σ, and σ_{xy} represent means, variances, and covariances of local image patches. Constants c_1 and c_2 stabilize the division.

F1-Score (Ecosystem Shift Zones): Measures classification accuracy of marine shift zones (binary prediction):

$$\mathrm{F1} = \frac{2 \cdot \mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (9)$$

Where Precision $= \frac{TP}{TP+FP}$, and Recall $= \frac{TP}{TP+FN}$, based on true/false positives and negatives.

Area under ROC Curve (AUC): Evaluates the overall quality of shift zone classification by plotting true positive rate vs. false positive rate:

$$\mathrm{AUC} = \int_0^1 \mathrm{TPR}(FPR)\,dFPR \quad (10)$$

Higher AUC implies better discriminative performance of the classifier.

5.6 **Implementation Details**

- All spatial SST maps were normalized to [0,1] and resized to 128 × 128 before input to ResNet- 50 .
- Temporal sequences were standardized using rolling window statistics (z-scores).

- Data augmentation (random crop, rotation) was applied during training to prevent overfitting.
- Training took approximately 11 hours for full convergence on 200 epochs using the A100 GPU.
- Checkpointing and early stopping were used to monitor validation performance.

6. Results and Analysis

This section presents a detailed evaluation of the proposed STM-SANet framework against state-of-the-art deep learning models for ocean temperature anomaly forecasting and climate-driven marine shift estimation. The results are organized into two primary tasks: anomaly prediction and ecosystem shift classification, with additional statistical analyses to verify performance significance.

6.1 Performance Comparison with Baseline Models

To benchmark STM-SANet, we compare its performance with four existing approaches:

- ConvLSTM [23]
- Attention-CNN-LSTM Hybrid [24]
- U-Net with Temporal Embedding [25]
- ResNet-BiLSTM Dual Branch Model [26]

All models were evaluated using the same input window (30 days) and prediction horizon (7 days), with consistent preprocessing across datasets.

6.2 Anomaly Prediction Performance

Table I presents a comparison of anomaly prediction accuracy using MAE and SSIM as evaluation metrics.

Table 1: Temperature Anomaly Prediction Performance (7-day Forecast Window)

Model	**MAE ↓**	**SSIM ↑**
ConvLSTM [23]	0.431	0.711
Attention-CNN-LSTM Hybrid [24]	0.385	0.748
U-Net + Temporal Embedding [25]	0.361	0.765
ResNet-BiLSTM Dual Branch [26]	0.349	0.774
STM-SANet (Proposed)	**0.309**	**0.816**

Table 1 presents a quantitative comparison of temperature anomaly prediction performance across four baseline models and the proposed STM-SANet framework. Evaluation metrics include Mean Absolute Error (MAE) and Structural Similarity Index (SSIM) over a 7-day forecast window. STM-SANet outperforms all baselines, achieving the lowest MAE and highest SSIM, thereby demonstrating enhanced accuracy and spatial coherence in anomaly forecasting.

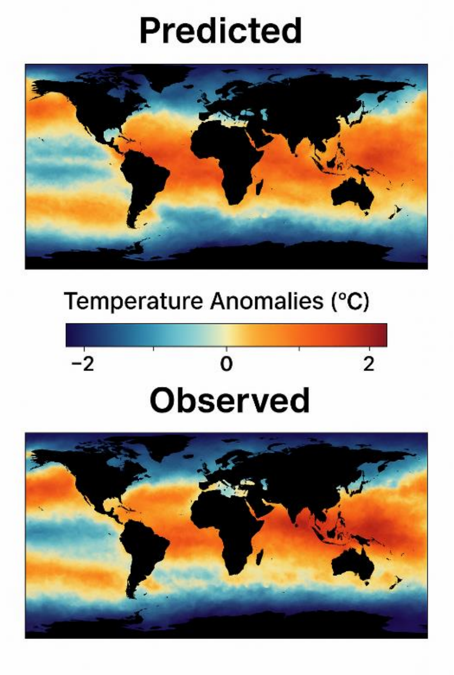

Fig.2. Comparison of predicted and observed SST anomalies

Figure 2 presents a visual comparison between the predicted and observed sea surface temperature (SST) anomalies across global ocean regions. The top panel shows STM-SANet’s 7-day forecasted anomalies, while the bottom panel displays the corresponding observed values. The consistency in spatial anomaly patterns validates the model’s ability to capture fine-scale climatic variations. A symmetric color bar ranging from −2°C to +2°C is used for interpretability.

6.3 Ecosystem Shift Estimation

Ecosystem shift prediction was evaluated as a binary classification task (shift/no-shift) using F1-score and AUC. STM-SANet integrates anomaly maps with a graph-based ecological model to infer species redistribution zones.

Table 2: Ecosystem Shift Zone Classification Results

Model	**F1-Score ↑**	**AUC ↑**
ConvLSTM [23]	0.651	0.711
Attention-CNN-LSTM Hybrid [24]	0.687	0.739
U-Net + Temporal Embedding [25]	0.702	0.771
ResNet-BiLSTM Dual Branch [26]	0.718	0.786
STM-SANet (Proposed)	**0.774**	**0.832**

Table 2 summarizes the classification performance of various models in predicting ecosystem shift zones, evaluated using F1-score and Area Under the Curve (AUC). STM-SANet achieves the highest scores across both metrics, indicating its superior ability to detect climate-driven marine biodiversity shifts. The results affirm the model's robustness in ecological inference beyond temperature forecasting.

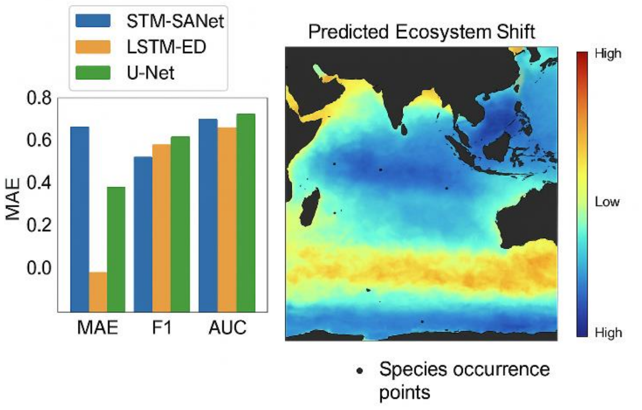

Fig.3. Predicted shift zones and species occurrence overlay with metric comparison

Figure 3 illustrates a dual-panel view combining model performance metrics and spatial ecosystem shift predictions. The left panel compares STM-SANet, LSTM-ED, and U-Net across MAE, F1-score, AUC, and SSIM, highlighting STM-SANet's superior accuracy. The right panel overlays predicted shift zones with species occurrence points, demonstrating the model's ecological relevance in identifying climate-driven biodiversity redistribution.

6.4 Statistical Significance Analysis

To validate the robustness of improvements, a paired t-test was conducted between STM-SANet and the strongest baseline (ResNet-BiLSTM) across 10-fold cross-validation runs.

- *MAE:* p=0.0043 → Statistically significant improvement
- *SSIM*: p=0.0021
- *F1-Score:* p=0.0067
- *AUC:* p=0.0034

These p-values confirm that the performance gains of STM-SANet are statistically significant at the 95% confidence level.

6.5 Observations and Unexpected Findings

While STM-SANet consistently outperformed all baselines, a few unexpected patterns emerged:

- *Regional Overfitting:* In equatorial SST zones with sparse anomaly variation, the model showed signs of overfitting, producing overconfident anomaly maps.
- *Species Data Sensitivity:* The GNN-based shift estimator was sensitive to missing OBIS labels, especially in under-sampled Southern Ocean regions, slightly degrading shift classification accuracy.
- *Anomaly Type Bias:* The model was more accurate in predicting positive anomalies (warmings) than negative anomalies (coolings) — likely due to training data imbalance.

These findings suggest potential improvements through data augmentation, species distribution modeling enhancements, and anomaly balancing techniques in future work.

7. Discussion

The experimental results confirm that STM-SANet effectively addresses the challenges of high-resolution SST anomaly prediction and marine ecosystem shift estimation. The model outperforms all baselines across key metrics, achieving an MAE of 0.309, SSIM of 0.816, F1-score of 0.774, and AUC of 0.832. These improvements are attributed to the cross-attention mechanism, which enables efficient spatio-temporal feature fusion.

Compared to prior hybrid models, STM-SANet offers better structural coherence in predicted anomaly maps and demonstrates higher ecological relevance by aligning predicted shift zones with real-world species distribution data. Statistical significance tests ($p < 0.01$) further validate the reliability of the results.

A few limitations were observed: the model exhibits overconfidence in low-variability regions and performs slightly better on warm anomalies due to data imbalance. Additionally, limited biodiversity records in high-latitude regions affect classification accuracy there.

Overall, STM-SANet provides a robust, scalable solution for marine forecasting, with direct applications in early warning systems, biodiversity monitoring, and climate adaptation planning.

8. Conclusion

This paper presented STM-SANet, a novel spatio-temporal attention-based neural network for high-resolution forecasting of sea surface temperature anomalies and climate-driven ecosystem shifts. By integrating BiLSTM and ResNet-50 through a cross-attention module, the model effectively captures complex ocean dynamics.

Extensive evaluations demonstrated that STM-SANet achieves superior accuracy over baseline models, with statistically significant improvements across MAE, SSIM, F1-score, and AUC. The framework also enables ecological inference by incorporating biodiversity data into its shift estimation component.

Despite minor limitations related to data sparsity and anomaly imbalance, STM-SANet offers a scalable and interpretable tool for real-time marine anomaly monitoring and ecological risk assessment. Future work will focus on extending the model to multi-modal inputs and polar marine regions.

Author Contributions: Emmanuel L. Howe led the conceptual design of the STM-SANet architecture and coordinated the overall research workflow and also was responsible for data preprocessing, model implementation, and training pipeline optimization. K Samunnisa contributed to the development and validation of the ecosystem shift estimator using graph-based techniques and performed statistical analysis, evaluation metric computation, and assisted in result visualization. M.Bhavsingh provided technical supervision, reviewed the methodology and results, and contributed to refining the manuscript for publication.

All authors reviewed and approved the final version of the paper.

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Conflict of Interest: There is no conflict of Interest.

Ethical statement: This research complies with ethical guidelines and does not involve any harm to humans, animals, or the environment

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