Environmental Data Science (2023), 2: e5, 1–8
doi:10.1017/eds.2022.35

CAMBRIDGE UNIVERSITY PRESS

APPLICATION PAPER

Learning the spatiotemporal relationship between wind and significant wave height using deep learning

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Received: 21 December 2022; **Accepted:** 21 December 2022

Keywords: Convolutional neural networks; long short-term memory; significant wave height; wind fields

Abstract

Ocean wave climate has a significant impact on near-shore and off-shore human activities, and its characterization can help in the design of ocean structures such as wave energy converters and sea dikes. Therefore, engineers need long time series of ocean wave parameters. Numerical models are a valuable source of ocean wave data; however, they are computationally expensive. Consequently, statistical and data-driven approaches have gained increasing interest in recent decades. This work investigates the spatiotemporal relationship between North Atlantic wind and significant wave height (H_s) at an off-shore location in the Bay of Biscay, using a two-stage deep learning model. The first step uses convolutional neural networks to extract the spatial features that contribute to H_s. Then, long short-term memory is used to learn the long-term temporal dependencies between wind and waves.

Impact Statement

In the context of climate change, the climate of ocean waves has major socioeconomic and environmental implications. Since ocean waves are generated by the wind blowing at the ocean surface, understanding the relationship between wind and waves is critical to assessing the impact of climate change on ocean waves. This work contributes to understanding the spatiotemporal relationship between wind conditions and ocean waves using deep learning. We propose a fully data-driven empirical wind-wave model that predicts the significant wave height at a location in the Bay of Biscay using the North Atlantic wind conditions. The proposed method is computationally inexpensive and can provide long time series of future significant wave heights or complete historical data if wind data are available.

1. Introduction

Characterization of wave climate is required for many marine applications, such as the design of coastal and offshore structures and the planning of ship operations. Wind waves are generated by the surface wind, with the local wind creating the wind sea and wind from distant areas creating waves that propagate

This research article was awarded Open Data and Open Materials badges for transparent practices. See the Data Availability Statement for details.

and form swells (Young, 1999). Waves in the Bay of Biscay depend on both local and large-scale wind conditions in the North Atlantic (Charles et al., 2012); however, swells generally dominate the sea state. Swells travel large distances and take up to 5 days to cross the Atlantic from Cape Hatteras to the Bay of Biscay (Ardhuin and Orfila, 2018). Consequently, waves observed at a given location depend on wind conditions over the North Atlantic in a time window of several days, and it is challenging to reproduce this complex spatiotemporal relationship using machine learning. The goal of this work is to propose a deep learning approach that learns this relationship.

The advantage of deep learning methods (Goodfellow et al., 2016) lies in their ability to build hierarchical representations of predictors. In particular, in the case of spatial data, convolutional neural networks (CNNs) allow to learn complex spatial features from the data (Gu et al., 2018). Moreover, long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997 has proven to be very successful in predicting time series and sequence data. In this work, we propose a nonexpensive data-driven approach that learns the underlying spatiotemporal structure of the relationship between wind and waves using a two-stage model based on CNNs and LSTM.

This paper is organized as follows. Section 2 presents the problem of downscaling of ocean waves and related works. Section 3 describes the data used in this work. Section 4 presents the proposed two-stage model, the architecture, and the training process. Section 5 discusses the results of this work. Finally, Section 6 presents the conclusions and future work directions.

2. Problem Statement and Related Work

The problem of improving the spatial resolution of climate variables is known under the name of downscaling (Maraun et al., 2010). Downscaling approaches attempt to construct a link, either numerical or statistical, between large-scale and local-scale variables. The advantage of statistical downscaling (SD) over numerical models is primarily in terms of computational efficiency. A rigorous comparison of the two approaches can be found in Wang et al. (2010) and Laugel et al. (2014).

In the case of ocean waves, wind (Obakrim et al., 2022) or sea level pressure (SLP) (Camus et al., 2014) are commonly used to downscale ocean wave parameters. However, in order to establish a link function between the wind (or SLP) and the local ocean wave parameters, it is necessary to consider a large spatial and temporal coverage and, consequently, a large number of potential explanatory variables that are highly correlated. Some methods determine the wave generation area for any ocean location worldwide. For example, ESTELA (Pérez et al., 2014) is a numerical model that uses spectral information to select the fraction of energy that travels to the target point from selected source points. The ESTELA method can be used to design SD methods. For instance, Camus et al. (2014) and Hegermiller et al. (2017) used the ESTELA method to define the predictors used in their SD model.

Obakrim et al. (2022) proposed a data-driven approach that determines the wave generation area by estimating the travel time of waves, generated in each considered sources point, that reach the target point. Then, the predictors were defined based on the wave generation area and finally, a SD model based on weather types was built.

As far as we know, the existing methods for SD of ocean wave parameters define a priori the spatiotemporal structure of the predictors, and then the SD model is built using these predictors. The aim of this study is to propose a deep learning approach that automatically learns the spatiotemporal relationship between wind and waves.

3. Data Preparation

The Climate Forecast System Reanalysis (CFSR) (Saha et al., 2010) hourly wind data is considered in this study as a predictor. CFSR is a global reanalysis developed by the National Centers for Environmental Prediction (NCEP) that covers the period from 1979 to the present with an hourly time step and a spatial resolution of 0.5° by 0.5°. The historical H_s data is extracted from the hindcast database HOMERE (Boudière et al., 2013) at the target location with spatial coordinates (45.2°N, 1.6°W) located in the Bay of

Biscay. The temporal resolution of both wind and H_s data is up-scaled to 3-hourly data. The period from 1994 to 2016 is considered in this study, leading to a dataset with $n = 67,208$ observations.

Instead of using both zonal and meridional components as a predictor, we use the projected wind (Obakrim et al., 2022) defined, at each location j and time t, as

$$W_j(t) = U_j(t)\cos^2\left(\frac{1}{2}\left(b_j - \theta_j(t)\right)\right), \tag{1}$$

where $W_j(t)$ is the projected wind, $U_j(t)$ the wind speed, $\theta_j(t)$ the wind direction and b_j is the great circle bearing from the source point j to the target point. Under the assumption that waves travel in great circle paths, grid points whose paths are blocked by land are neglected (Figure 1). Therefore, we define the global predictor at time t as

$$X^{(g)}(t) = \left(W_1^2(t), \ldots, W_p^2(t)\right), \tag{2}$$

where $p = 5,651$ is total number of grid points.

Following Obakrim et al. (2022), in order to capture the wind sea, we also define the local predictor as

$$X^{(\ell)}(t) = \left\{U(t), U^2(t), U^3(t), U^2(t)F(t), U(t-1), U^2(t-1), U^3(t-1), U^2(t-1)F(t-1)\right\}, \tag{3}$$

where $U(t)$ is the wind speed at the target point and $F(t)$ is the fetch length at time t, calculated as the minimum of the distance from the target point to shore in the direction from which the wind is blowing and 500km. The fetch has an important effect on wind sea characteristics (Ardhuin and Orfila, 2018); therefore, it is commonly used to construct empirical wind wave models.

4. Proposed Methodology

As mentioned in the last section, state of the art statistical methods for downscaling wave parameters usually use a preprocessing step to create features that take into account the wave generation area. In this

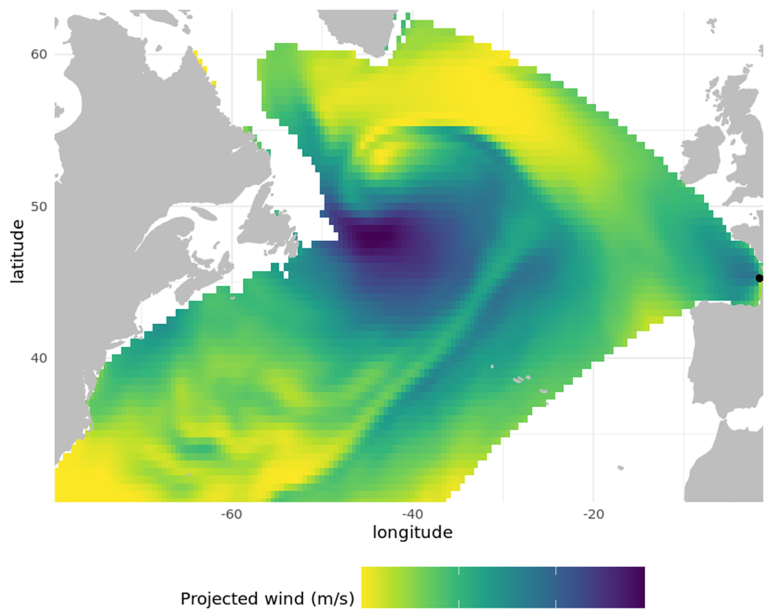

Figure 1. *The projected wind, defined in (1), in January 1, 1994, 00:00 hr. The black point represents the target point.*

https://doi.org/10.1017/eds.2022.35 Published online by Cambridge University Press

study, we propose a deep-learning approach that automatically extracts these features. Since waves may take several days to reach the target point, the history and current wind can be used to predict H_s. An example of this type of model could have the following form:

$$H_s(t) = f\left(X^{(g)}(t - t_{\max}), \dots, X^{(g)}(t)\right), \tag{4}$$

where, $t_{\max}$ can be interpreted as the maximum travel time of the waves and will be referred to as such in the following. However, this approach can be computationally challenging given the dimension of the predictor (5,651 in our case). Instead, in this study, we propose to use current wind conditions to estimate current and future H_s.

In order to describe the complex spatiotemporal relationship between wind and H_s, we propose the following two-stage model:

$$\begin{array}{ll} \text{First stage}: & \left[H_s\left(t|X^{(g)}(t)\right), \dots, H_s\left(t+t_{\max}|X^{(g)}(t)\right)\right] = f\left(X^{(g)}(t)\right) + \varepsilon(t), f: \mathbb{R}^p \to \mathbb{R}^{t_{\max}} \\ \text{Second stage}: & H_s(t) = g\left(X^{(g)}(t), f\left(X^{(g)}(t-t_{\max})\right), \dots, f\left(X^{(g)}(t)\right)\right) + \varepsilon'(t),\ g: \mathbb{R}^{t_{\max}\times t_{\max}+8} \to \mathbb{R} \end{array}, \tag{5}$$

where the notation $H_s\left(t_1|X^{(g)}(t_2)\right)$ represents the contribution of wind conditions at time t_2 in H_s at time t_1. ε and ε' are the errors of the first stage and second stage, respectively. The first stage estimates the current and future H_s using current wind conditions. The second stage estimates H_s using the past predictions obtained from the first stage. Along with the local predictor $X^{(g)}$, the input for the second stage is a $t_{\max} \times t_{\max}$ matrix of the form

$$\begin{pmatrix} \widehat{H}_s\left(t-t_{\max}|X^{(g)}(t-t_{\max})\right) & \dots & \widehat{H}_s\left(t|X^{(g)}(t-t_{\max})\right) \\ \vdots & \ddots & \vdots \\ \widehat{H}_s\left(t|X^{(g)}(t)\right) & \dots & \widehat{H}_s\left(t+t_{\max}|X^{(g)}(t)\right) \end{pmatrix}, \tag{6}$$

where $\widehat{H}_s\left(t_1|X^{(g)}(t_2)\right)$ represents the prediction, obtained from the first stage, of the contribution of wind conditions at time t_2 in the H_s at time t_1. When $t_1 = t_2$, this prediction represents the wind sea (first column of the matrix in equation (6)); for $t_1 > t_2$, on the other hand, the prediction represents the H_s caused by swells.

The general structure of the model is shown in Figure 2. The first stage consists of a series of 3 × 3 convolutions followed by the ReLU activation function, 2 × 2 max pooling layer, Batch Normalization, then a flatten followed by a dense layer. The second stage starts with an LSTM layer that learns the long-term dependencies of the $(t - t_{\max}, \dots, t)$ outputs of the first stage. The output of the LSTM layer is then concatenated with the local predictor X^l and fed into two fully connected layers. The dropout layer is used in both stages to prevent the network from overfitting. The loss function choosed in this study is the mean squared error (MSE) which is expressed as

$$\begin{aligned} \text{MSE(First stage)} &= \frac{1}{t_{\max}} \sum_{i=0}^{t_{\max}} \frac{1}{n - t_{\max} - 1} \sum_{t=1}^{n-t_{\max}} \left(H_s(t+i) - \widehat{H}_s\left(t+i|X^{(g)}(t)\right)\right)^2, \\ \text{MSE(Second stage)} &= \frac{1}{n} \sum_{t=1}^{n} \left(H_s(t) - \widehat{H}_s(t)\right)^2, \end{aligned} \tag{7}$$

where n is the total number of observations and $\widehat{H}_s$ is the prediction of H_s. The Keras framework with Tensorflow backend (Chollet et al., 2015) is used in this work to train the model, on a Nvidia K80s GPU using the Adam optimizer (Kingma and Ba, 2017) and mini batches of 64.

5. Results

The period from 1994 to 2011 is used to train the two-stage model and the period from 2012 to 2014 serves as the validation period. The measures chosen in this paper to validate the analysis are the correlation

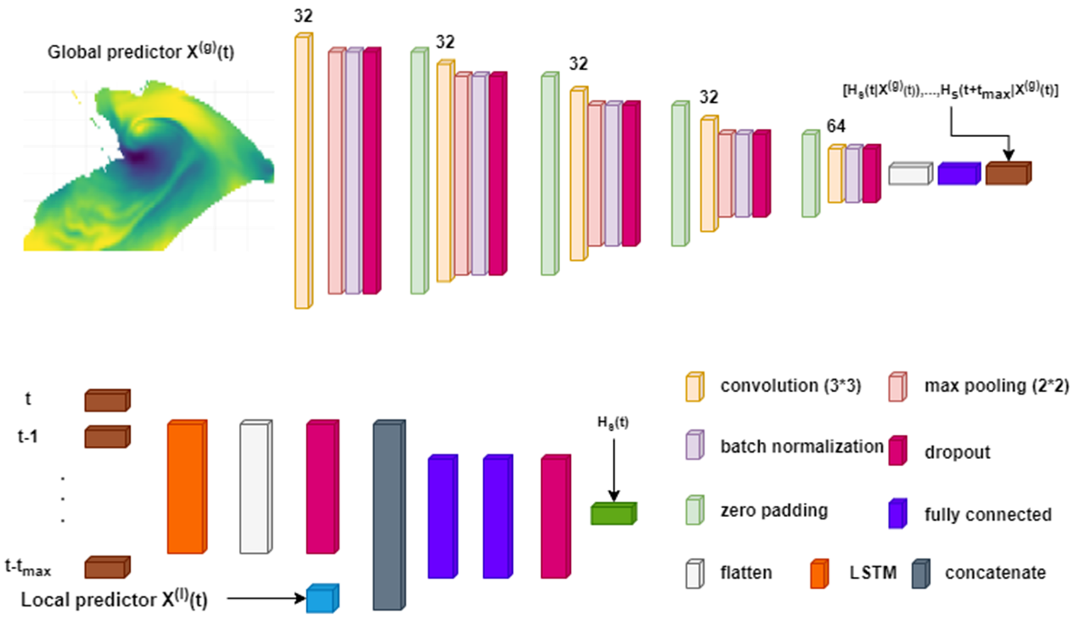

Figure 2. *Architecture of the two-stage model in equation (5).*

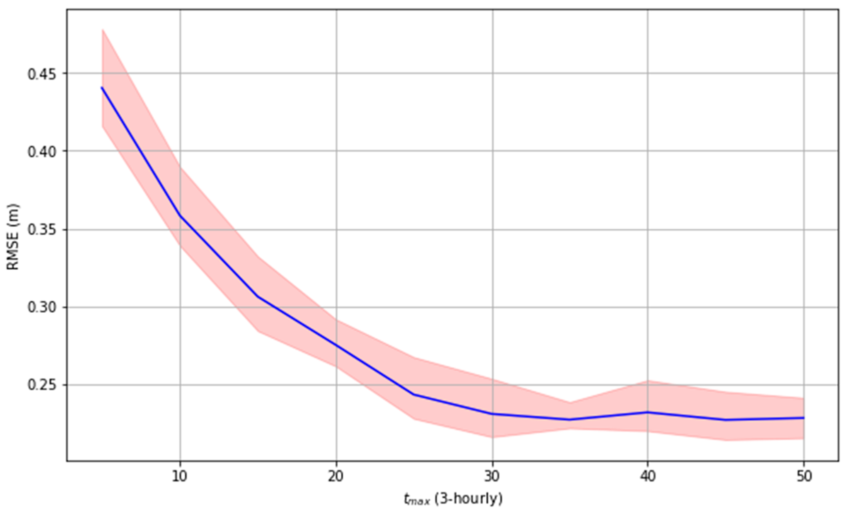

Figure 3. *Results of cross-validation using different values of* $t_{\max}$. *The blue line represents the mean of root mean square error (RMSE) and the red interval represents the minimum and maximum RMSE.*

coefficient (r), the root mean square error (RMSE), and the bias. Different values for the maximum travel time of waves $t_{\max}$ are tested, and the results of k-fold cross-validation (with $k = 5$) are shown in Figure 3. The RMSE stabilizes approximately at $t_{\max} = 30 \times 3$ hr, which corresponds to about 3.3 days, and the gain is substantial compared to using $t_{\max} = 5$. This means that wind conditions over a time window of at least 3.3 days must be considered to characterize the wave climate at the target location. In the following, the value of $t_{\max}$ is chosen equal to 30.

Figure 4 shows the scatter plot of observed versus predicted values of H_s using the two-stage model (5). The RMSE in the validation period is equal to 0.21 m for an H_s of mean 1.9 m and standard deviation

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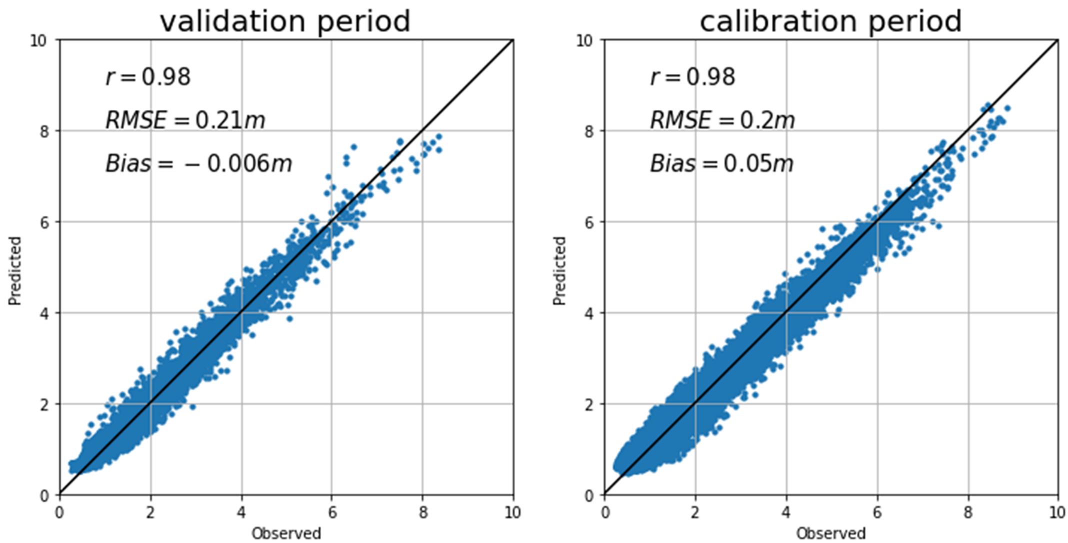

Figure 4. *Observed versus predicted H_s in the validation period (left panel) and calibration period (right panel).*

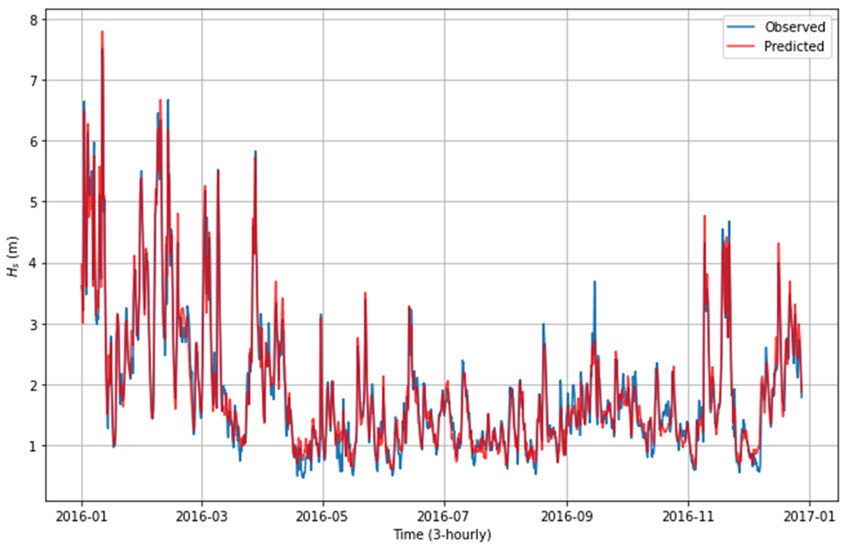

Figure 5. *Time series of observed (blue line) and predicted (red line) H_s in 2016.*

1.1 m. The model performs well in predicting H_s and accounts for both wind and swell. The validation measures in the calibration and validation periods are almost the same. This means that the model does not overfit the training data and generalizes well the relationship between wind and waves. Furthermore, the seasonality of H_s is well captured by the two-stage model, as can be seen in Figure 5.

A comparison of the two-stage model with two other statistical approaches is done in Table 1. The first approach, described in Obakrim et al. (2022), is based on weather types (Maraun et al., 2010). As for the present work, the local and global predictors were considered. However, in order to reduce the dimension of the predictor a single predictor is extracted at each spatial location j to predict H_s at time t. It is defined a priori as

https://doi.org/10.1017/eds.2022.35 Published online by Cambridge University Press

Table 1. Comparison of the two-stage model, weather types, and H-CNN methods.

Method	r	RMSE (m)	Bias (m)
Two-stage model	0.98	0.21	−0.006
Weather types	0.97	0.27	−0.03
H-CNN	0.97	0.27	−0.04

Abbreviation: RMSE, root mean square error.

$$X_j^{(g)}\left(t;t_j,\alpha_j\right)=\frac{1}{2\alpha_j+1}\sum\nolimits_{i=t-t_j-\alpha_j}^{t-t_j+\alpha_j}W_j^2(i),\quad t_j+\alpha_j+1\le t\le t_j-\alpha_j+n, \tag{8}$$

where t_j is the travel time of waves, α_j controls the length of the time window, and W_j is the projected wind at location j. The parameters t_j and α_j were estimated using the maximum correlation between h_s and the global predictor. The second method proposed by Michel et al., 2022, called H-CNN, uses CNNs to predict H_s using the same predictors as in Obakrim et al. (2022). Thus, the main difference with the approach proposed in this work is that the temporal dimension of the global predictor is reduced a priori using the preprocessing step based on the maximum correlation described above. The numerical results in Table 1 indicate that the two-stage model significantly outperforms the other two methods in term of the validation measures.

6. Conclusion

In this study, a two-stage model based on deep learning is proposed to predict H_s using wind conditions. The model is capable of learning automatically the underlying spatiotemporal structure of the relationship between wind and waves. The model does well in predicting H_s and is computationally inexpensive (about 5 min using a computer of 30GB RAM, 2 cores CPU, and a 16GB GPU). The proposed methodology is based on two stages which are trained separately. A natural question that arises for future work, is whether we can estimate the parameters jointly using back-propagation and eventually speed up the training process and improving the results. Future work also includes using the method to predict other sea state parameters, such as wave direction and period.

The proposed method can be used for climate and weather studies at any ocean location worldwide. For nearby locations, one can train only the second stage at each location, using the weights of one location as initialization for the others and leaving the first stage the same. The model can also learn from buoy data instead of hindcast data and eventually fill in the gaps and complete historical data.

Author Contributions. Conceptualization: S.O., V.M., N.R., P.A.; Data curation: S.O., N.R.; Data visualization: S.O.; Methodology: S.O., V.M., N.R., P.A.; Software: S.O.; Supervision: V.M., N.R., P.A.; Writing—original draft: S.O., V.M., N.R., P.A. All authors approved the final submitted draft.

Competing Interests. The authors declare no competing interests exist.

Data Availability Statement. The hindcast data Homere is available on their website: https://marc.ifremer.fr/produits/rejeu_d_etats_de_mer_homere. The wind data is available from the CFSR website: https://climatedataguide.ucar.edu/climate-data/climate-forecast-system-reanalysis-cfsr. For reasons of reproducibility, Python code and the processed data are available at https://github.com/SaidObakrim/Two-stage-CNN-LSTM-.

Ethics Statement. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

Funding Statement. This work received no specific grant from any funding agency, commercial, or not-for-profit sectors.

Provenance. This article is part of the Climate Informatics 2022 proceedings and was accepted in *Environmental Data Science* on the basis of the Climate Informatics peer review process.

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Cite this article: Obakrim S. Monbet V. Raillard N. and Ailliot P. (2023). Learning the spatiotemporal relationship between wind and significant wave height using deep learning. *Environmental Data Science*, 2: e5. doi:10.1017/eds.2022.35