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Climate Change AI

ICML 2021 Workshop
Tackling Climate Change with Machine Learning

DEEP LEARNING NETWORK TO PROJECT FUTURE ARCTIC OCEAN WAVES

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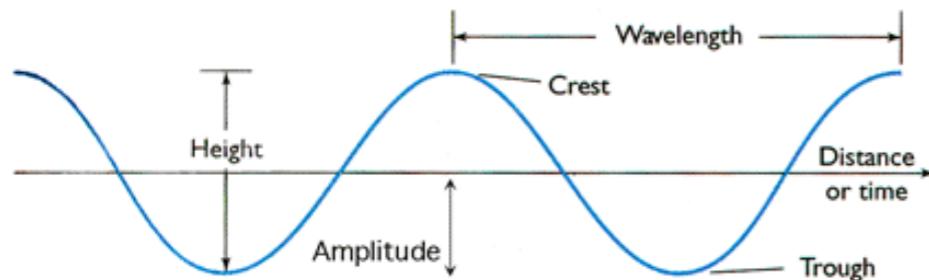
Shady Mohammed



July 23rd 2021

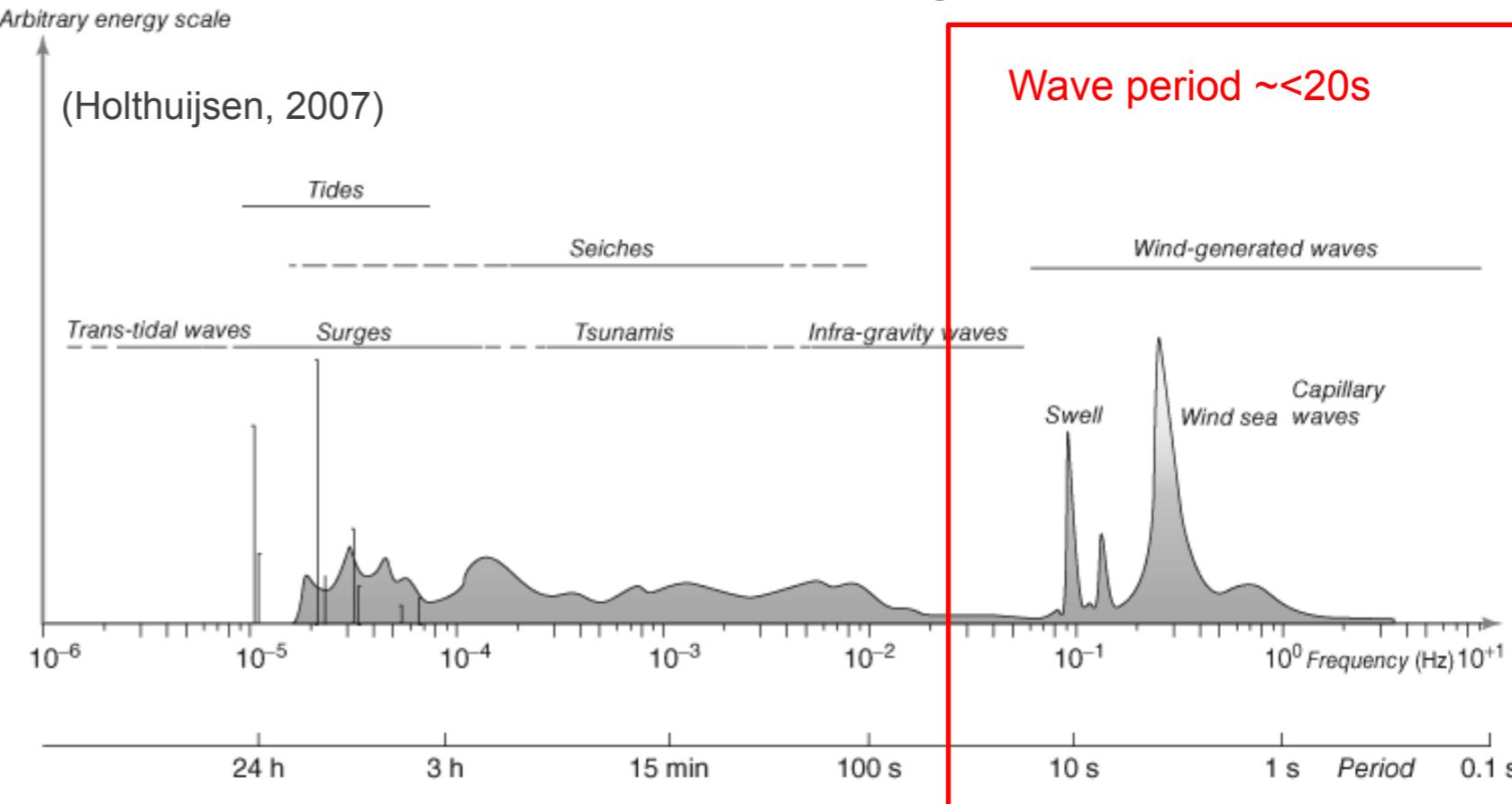
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WHAT OCEAN (WIND) WAVES are and WHY they are important

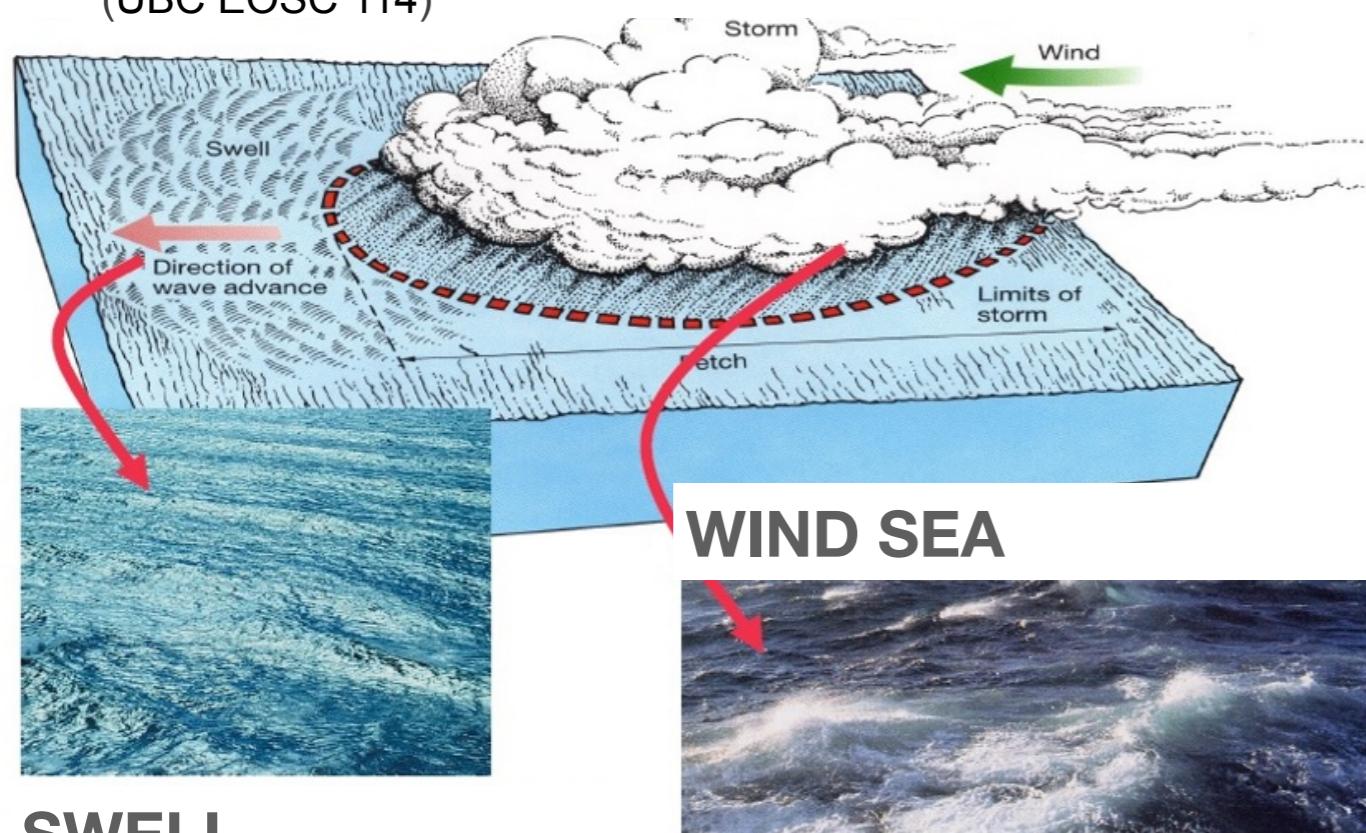


wave height, wave period

Surface wind is the main driver of ocean (wind) waves



(UBC EOSC 114)



There are two main types of sea states:

- **Wind sea** (waves induced by local storms)
- **Swell** (remotely generated waves)

Waves can cause **coastal damage** (flooding, erosion, etc), **offshore damage** (infrastructure damage, affect navigation safety, etc). They are also a potential **source of energy**.

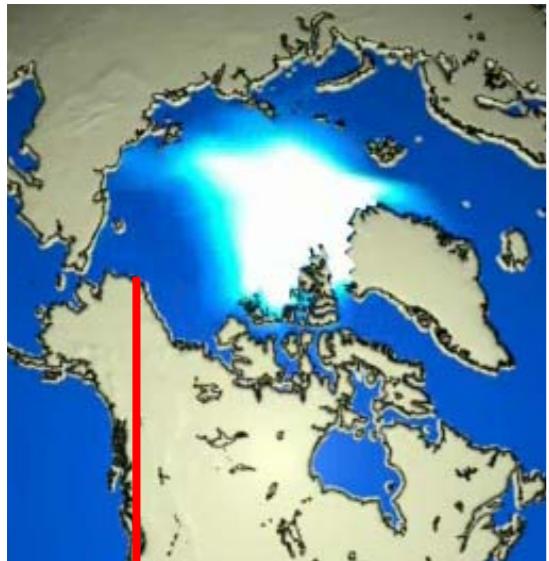
Climate feedback processes (e.g. waves might accelerate sea ice retreat).

THE ARCTIC OCEAN: A HOT SPOT

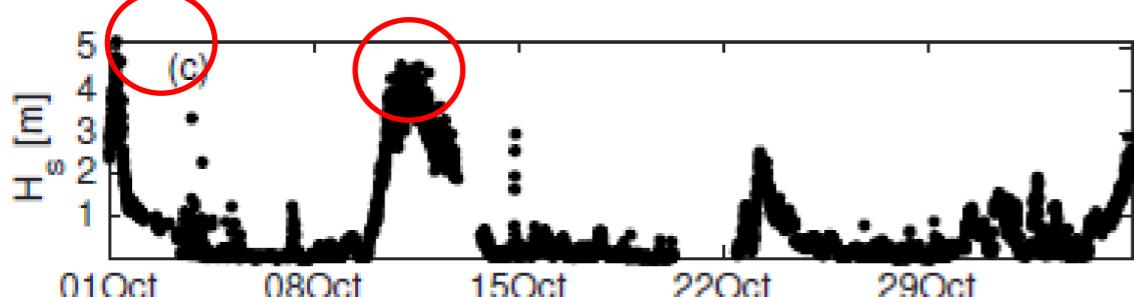
The Arctic is warming twice as fast as the global average: **sea ice retreat**

Sea ice cover -13% decrease/decade

2012 & 2020: two min. sea ice cover records



October 2016



(from Thomson et al 2018)

2019 storm in Tuktoyaktuk: ocean waves damaged buildings and homes



A wave washing up on the Inuvialuit hamlet of Tuktoyaktuk in Canada's Northwest Territories during an August 2019 storm.

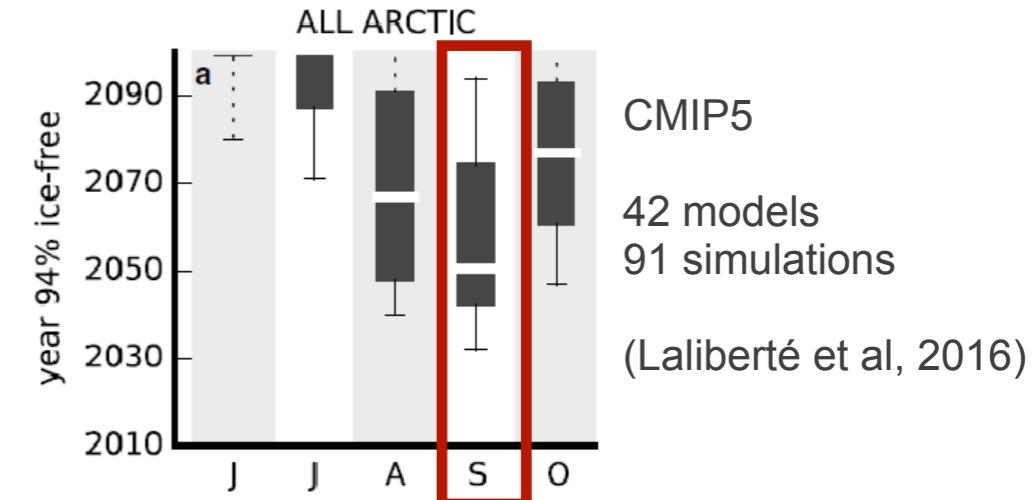
Credit: Weronika Murray.

Sea ice retreat (and wind intensification) leads to **higher waves** over larger (water) areas, and during a longer ice-free season.

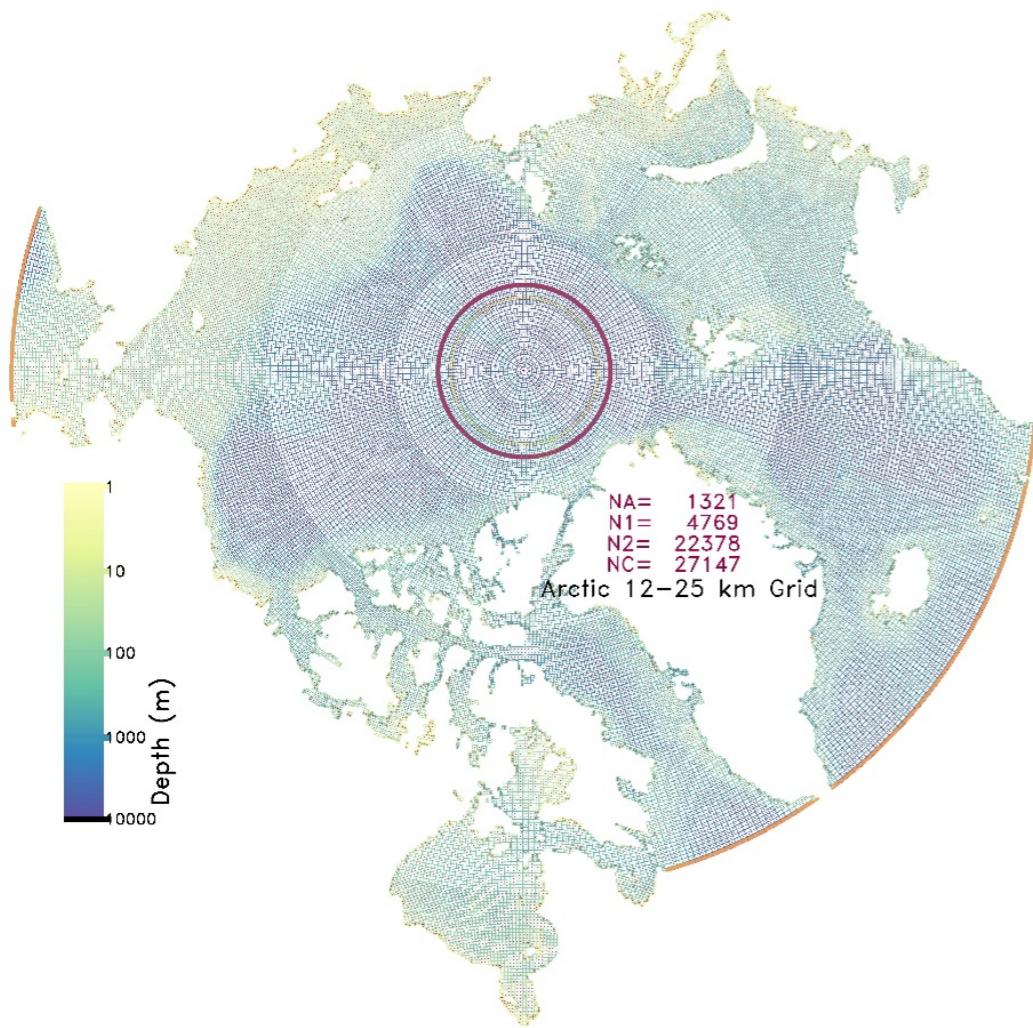
WHY ML?

- Climate models are constantly updated to produce (improved) **climate projections**. These **large ensembles** are needed to account for **factors of uncertainty**: model parameterizations, internal climate variability, greenhouse gas scenarios, etc. These coordinated efforts are part of the Coupled Model Intercomparison Projects (CMIP). The last two are **CMIP5** (2013) and **CMIP6** (2020).
- **Ocean wave heights are not included in most climate models** (yet), therefore there is **need to develop a large ensemble of ocean wave projections**.
- **Traditional approach is numerical modelling**, the so-called dynamical approach, which is computationally expensive.
- Computationally inexpensive methods developed to date are mainly **physically-based (standard) statistical methods** (regression, weather maps, etc) . Their **performance** is often as **good** as, if not better, than the dynamical approach. However they have some **shortcomings**: tendency to underestimate swells, challenging implementation of the sea ice (retreat) effect, etc.
- **Machine learning (ML)**, and in particular deep learning, has been proven to be a **useful tool in a wide range of applications**, in particular (time-series) image understanding/prediction (computer vision). **ML is a more versatile approach** than physically-based statistical methods: it has the **potential to be easily adapted to predict different wave parameters at different spatial scales** (global, regional, etc.)

Arctic Ocean projected to become ice-free by 2045-2070 in September: timing uncertainty!



TRADITIONAL APPROACH: WAVEWATCH III (WW3)



Five CMIP5 models were chosen to simulate ocean waves in the Arctic region.

Input: 3-h surface winds (U10)

Input: Daily sea ice concentration (SIC)

Output: Significant wave height (Hs)

Periods: 1979-2005 and 2081-2100

JGR Oceans

Research Article | Free Access |

Projections of extreme ocean waves in the Arctic and potential implications for coastal inundation and erosion

Mercé Casas-Prat , Xiaolan L. Wang

First published: 07 July 2020 | <https://doi.org/10.1029/2019JC015745>

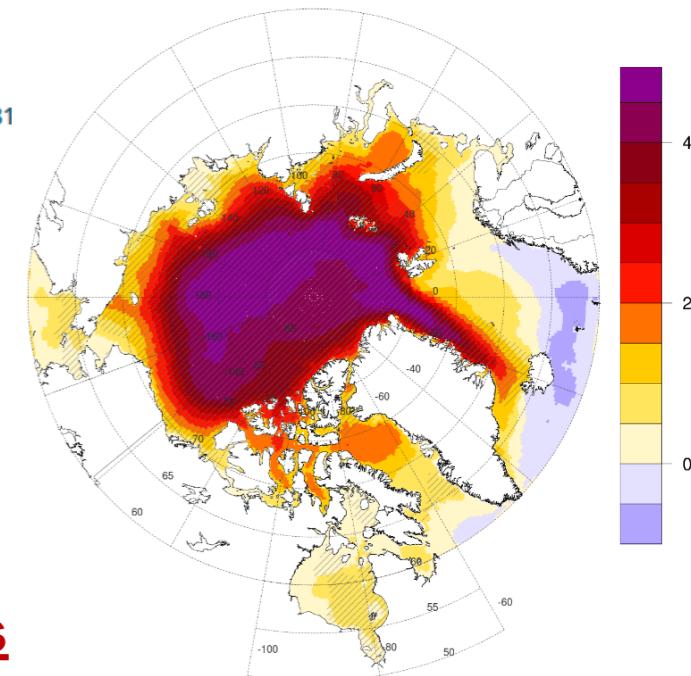
Geophysical Research Letters

Research Letter | Open Access |

Sea-ice retreat contributes to projected increases in extreme Arctic ocean surface waves

Mercé Casas-Prat , Xiaolan L. Wang

First published: 10 May 2020 | <https://doi.org/10.1029/2020GL0881>



Annual maximum Hs
Increase <6m offshore
Factor 2-3 along coastlines

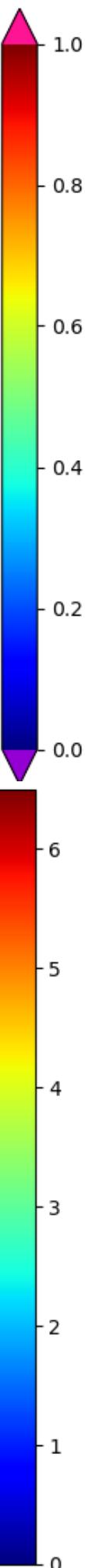
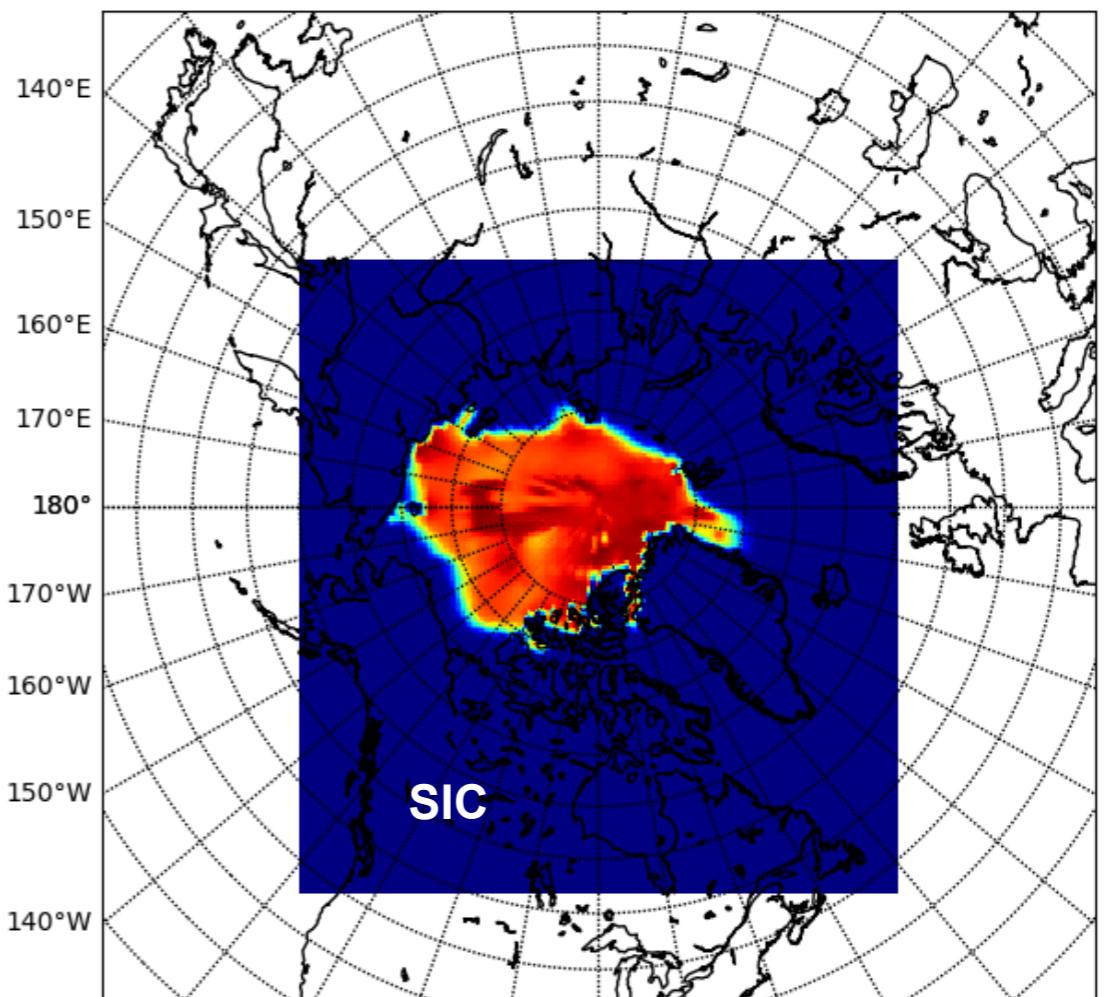
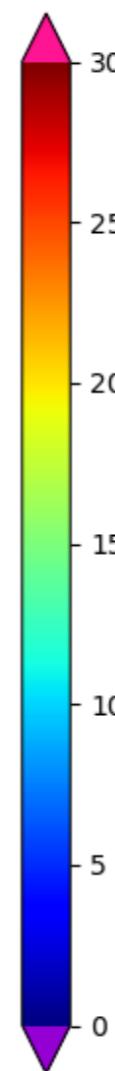
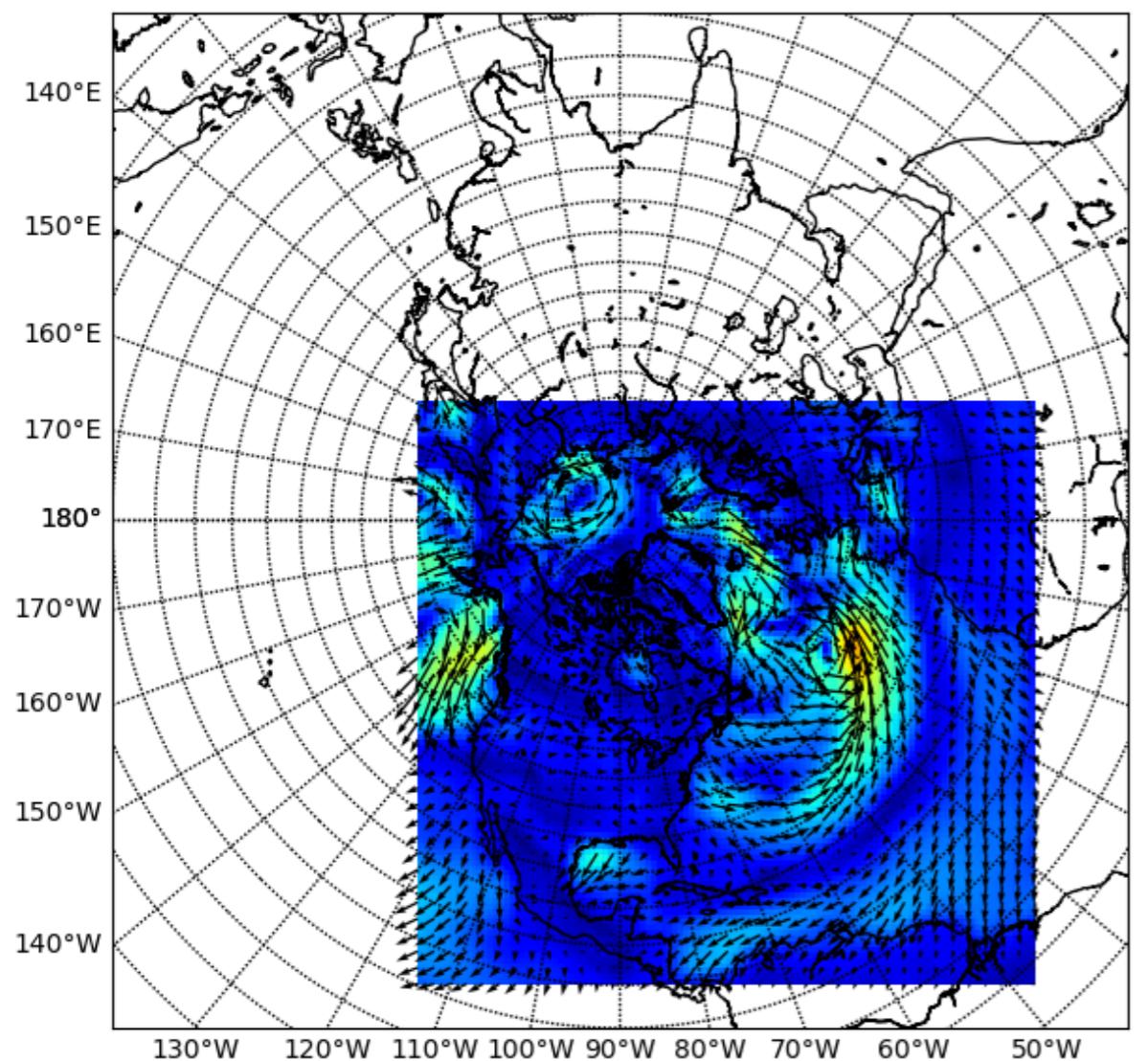
Robust increase but low confidence due to limited sample size.

Better performance for historical period does not imply better performance for future period.

PROPOSED FRAMEWORK

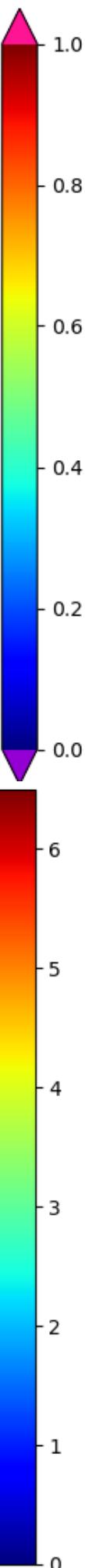
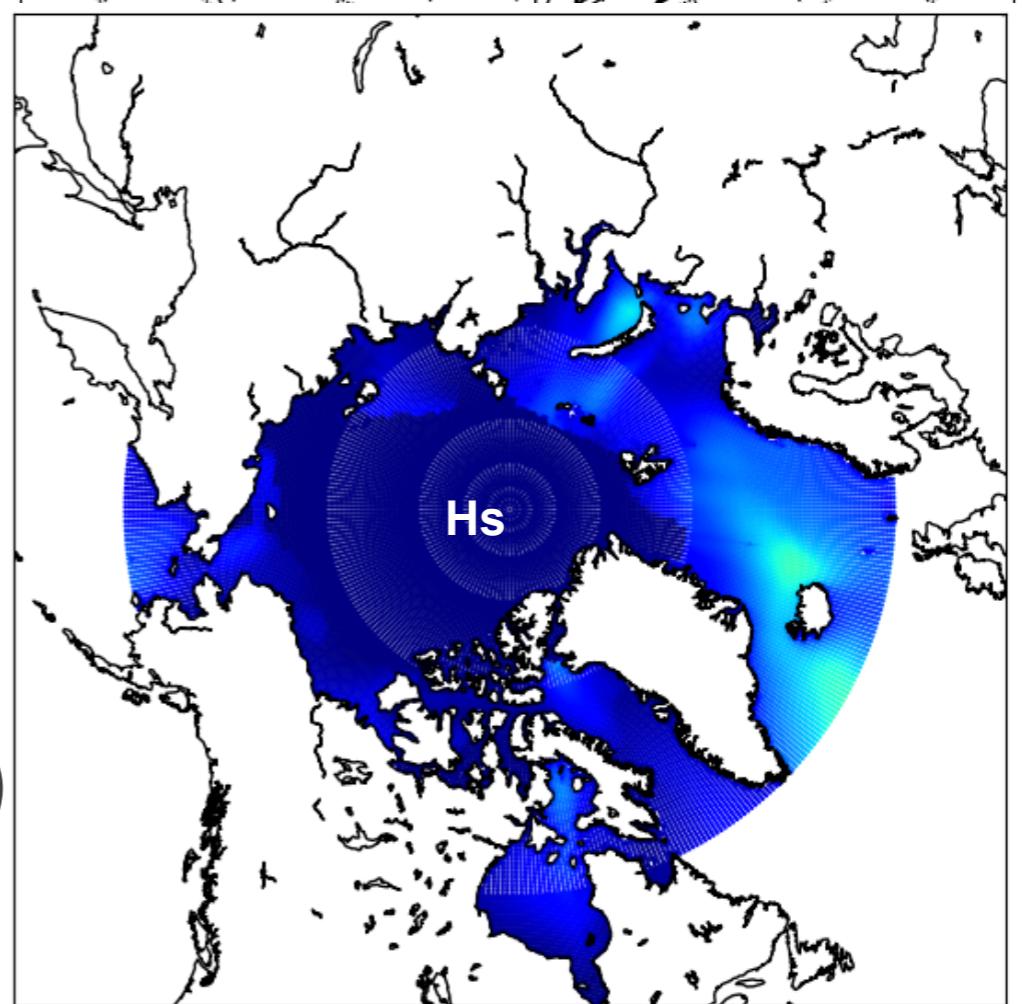
- **Train/validate** a CNN with **one set** of the previously mentioned CMIP5-based historical and future simulations.
 - **Test** the trained network with the **remaining 4 sets** of CMIP5-based historical and future simulations.
 - **Further testing**: investigate whether the choice of the one CMIP5 model used to train the network is relevant, and whether both historical and future conditions are needed for the training process.
 - Once satisfied with the trained CNN (low RMSE), infer wave simulations using the more recent **CMIP6 wind/sea ice projections** to develop a **large ensemble of CMIP6-based ocean wave projections**.
-

U10

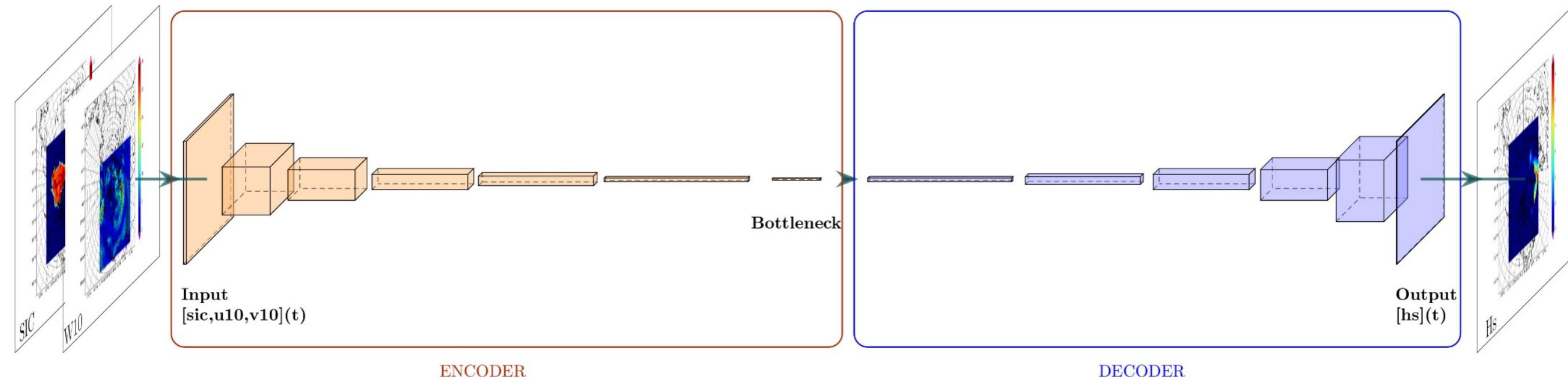


Use of polar projections to convert our data into images and avoid dependencies among image's edges.

PRE-PROCESSING OF INPUT(U10,SIC) & OUTPUT (Hs)



CNN NETWORK



Reshape by striding in Conv

Normalization

LeakyReLu activation function (ReLU
for the output layer)

RMS loss function

Batch size: 128

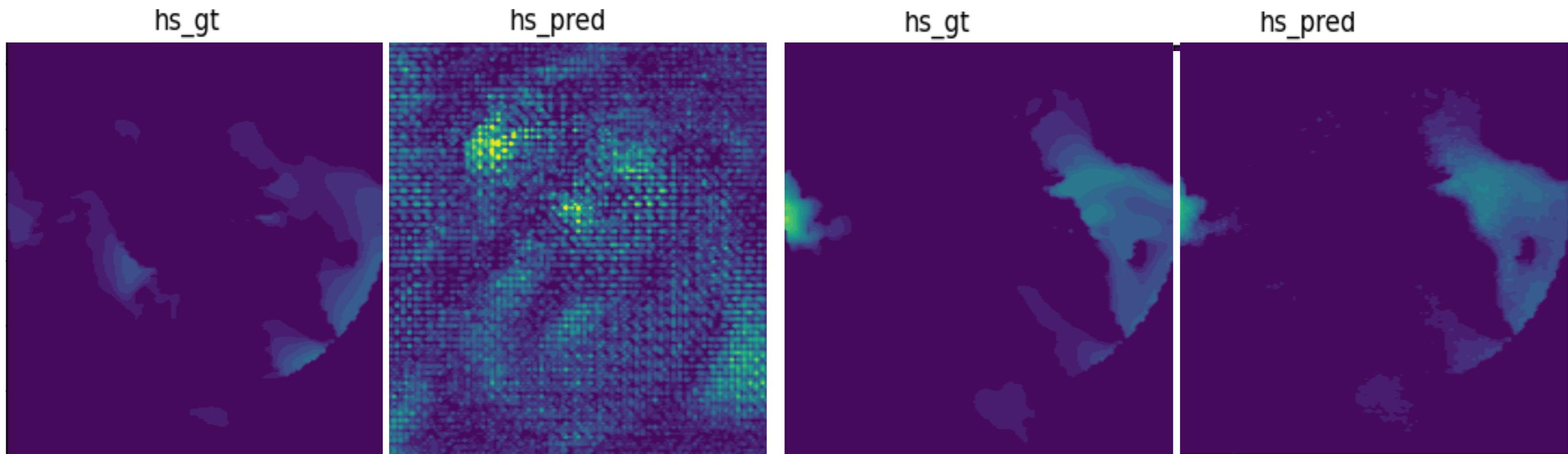
Learning rate $\sim 3.6\text{e-}4$

Adam optimizer

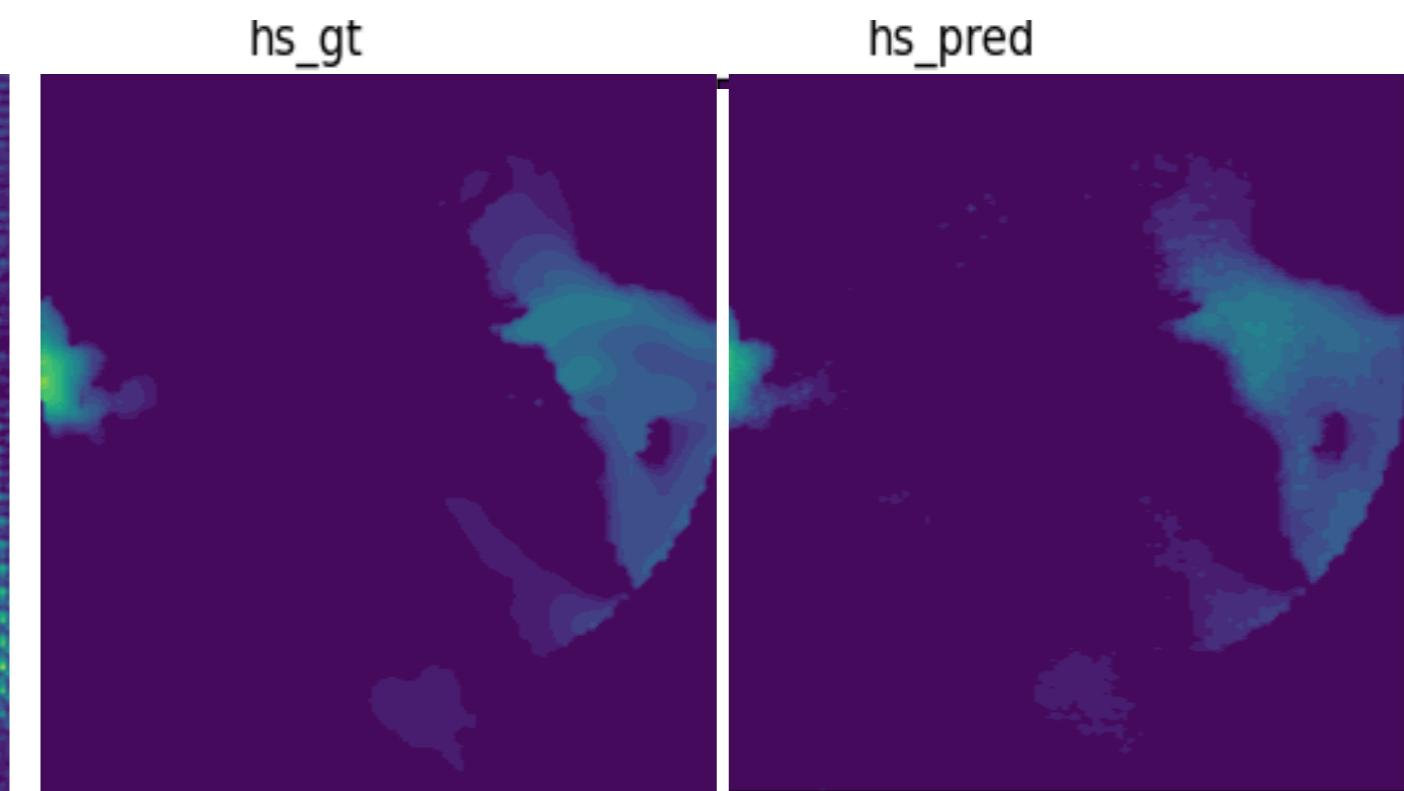
Early stopping: avoid overfitting

PRELIMINARY RESULTS (CNN)

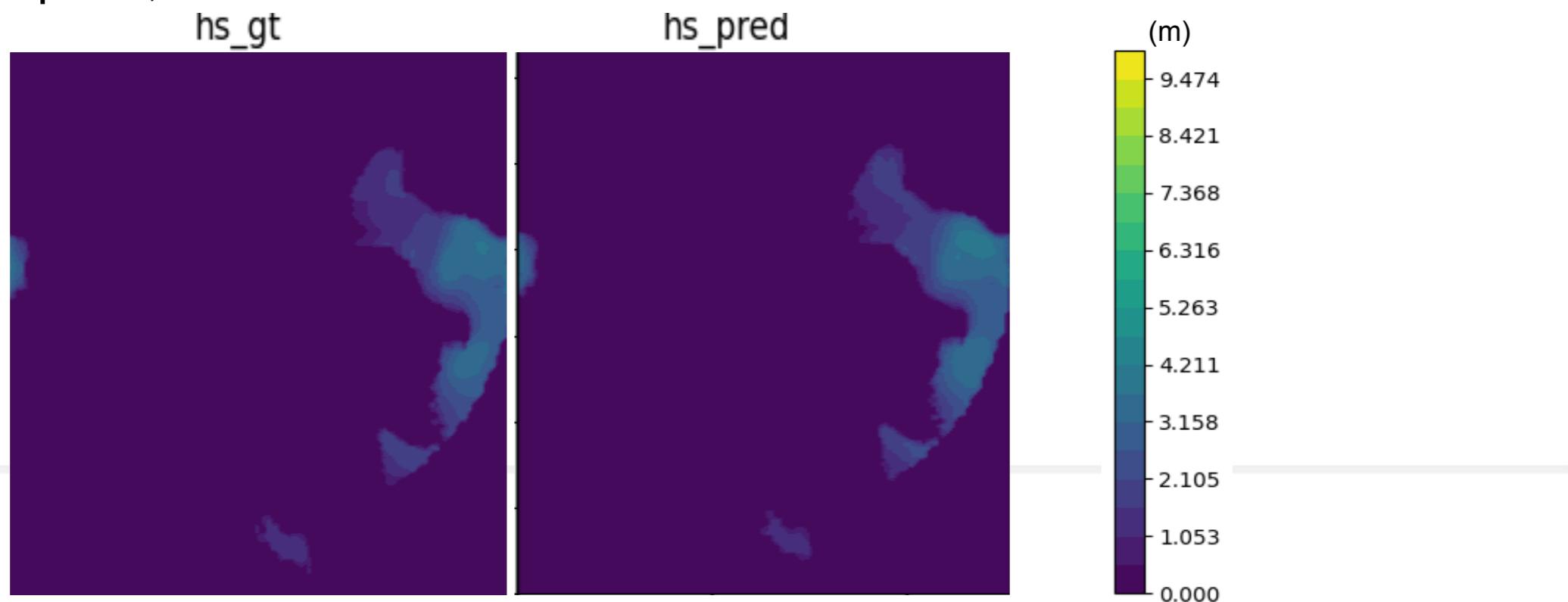
Ep=0, RMSE = 5.312 m



Ep=3, RMSE = 0.020 m



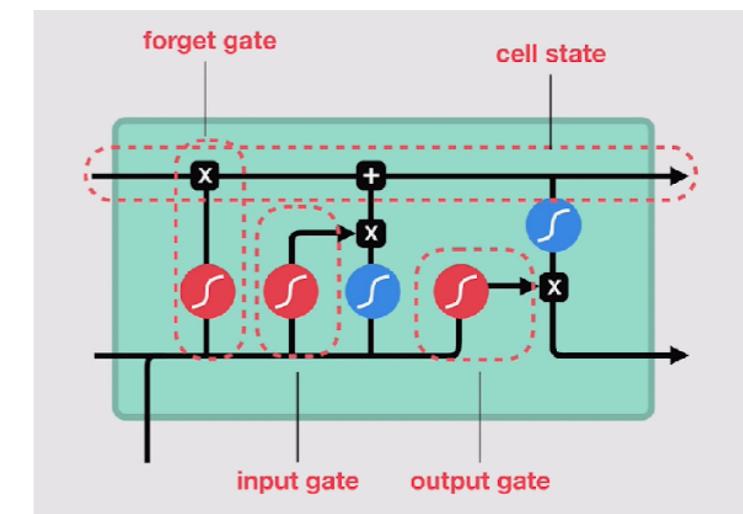
Ep=71, RMSE = 0.003 m



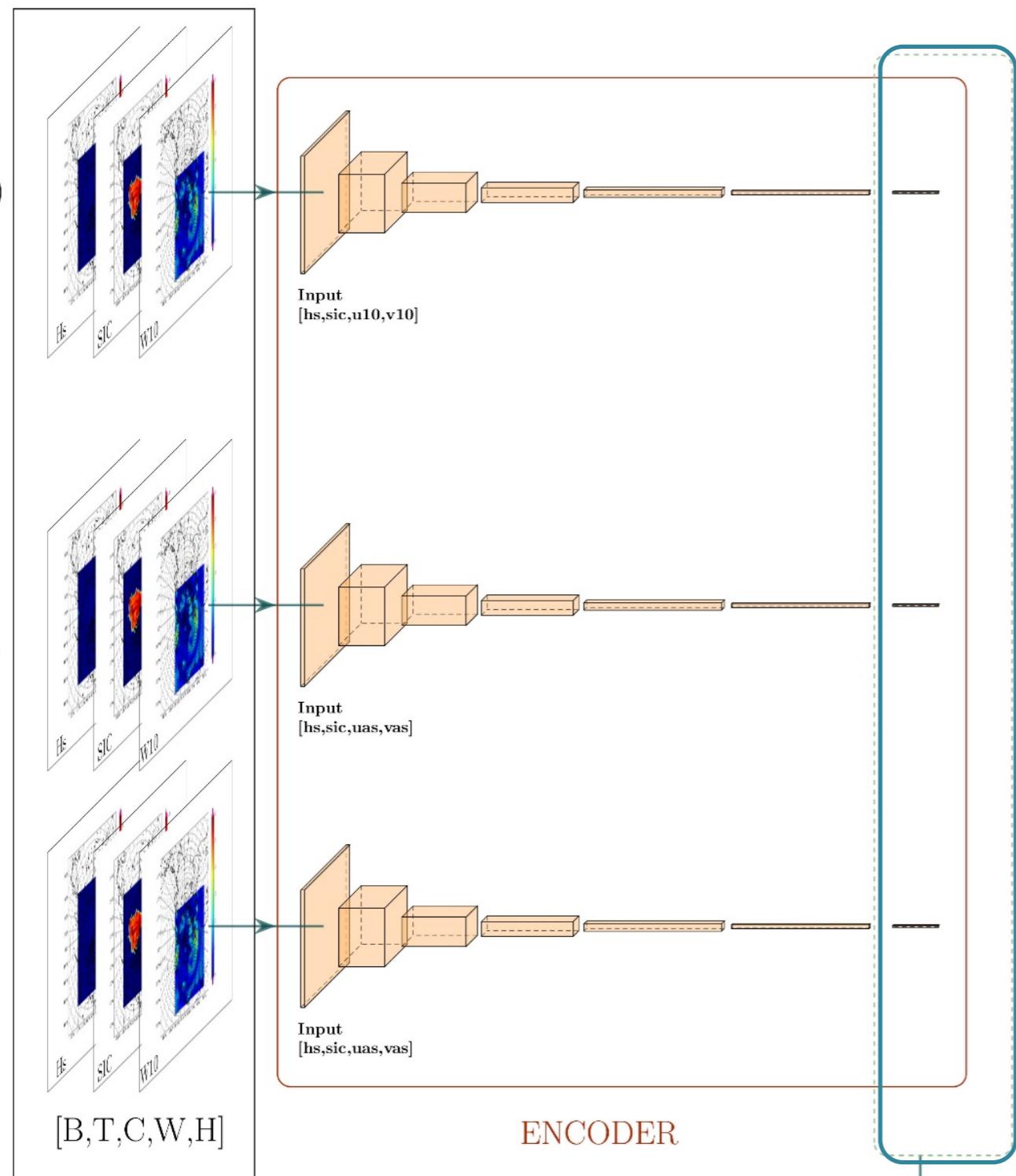
NEXT STEP: CNN-LSTM NETWORK

Include temporal dependency in input and/or output with a **Recurrent Neural Network (RNN)**:

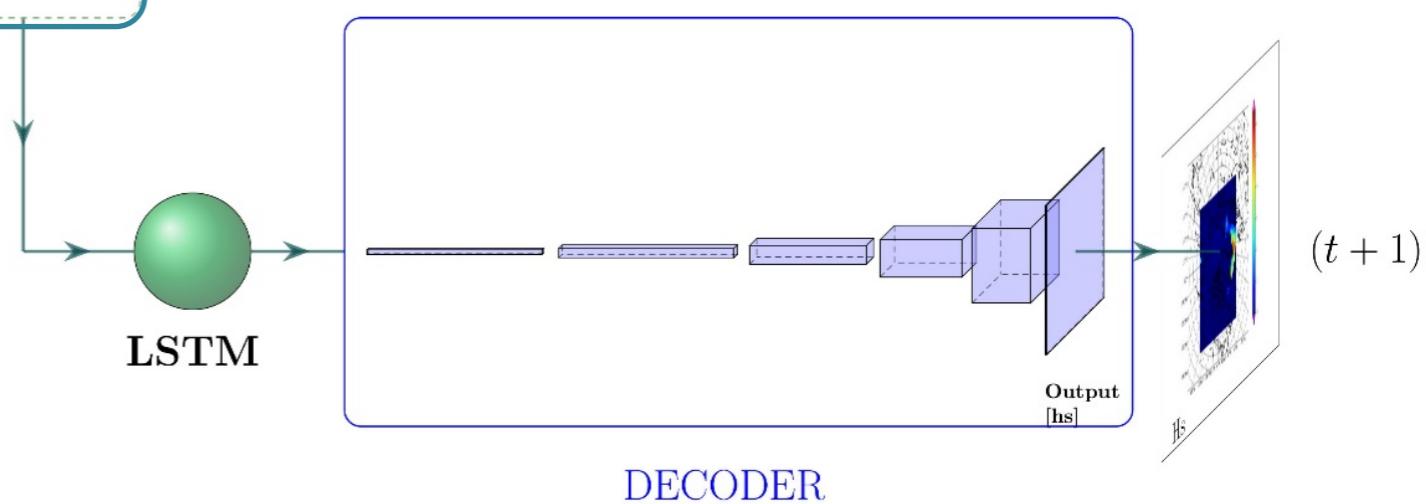
Long Short-Term Memory network



(Source: <https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21>)



It helps to select what information is relevant in the chosen time window with a combination of dense layers of sigmoid and tanh activation functions.



CONCLUSIONS

- Future dramatic changes in ocean waves in the Arctic that will likely lead to increased coastal erosion and flooding.
- However, there is need for a larger ensemble to increase confidence in such estimates.
- CNN has the potential to be a computationally inexpensive tool to simulate a large ensemble of waves.
- Ongoing work: we need to further test the CNN and assess the improvement of adding time dependency. Maybe the spatial information gives enough implicit temporal information. Apply to CMIP6 data.
- Developed CNN can also be likely applied to other regions/scales and for other variables thanks to their versatility.

Thanks!

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