PREDICTIVE MODELING OF COASTAL UPWELLING FEATURES USING ARTIFICIAL INTELLIGENCE A:ROACH

[1,2]Dametoti, Y. and [1,2]Balogun, I. A.

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ABSTRACT

The Northwest African coastal upwelling is a one of the complex systems that global and regional climate models struggle to capture its features. In this study, the artificial intelligence (AI) statistical models including machine learning and advanced deep learning architectures were used to predict the time series of the interannual variability of coastal upwelling indices, such as Ekman transport and sea surface temperature (SST) based. The results show good performances with high score of the coefficient of determination (R2>70%) and minimum Root Mean Square Error (<0.09) of machine learning and deep learning models, such as Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN), in simulating monthly Ekman transport and SST-based along the Senegal-Mauritania and Gulf of Guinea coasts. The best performance was obtained with LSTM-CNN hybrid architecture, indicating the capacity of AI technology to capture finesse scale processes such as coastal upwelling features at the interannual scale. However, the spatial representation of coastal upwelling using the AI techniques remains a future challenge.

Keywords: Coastal Upwelling, Artificial Intelligence (AI), Predictive Modeling, Deep Learning, Northwest Africa

[1]Department of Meteorology and Climate Science, Federal University of Technology, Akure, Nigeria

[2]West African Science Service Centre for Climate and Adapted Land Use, Federal University of Technology, Akure, Nigeria

Correspondence
yamoula.d@edu.wascal.org

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1 | Introduction

Coastal upwellings in the eastern Atlantic boundary are complex ocean and atmosphere interaction systems modulated by several environmental factors, including wind stress forcing equatorial waves, regional climate, ocean currents and other local and remote forcings (Brandt *et al.*, 2023). Different upwelling indices were proposed as powerful tools to understand the dynamical process, spatial and temporal variability of these coastal upwelling currents, in particular in the Senegal-Mauritania upwelling regions.

Despite that the physical mechanisms and drivers of upwelling are well-documented over the West African coast, the predictability of coastal upwelling remains a topic of active scientific debate due to a lack of knowledge on all factors and the incapacity of the dynamical climate models (global and regional) to resolve coastal processes. In the literature review, numerical global and regional climate models were used to resolve these complex systems. In the Senegal-Mauritania coastal upwelling system, Ndoye *et al.,* (2014, 2017) have performed the regional ocean model system to simulate the physical processes that drive this coastal upwelling. Their results highlighted the influence of coastal shape, bathymetry and other geographical and hydrometeorological factors that disrupt Ekman upwelling. The same model with sensitive experiments were used in Adaptive Grid Refinement in Fortran (AGRIF) program (Djakouré *et al.,* 2014, 2017) to simulate the coastal upwelling process north of Gulf of Guinea. The findings highlighted two upwelling cells located in the eastern of the capes Palmas and Three Points. This model experiments showed its limitations in representing the physical mechanisms of upwelling in both coastal upwelling regions. Using the last versions of Climate Model Intercomparison Project (CMIP) outputs, Sylla *et al.,* (2019, 2022) and Varela *et al.,* (2022), have also demonstrated the limitations of the global climate models to capture upwelling processes along the Senegal-Mauritania coast.

Since the beginning of the 2020s, the AI has been used as an effective tool in meteorology and climate science, to predict atmospheric and oceanic phenomena in real time, in both short and long term. Previous shows that AI models can be powerful tools for significantly improving climate model simulations. Historically, Artificial Neural Networks (ANNs) have been employed for the prediction of SST patterns (Tangang *et al.,* 1997, Tang *et al.,* 2000) using the empirical orthogonal functions of wind stress and SST anomalies as inputs data. Further advance, works of Wu *et al.,* (2006) and Tripathi *et al.,* (2006), who developed multi-layer perceptron models for forecasting SST anomalies, have demonstrated the superior predictive capabilities of ANNs over traditional methods of linear regression and canonical correlational analysis (Gupta and Malmgren, 2009, Patil and Deo, 2019).

Based on these historical techniques, the study explores the application of two sophisticated machine learning (ML) and two advanced deep learning (DL) models for upwelling index predictions along the Senegal-Mauritania coast and in the north of Gulf of Guinea. Random Forest, Gradient Boosting, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) including LSTM architectures were particularly adept at processing the time-series data of Ekman transport and SST gradient, marking a significant leap forward in the ability to predict offshore Ekman transport and SST-based upwelling index with accuracy (Reichstein *et al.,* 2019). The a:roach also combines the pattern recognition of CNNs with the sequential data processing power of LSTMs, creating a hybrid model that can effectively forecast SST-based and Ekman transport by understanding the underlying climatic trends and anomalies. Each model was designed to capture temporal variablity of upwelling indices, as the predicted model's output, providing a high-resolution forecast that incorporates the temporal dependencies learned by the models.

2 | Materials and Methods

Study Domain

This study is focused on the Northwest African coastal upwelling systems, including Senegal-Mauritania and Gulf of Guinea coastal upwelling regions (Figure 1, white boxes). These two coastal upwelling located at 10-25N and 10W-5E, are governed by the North Atlantic Subtropical and North Atlantic Tropical current systems (Gyres), and the position of Intertropical convergence zone that modulate coastal upwelling systems variability.

2.1 | Data Source

This study covered 41 years, from 1982 to 2022. The monthly SST, wind stress, sea level height (SSH) and sea level anomaly (SLA) were extracted from Copernicus Marine Environmental Monitoring Service open ocean data source (https://cds.climate.copernicus.eu/). SST and wind stress were used to compute SST-based upwelling index and Ekman transport in each upwelling region. The monthly climate indices including El Nino Southern Oscillation (ENSO), Atlantic Nino (ATL3) and Atlantic Meridional Mode (AMM), were freely downloaded on the platform of NOAA

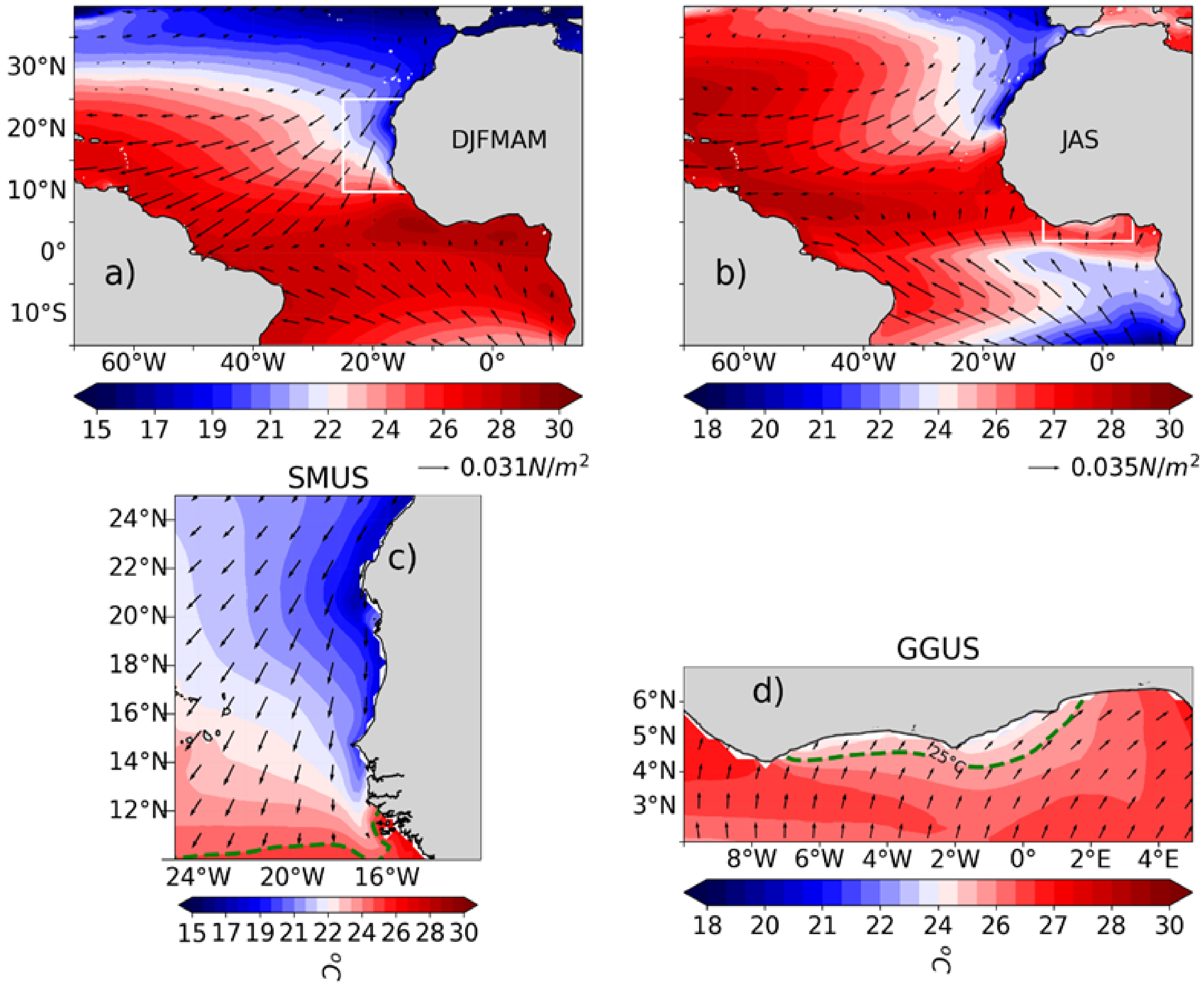

Figure 1 | a, b Sea surface temperature (shading) and wind stress vectors (arrows) during winter-spring (December-May) and summer (JAS) seasons in the Tropical Atlantic, respectively. White boxes are the Senegal-Mauritanian and Gulf of Guinea coastal upwelling regions isolate in panels c and d.

Climate Prediction Center (https://psl.noaa.gov/data/climateindices/list/). The geostrophic currents derived from SSH and the SLA were extracted as other indicators of coastal upwelling, and used with climate indices as the model inputs. The outputs of Climate Model Intercomparison Project phase six (CMIP6) exercise were also used. These climate model outputs were granted by Deutsches KlimaRechenZentrum (DKRZ). The ensemble members mean were calculated from 59 and 47 models of SST and wind components, respectively. Time series were extracted for model comparison between AI architectures and climate model experiements.

2.2 | Methods

This study examines the performances of two statistical linear regression models of machine learning and two advanced deep learning models such as Random Forest regressor, Gradient Boosting regressor, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) including Long Short-Term Memory (LSTM), in predicting the interannual variability of coastal upwelling indices such as offshore Ekman transport and SST gradient.

Upwelling indices

Upwelling indices are used as powerful tools to analyse coastal upwelling dynamics. Both Ekman transport and SST-based were computed over the offshore and coastal boxes, using the monthly data of near surface wind stress and SST. The zonal (Mx) and meridional (My) components of Ekman transport were derived from the following Bulk formula:

$$M_x = \frac{\tau^y}{\rho_w \cdot f} \quad M_y = -\frac{\tau^x}{\rho_w \cdot f} \qquad (1)$$

where $f = 2\Omega.sin(\varphi)$

Where τ^x τ^y are the zonal and meridional wind stress; ρ_w=1025 kg/m^3 is sea water density; f is Coriolis parameter; Ω= 7.14*10-5 rad. s-1 is the angular velocity of Earth's rotation; and φ is the geographical latitude.

The SST-based (SST_{index}) upwelling index was obtained through the difference of gradient between offshore SST (SST_{off}) and coastal SST (SST_{in}).

$$SST_{index} = SST_{off} - SST_{in} \qquad (2)$$

The offshore Ekman transport and SST-based were used as indices to measure the dynamic and intensity of coastal upwelling in each area, respectively. In the following section, these upwelling were predicted with AI tools and compare to climate model simulations.

Model Architectures

For the prediction of upwelling indices including Ekman transport and SST gradient, both traditional machine learning algorithms and advanced deep learning architectures were employed. The selected methods include two ensemble-based machine learning algorithms such as Random Forest Regression (RFR) and Gradient Boosting Regression (GBR), two deep learning a:roaches of models such as LSTM and CNN, and the hybrid model of LSTM-CNN. This multi-model framework was designed to assess the capacity of various algorithms in capturing spatio-temporal variability in ocean-atmosphere interactions that drive coastal upwelling. These models were selected due to their ability to capture complex and non-linear relationship between multiple predictors and target variables, which are characteristic of ocean-atmosphere interactions influencing coastal upwelling.

Random Forest: Random Forest is an ensemble of learning method constructs with a large number of trees during training and outputs to reduce variance and predictive performance. In this study, the RFR model was used to estimate upwelling indices using a range of atmospheric and oceanographic predictors and large-scale climate indices (e.g., ENSO, NAO, ATL3, AMM).

Gradient Boosting: Gradient Boosting is a powerful learning technique constructs with a sequence of shallow decision trees, where each new tree corrects the errors made by the previous ensemble, minimizing a specific loss function, and provides superior performance on structured datasets. In this research, GBR were training on the same input variables as the RFR model, allowing the comparative assessment of their relative accuracies in capturing the temporal dynamics and variability of the upwelling indices.

LSTM: LSTM networks are a type of Recurrent Neutral Network (RNN) particularly well-suited for modelling time series due to their ability to learn long-term dependencies and temporal patterns. In this study, LSTM was used in sequential relationship between historical climate and oceanographic variables that influence on coastal upwelling. The input features were normalized and structures as multivariate sequences over time windows to serve as input to the LSTM layers.

CNNs: CNNs are widely used for spatial pattern recognition. In this study, CNNs were designed and adapted to handle spatio-temporal input features such as gridded SST and wind fields, treating them as image-like data. Convolutional layers extracted local spatial feature relevant to upwelling dynamics, which were then passed through dense layers for regression output. This a:roach enabled the model to detect local patterns in SST and wind stress associated with coastal upwelling.

Hybrid LSTM-CNN: The Hybrid LSTM-CNN model was designed to leverage the strengths of both temporal and spatial pattern learning. The model architecture integrated convolutional layers followed by LSTM layers. This hybrid setup allowed for an improved representation of the spatio-temporal processes underlying upwelling variability, particularly for capturing interactions between local winds, SST, and large-scale climate signals.

Training and Validation

Target and Features

For the predictive modelling a:roach, the monthly upwelling indices based on SST and wind stress were predicted at the interannual scale, from 2015 to 2022. The most relevant principal components (PCs) of of local wind stress and SST anomalies, sea level anomaly, geostrophic transport components were extracted and used as model predictors (input features). All the variables were normalized to ensure models learn effectively. Additional climate indices selected based on their significant correlation coefficient with upwelling indices, were used to improve predictive skill. The results of the models were compared with observations and outputs of CMIP6 models, in particular the multi-model mean of SSP5-85 scenario.

Model Implementations

All the model fits were implanted using the Scikit-learn and TensorFlow libraries in Python. The training involves several key steps which were carried out to ensure the model accurately captures the complex temporal dynamics of coastal upwelling. For the model training, the data was spilt into training (60%), validation (20%), and testing (20%) sets based on temporal continuity. These datasets was then structured with the input Xtrain being the sequence at previous timesteps and the target Ytrain being the subsequent timestep. The model was trained using the Root Mean Square Error (RMSE) as the loss function (Hastie *et al.,* 2009) monitoring both the training and validation datasets. This monitor is one of the standard statistical metrics for regression problems. It was defined by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y^i - \hat{y}^i)^2} \quad (3)$$

Where y^i is the actual values; $\hat{y}^i$ is the predict values; and n is the number of observations.

The hyperparameters such as the number of estimators, maximum tree depth, and learning rate (for GBR) were optimized through grid search and cross-validation. Hyperparameter tuning of the Hybrid coupled model (LSTM-CNN) was performed to optimize model accuracy.

During the training, the GBR model with a learning rate set at 0.01. This learning rate was chosen after several experimentations to ensure that the model converges efficiently without compromising the stability of the learning process.

Model Evaluations

Model predictions were validated against upwelling indices derived from observations and SSP5-85 scenario. The model validation was performed with the Cross-Validation using time-series k-fold validation to prevent data leakage. The model's performance was assessed using standard metrics including the coefficient of determination (R^2), RMSE, and Mean Absolute Error (MAE); and visualized through a convergence plot, which illustrates the decrease in RMSE over successive training epochs, indicating that the model is learning to predict SST more accurately.

The important feature was extracted to identify the most influential predictors of upwelling dynamics. Finally, model interpretability was assessed using SHapley Additive exPlanations (SHAP) tool, which provided both global and local explanations of feature contributions. SHAP values were computed for each model to identify the most influential variables driving predictions of upwelling indices. Visualization of SHAP summary and individual force plots allowed insights into the model's decision process, ensuring alignment with known physical mechanisms. The model outputs were finally analysed to assess their ability to capture seasonal and interannual variability in upwelling dynamics.

3 | Results and Discussion

3.1 | Single Model predictions

The results revealed that AI models provided a significant improvement over SSP5-85 (Figure 2). Almost all the models show good performance, yielding the lowest RMSE (<0.09) and MAE (<0.07) values alongside the highest score of R^2 (R^2>70). This indicates a closer alignment of models with observations, underscoring the efficacity of integrating AI models features to extract the temporal dynamics of coastal upwelling SST and wind stress anomalies.

Although the four models used performed well in capturing temporal patterns of upwelling indices (Table 1), they did not achieve the same level of accuracy. CNN was slightly less precise (R^2=0.5) in predicting monthly SST-based and zonal offshore transport variations in the Senegal-Mauritania permanent upwelling region. Including climate indices (e.g., ENSO, ATL3, AMM), RF and GB effectively fall (R^2 = 0.004 and 0.005, respectively) in the temporal prediction of SST anomalies in the eastern of cape Plamas (7W-2W), with RMSE around 0.87 and 0.84, respectively. This result suggests that the large-scale drivers influence negatively the model results. These results confirm the performance of multi-task ML and DL techniques especially RF, GB, LSTM and CNN models in simulating ocean processes even during the extreme events such as the Indian Ocean Dipole (IOD) well up to 7-month ahead (Ling *et al.,* 2022), marine heatwaves in the Mediterranean Sea (Bonino *et al.,* 2024). The models used in this study were also applied elsewhere to predict SST time series. Using atmospheric variables as potential predictors of MHWs, Bonino *et al.,* (2024) show that all the ML methods performed with minimum RMSEs of about 0.1 °C at a 1-day lead time and maximum values of about 0.8 °C at a 7-day lead time. However, they observed that ML techniques show results similar to the dynamical Copernicus Mediterranean Forecasting System (MedFS) for both SST and MHW forecasts, especially in the early forecast days, but with different highest predictive skill of LSTM in different regions at all lead times. These results enhance the comprehension of model performances in predicting SST gradient in the Northwest African coast. As Bonino *et al.,* (2024), all models used predict the SST gradient with a confidence level greater than 50 % in each region.

3.2 | Hybrid Model Prediction

In addition, to isolate the impact of the individual deep learning model on the prediction of the temporal dynamics of upwelling indices, the LSTM hyperparameters were integrated to the CNN shape. This integration improved simulations, in resulting a lower RMSE and MAE scores, and a higher determination coefficient, compared to a single LSTM or CNN model. This improvement highlights the hybrid model LSTM-CNN effectiveness in capturing temporal dependencies within the SST and wind stress anomalies data, which are crucial for accurately predicting monthly coastal upwelling scenarios. Focusing on the prediction of SST using deep learning model experiements, Snoussi *et al.,* (2024) have recently show the performance of IA models in predicting the feature spatio-temporal variabily of SST in the Marocco cosatal upwelling region. This result supported the output of the LSTM and LSTM-CNN hybrid in simulating SST anomalies. Simular result was presented by Ronneberger *et al.,* (2015) in the biomedical analysis. However, using a mixite a:roch of artificial neural network (ANN) techniques, Kriebel *et al.,* (1998) found difficulties in predicting Northwest coastal upwelling limited by the quantity of the input data.

Although the LSTM-CNN hybrid architecture reveals its superior capability for high simulations of Ekman transport and SST-based, essential for the precise identification of coastal upwelling, it is completely unable to capture upwelling indices in the eastern of cape Palmas.

3.3 | Comparison between AI predictive Models and SSP5-85 Scenario

The visual analysis focused on the coherences with the SSP5-85 projection trends, and the overall resemblance with observation data. The selected models demonstrated a remarkable ability to capture

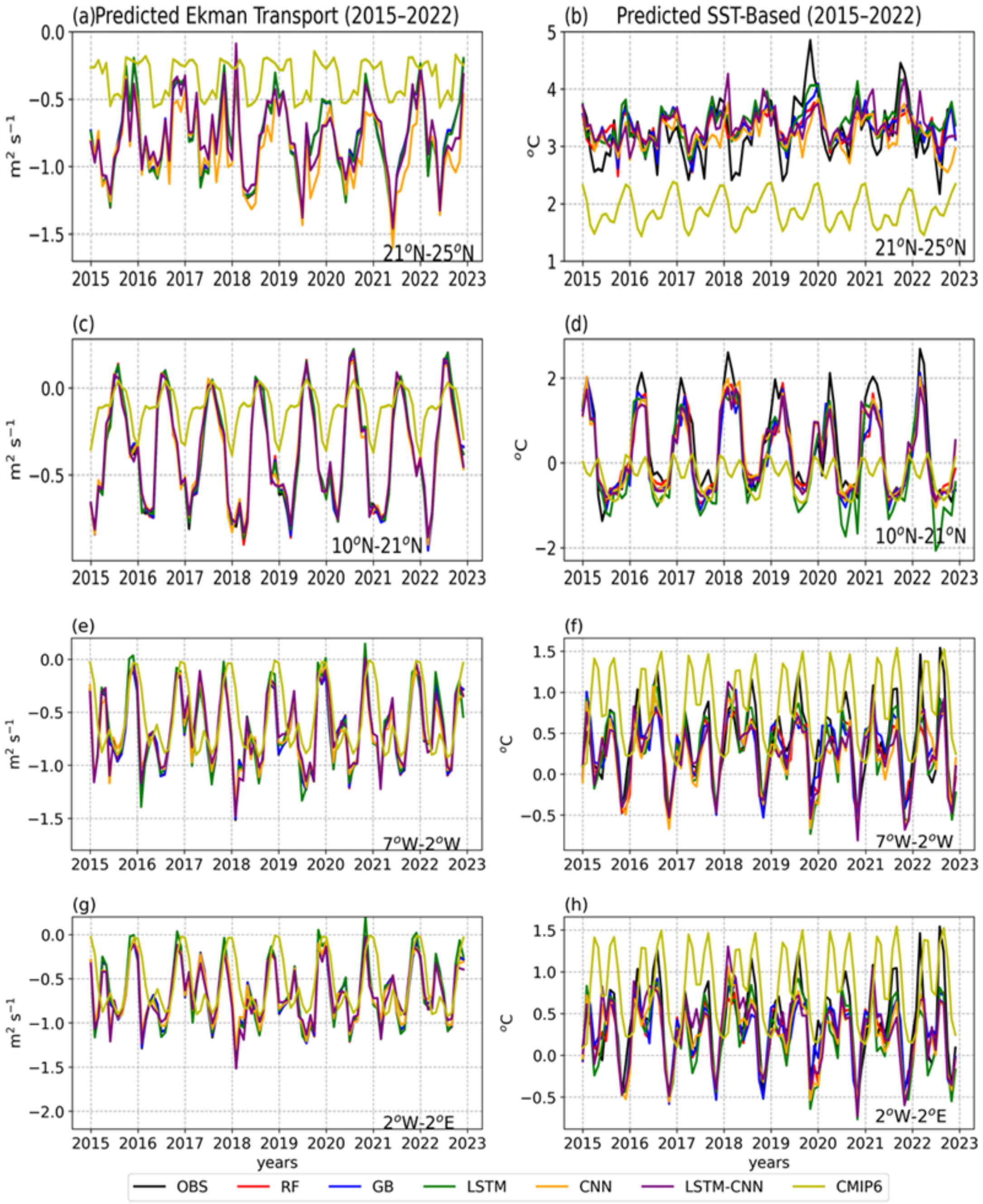

Figure 2 | Interannual variability of offshore Ekman transportand SST-based simulated simulated by AI models in the Senegal-Mauritania (a-d) and Gulf of Guinea (e-h) coastal upwelling systems.

both SST gradients and offshore Ekman transport at fine-scale details using large-scale climate patterns (e.g., ENSO, NAO), and localized cold upwelled structures near the coast, which are essential for accurate representation of coastal upwelling events. (Table 1)

The combination LSTM-CNN presents the best score (R^2>0.9) of AI models over all the simulated regions. The comparative analysis clearly show the AI regression models' exceptional capability in generating high-resolution forecasts that exhibit a remarkable coherence with observations. The AI models despite their efficacity were inadequate in resolving upwelling indices in the Guf of Guinea, in particular in the east of cape Palmas, can be linked to some inputs variables that the models were not successful in resolving their variability and correlations with SST and wind stress components.

These findings underscore the efficacity of advanced AI techniques in refining the accuracy of SST-based and Ekman transport predictions, thereby offering significant implications for future advancements and applications of AI tools within the domain of marine sciences. The analysis reveals the effective capacity of MLearning and advance DL regression models such as Random Forest, Gradient Boosting, Long Short-Term, Convolutional Neural and the integration LSTM with CNN architectures, to capture the interannual variability of SST and wind stress patterss (Ekman transport), critical factors

Table 1 | Model scores in simulating Ekman transport SST-based upwelling Index

Region	Model	MAE	MSE	RMSE	R^2
21-25°N	Random Forest	0.035	0.005	0.070	0.812
	Boosting Gradient	0.031	0.004	0.063	0.846
	LSTM	0.039	0.004	0.065	0.841
	CNN	0.085	0.013	0.113	0.568
	LSTM-CNN	0.040	0.004	0.064	0.851
10-20°N	Random Forest	0.032	0.003	0.059	0.944
	Boosting Gradient	0.033	0.004	0.062	0.938
	LSTM	0.044	0.005	0.072	0.915
	CNN	0.060	0.006	0.079	0.896
	LSTM-CNN	0.034	0.003	0.054	0.953
7-2°W	Random Forest	0.029	0.003	0.058	0.887
	Boosting Gradient	0.030	0.003	0.059	0.880
	LSTM	0.037	0.004	0.060	0.879
	CNN	0.051	0.006	0.074	0.825
	LSTM-CNN	0.031	0.003	0.052	0.910
2°W-2°E	Random Forest	0.027	0.003	0.051	0.900
	Boosting Gradient	0.025	0.002	0.048	0.912
	LSTM	0.033	0.004	0.060	0.864
	CNN	0.062	0.007	0.082	0.797
	LSTM-CNN	0.027	0.002	0.049	0.911

of coastal upwelling along the Northwest African coast.

Comparatively, the selected AI models represent well the observed Ekman transport and SS-based than SSP5-85 multi-model mean (Table 2), which understimates the observed upwelling indices in both upwelling systems. All the statiscal model used are close to observed. All the RMSE computed successively over the training epochs are negative and strong in the Senegal-Mauritania permanent upwelling region (21-25°N). This indicates that the AI models are learning to predict refinement SST and wind anomalies more accurately than the dynamic climate models that are not enable to resolve well coastal processes maybe because of their spatial resolution.

Table 2 | Model scores in comparison with scenario SSP5-85

		21-25°N		**10-20°N**		**7-2°W**		**2°W-2°E**	
Model	Index	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Random Forest	Ekman transport	0.960	-8.103	0.516	-1.628	0.356	-0.255	0.658	-3.280
Gradient Boosting		0.959	-8.101	0.516	-1.629	0.356	-0.254	0.658	-3.281
LSTM		0.942	-7.782	0.528	-1.754	0.358	-0.268	0.656	-3.251
CNN		0.934	-7.624	0.539	-1.867	0.322	-0.022	0.568	-2.193
LSTM-CNN		0.965	-8.205	0.525	-1.721	0.336	-0.118	0.621	-2.811
Random Forest	SST-based	2.575	-30.239	1.213	-5.934	0.721	-1.446	0.730	-1.507
Gradient Boosting		2.606	-30.988	1.282	-6.737	0.710	-1.374	0.748	-1.636
LSTM		2.669	-32.565	1.490	-9.455	0.774	-1.820	0.805	-2.055
CNN		2.477	-27.902	1.245	-6.300	0.745	-1.614	0.751	-1.657
		2.614	-31.174	1.260	-6.481	0.719	-1.438	0.754	-1.678

SHAP was to assess the model impacts, in particular RF and GB on the on the predictions. In the Senegal-Mauritania coastal upwelling regions, SHAP results show wide spread of SHAP values, mostly positive, especially when SLA is high. This suggests that stronger SLA increases the predicted SST-based upwelling index and ooffshore Ekman transport. The high values Tugo, Tvgo, taux, tauy push prediction positive, while the high High SSTA often push output lower, possibly indicating warm SSTs correlate with changes in upwelling behavior.

In the seasonal upwelling region (10-20°N), the SHAP outputs show that the higher values of the features push prediction lower while the decrease in values of the features seems to increase model capacity to simulate simultamous both upwelling indices.

In the two upwelling cells of the Gulf of Guinea (7-2°W and 2°W-2°E), the SHAP (Figure 3) plots show more scattered impact but important, suggesting all the selected features play a significant role in modifying upwelling. This shows the complexity of

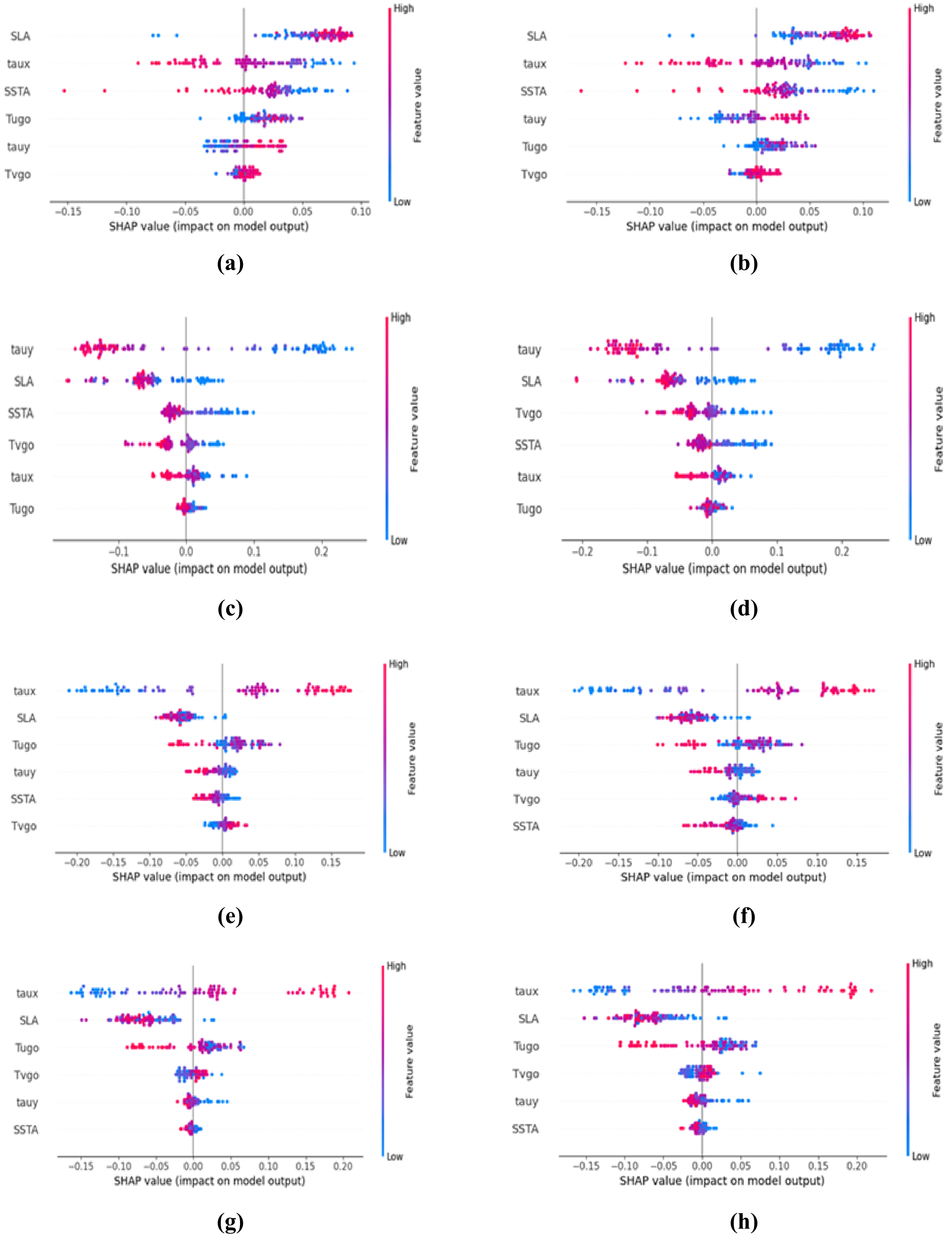

Figure 3 | SHAP summary plots for the Random Forest and Gradient Boosting models used in the prediction of SST-based and Ekman transport in the Senegal-Mauritanian and Gulf of Guinea coastal upwelling systems.

the upwelling, and selected models the main driver of this coastal process. However, stronger zonal wind stress was found to increase the predicted SST-based upwelling index or Ekman transport. Climatic Indices such as AMM, NAO, ATL3, NTA, ENSO, SOI, PDO, show lower importance with smaller SHAP ranges indicating less influence or indirect influence of large-scale modes (e.g., via wind or current anomalies) on coastal upwelling.

4 | Summary and Conclusion

In summary, the study has evaluated the performance of AI statistical models such as Random Forest, Gradient Boosting, Long Short-Term and Convolutional architectures to simulate Northwest African coastal upwelling indices over SSP5-85 scenario, including Ekman transport and SST-based. These techniques provide a comprehensive analysis and understanding of complex oceanographic phenomena, specifically coastal upwelling, which significantly impacts marine ecosystems and climate. The adoption of these sophisticated AI models has led to a notable improvement in predicting SST fields, reduction in RMSE and increasing the coefficient of determination. This enhancement over the ML and DL models, underscores the selected models' capability to accurately capture the dynamic and interannual variability of coastal upwelling. All the models have shown to be adept at extracting complex temporal time-series within upwelling regions, unveiling both low-level and high-level features (Krizhevsky *et al.,,* 2012), while RNNs, and particularly their extension Long Short-Term Memory (LSTM) networks, capture temporal sequences (Sherstinsky 2020). This study also investigates the fusion of CNNs and LSTMs into a hybrid model to improve the accuracy and upwelling forecasts (Shi *et al.,* 2015) compared to the single model experiment. In conclusion, this study AI is better suited to predicting ocean processes than the use of climate models. However, the results of the present study offer o:ortunities for future research in marine meteorology, highlighting the potential of AI techniques in simulating upwelling features and improving climate model predictions in meteorology and climate science. Despite, of the high performance of the selected AI models, they struggle to capture well the extreme event of upwelling and need more conceptions. Further investigation employing models that include spatial and temporal dimensions of coastal upwelling will be necessary to enhance the short forecasting and long-term predictions of coastal upwelling.

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