A deep learning model for forecasting global monthly mean sea surface temperature anomalies using CNN (Unet-LSTM) and transformers (TUnet)

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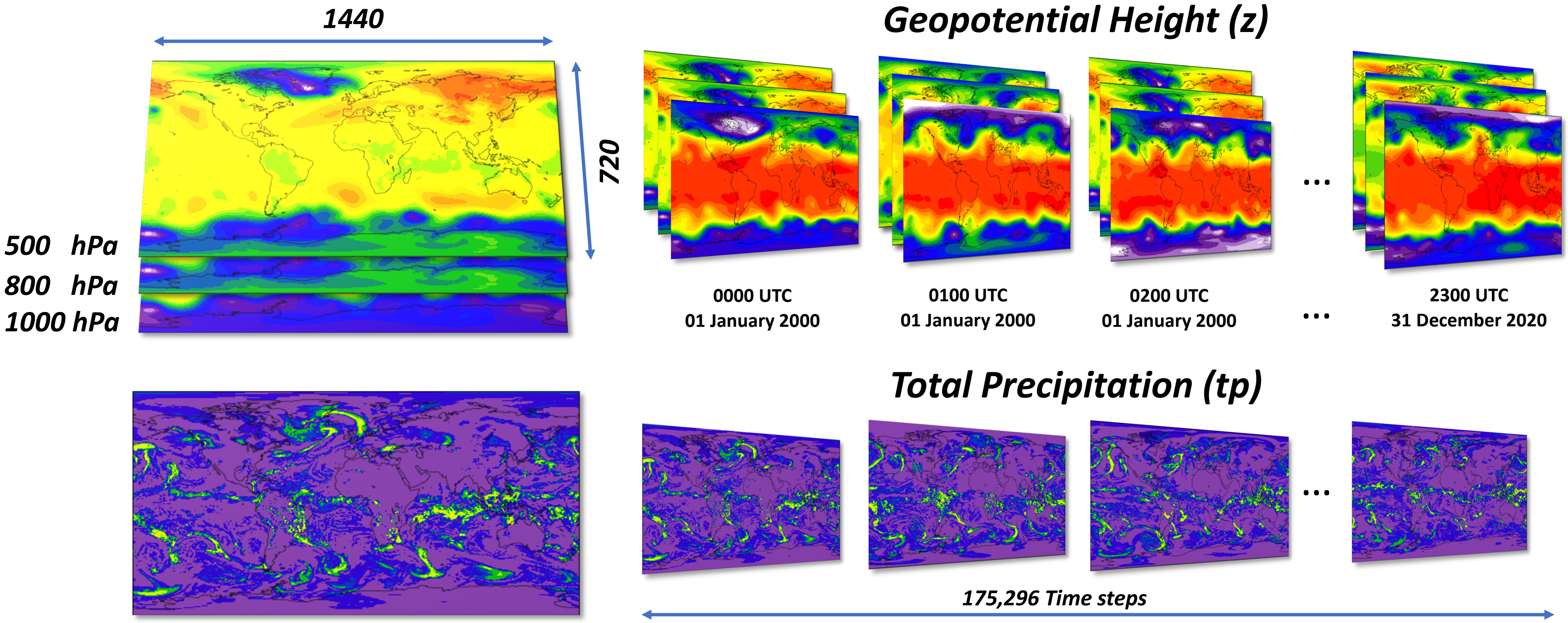
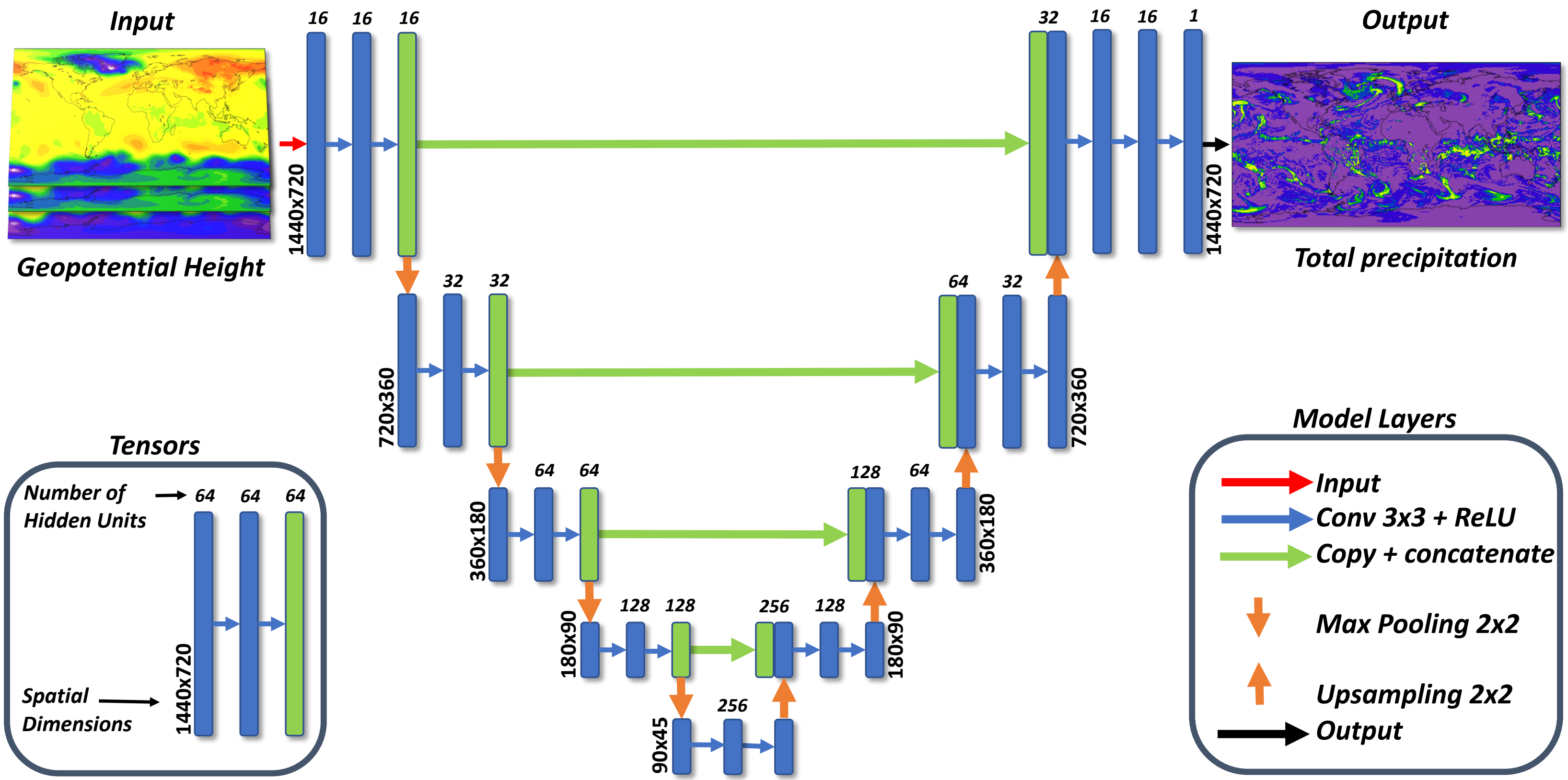
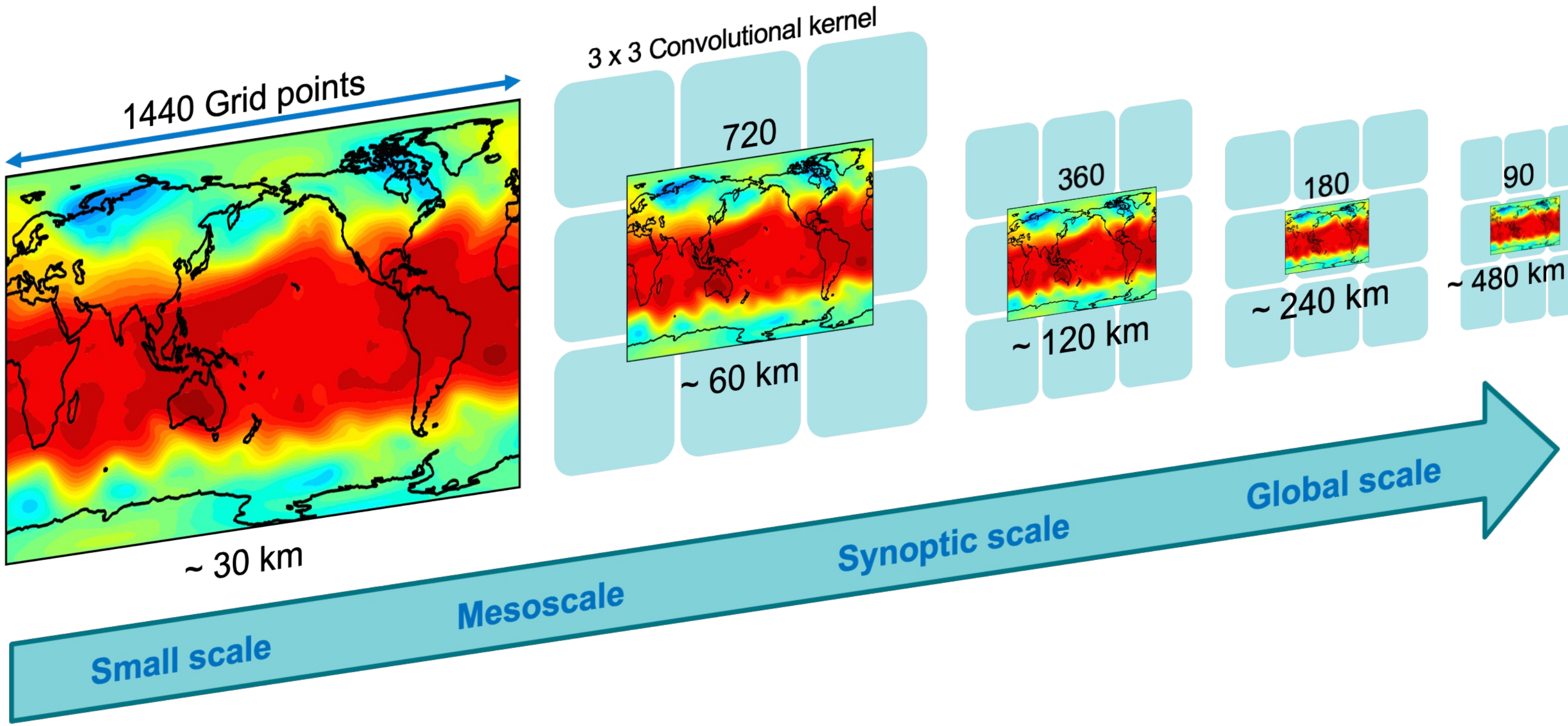


A schematic representation of the data set that we have utilised for model training and validation. The data for model training is selected from the ERA5 data set and provides hourly estimates of variables with global coverage at a spatial resolution of 0.25 degrees ~ 30km.



A summary of the architecture of the DNN we have trained to predict surface total precipitation fields. The model is based on the U-net DNN model. The model shown was implemented in python using the TensorFlow 2.x API.

Unet encoding global weather



Scaling Model Training

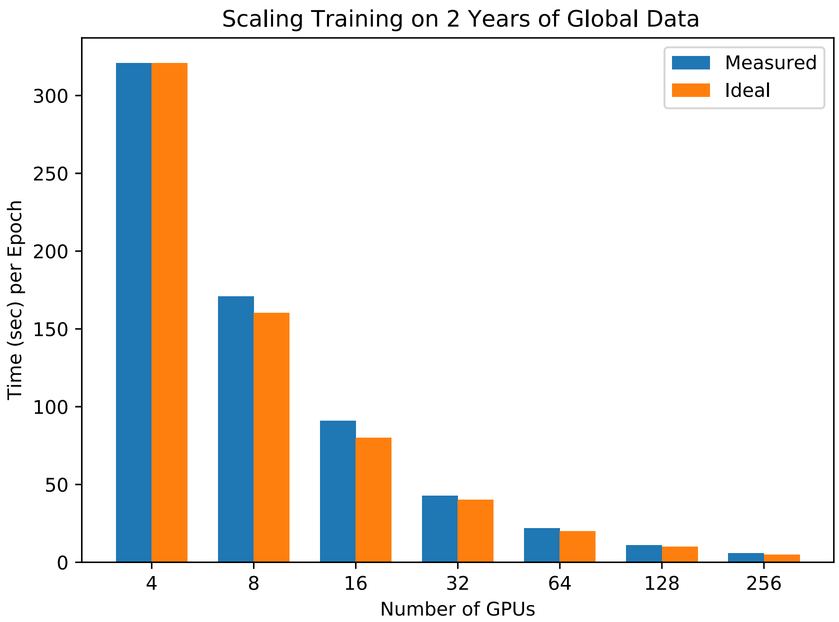
Horovod is a distributed training framework for TensorFlow, Keras, and PyTorch.

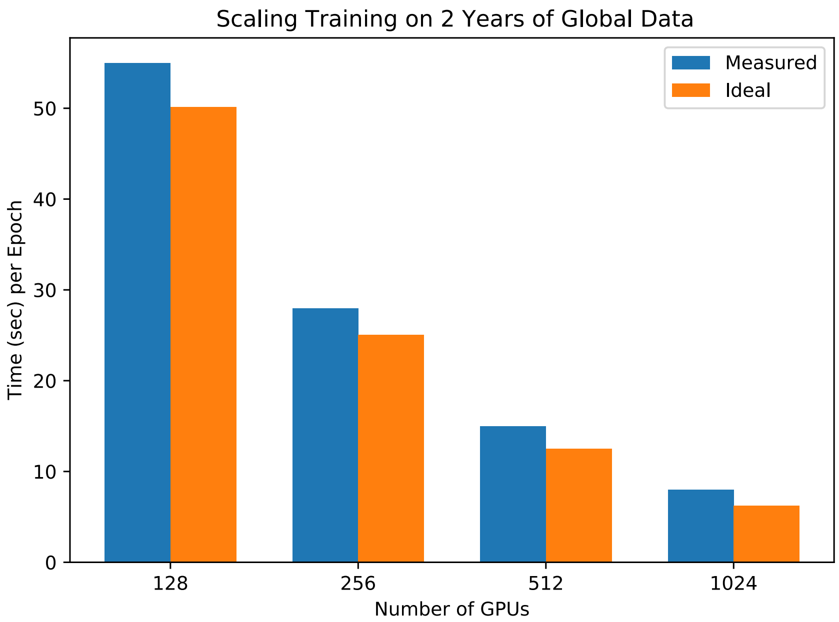
Uber

HOROVOD

https://github.com/uber/horovod

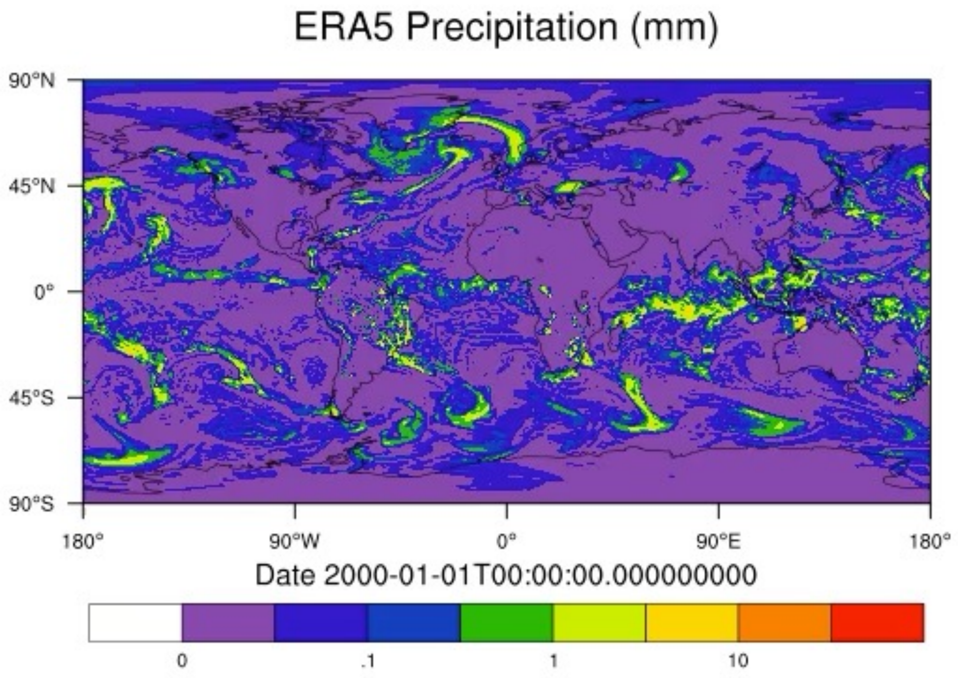
https://horovod.readthedocs.io/en/stable/

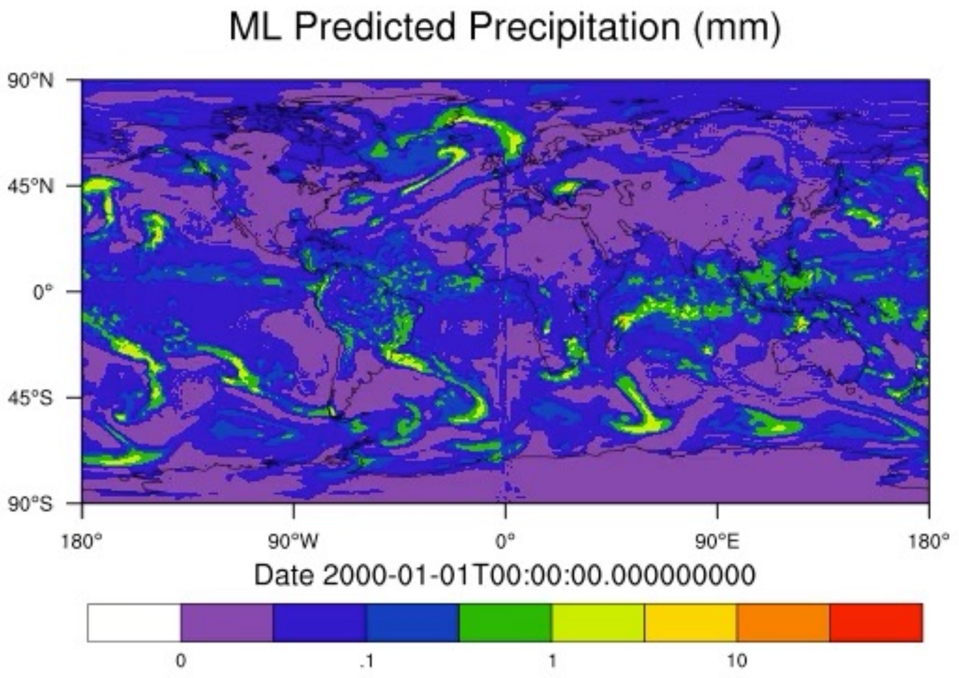


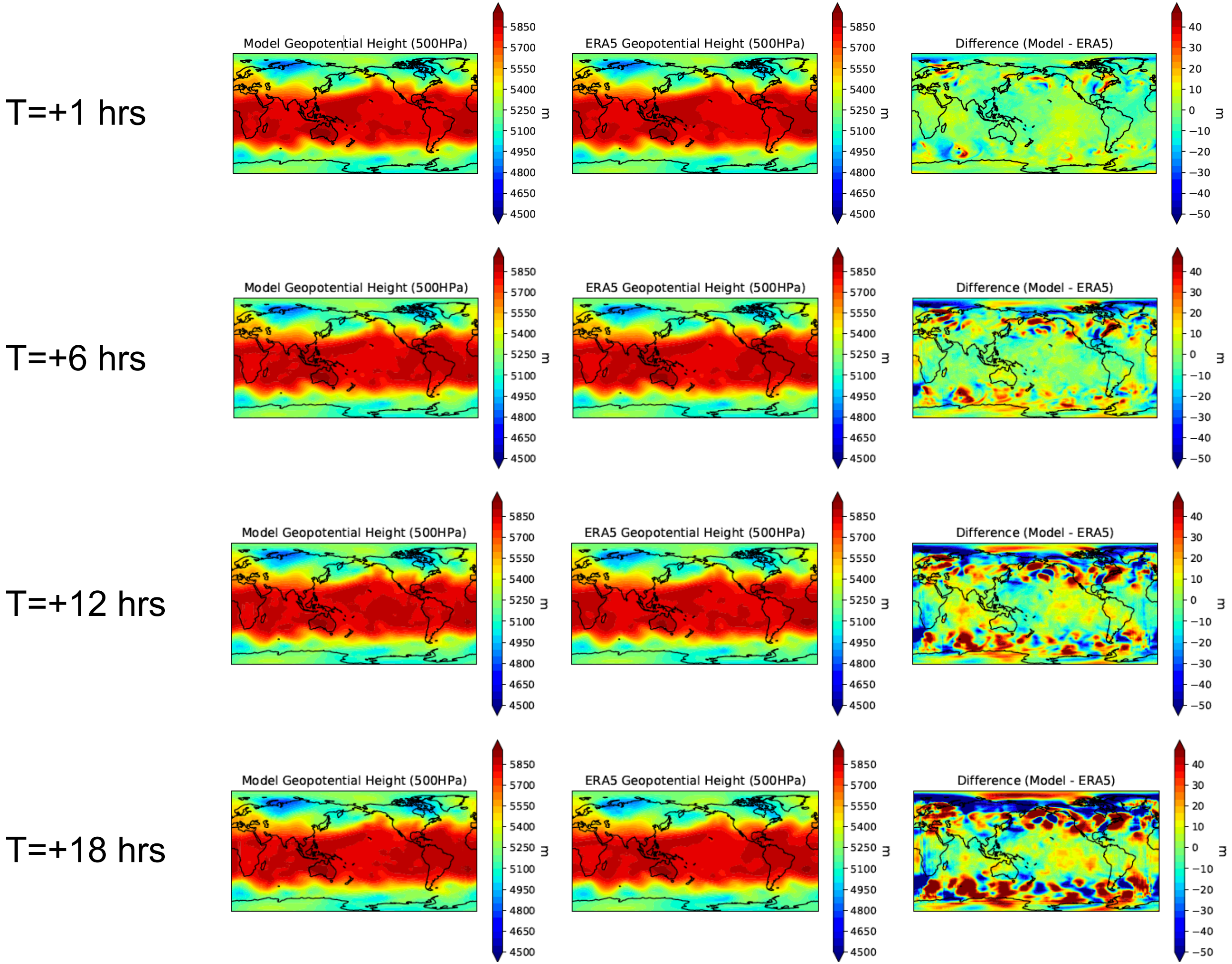


Scaling DNN training on multiple GPU devices

ML Global Precipitation Prediction





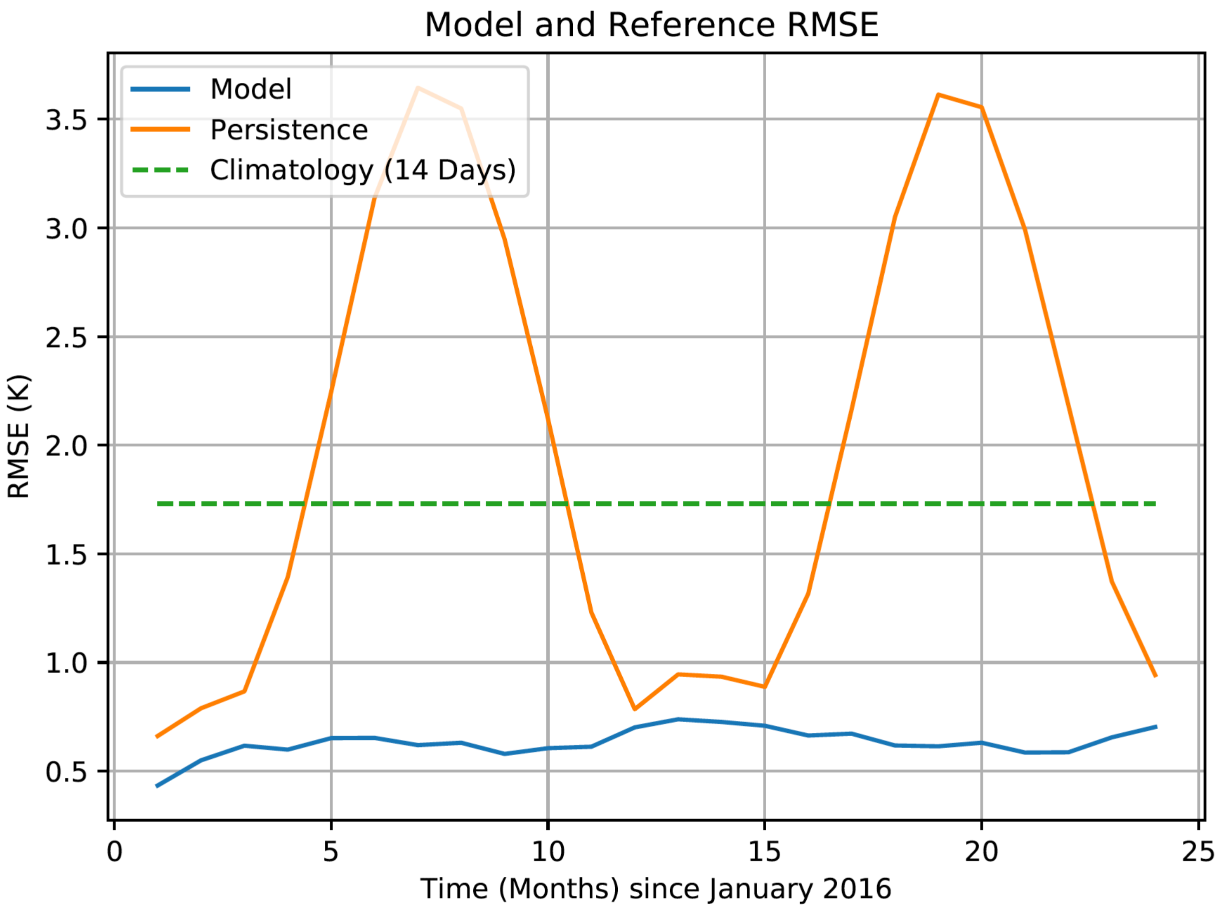


The difference plots have a scale that is 15x higher resolution than the Geopotential height plots

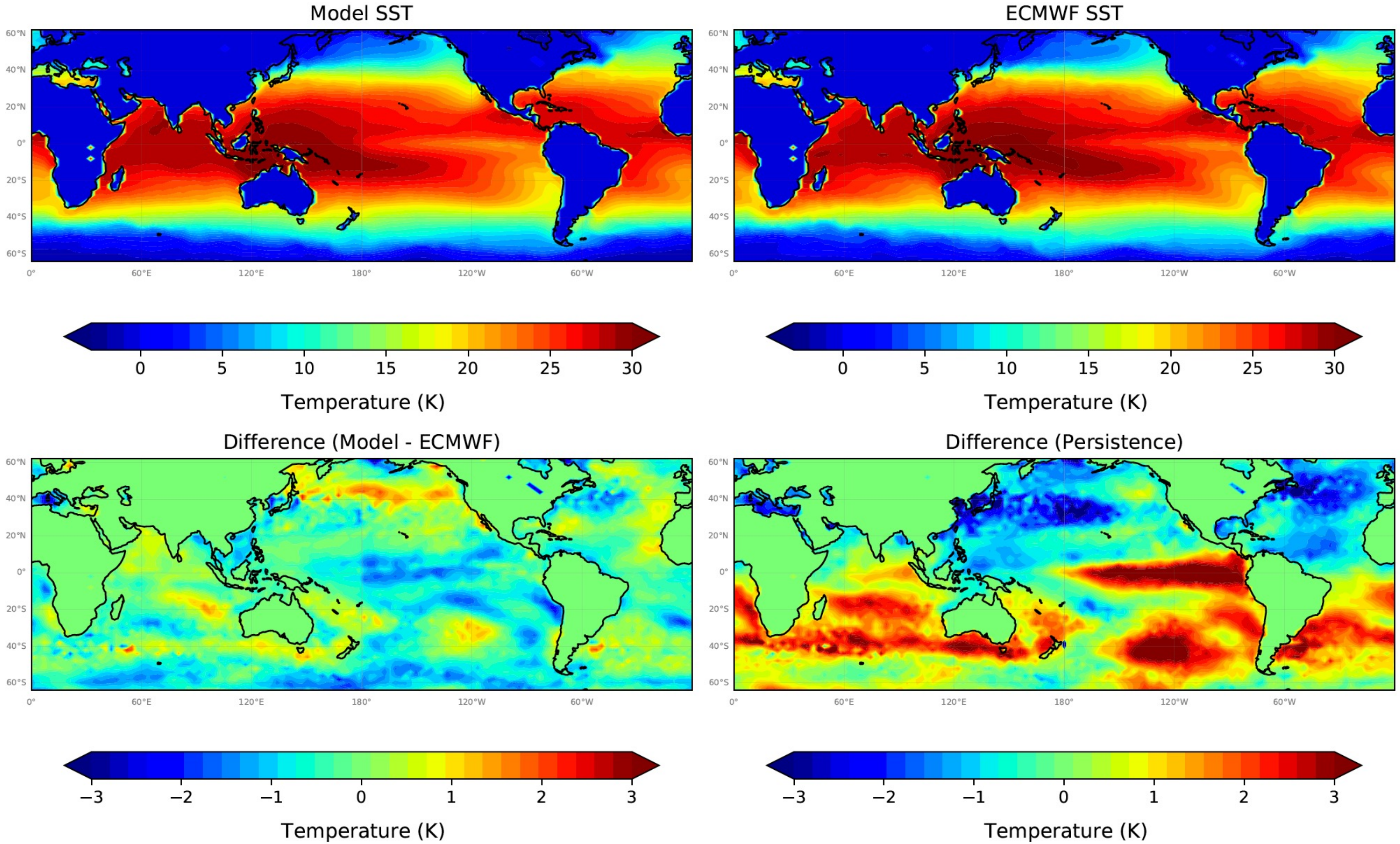
Data Driven Model to predict Sea Surface Temperatures (SST)

- We use the same approach to modelling SSTs as we have used to model the 500 hPa geopotential heights
- We use ERA5 monthly mean SSTs over a 70 year period from 1950-2020 to train the model
- We adjust the hyperparameters in order to achieve the best model fit to the training data
- We make model predictions using our validation data - predictions over 24 months starting in January 2016

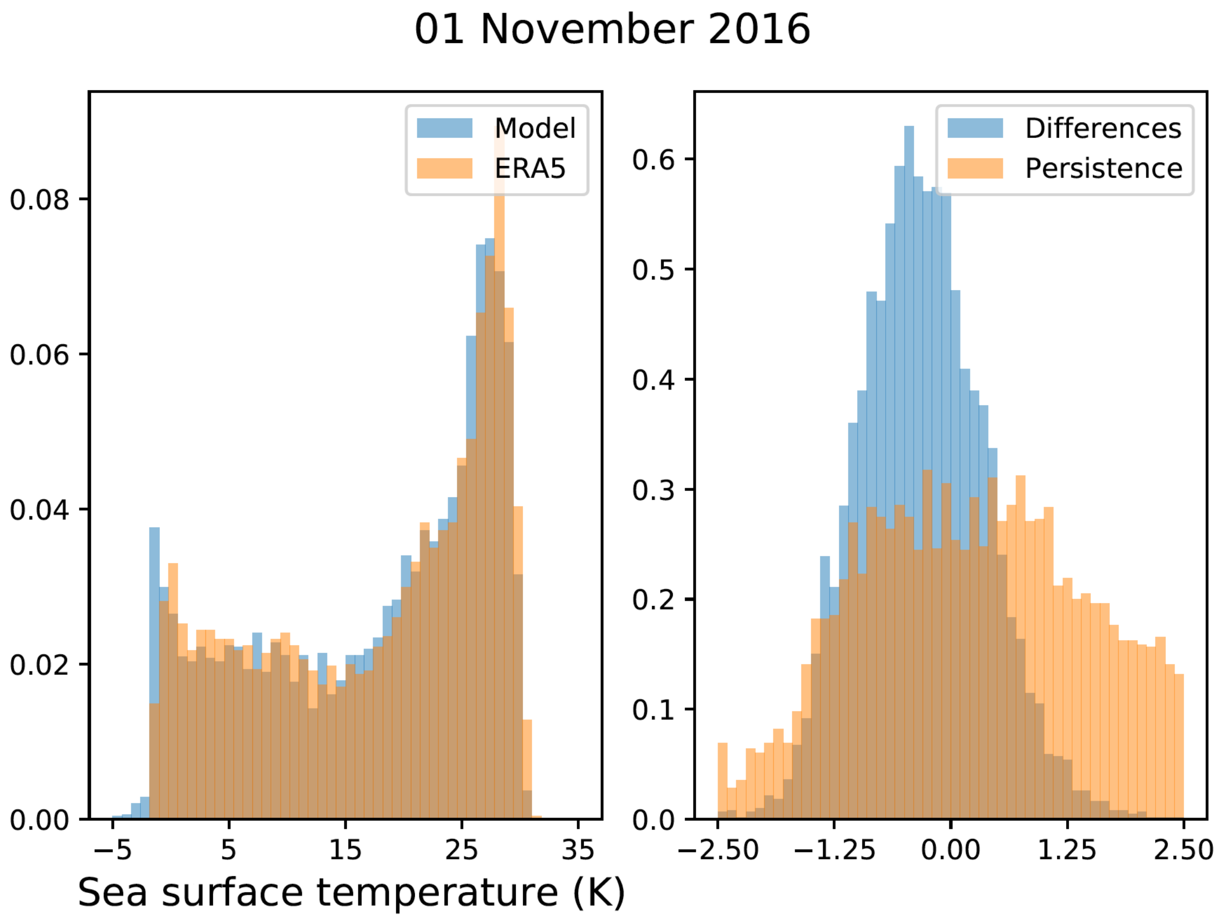
Model predicted (24 month) SST vs ERA5 SST data



01 November 2016



Histograms of model predicted SSTs vs ERA5 data



Predicting Nino3.4 Index

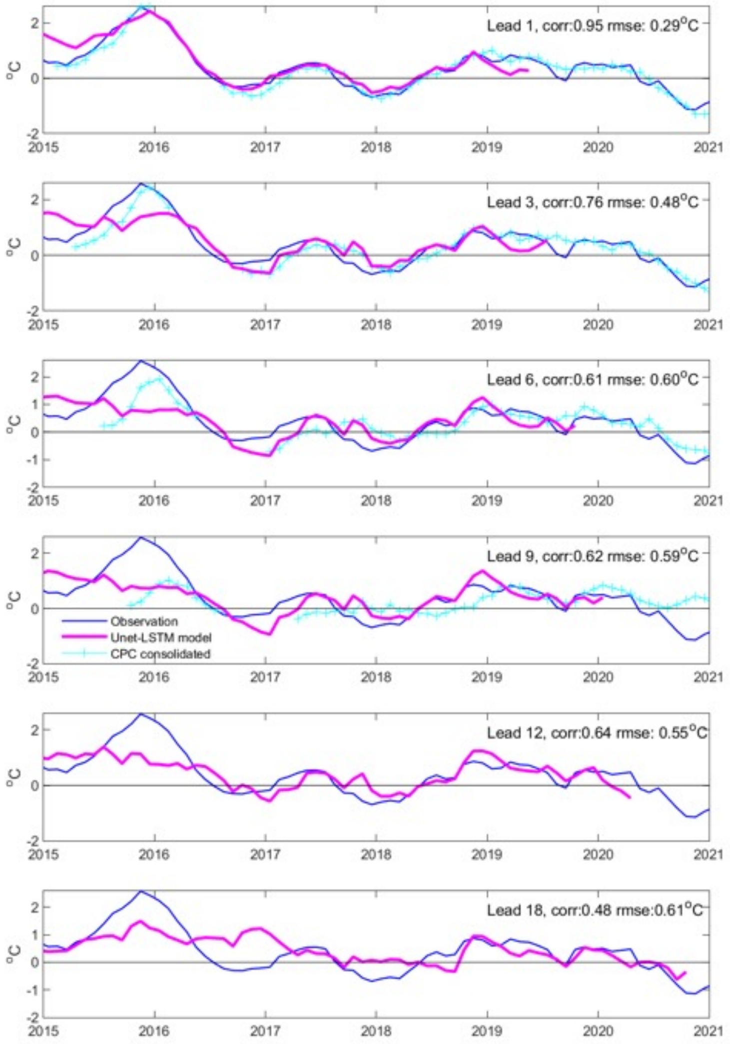
Comparison between the Unet-LSTM model predictions of Nino3.4 index during 2015-2020 and the consolidated predictions of NOAA/CPC, with lead times of 1, 3, 6, 9, 12, and 18 months.

The correlation and RMSE numbers are denoted for each lead time.

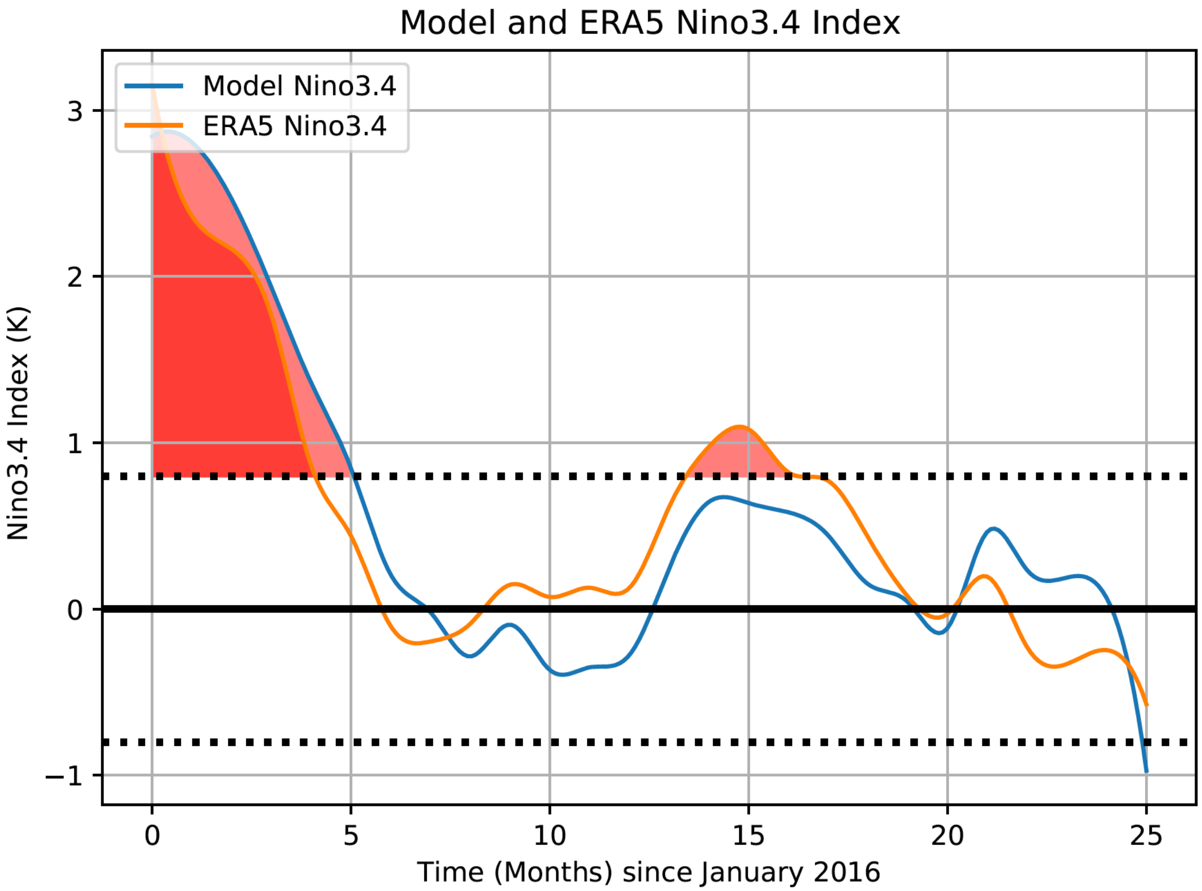
The NOAA consolidated predictions are three-month averages for up to a 9-month lead.

In 2016, there are no NOAA consolidated predictions during the first 6 months. The ERA5 monthly Nino3.4 SST anomalies are plotted as references.

The National Oceanic and Atmospheric Administration (NOAA) archived at the Climate Prediction Center (CPC) website (https://iri.columbia.edu/forecast/ensofcst/Data/archive/



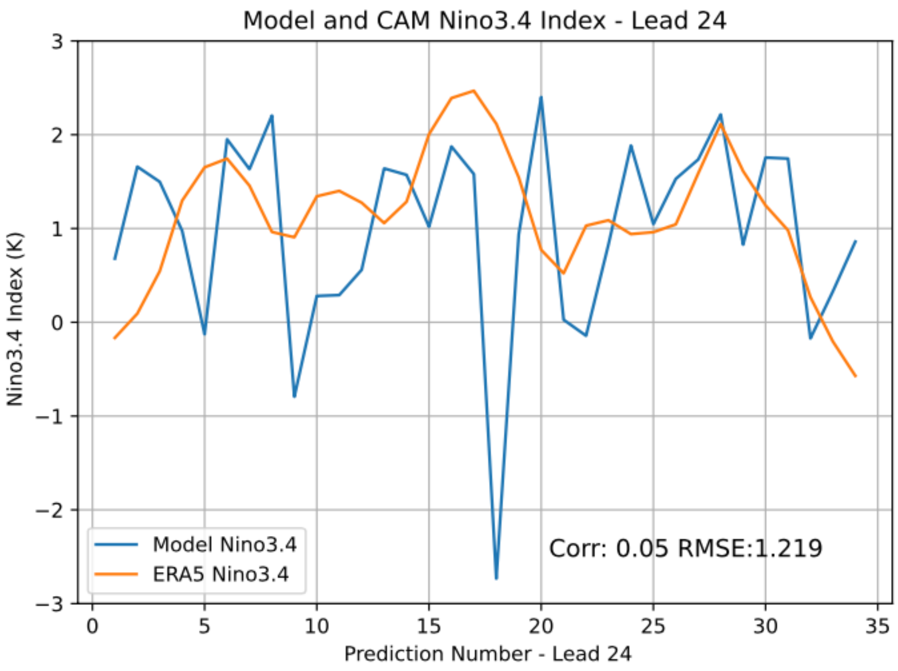
A 24 Month Prediction of the Nino3.4 index

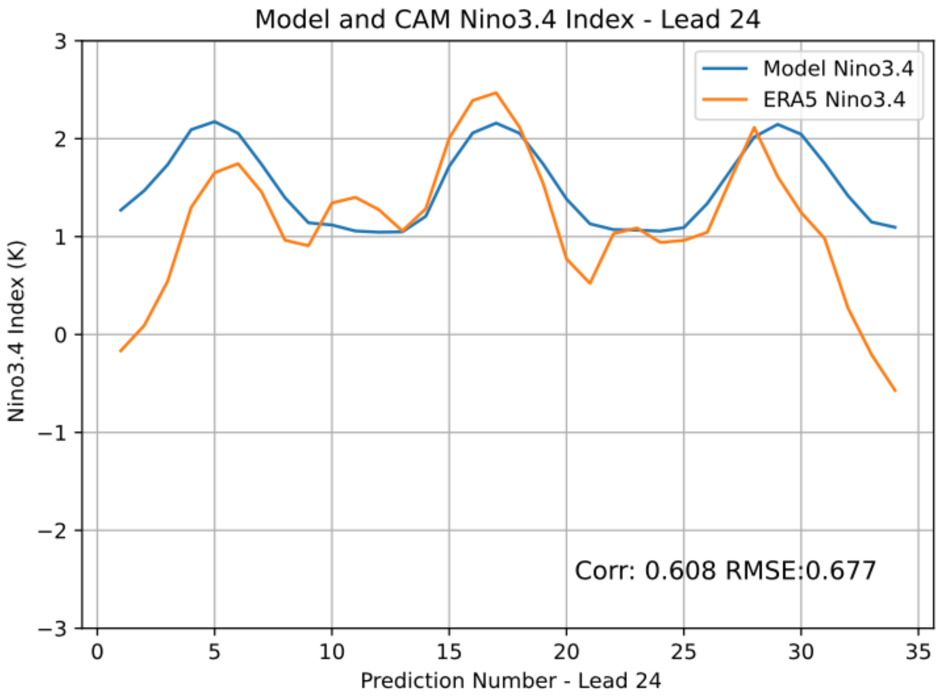


Latest SST Modelling Approach

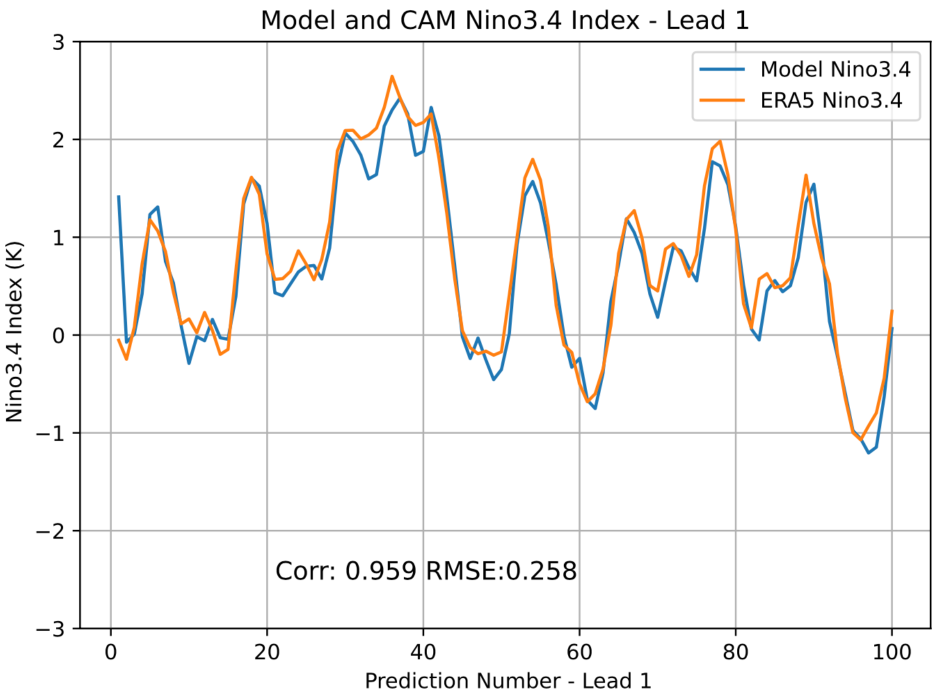
- Initial modelling study based on the Unet-LSTM – a convolutional neural network to account for spatial variability in the SST fields combined with an LSTM for temporal variation in the SST fields
- Transformers replaced LSTM models for analysis of text eg Large language models
- Vision transformers (ViT) using ‘attention’ can replace CNN models
- For SST modeling we have investigated using the FourCastNet model included in the Nvidia Modulus package which is not predicting well past three months
- We have investigated using a transformer+Unet (TUnet) model – producing results comparable or better than the original Unet-LSTM with the advantage of a reduced memory footprint.

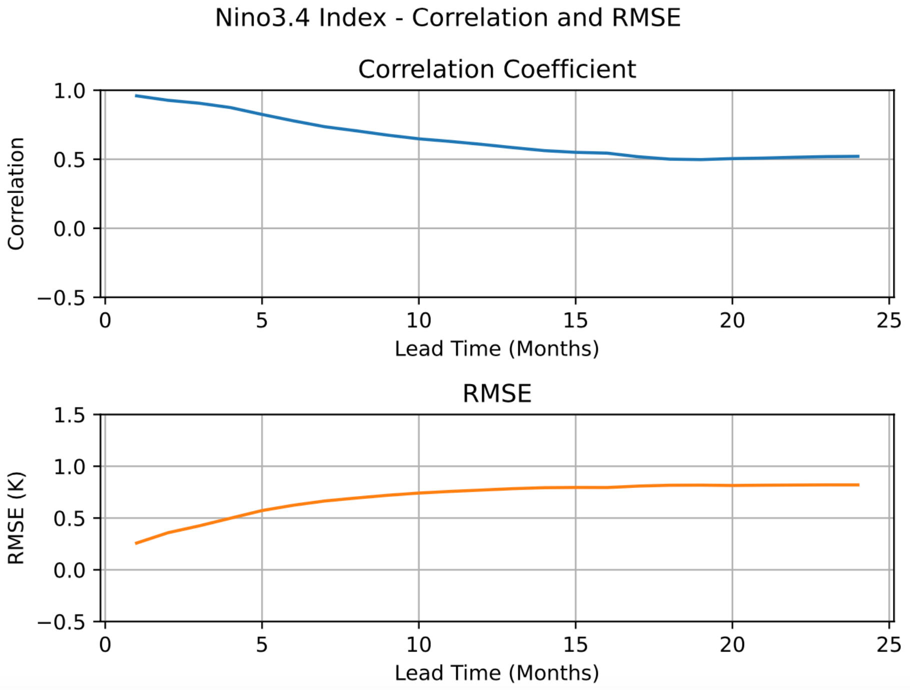
FourCastNet vs Transformer-Unet





Transformer-Unet

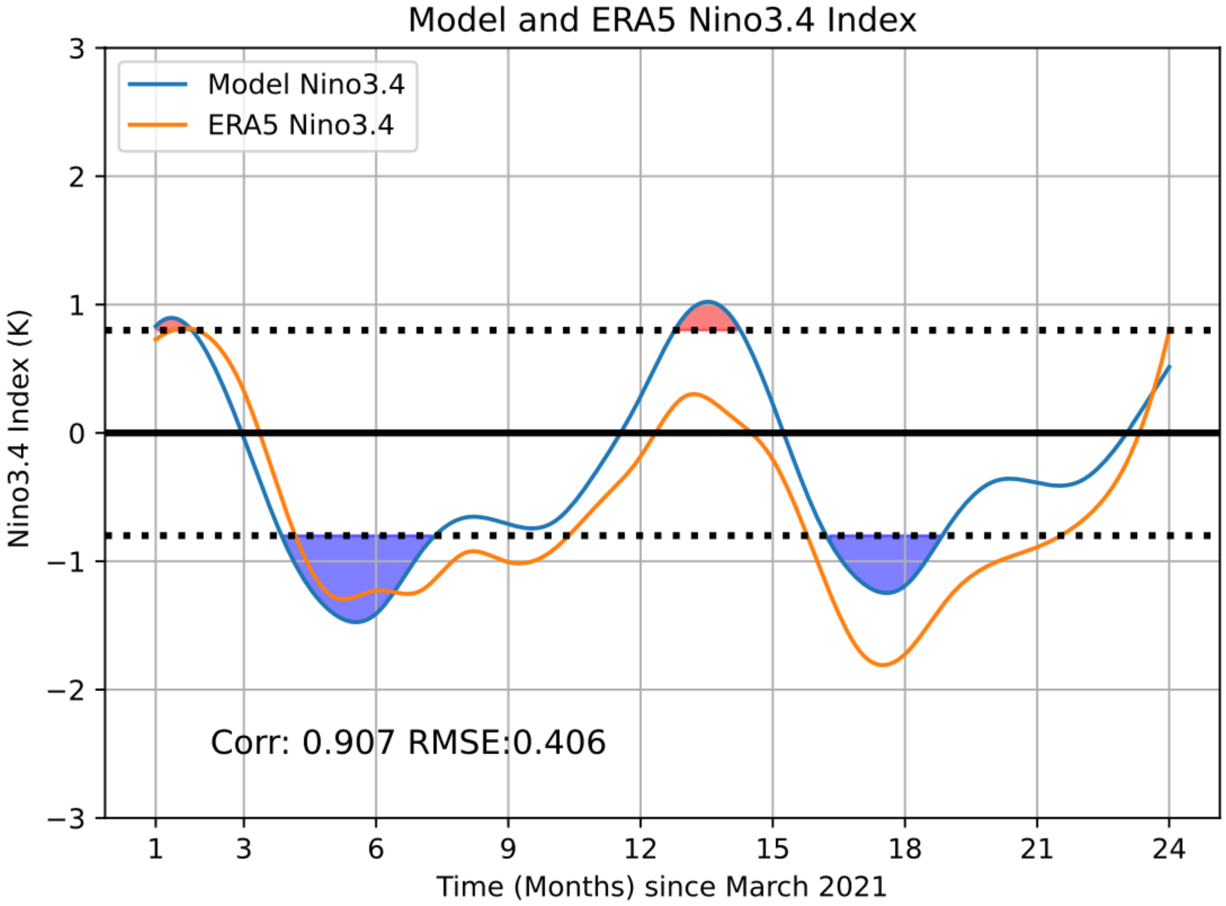




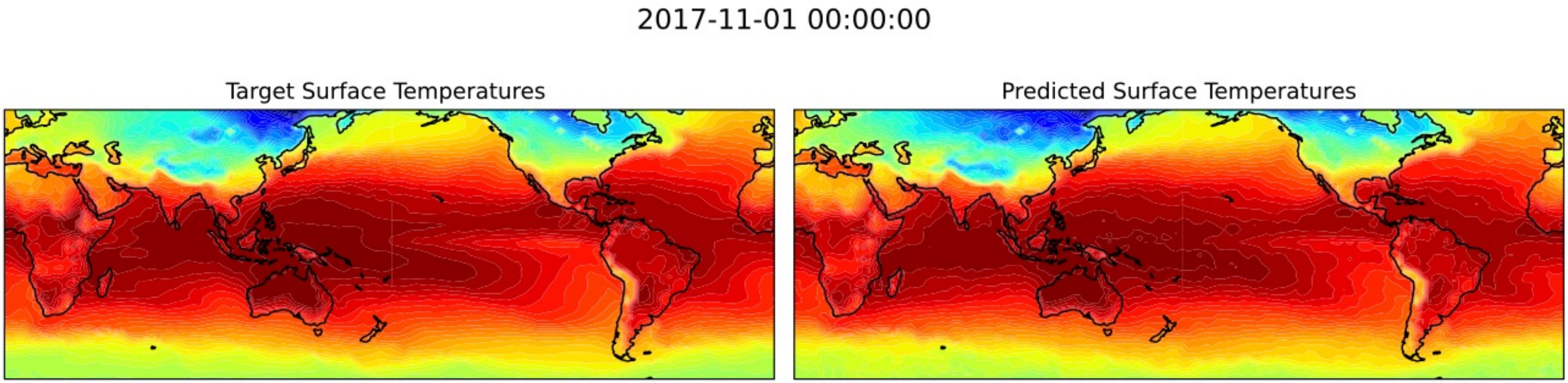
Transformer-Unet

Double dip La Nina

24-month forecast from March 2021 - March 2023



Transformer-Unet



Surface temperatures = SST over the oceans + 2-metre air temperature over the continents

"The progress and potential for AI in DOE science was captured in the 2020 "AI for Science" report. In the short interim, the scale and scope of AI have accelerated, revealing new, emergent properties that yield insights that go beyond enabling opportunities to being potentially transformative in the way that scientific problems are posed and solved.

These AI advances also highlight the crucial importance of responsible development of AI, focusing on challenges relating to AI *technology* (e.g., explainability, validation, security and privacy), *implementation* (e.g., transparency, safety engineering, ethics), and *application* (e.g., AI-Human interactions, education, and employment impacts)."

Conclusions

- An assessment of the predictions of the 2019–2020 El Niño and the 2016–2017 and 2017–2018 La Niña show that the model has skill up to 18+ months in advance.

- Note that the model makes predictions of the 2-d monthly SST field and Nino 3.4 is just one region embedded in the global field.

- The pace of innovation is accelerating – US DOE plans multi-billion dollar investment in AI for Science, Energy and Security

Research Articles

Data-driven global weather predictions at high resolutions
International Journal of High Performance Computing Applications (2021)
John A Taylor, Pablo Larraondo, Bronis R de Supinski
https://doi.org/10.1177/10943420211039818

A Deep Learning Model for Forecasting Global Monthly Mean Sea Surface Temperature Anomalies, *Frontiers in Climate (2022),* John Taylor and Ming Feng
https://doi.org/10.3389/fclim.2022.932932

A precipitation downscaling method using a super-resolution deconvolution neural network with step orography
Environmental Data Science (2023), PJ Reddy, R Matear, J Taylor, M Thatcher, M Grose
DOI: https://doi.org/10.1017/eds.2023.18

Python Code

unet_lstm - A machine learning model for the spatial and temporal evolution of 2D and 3D fields
https://doi.org/10.25919/3tvm-fw28