A Deep Learning Filter for Intra-seasonal Variability of the Tropics.

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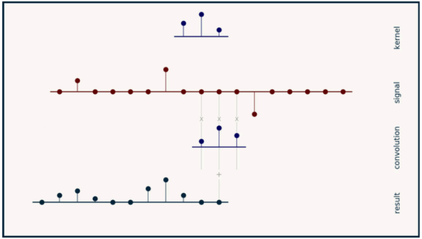
- For instance, filtering Intra-seasonal varaibility using a conventional band-pass filter (Lanczos) on a three-month CFSv2 forecast is not practical as it leaves with missing data in both ends and requires extrapolation.
- A new method based on machine learning, namely, convolutional neural network (CNN), is developed to extract the Intra-seasonal anomalies in operational monitoring and forecast data.

What is Convolution?

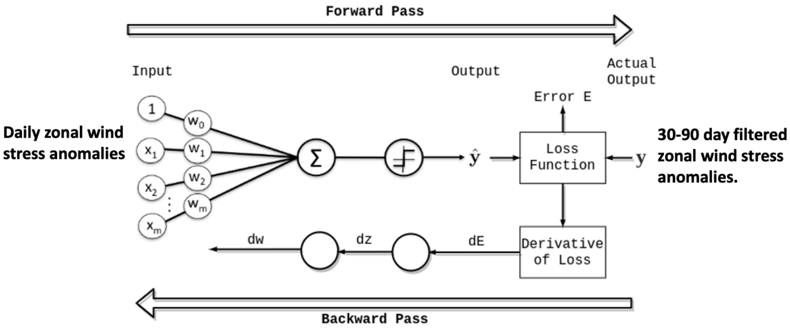


Source: https://e2eml.school/convolution_one_d.html

$$x = [x_0, x_1, x_2, \ldots, x_{m-1}]$$
$$w = [w_{-p}, w_{-p+1}, \ldots, w_0, \ldots, w_{p-1}, w_p]$$
$$y = [y_0, y_1, y_2, \ldots, y_{m-1}]$$

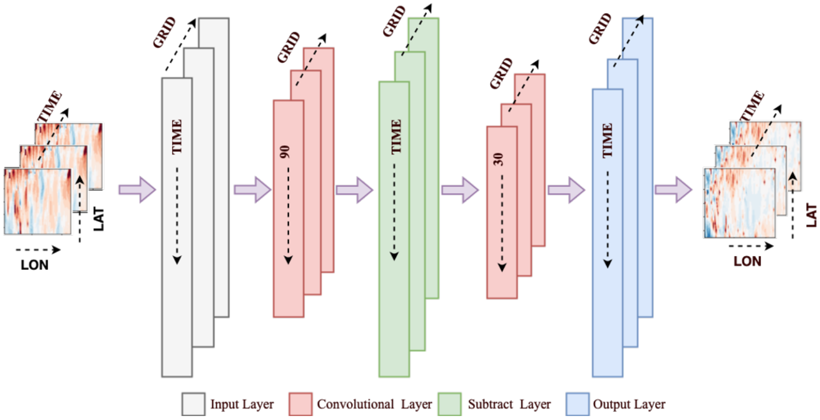
$$y_j = \sum_{k=-p}^{p} x_{j-k} w_k$$

How Neural Network Works?



https://www.baeldung.com/cs/epoch-neural-networks

1D CNN Architecture



Data and CNN Hyperparameters

Data:

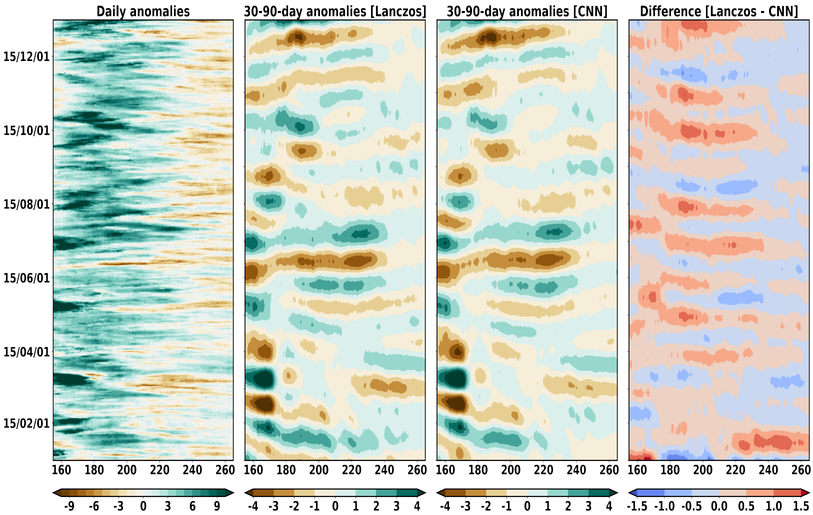
1. Blended scatterometer daily zonal wind stress anomalies
   Training period: 1988 - 2014
   Testing period: 2015 and 2016
2. NOAA interpolated daily OLR anomlaies
   Training period: 1980 - 2018
   Testing period: 2019 and 2020

CNN Hyperparameters:

1. Optimizer - Adaptive Moment Estimation (Adam) optimizer.
2. Loss function - Mean Squared Error
3. Epochs - 500

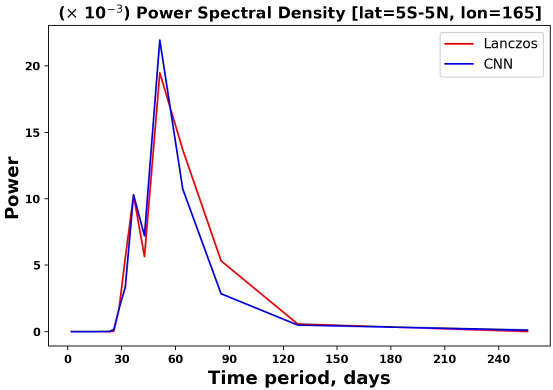
The CNN is trained using Lanczos filtered anomalies.

Result - 1: Hovmoller of zonal wind stress anomalies

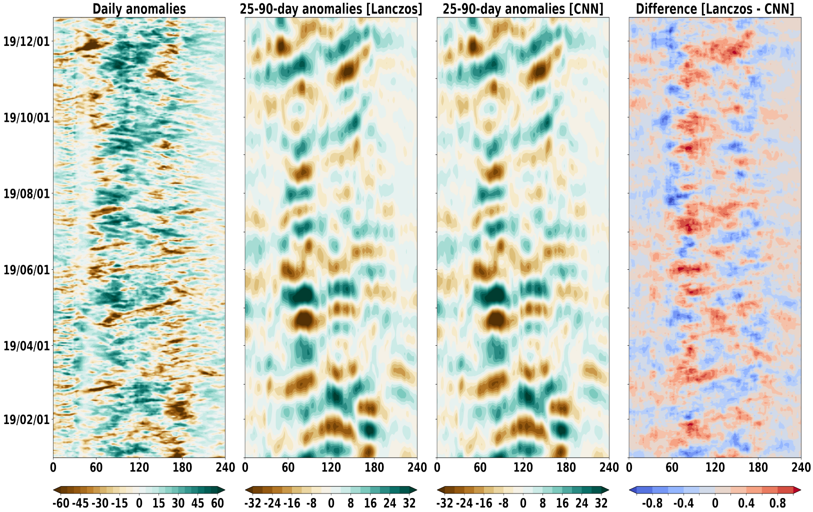


$10^{-3} Nm^{-2}$

Result - 2: Power Spectral Density

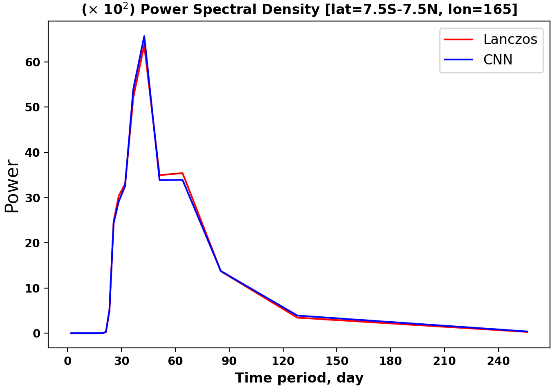


Result - 3: Hovmoller of OLR anomalies



Wm^{-2}

Result - 4: Power Spectral Density



Index of Agreement

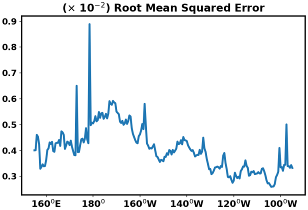
$$d = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad , \qquad 0 \leq d \leq 1$$

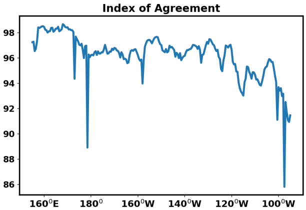
The index of agreement represents the ratio of the mean square error and the potential error.

The agreement value of 1 indicates a perfect match, and 0 indicates no agreement at all.

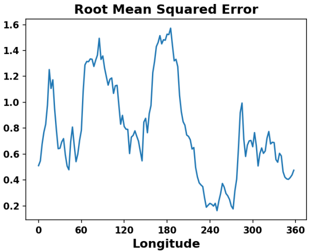
Result 5: Error Analysis

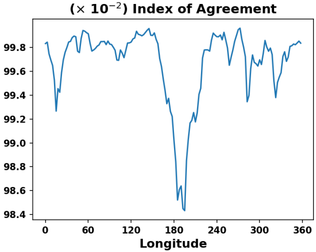
Zonal Wind Stress:





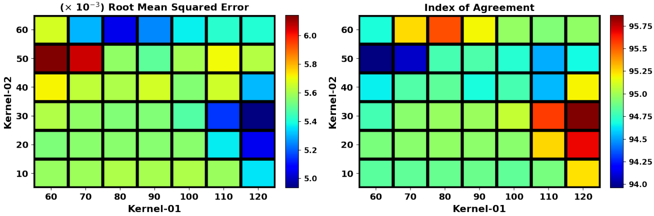
OLR:



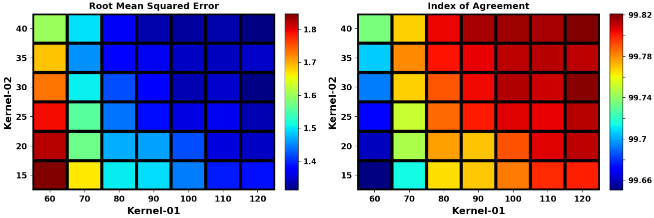


Result 6: Sensitivity of convolution kernel size

Zonal Wind Stress:



OLR:



Application 01: Reconstruction of MJO zonal wind stress

- Lybarger and Stan (2020) developed a dynamical framework for forecasting MJO influence on El Niño. This dynamical framework requires MJO filtered wind stress as input.

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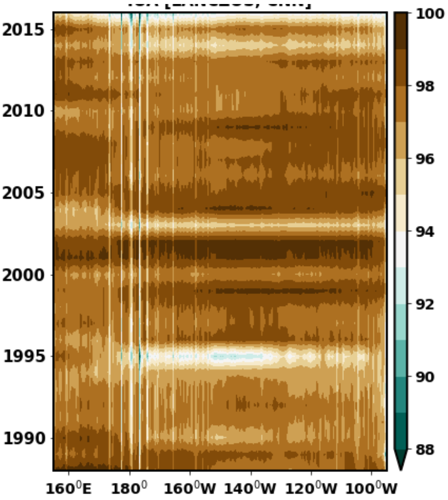
- This framework when applied to operational monitoring or forecast data uses MJO zonal wind stress constructed from unfiltered wind stress anomalies using Hilbert singular value decomposition.
- However, isolating MJO wind stress can be improved by first applying the 1D CNN filter on the daily anomalies and then projecting on to the dominant empirical orthogonal functions (EOFs).

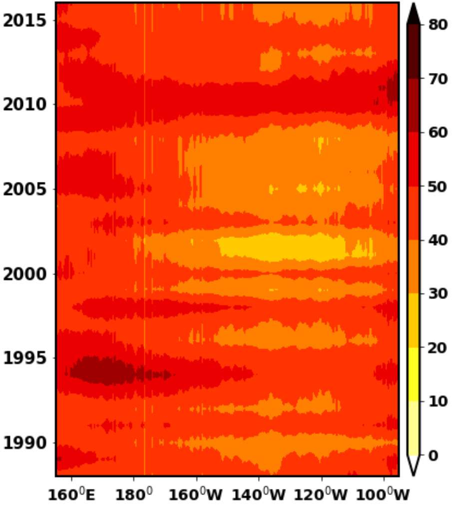
Time vs Longitude Hovmoller of Index of Agreement (IOA)

$$IOA[\tau_{(MJO,Lanczos)}, \tau_{(MJO,CNN)}]$$



Time vs Longitude Hovmoller of Index of Agreement (IOA)

$$IOA[\tau_{(MJO,Lanczos)}, \tau_{(MJO,CNN)}] - IOA[\tau_{(MJO,Lanczos)}, \tau_{(MJO,unfiltered)}]$$



Application - 02: Real time filtering of Intra-seasonal anomalies

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- Kikuchi (2020) used extended EOFs to reconstruct the MJO and BSISO.
- Kikuchi (2020) removed the low-frequency and high-frequency signals from the daily anomalies by subtracting the mean of previous forty days from the daily anomalies and then applying the 5-day tapered running mean.

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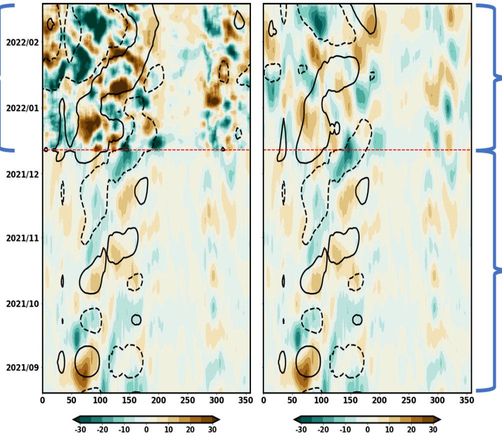
- Kikuchi (2020) removed the low-frequency and high-frequency signals from the daily anomalies by subtracting the mean of previous forty days from the daily anomalies and then applying the 5-day tapered running mean.
- However, extrating ISOs in recent observations can be improved by first applying the 1D CNN filter on the daily anomalies and then projecting on to the dominant EOFs.

Time vs Longitude Hovmoller of OLR

Filtered anomalies (shading) following Kikuchi (2020); MJO (contours) reconstructed using anomalies in shading.



CNN filtered 25-90 day anomalies (shading); MJO (contours) reconstructed using anomalies in shading.

Lanczos filtered 25-90 day anomalies (shading); MJO (contours) reconstructed using anomalies in shading.

Wm^{-2}

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- MJO zonal wind stress constructed using CNN filtered anomalies has a greater Index of Agreement score than MJO zonal wind stress constructed using unfiltered anomalies.
- Real time extraction of intra-seasonal anomalies can be improved using CNN filter.
- The CNN filter can be applied to operational monitoring and forecast data for extracting Intra-seasonal variability.