Developing a deep learning network to simulate future changes in the emerging Arctic Ocean wave climate

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Abstract

The Arctic Ocean is warming at an alarming rate and will likely become ice-free in summer by mid-century. This will be accompanied by higher ocean surface waves, which pose a risk to coastal communities and marine operations. In order to develop climate change adaptation strategies, it is imperative to robustly assess the future changes in the Arctic ocean wave climate. This requires a large ensemble of regional ocean wave projections to properly capture the range of climate modeling uncertainty in the Arctic region. This has been proven challenging, as ocean wave information is typically not provided by climate models, ocean wave numerical modeling is computationally expensive, and most global wave climate ensembles exclude the Arctic region. Here we present a framework to develop a CNN-LSTM deep learning network which could be potentially used to obtain such a large ensemble of Arctic wave projections at an affordable cost.

1. Introduction

The Arctic is a hot spot for global climate change as it is warming about twice as fast as global temperatures due to the so-called Arctic amplification. This is leading to a rapid decline in sea ice extend; the Arctic sea-ice extend has shrunk by an average of 13.4% with the last two lowest records occurring over the last decade (Witze, 2020). Recent climate simulations project a likely ice-free Arctic summer by mid-century (Wei et al., 2020) although it could be as early as 2035 (Guarino et al., 2020). Extended ice-free seasons and expanded open water areas favor the increase of ocean surface waves (Casas-Prat & Wang, 2020a). This poses a great risk to coastal communities (due to increased infrastructure damage, coastal erosion and flooding), and threatens the safety of existing and emerging offshore operations. This is a pressing issue as this exacerbates existing vulnerabilities in low-lying Arctic coastal areas, which have already experienced coastal damage in the last few years (Casas-Prat & Wang, 2020b).

Climate models are constantly updated to produce (improved) simulations of future climate. These coordinated efforts are part of the international Coupled Model Intercomparison Projects (CMIP), in the context of the Intergovernmental Panel on Climate Change (IPCC). The 2013 IPCC fifth assessment report (AR5) featured climate models from CMIP5, while the upcoming 2021 IPCC sixth assessment report (AR6) will feature new state-of-the-art CMIP6 models. A key objective of CMIP is to develop large ensembles of standard climate projections that account for the main factors of uncertainty: climate model parameterizations, internal climate variability, greenhouse gas scenario. Morim et al. (2019) showed, for instance, that a single method to asses projected changes in ocean wave heights might be unable to capture up to 50% of the total uncertainty.

An in-depth understanding of the future changes in ocean wave climate is key to develop a climate adaptation strategy that properly addresses the aforementioned challenges. Casas-Prat & Wang (2020b) developed and presented the first regional multi-model Arctic ocean wave ensemble, which was obtained with a dynamical numerical modelling approach driven by simulations from five CMIP5 models. Their historical simulations were validated against state-of-the-art reanalysis (historical simulated data that assimilate observations) and found that their simulations were within the range of uncertainty of such reference products. Their future simulations showed that the annual maximum wave heights along coastlines would increase about 1–3 m by the end of the century, representing a relative increase up to 2–3 times their historical value. While these projected changes are statistically robust, confidence is low due to using a small ensemble.

Currently, there is lack of evidence that a climate model of better performance in simulating the historical climate will necessarily produce better projections of future climate. This lack of evidence is more so in the dramatically chang-

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ing Arctic region as climate biases might change over time due to the strong climate change responses. Therefore, a large ensemble of wave projections is needed to cover major sources of uncertainty. This has been proven challenging as most climate models do not include information about ocean surface waves and ocean wave numerical modelling is computationally expensive. Also, most global wave projections (needed to provide boundary conditions for Arctic regional numerical modelling) exclude the Arctic region or do not account for sea ice (Morim et al., 2019). To reduce computational cost, statistical methods have been developed and implemented in the past decade. These are typically based on weather maps or grid point regression models with physical-based predictors, and their performance can be comparable to that of numerical simulations. However, none has been applied to the Arctic region, probably due to the complex explicit implementation of the sea ice driver in simplified predictors, and the inability to use reanalysis data (only) to infer the relationship between input and output data in the future climate, as explained in Section 2.

Machine learning application to ocean wave modelling is still rather limited, and has focused mostly on wave forecasting (James et al., 2018). Deep learning, and in particular CNN are a promising approach to address this problem given their success in computer vision, and particular image/video generation (e.g. Castrejón et al., 2019). Here we present a CNN approach with preliminary results using the CMIP5-based dataset developed by Casas-Prat & Wang (2020b). Future work involves further testing and model tuning with more CMIP5-based ensemble members as well as assessing whether the inclusion of time recurrence (using the proposed LSTM-CNN model) contributes to significant model improvement. The successfully trained model will be employed to develop a large multi-model, multi-scenario and multi-run ensemble of Arctic wave projections using the latest CMIP6 climate simulations.

2. Data

As mentioned in the Introduction, we use the wave projections developed by Casas-Prat & Wang (2020b), which span the periods 1979–2005 (historical period) and 2081–2100 (future period) and were obtained using the WAVEWATCH (WW3) wave model (The WAVEWATCH III Development Group (WW3DG), 2016). Simulations of hourly significant wave heights (SWH) were obtained by driving WW3 with 3-hourly 10-m surface winds (W10) and daily sea ice concentrations (SIC) simulated by five CMIP5 models for the historical and RCP8.5 scenario future period, respectively. WW3 was forced at the boundaries with wave spectra extracted from global wave projections. In particular, the GFDL-ESM2M-derived ocean wave ensemble member is used to train and validate our network with 75% and 25% of the data, respectively.

In-situ observations in the Arctic are scarce and satellite data is limited to the last couple of decades. The notable differences between historical and future spatial features in this drastically changing environment hinders the use of reanalysis (historical) data even if that is less affected by model biases thanks to data assimilation. A model trained with historical data only would likely fail to predict future patterns in the emerging open waters. Therefore, the CMIP5-based simulations corresponding to the selected ensemble member are here considered as the ground truth of our deep learning approach, for which both training and validation datasets are comprised by frames from both the historical and future periods. Further testing of the proposed model will be carried out with the remaining four CMIP5 projection sets developed by Casas-Prat & Wang (2020b). Once achieving a desirable performance (low RMSE), inference will be applied to the CMIP6 data to develop a large ensemble of Arctic wave projections derived with the most up to date climate projections.

Input data are daily SIC, and 3-hourly u- and v- components of W10, noted as U10 and V10. Output data is the hourly SWH. The original dataset, which is comprised by regular and unstructured lon-lat grids, is projected and interpolated to obtain regular 128×128 pixel frames on a polar stereographic projection. As we want to avoid having to rely on boundary conditions provided by global wave projections, we extend the W10 domain to lower latitudes to capture remotely generated waves coming from the Atlantic Ocean.

3. Proposed deep learning framework

Based on the parsimony principle, we start with a rather simple network shown in Figure 2. This model uses a CNN to encode the SIC, U10 and V10 frames via six convolutional layers, using striding to reshape and reduce dimensionality. After the bottleneck, an almost symmetrical encoder is applied to predict the corresponding SWH frame at the same time step. Normalization and LeakyReLu activation functions are employed with the exception of the output layer for which a ReLu function is used as SWH is strictly positive by definition. A RMS loss function is used and Adam optimizer is implemented with early stopping to avoid overfitting. Preliminary results show a rapid reduction of the training and validation loss in the first few epochs, with RMSE dropping from about $\sim$m to $\sim$cm. As illustrated in Figure 1, this model is promising despite not including time recurrence. We argue this is thanks to relating input and output data with an imaging approach with CNN that can retain spatial features that implicitly provide information about the past. This contrasts with a numerical modelling scheme that is implemented at each grid point, with local source terms, and interaction with nearby cells only.

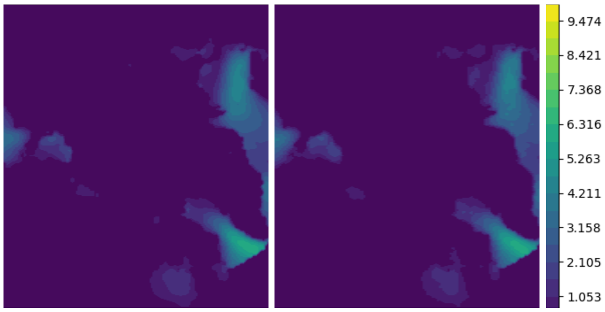

Figure 1. Preliminary results for the proposed CNN model: ground truth (left) vs prediction of a random SWH frame (right) in m.

Next, we propose to investigate a more complex RNN approach, as shown in Figure 3. LSTM helps to select what information is relevant in the chosen time window by a combination of sigmoid and tanh functions. It can also keep information up to about 100 steps reasonably well, which is likely enough to capture the traveling time of the remotely generated waves propagating across the domain. Note that ocean waves are affected by two main temporal dependencies acting at two different spatial scales: the non-instantaneous transfer from wind to wave energy during local wave growth and wave propagation and swell development from waves that are remotely generated. The LSTM is applied at the encoded data (which here includes SWH as input data as well) corresponding to the frames of a time window prior to the predicted SWH frame.

4. Limitations and future work

The proposed CNN/RNN model is trained by numerically simulated data produced by WW3 and therefore we can only aim to replicate the performance of such numerical model configuration. Therefore, any possible biases present in the Casas-Prat & Wang (2020b) dataset that were derived by the inherent limitations of the WW3 modelling approach, or by the chosen parameterizations for this particular experiment will also be present in the predictions obtained by our proposed deep learning model. However, the (likely larger) uncertainties derived by the ocean wave drivers (i.e. W10, SIC), which relate to climate model parameterizations, internal climate variability and greenhouse gas emissions, will be well covered thanks to considering a large number of simulations of W10 and SIC projected by CMIP6. This relies on the reasonable assumption that this five-model CMIP5 wave ensemble capture most representative wave processes that can occur in the large CMIP6 ensemble.

Besides the steps mentioned in Section 3, future work also includes to study the sensitivity of the proposed deep learning model performance to the choice of the training vs. test datasets from the available five model ensemble, and to assess the degree of performance possibly achieved when using only historical data to train the model. Also, the potential model to be used to develop the large ensemble will be subject to further testing that targets the extremes via extreme value analysis.

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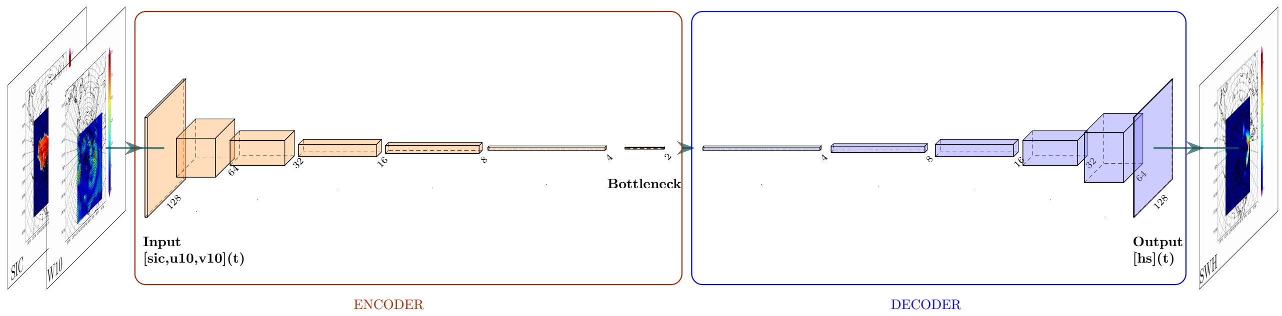

Figure 2. Proposed network architecture without time recurrence: this model uses a CNN to encode frames of SIC, UAS, VAS at a given timestep, which is later encoded to predict the corresponding SWH at the same time step

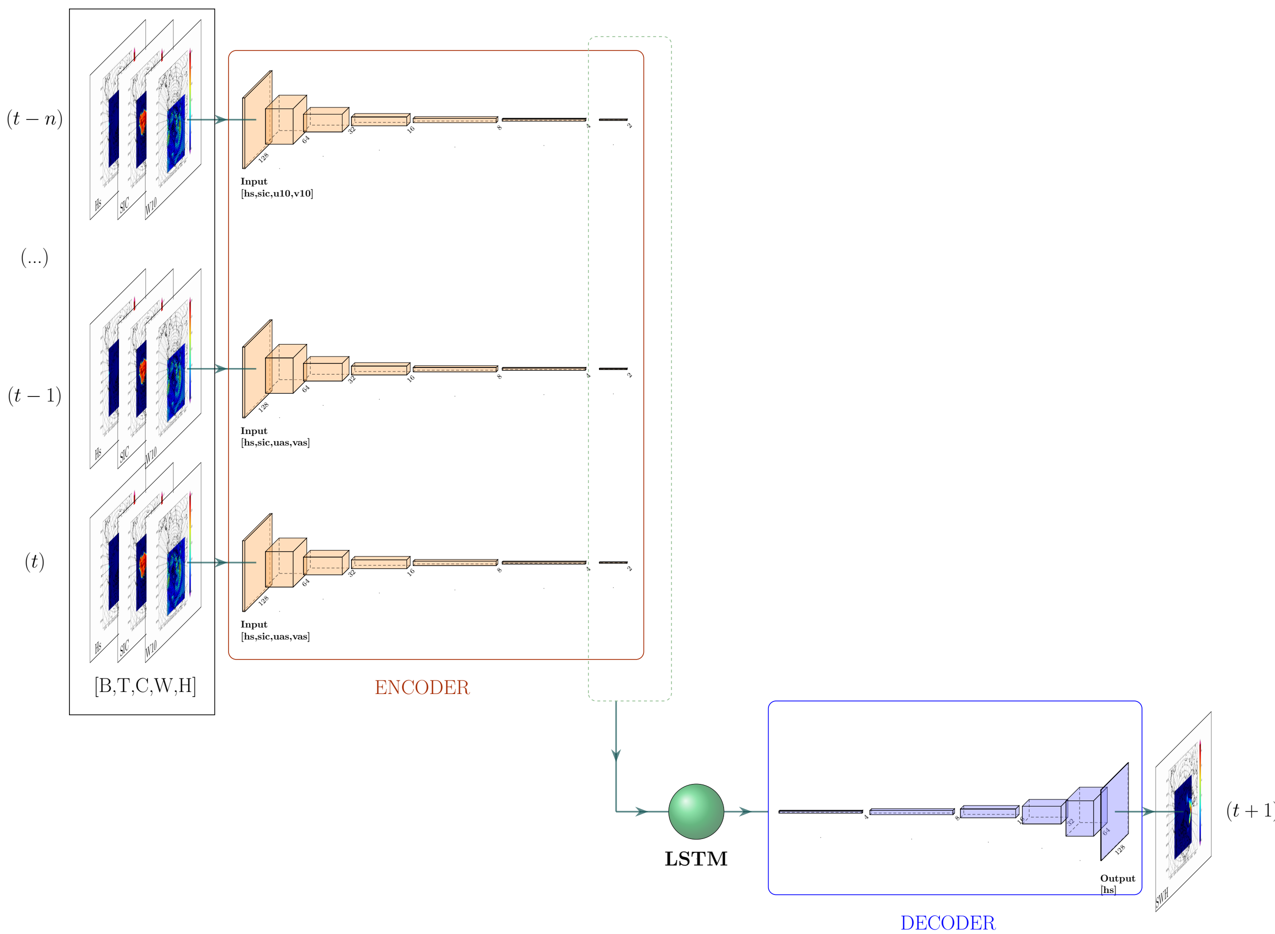

Figure 3. Proposed network architecture with time recurrence: this model uses a CNN to encode the frames of SIC, UAS, VAS and SWH for each time step individually. At each timestep a LSTM receives an encoding corresponding to the previous $t - n$ to t time window, which is later decoded to predict the SWH frame at timestep $t + 1$