Australia's National Science Agency

Marine extremes in the Indian Ocean and machine learning model predictions of sea surface temperature

Ming Feng | 8 February 2023

Outline of the talk

1. Marine extremes in the Indian Ocean (heatwaves and cyclones)

2. Machine learning-based SST predictions
   - **CNN** - A simple **convolutional neural network** model to predict a single EIOD SST index
   - **Unet (encoder-decoder)** model to predict 2-dimensional global SST

Extreme events in the Indian Ocean

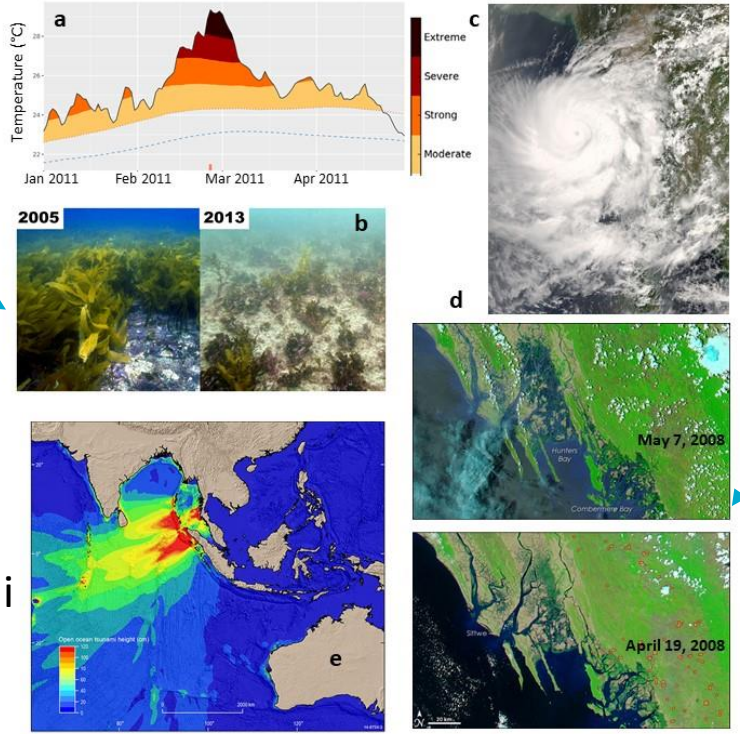
2011 Western Australian SST anomalies

Devastating impacts on marine ecosystems

2004 Indian Ocean tsunami

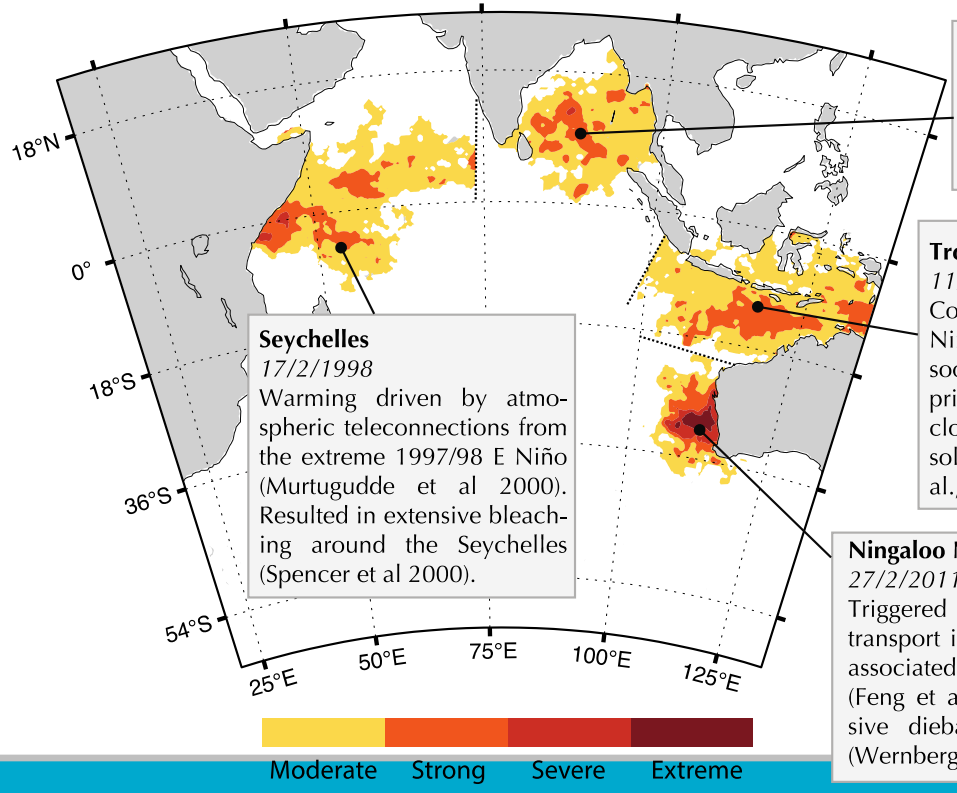
TC Nargis, 2008

Flooding in Myanmar



Feng, Lengaigne, Manneela, Sen Gupta, Vialard 2023 Book chapter

Prominent marine heatwave events in the IO



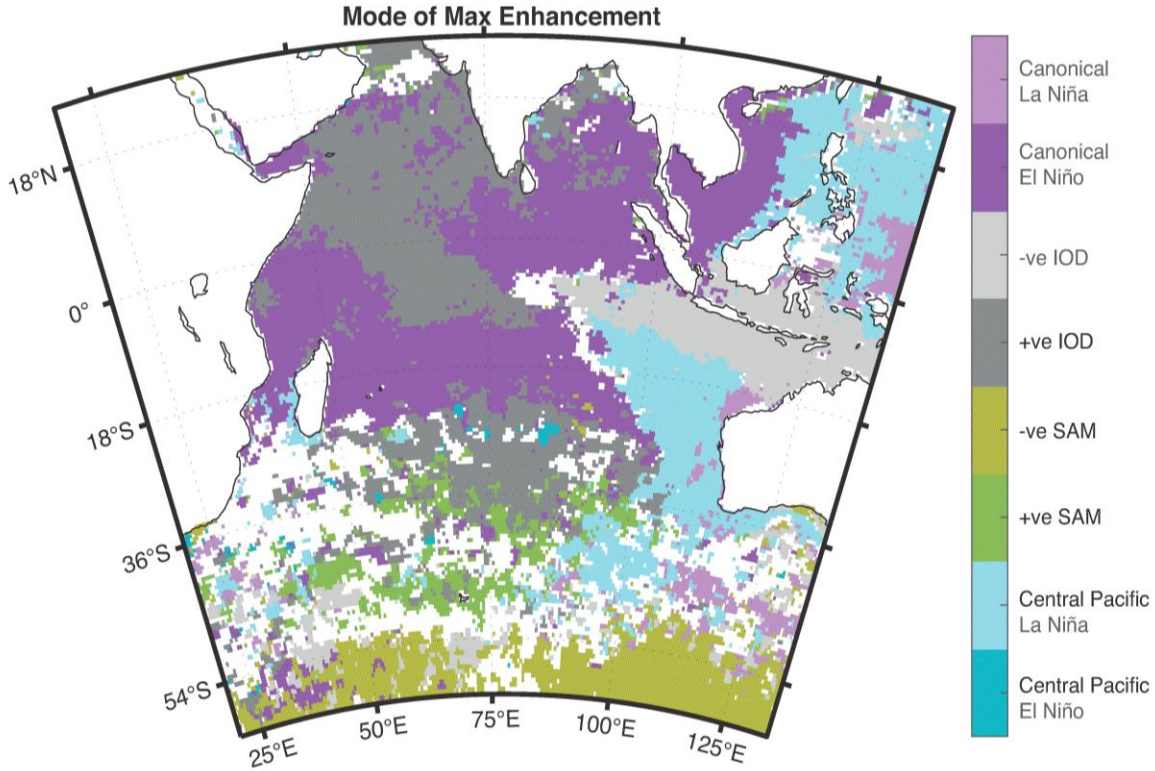
Bay of Bengal
15/5/2010
Associated with extensive coral bleaching in the Andaman Seas.

Tropical Australia
11/3/2016.
Coincided with strong El Niño and weakened monsoon activity. Warming primarily related to reduced cloud cover and increased solar heating (Benthuysen et al., 2018).

Seychelles
17/2/1998
Warming driven by atmospheric teleconnections from the extreme 1997/98 E Niño (Murtugudde et al 2000). Resulted in extensive bleaching around the Seychelles (Spencer et al 2000).

Ningaloo Nino
27/2/2011
Triggered by increased heat transport in the Leeuwin current associated with a strong La Niña (Feng et al 2013). Caused massive dieback of kelp habitats (Wernberg et al 2016)

Climate mode/phase that causes the largest significant enhancement in the likelihood of MHW days



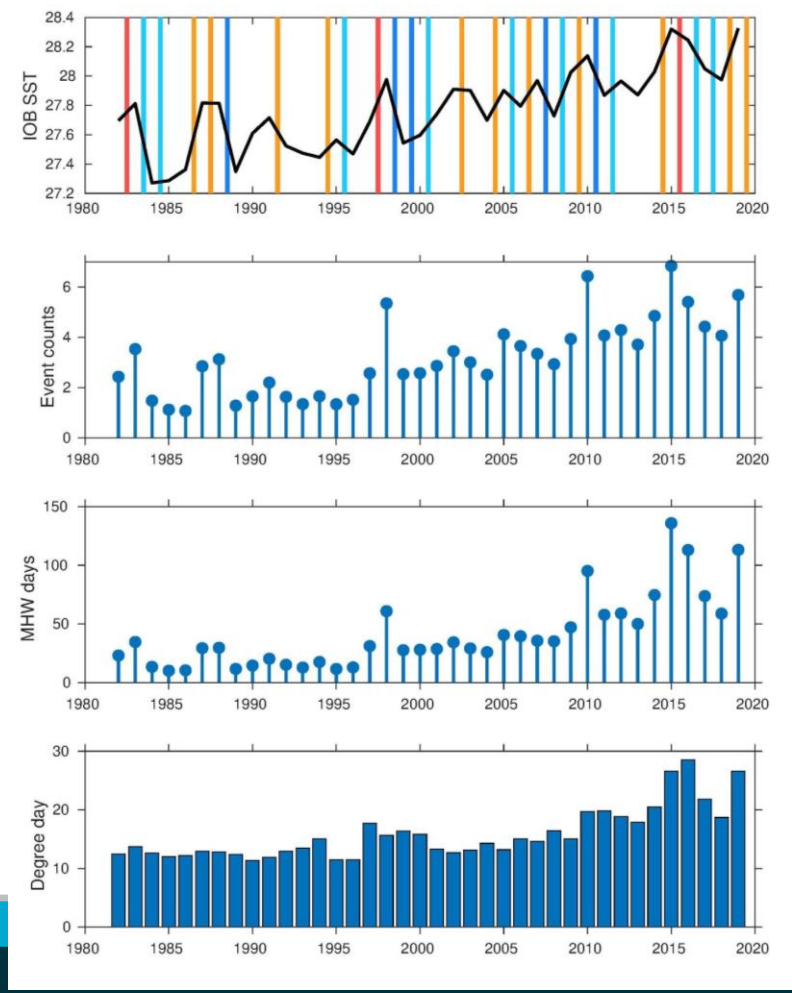
The Indian Ocean Basin Mode index

red and blue shadings denote the El Niño and La Niña

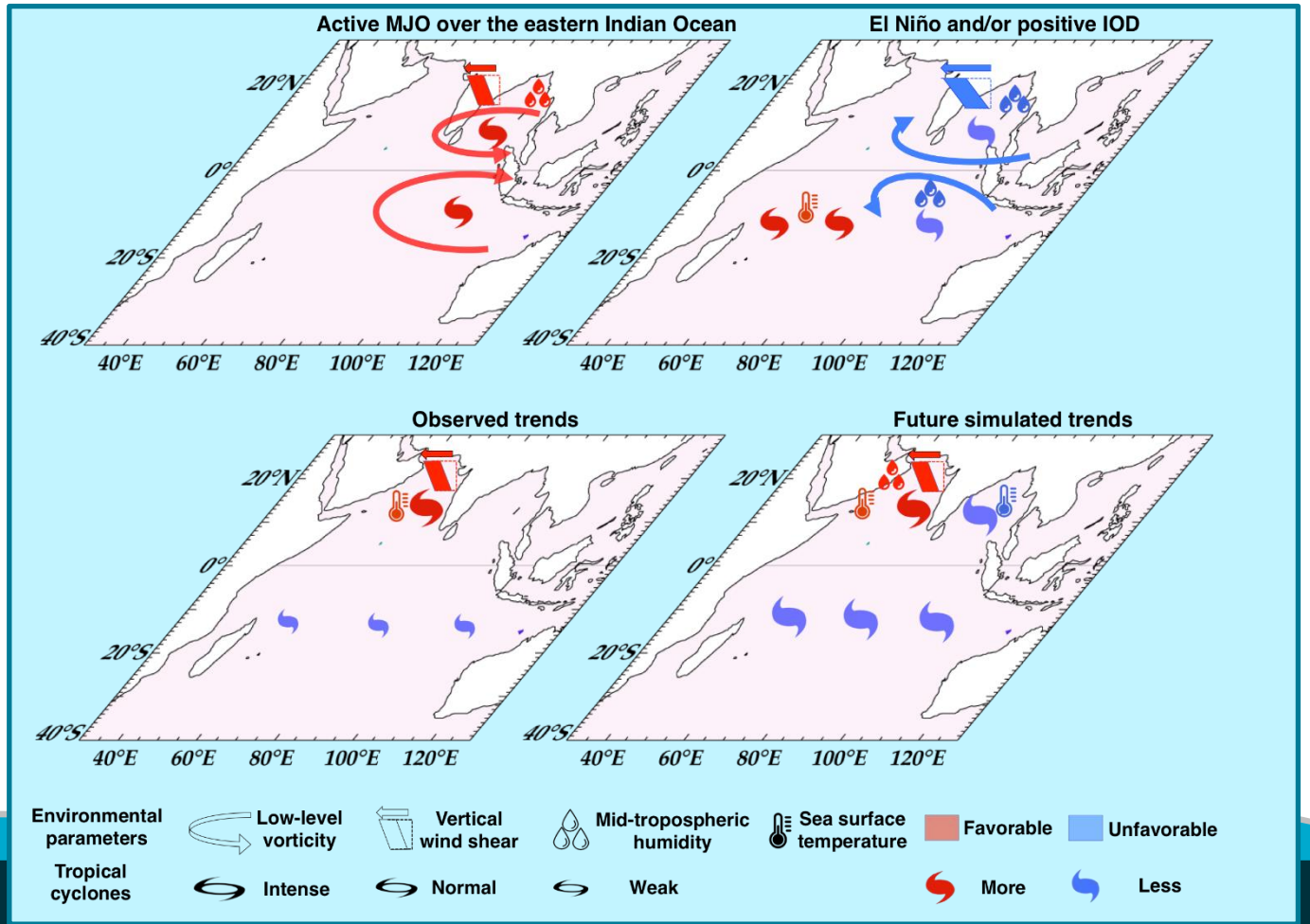
Marine heatwave events

Marine heatwave days

Cumulative intensity



TCs changes and controlling large-scale environmental factors



Two machine learning approaches

ORIGINAL RESEARCH article

Front. Clim., 25 August 2022
Sec. Predictions and Projections
https://doi.org/10.3389/fclim.2022.925068

This article is part of the Research Topic
Dynamics and Impacts of Tropical Climate Variability: Understanding Trends and Future Projections
View all 5 Articles >

Predictability of sea surface temperature anomalies at the eastern pole of the Indian Ocean Dipole—using a convolutional neural network model

Ming Feng[1,2*], Fabio Boschetti[1], Fenghua Ling[3], Xuebin Zhang[4], Jason R. Hartog[4], Mahmood Akhtar[5], Li Shi[6], Brint Gardner[5], Jing-Jia Luo[3] and Alistair J. Hobday[4]

ORIGINAL RESEARCH article

Front. Clim., 28 September 2022
Sec. Climate, Ecology and People
https://doi.org/10.3389/fclim.2022.932932

This article is part of the Research Topic
Advances in Marine Heatwave Interactions
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A deep learning model for forecasting global monthly mean sea surface temperature anomalies

John Taylor[1*†] and Ming Feng[2,3†]

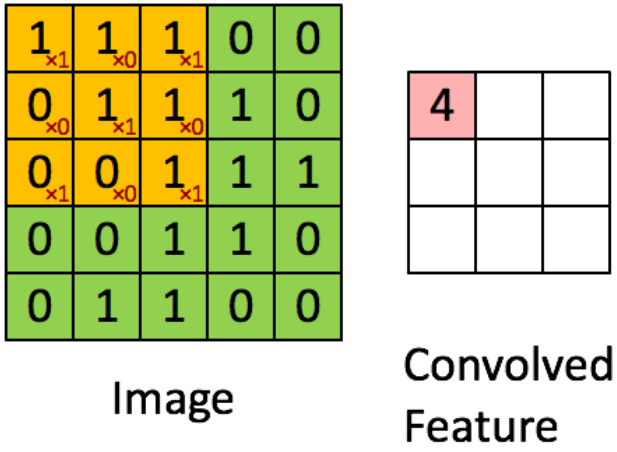
[1] Data61, Commonwealth Scientific and Industrial Research Organisation (CSIRO), Canberra, ACT, Australia
[2] Oceans and Atmosphere, Commonwealth Scientific and Industrial Research Organisation (CSIRO), Perth, WA, Australia
[3] Centre for Southern Hemisphere Oceans Research, Commonwealth Scientific and Industrial Research Organisation (CSIRO), Hobart, TAS, Australia

Convolutional Neural Network (CNN)

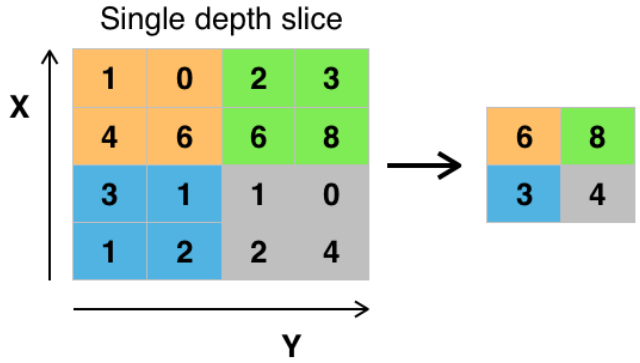
A **Convolutional Neural Network** is a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other.

CNN model layers

Convolutional layer – extract high-level features



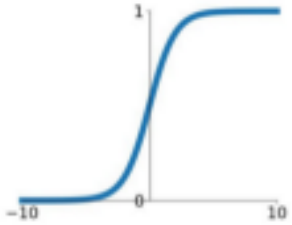
Pooling layer – dimensionality reduction and extracting dominant features



Activation Functions

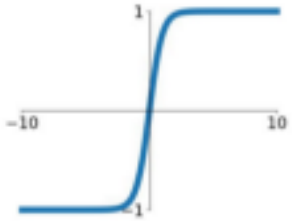
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



tanh

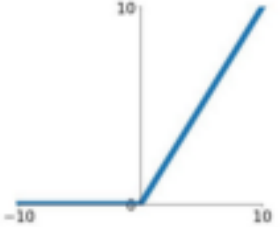
$\tanh(x)$



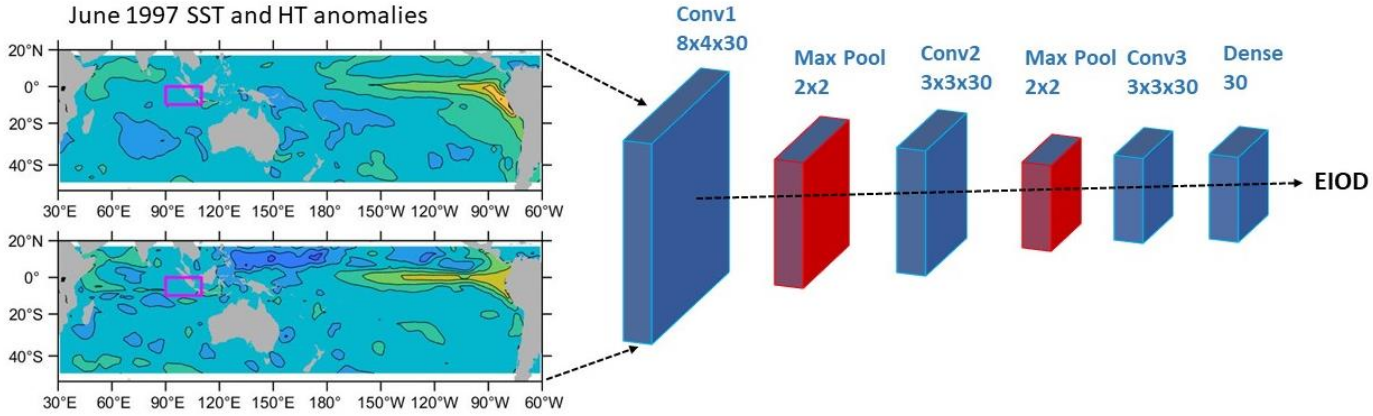
$$f(x) = \frac{\left(e^{x} - e^{-x}\right)}{\left(e^{x} + e^{-x}\right)}$$

ReLU

$\max(0, x)$



Prediction of Eastern IOD pole SST variability

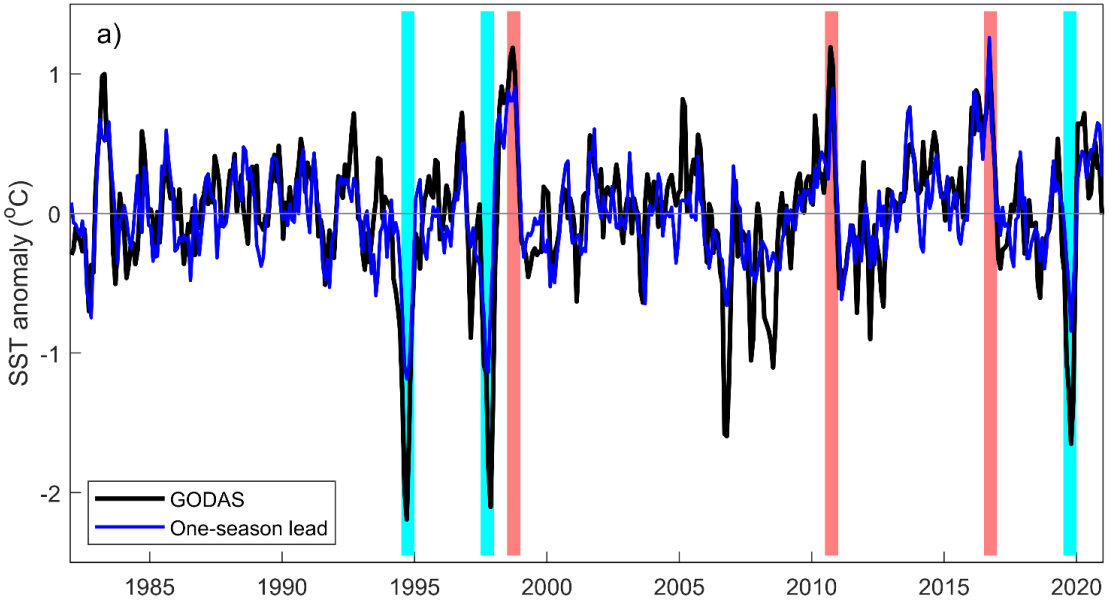


- SST and heat content anomalies CMIP5/6 model outputs (Historic runs, detrended anomaly)
- 3-monthly Indo-Pacific anomaly data as **input**
- Single month eastern IOD SST anomaly as **output (label)**
- *tanh* activation, 10 ensemble members, 1-14 months lead (~500,000 parameters)
- Bracewell, Python, Keras, Tensorflow

Feng et al. 2022

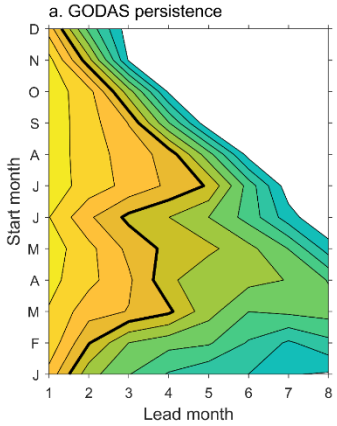
Model evaluation

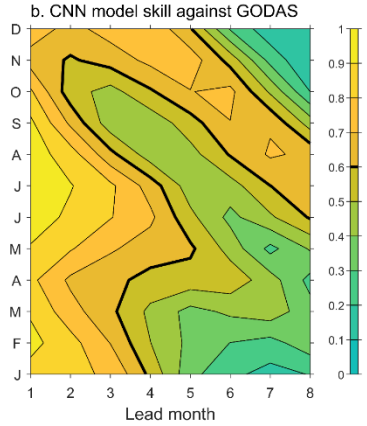
Use GODAS reanalysis data anomalies as model inputs and use the trained model to make predictions



CNN model Pearson correlation skills

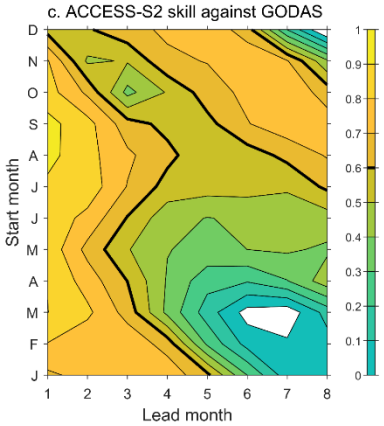
Persistence





CNN model

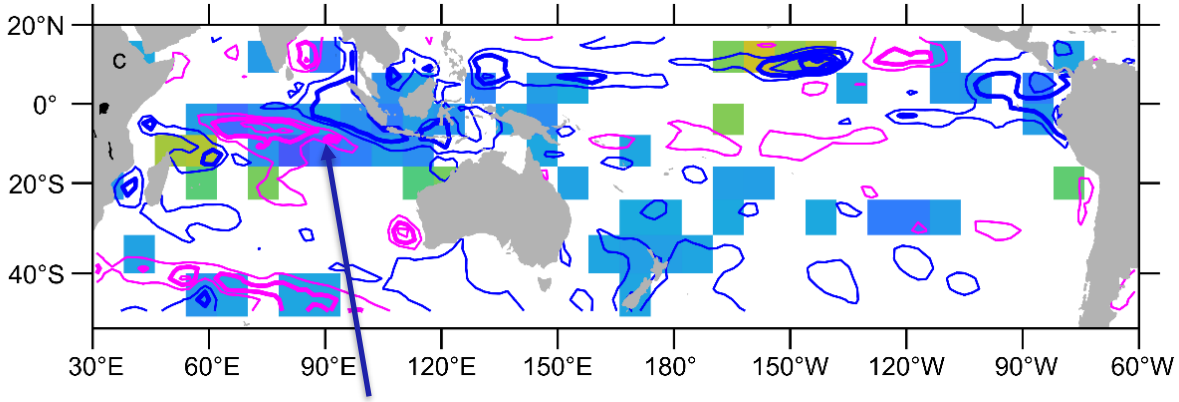
ACCESS-S2 Model (Australian Bureau of Meteorology)



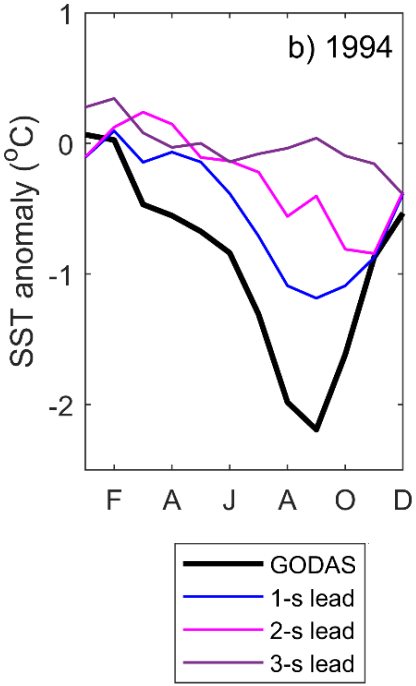
Feng et al. 2022

Activation map to predict Sep 1994 EIOD index

Blue shading: negative activation, to promote cold SST anomalies in EIOD
green-red: positive activation

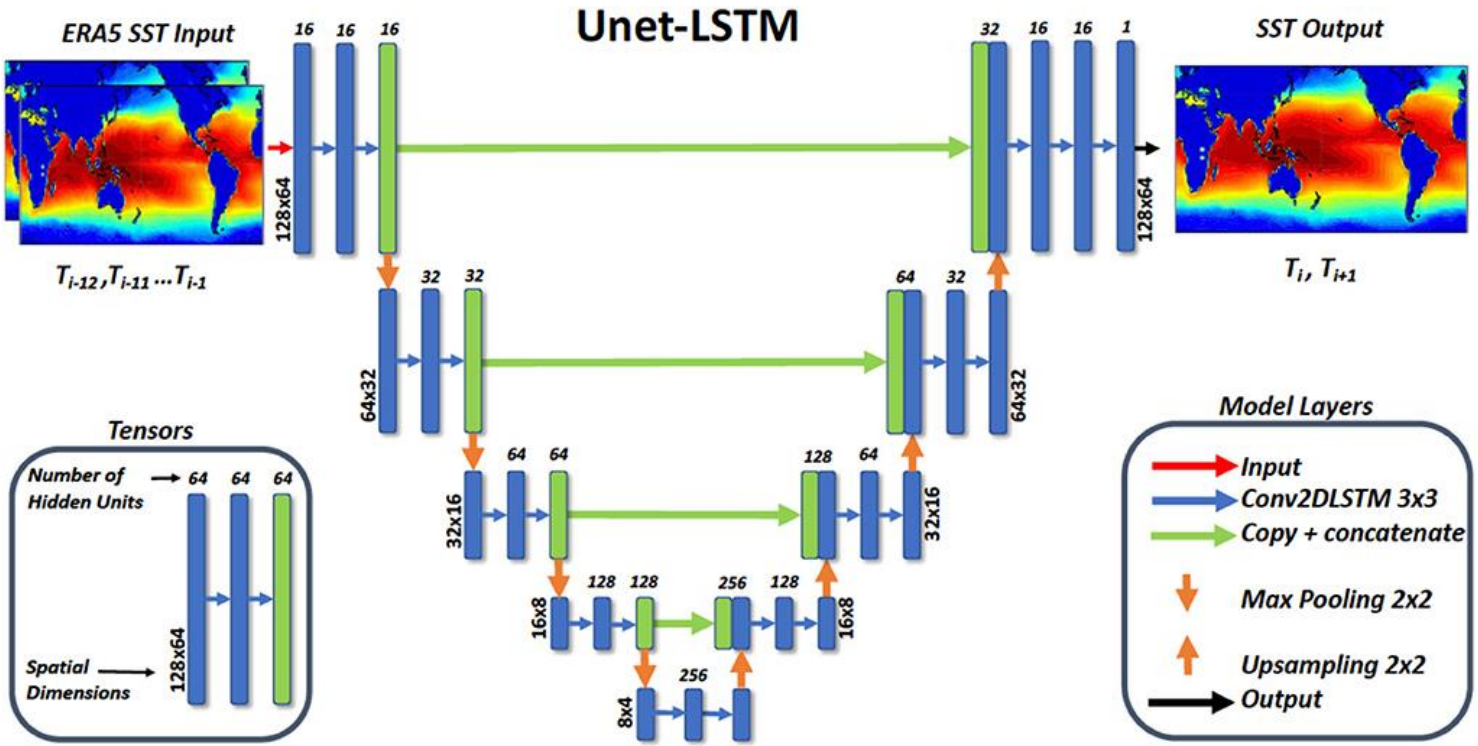


Kelvin wave – Rossby wave dipole



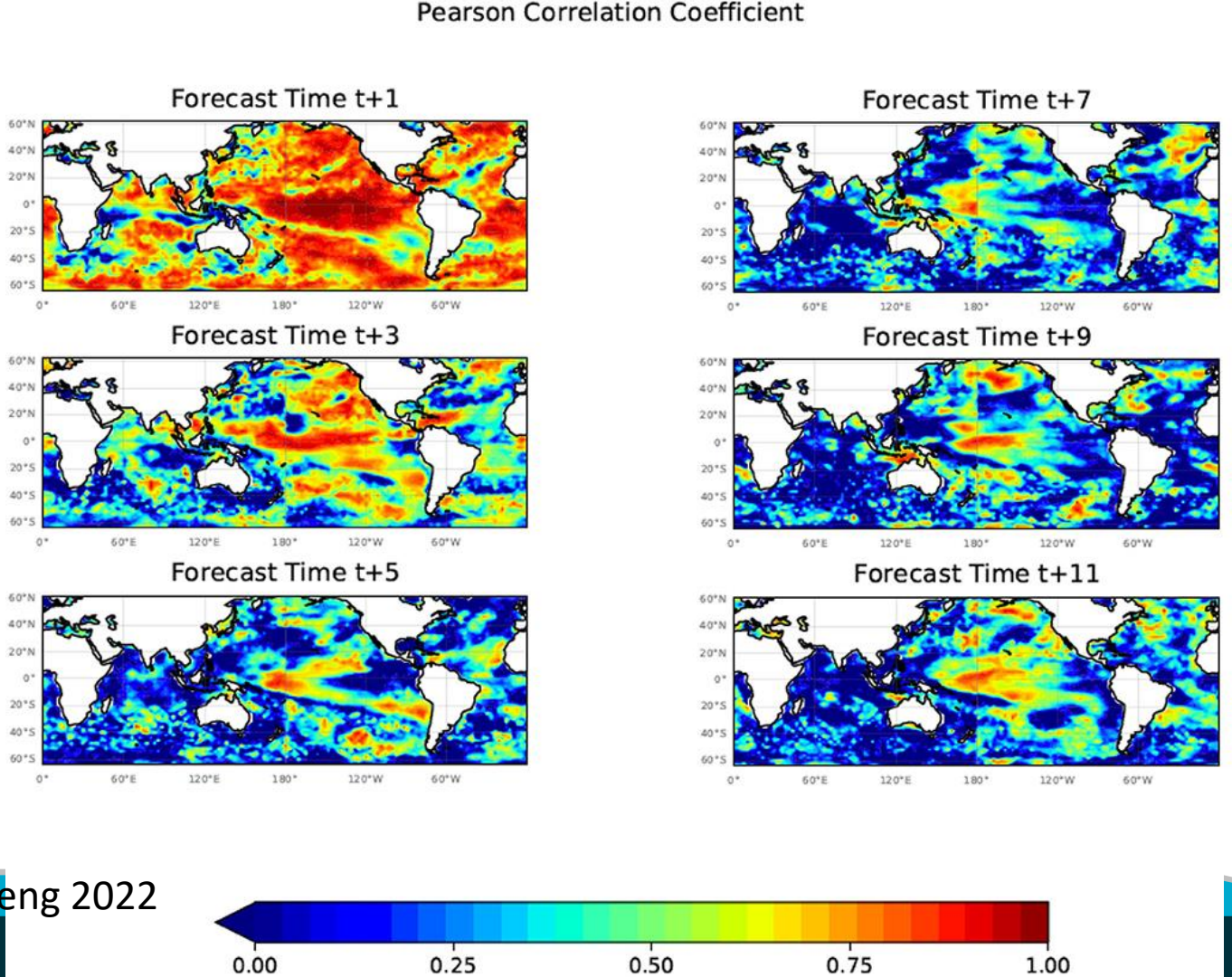
Contour: June 1994 heat content anomaly
Positive: magenta; negative: blue

Feng et al. 2022



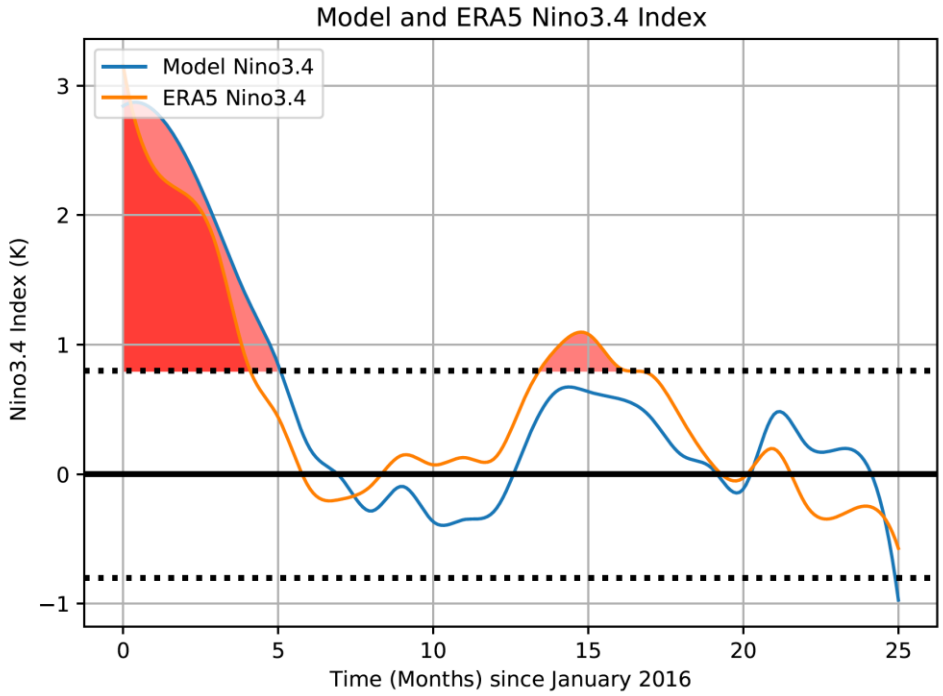
Input data **12 monthly time steps** (1 year), which capture the seasonal cycle in SST;
2-month prediction and predicted values are used as new inputs to predict the next 2m

Taylor and Feng 2022

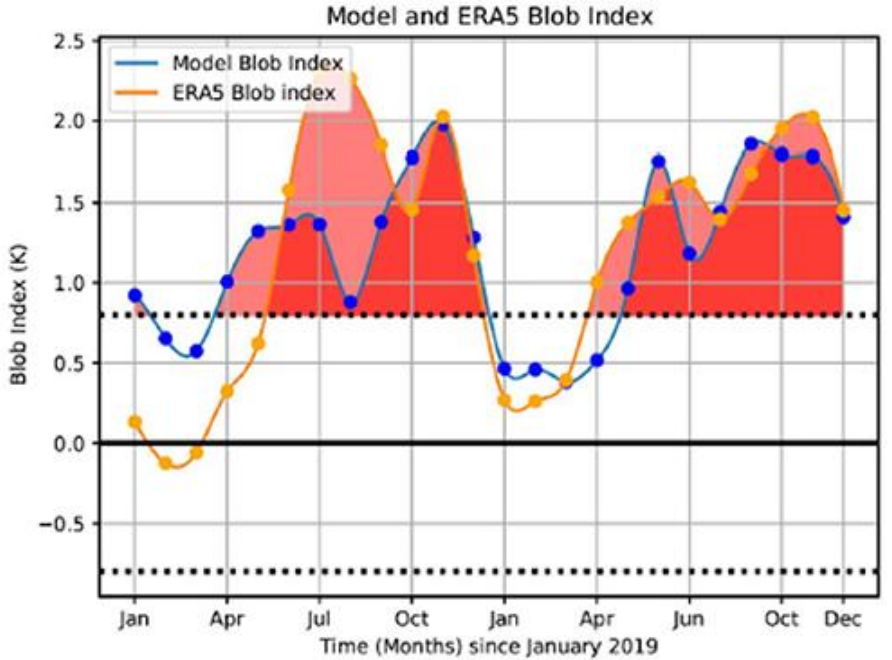


Taylor and Feng 2022

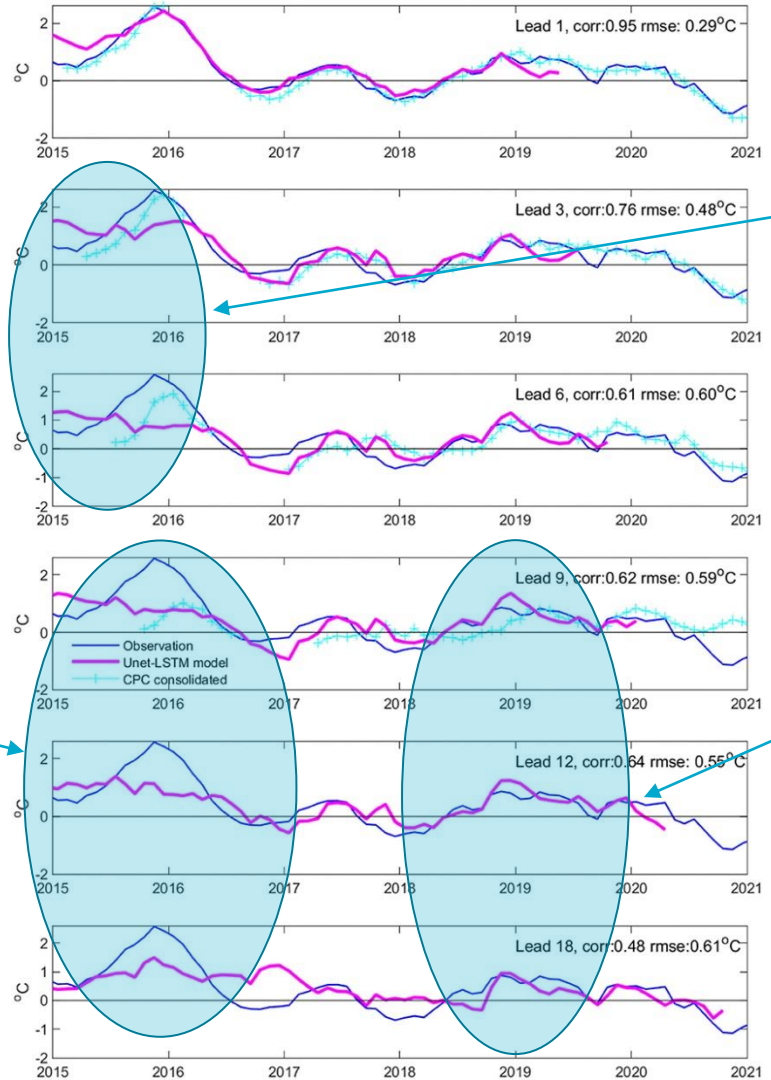
A 24 Month Prediction of the Nino3.4 index



Model predictions of the Blob index over 24 month



Unet model Nino3.4 predictions



Overestimate the 2014-15 event, significantly underestimate the 2015-16 event at short lead

At long lead (>= 9 months), well predicts the 2015-16 event with reduced magnitude – better than CPC consolidated pred.

Better long-lead prediction for the 2018-19 event

Comparing the two models

CNN	Unet-LSTM
Predict single index	predict 2-d SST
SST and ocean heat content	SST/air temperature
Use anomaly field	Use full SST field
Detrended data	With trend
3-monthly	12-month (memory of annual cycle and temperature warming)
Trained with CMIP model data	Trained with Reanalysis data

Summary

- **Reviewed spatial and temporal distribution and drivers of marine heatwaves in the Indian Ocean**
  - Influences on the tropical cyclone genesis
- **The CNN model trained only using the CMIP model can be applied to the EIOD prediction**
  - The CNN model can beat persistence, and be on par with ACCESS-S2 model prediction skills
- **Unet model, using monthly reanalysis of global surface temperature, shows ability to predict 2-d SST variability at various lead times**
  - Long-lead skills in the equatorial Pacific and northeast Pacific
  - Failed to predict the 2015-16 El Nino; having >18 month skills for the CP El Nino
  - Good skills for the Blob marine heatwaves

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Postdoc on machine learning-based marine extreme prediction at CSIRO Perth

https://jobs.csiro.au/job/Perth%2C-WA-CSIRO-Postdoctoral-Fellowship-in-Unlocking-Marine-Extreme-Predictability-with-AI/934412410/

Thank you

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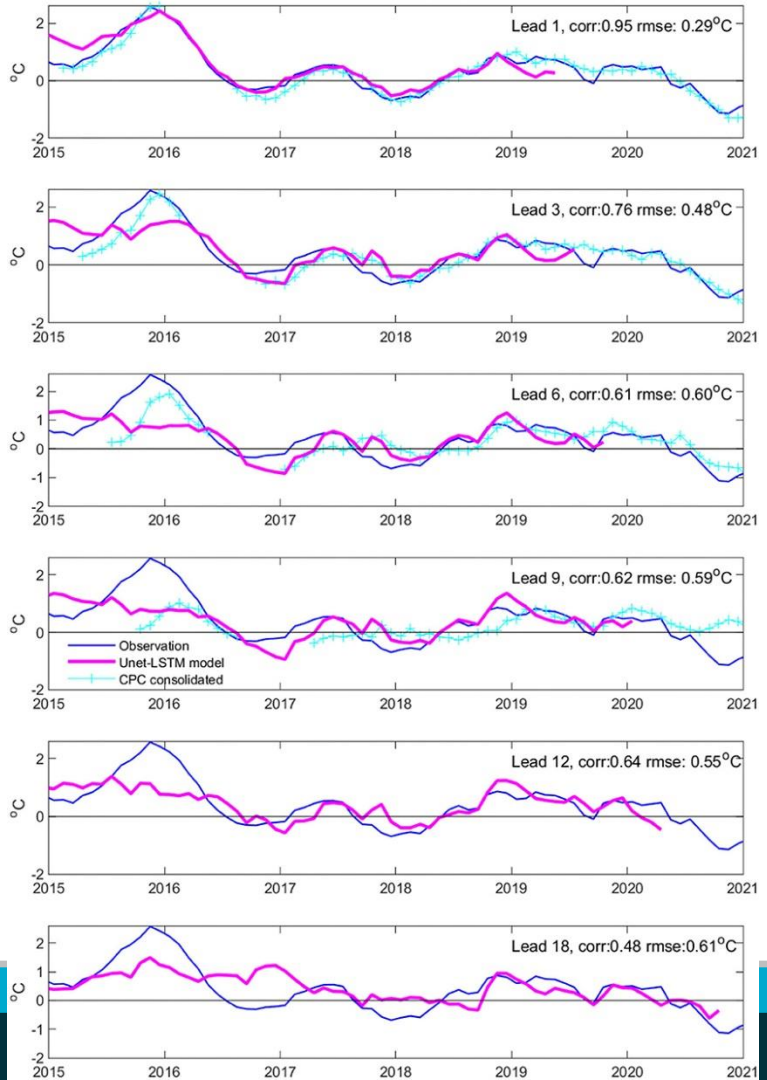
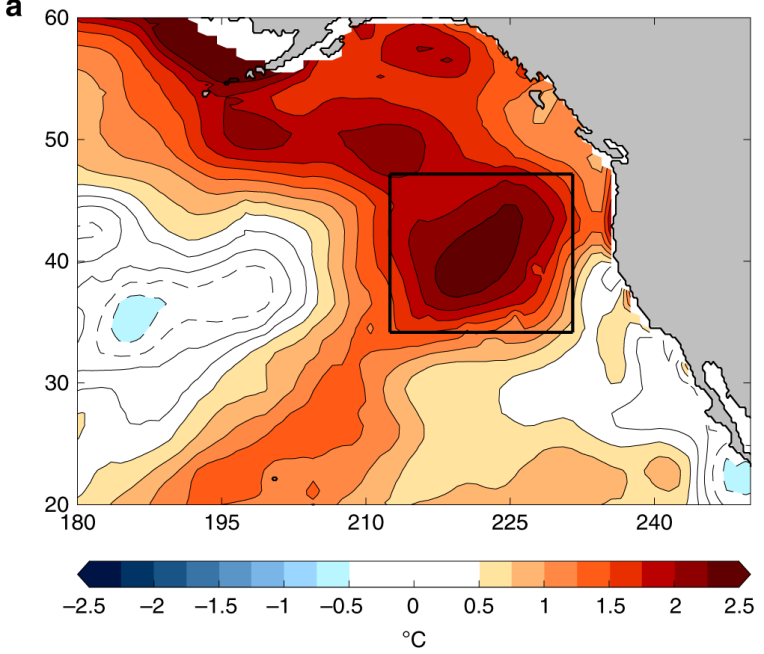
Unet model Nino3.4 predictions



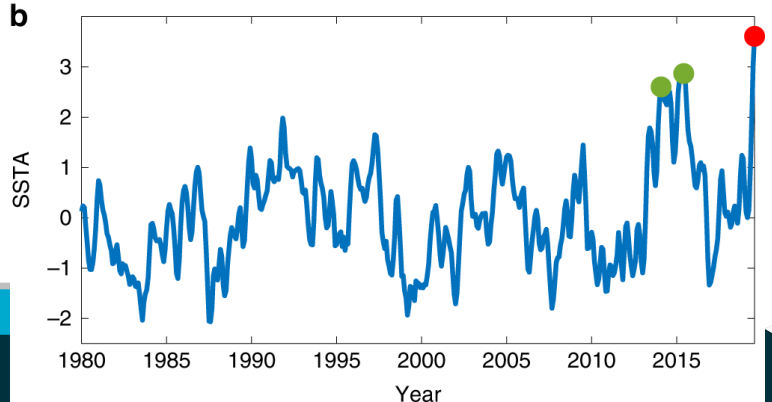
Blob marine heatwaves

Surface ocean temperature anomalies (°C) averaged for June–August (JJA) 2019



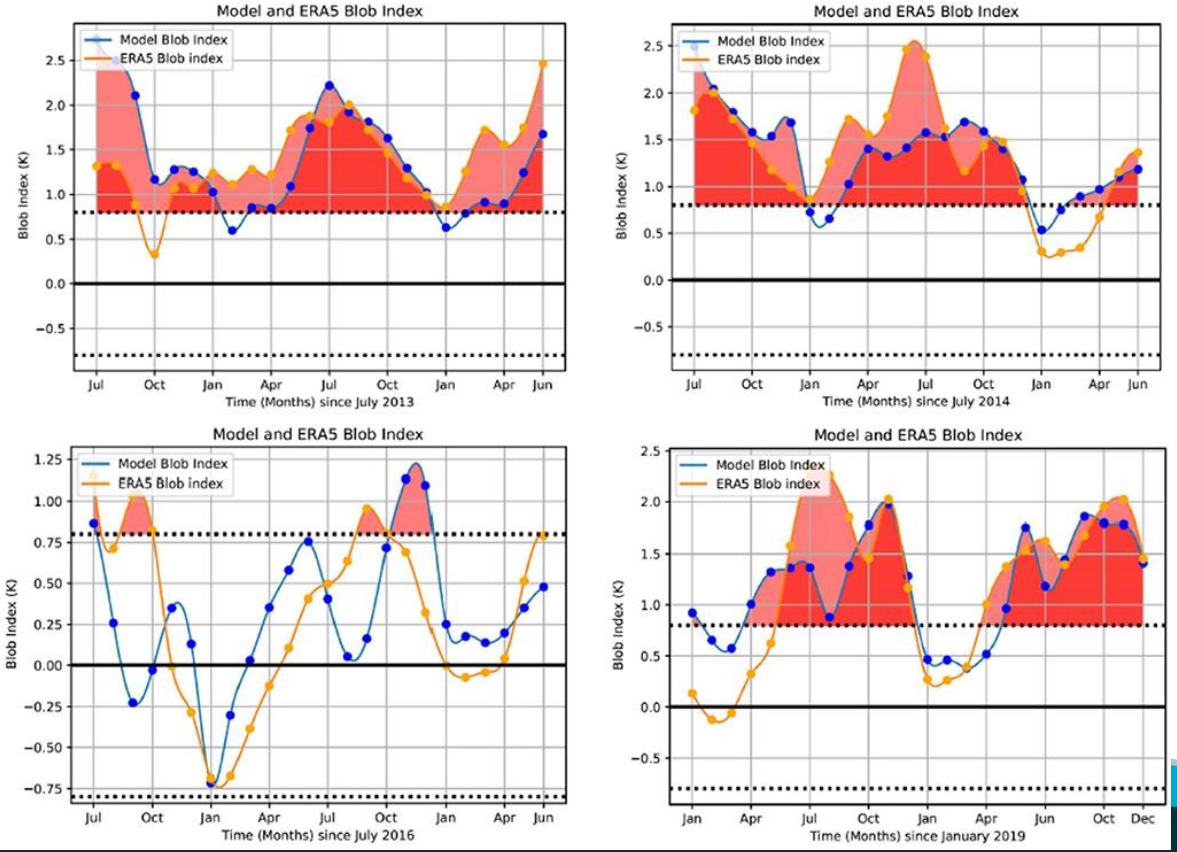
Remote SST forcing from the central equatorial and, surprisingly, the subtropical North Pacific Ocean contribute to the weakened North Pacific High

Amaya et al. 2020

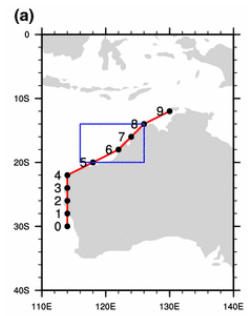


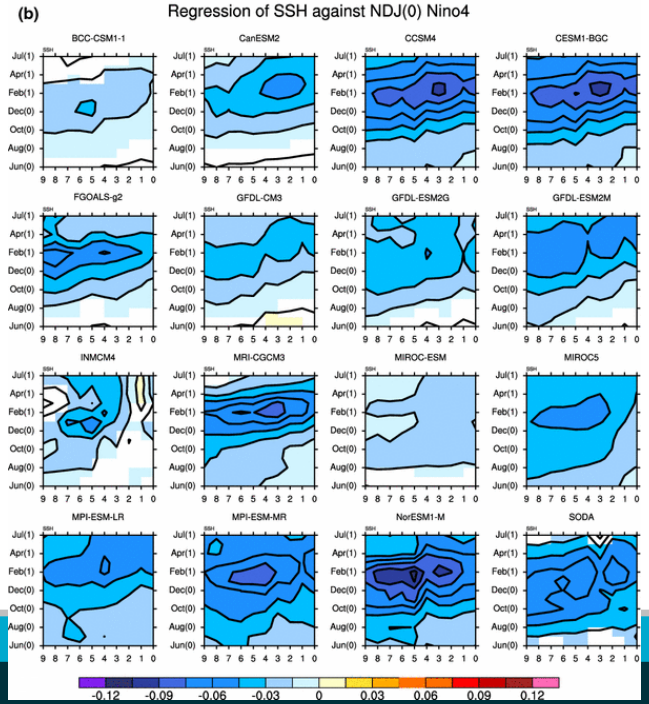
Model predictions of the Blob index over 24 month

commencing in July 2013, 2014, 2015, and January 2019



Selection of CMIP models





CMIP model list	
CMIP5 models	CMIP6 models
CCSM4	ACCESS-CM2
CanESM2	CanESM5
CESM1-BGC	CESM2
FGOALS-s2	CMCC-CM2-SR5
GFDL-CM3	FGOALS-g3
GFDL-ESM2G	GFDL-CM4
GFDL-ESM2M	GFDL-ESM4
MRI-CGCM3	MRI-ESM2-0
NorESM1-M	NorESM2-MM

~2500 samples for each prediction

Kido et al. 2016

Model summary

- The CNN model trained only using the CMIP model can be applied to the real-world prediction
- The CNN model can beat persistence, and be on par with ACCESS-S2 model prediction skills
  - Overcome winter barrier to predict eastern IOD SST variability

Grad-CAM (Gradient-weighted Class Activation Mapping) activation map

A spatial map of how intensely the input image activates the class

$$\alpha_k = \frac{1}{Z} \sum_{x,y,t} \frac{\partial y}{\partial A^k_{x,y,t}}$$

$\frac{\partial y}{\partial A^k}$ is the gradient of *y* with respect to a feature map A^k of the last convolutional layer

$$L_{\text{Grad}-\text{CAM}} = \sum_k \alpha_k A^k$$

Linear combination of the weighted activation maps

Summary

- **Grad-CAM visualisation of the CNN model provides useful clues about the potential drivers of the IOD events**
  - 1994 IOD – Indian Ocean processes play a key role
  - 1997 IOD – with ongoing Pacific El Nino and teleconnection into the west Indian Ocean, negative SST and heat content anomalies seem important
  - 2019 IOD – cool SST anomalies in the southeast Indian Ocean (Ningaloo Nino region)
  - CMIP models are able to capture the coupled processes and teleconnection associated with the IOD development

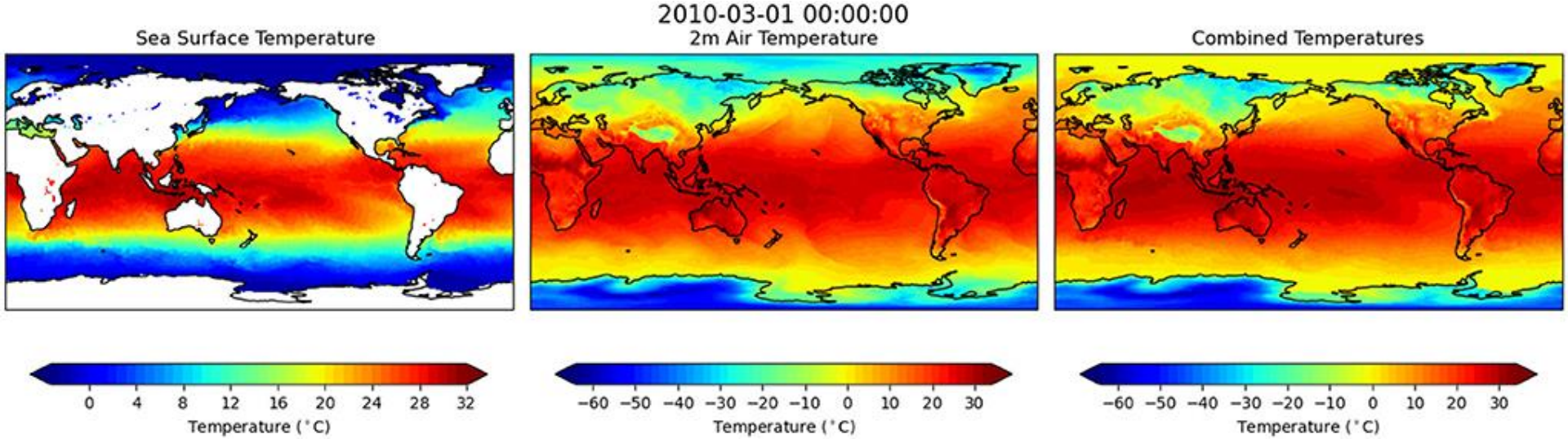
ERA5 Reanalysis

- The ERA5 reanalysis data set (Hersbach et al., 2020) provides monthly estimates, currently commencing in 1979, of many atmospheric, land, and oceanic variables at global scale with a spatial resolution of 0.25°, ≈ 30 km
- An ERA5 preliminary analysis commencing in 1950 and covering the period up to December 1978 is also available
- The ERA5 data set includes surface variables, including SST, and atmospheric variables

Training data: ERA5

- ERA5 reanalysis (from 1979) and Preliminary Analysis (1950-1978)
- Use monthly SST (ERA5 label “sst”) and 2-m atmospheric temperature (ERA5 label “t2m”) variables
- The 2-meter atmospheric temperature data was used only over the land surface in order to complete a global grid of data for use with the 2-D convolutional model layers

Combined surface temperature data



Construction of the Unet-LSTM model

- We first averaged the [720,1440] data set to a 1 x 1° grid [180,360] and then used bilinear interpolation to a [64,128] latitude (–64°S to 62°N in 2° increments) and longitude (–180°S to 180°N in 2.8125° increments) grids.
- Input data used for training the model were selected as a moving window **using 12 time steps** (1 year), which capture the seasonal cycle in SST, as this was found to yield the best model predictions of SST.
- The model is trained to make **2-month predictions**, and the predicted values are then used as new inputs to predict the next 2 months

Issue and future research

Issue: Unet-LSTM model fails to predict the peak of the 2015-16 El Nino – likely due to lack of training data (70 years of reanalysis)

- Train using model data (CMIP, spinup runs)
- Knowledge informed ML

A new and rapidly evolving area of research is physics-informed ML (Karniadakis et al., 2021) that combines ML with physical constraints

Issue: SST vs ocean heat content

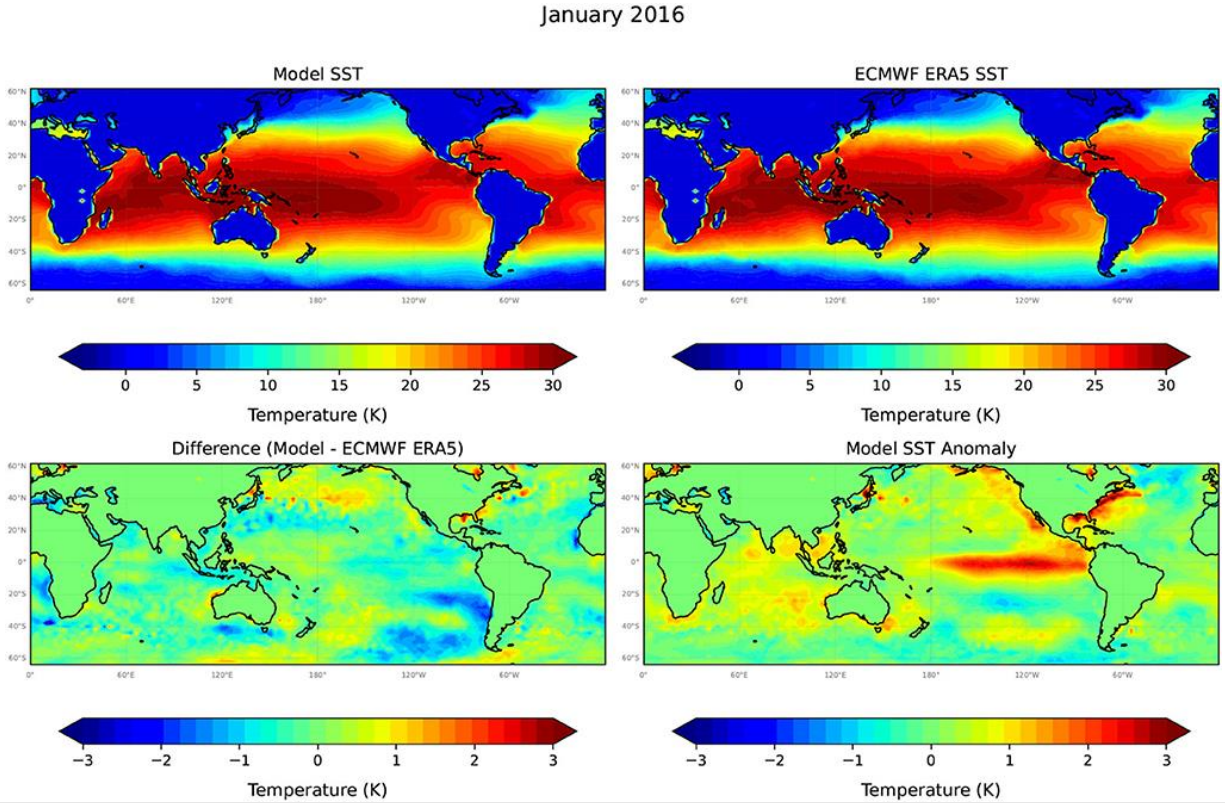
Surface SST and land surface temperatures drive global surface wind anomalies and then subsequently drive the planetary ocean waves to store the upper ocean heat content anomalies.

Prediction starting in January 2015 fails to predict the 2015–2016 peak during the rare occurrence of two consecutive El Ninos, likely due to a lack of similar cases in the training data based on existing observations.

Model training

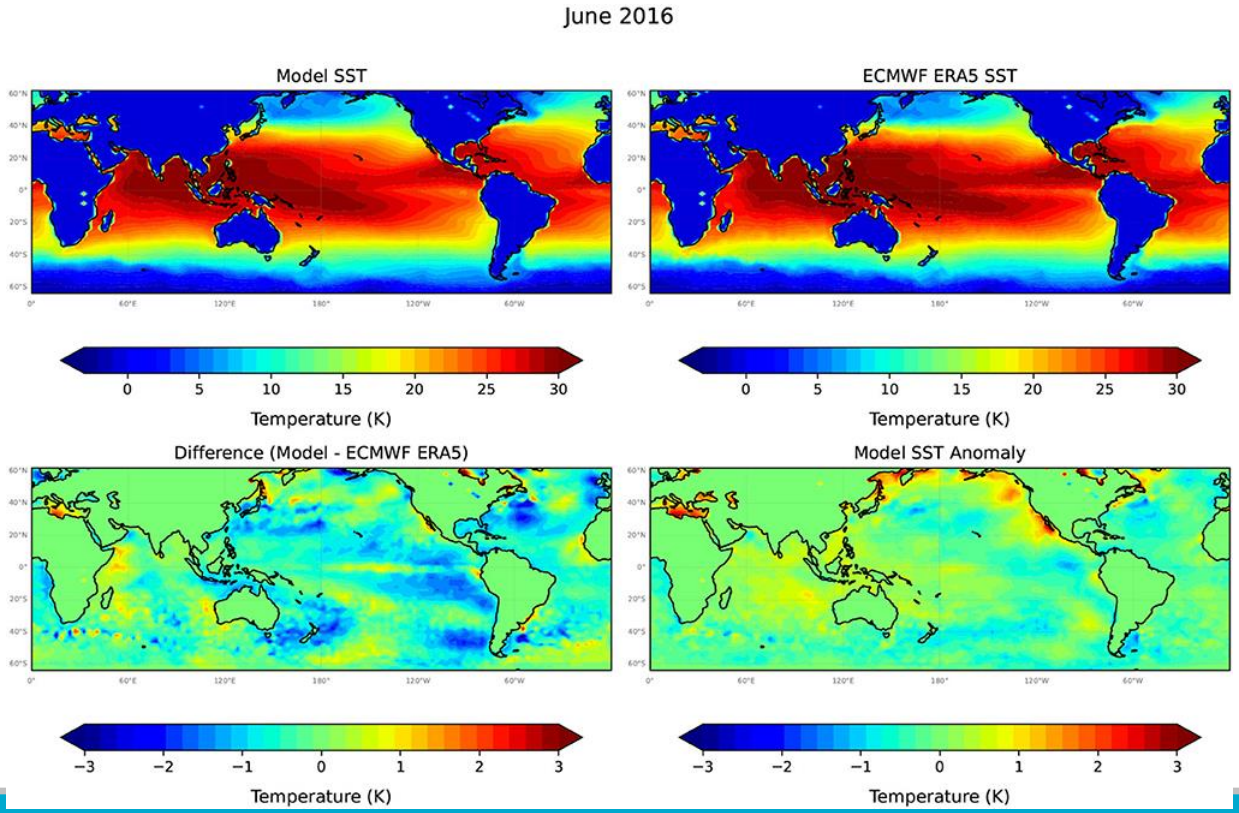
- Use 760 of the available time steps from January 1950 to April 2013 for training and the remaining 97 time steps for validation and testing
- Normalise data to [0 1], use tanh activation function
- The Unet-LSTM model uses the prior 12 months of SST data in order to predict the following 2 months of SST data, the predicted values are then used as new inputs to predict the next 2 months
- 24-month prediction

Global scale 2-D SST prediction

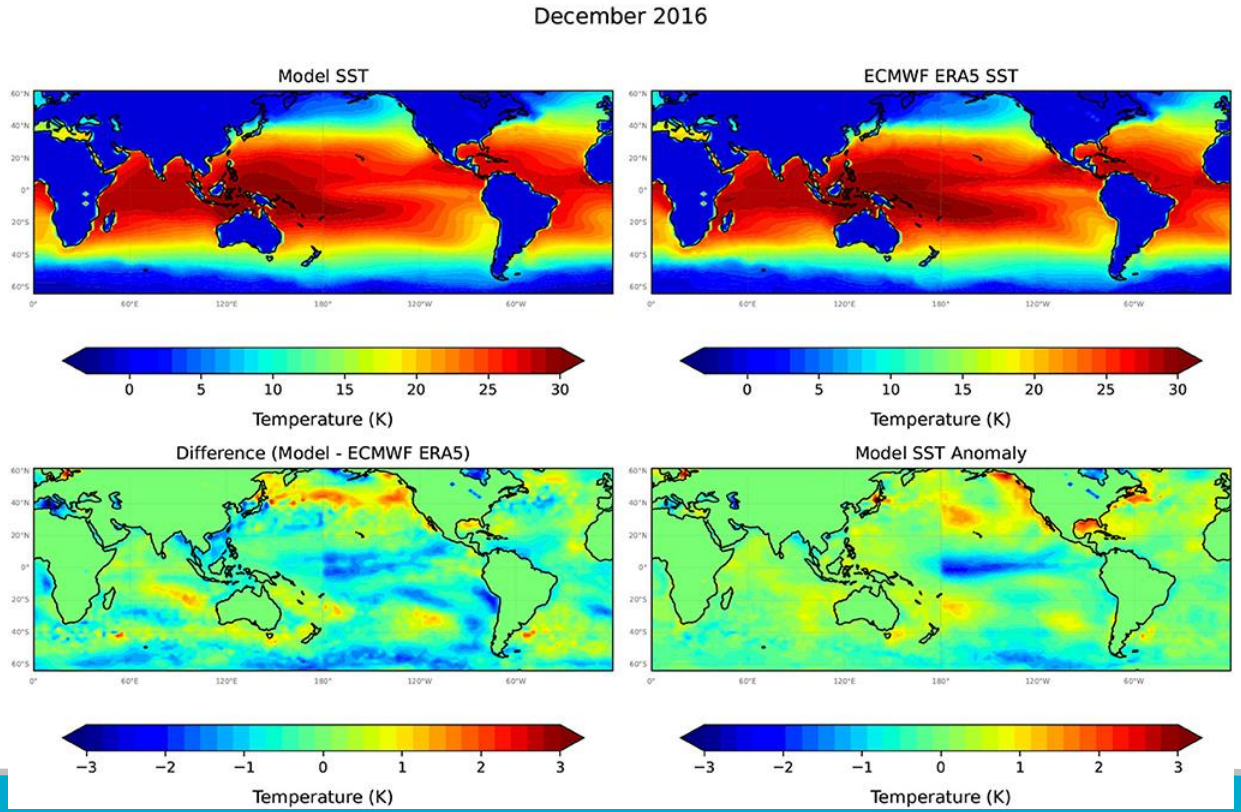


Model predicted SST at +1 month (January 16), from a model forecast initiated in December 2015

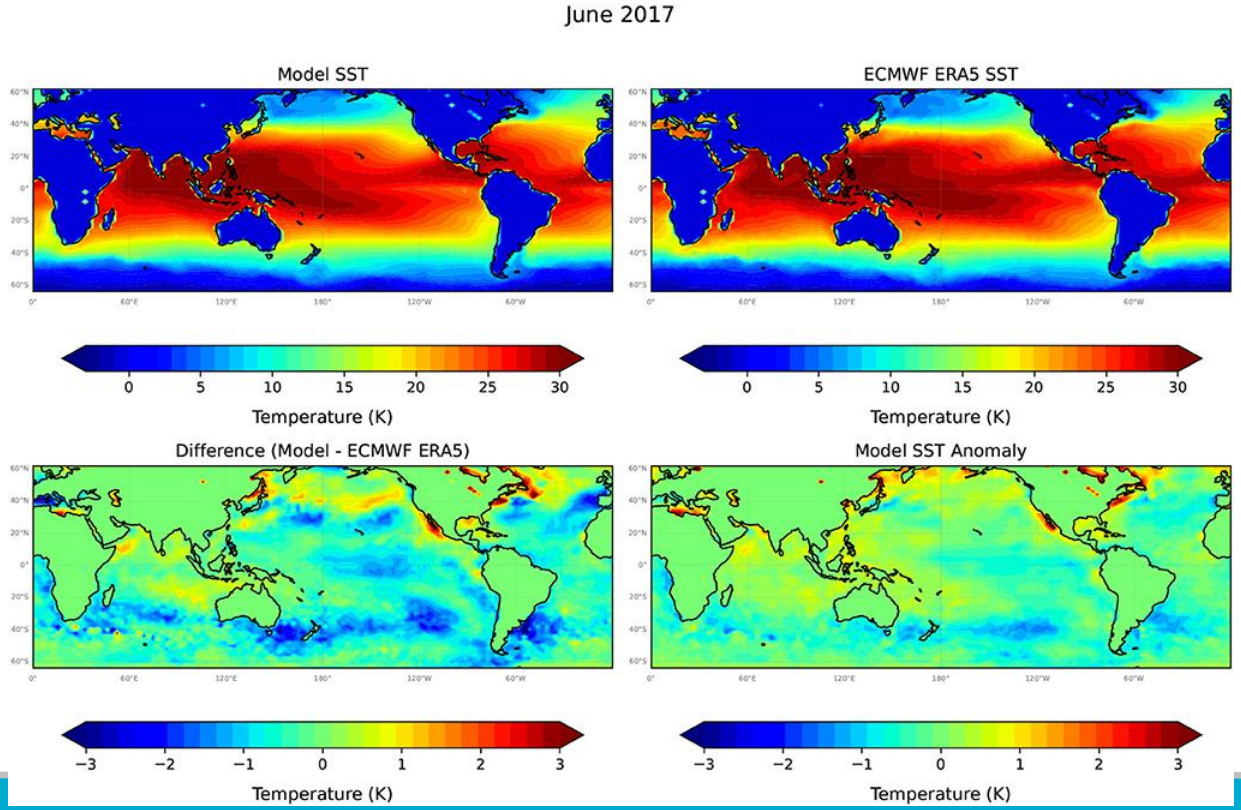
6-month lead prediction



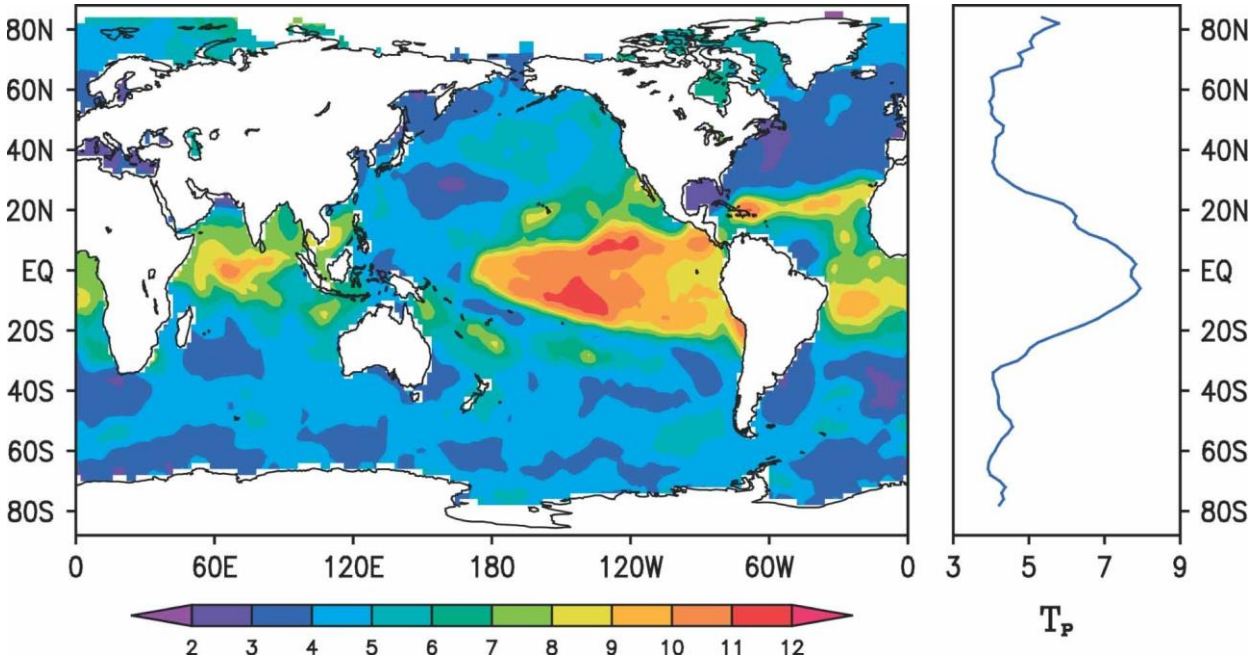
12-month prediction



18-month prediction



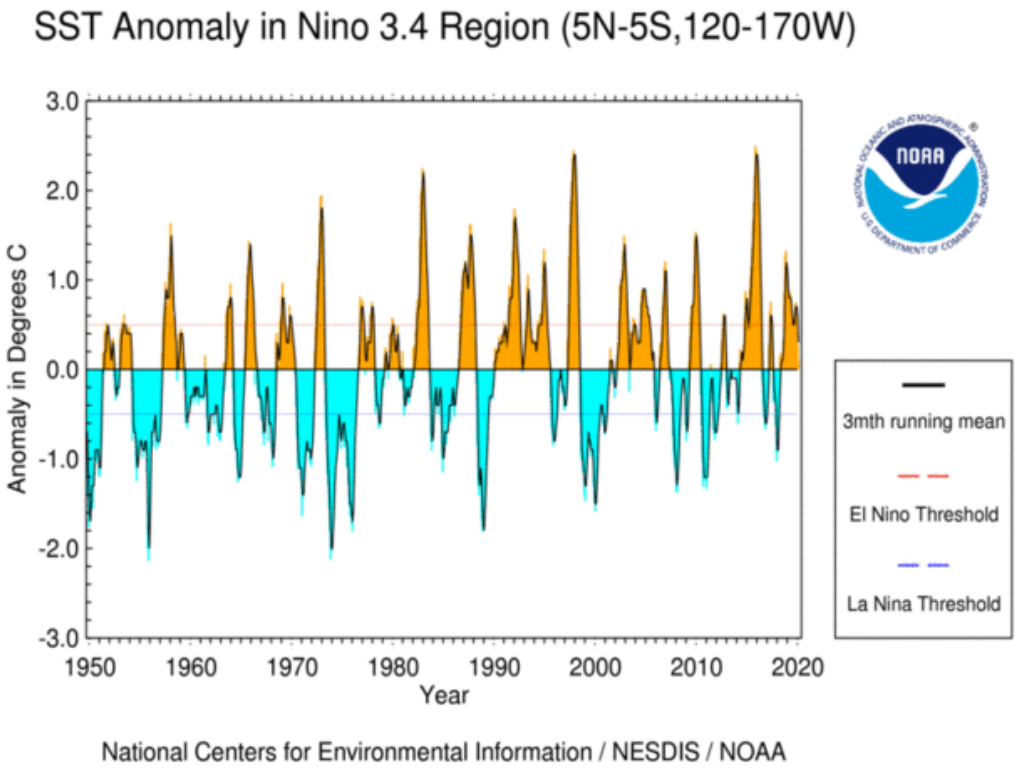
Predictability limit of monthly sea SST temperature in the global oceans



Li and Ding 2012

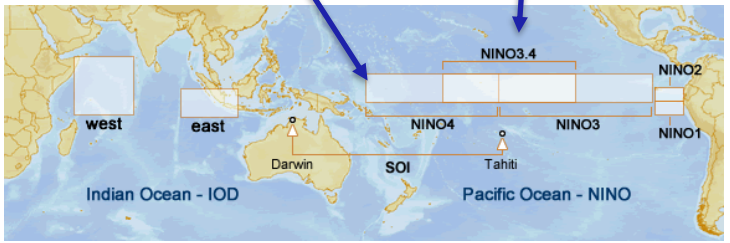
Nonlinear local Lyapunov exponent

Nino 3.4 Index

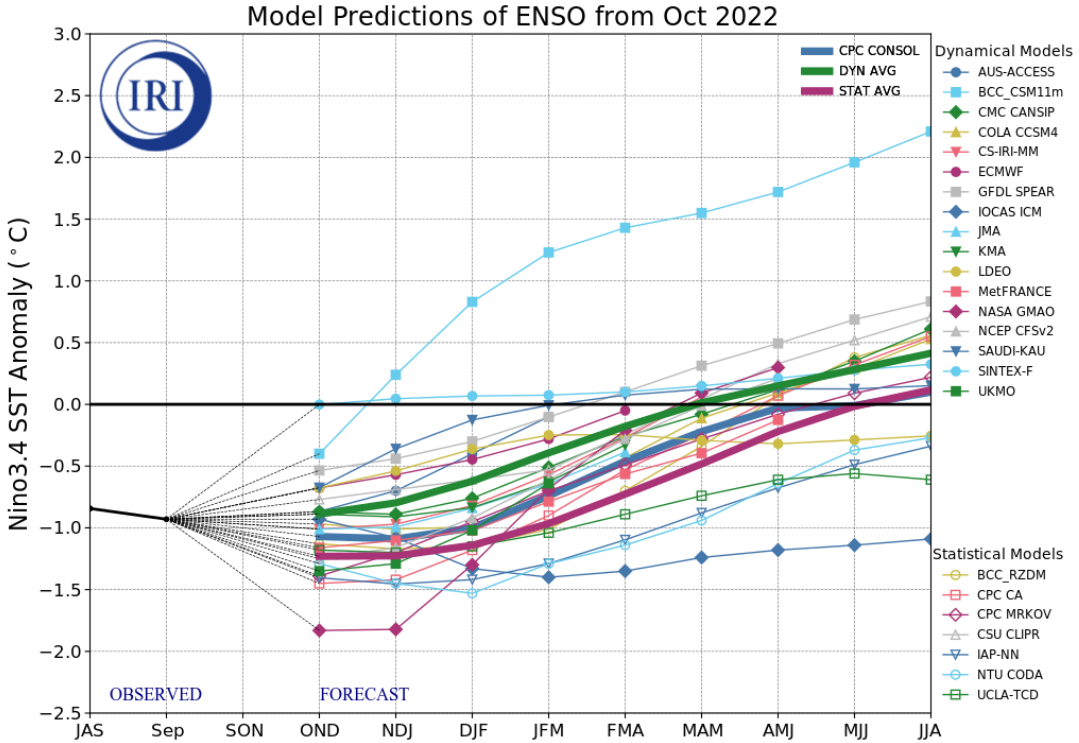
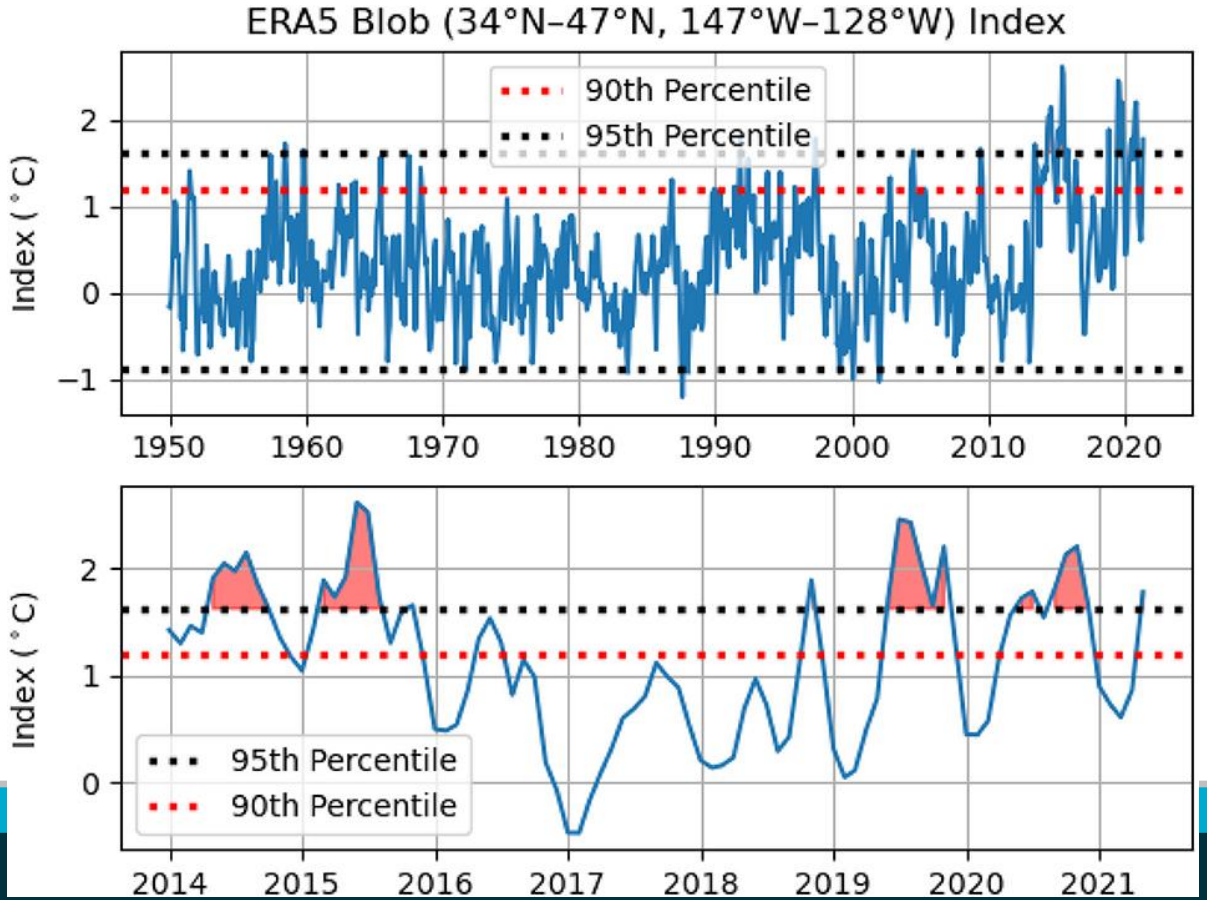


Nino 3.4

Niño-4W region
(5°S-5°N, 160°E-175°W)



ENSO prediction, NOAA Climate Prediction Center



Blob index from ERA5