Significant Improvement of Dynamical ENSO Forecast with an Artificial Neural Network

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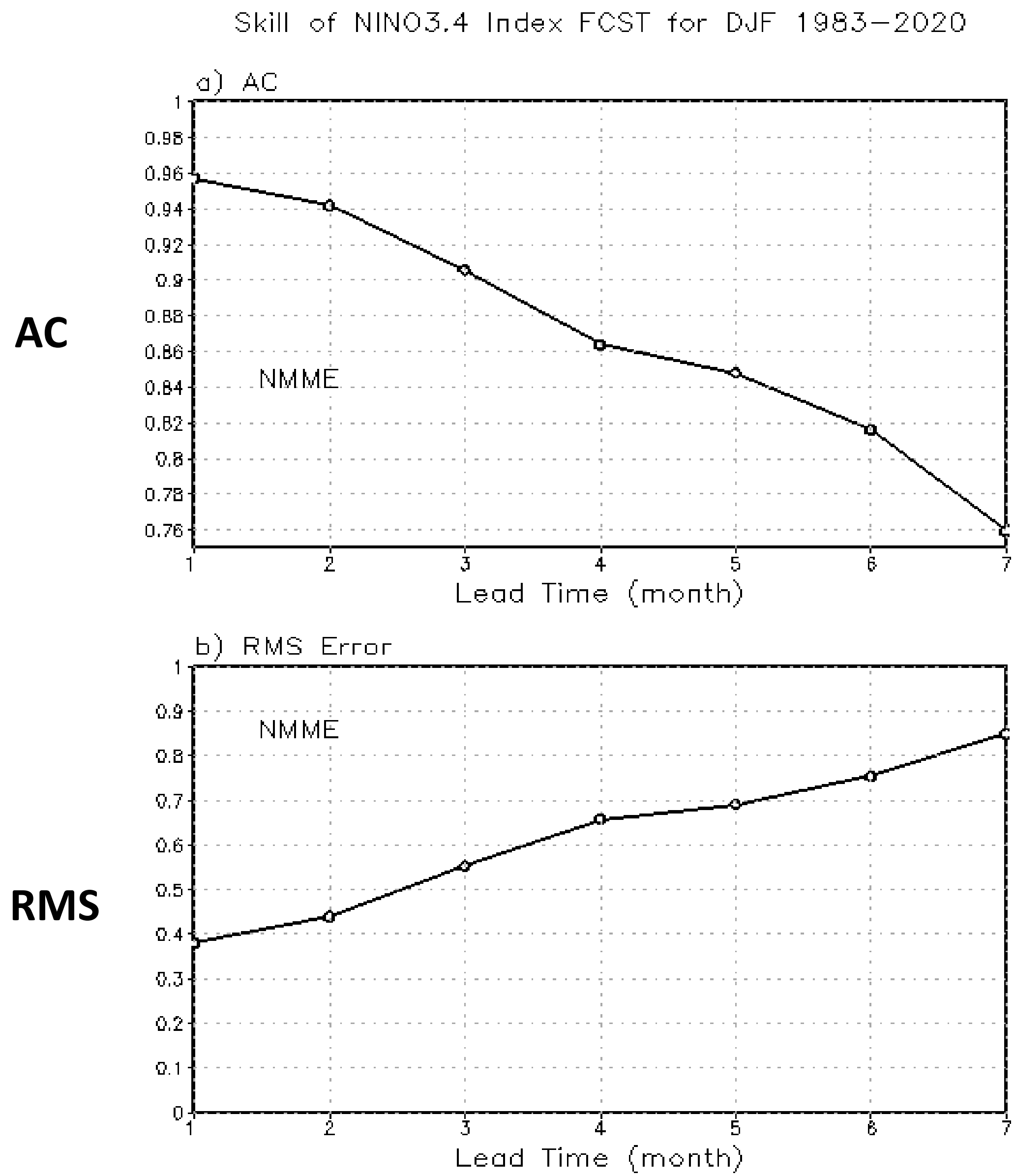
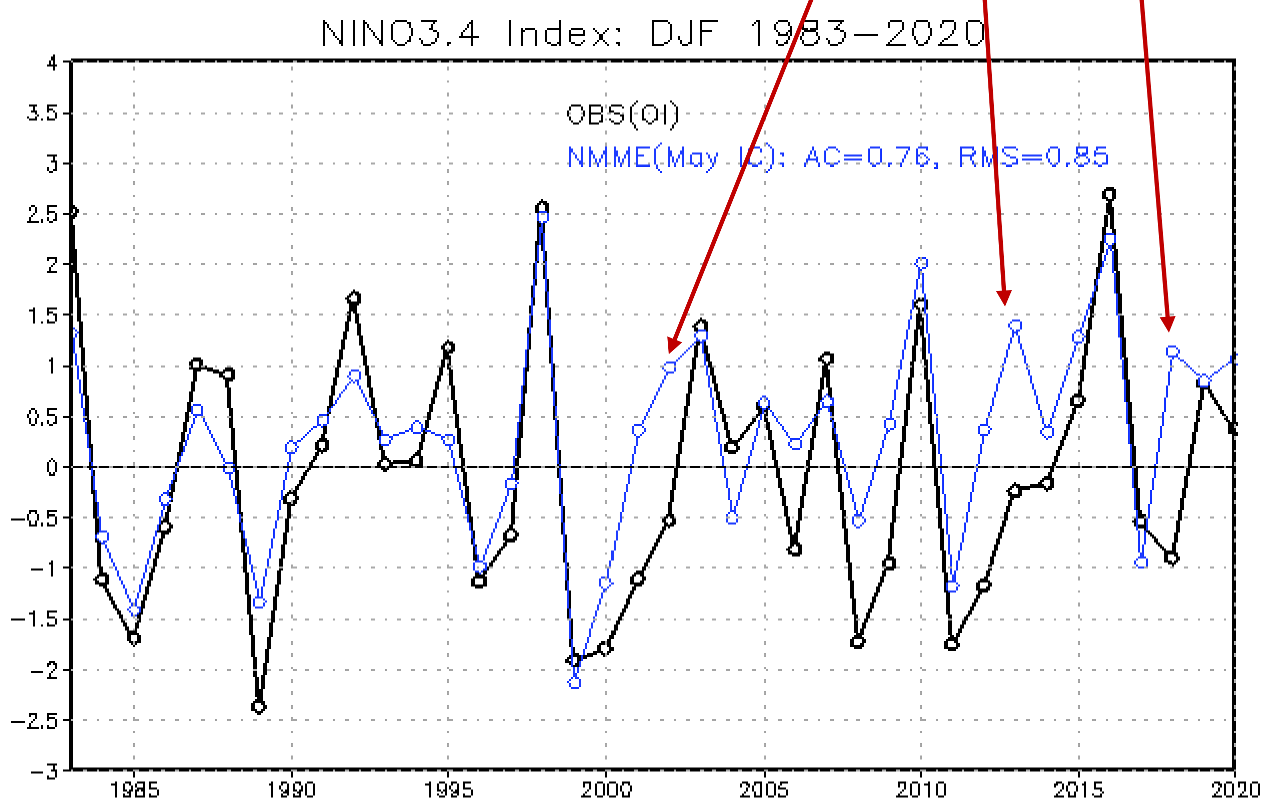
Dynamical ENSO Forecast: Achievement



NMME Hindcast/Forecast skill of Nino3.4 index vs lead time for DJF seasons over 1983-2020

Dynamical ENSO Forecast: Deficiencies

False Alarms in NMME with May ICs for 2002, 2013, 2018 DJF



More about the false alarm error are in Tippett et al. 2020 GRL

How to Improve Dynamical Forecast?

1. Model improvement (modeling centers' job)
2. Statistical correction (Can we do it?)

Why Neural Networks (NN)?

1. Well suited for big dataset

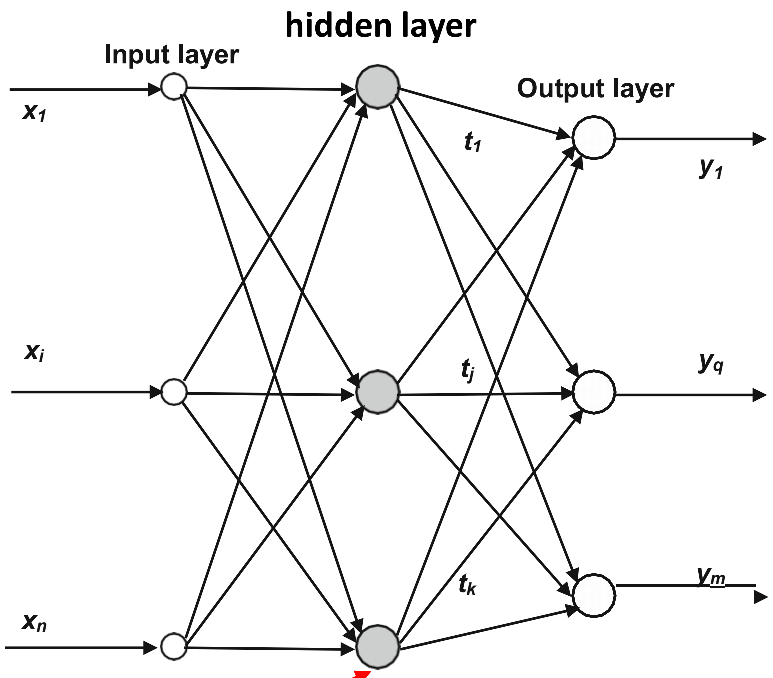
2. No prior assumption about
   the data distribution

3. Collinearity problem avoided

4. Can handle nonlinearity

A Simple Multilayer Neural Network

X: input vector



Y: output vector

1. Is a model representing a mapping Y=M(X)

2. Each **hidden neuron** is an activation function, can be linear or nonlinear

A Simple Multilayer Neural Network (cont.)

Mathematical Expression:

$$y_q = NN(X, a, b) = a_{q0} + \sum_{j=1}^{k} a_{qj} \cdot t_j; \quad q = 1, 2, \ldots, m$$

where

$$t_j = \phi\left(b_{j0} + \sum_{i=1}^{n} b_{ji} \cdot x_i\right) \longrightarrow \text{hyperbolic tangent, nonlinear}$$

1. NN can approximate any smooth and measurable mapping function, as long as a suitable set of parameters (weights) a&b is selected;
2. Parameters a & b are determined by minimizing error $E=(Y-O)^2$ in training stage
   In this case, Y: NN corrected Nino 3.4 index; O: observation

Input/output examples for correcting Dynamical Nino3.4 index

1. Based on forecasted Nino3.4 index itself
   - Input: x1 (raw forecast of Nino3.4 anomaly)
   - Output: y1 (corrected forecast of Nino3.4 anomaly)
2. Based on forecasted SST over the tropical Pacific
   - Input: x1, x2, x3, …, xn (raw forecast of SSTs in the tropical Pacific)
   - Output: y1 (corrected forecast of Nino3.4 anomaly)

Data used

1. Ensemble mean DJF SST hindcast/forecast with 1-7 month lead from NMME and CFSv2

2. DJF Nino 3.4 Index from OI SST

3. Period: 1982/83 – 2019/20, NT=38 DJFs

4. Area: The Tropical Pacific (TP) (120E-290E, 20S-20N)

Procedure

1. **Training stage**: Take one DJF out as target season, use other 37 DJF data to train NN to determine its parameters. In this stage, input is the DJF mean SST of model forecast, output is a scalar best fitting OI Nino 3.4 index over the period;

2. **Correction stage:** Input target DJF SST of model forecast, calculate corrected Nino 3.4 index (output) with the parameters determined in the training stage.

3. Loop 1-2 over all 38 DJF seasons

   (Above procedure is referred as cross-validation with one-year-out (**CV-1**))

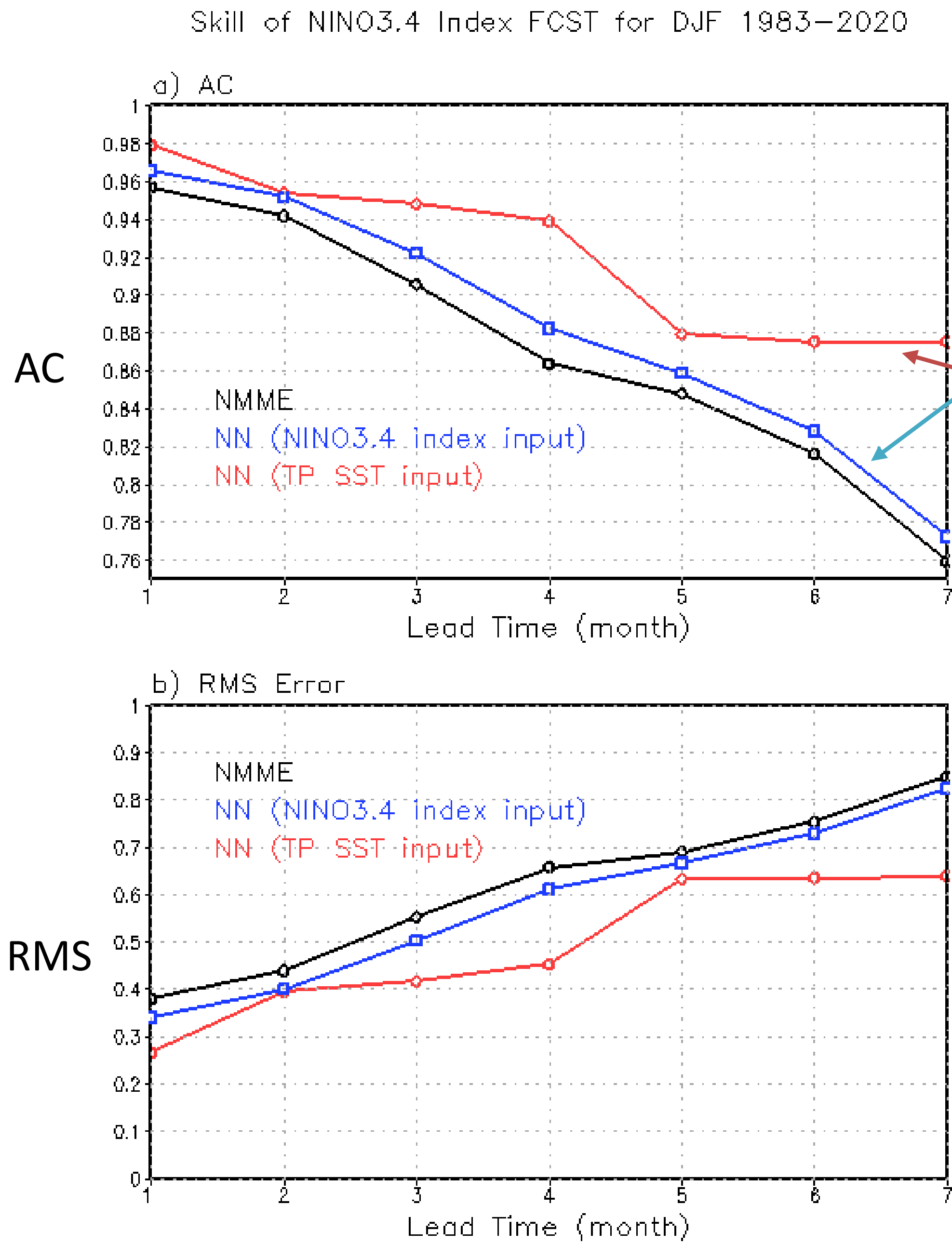
4. Test two types of input, one is the Nino 3.4 index alone; the other is the whole tropical Pacific (TP) SST on grid.

5. Repeat 1-4 for each lead time

Note: Target season data is independent of the training data

Results of NN Correction to NMME

Result: Improved skill

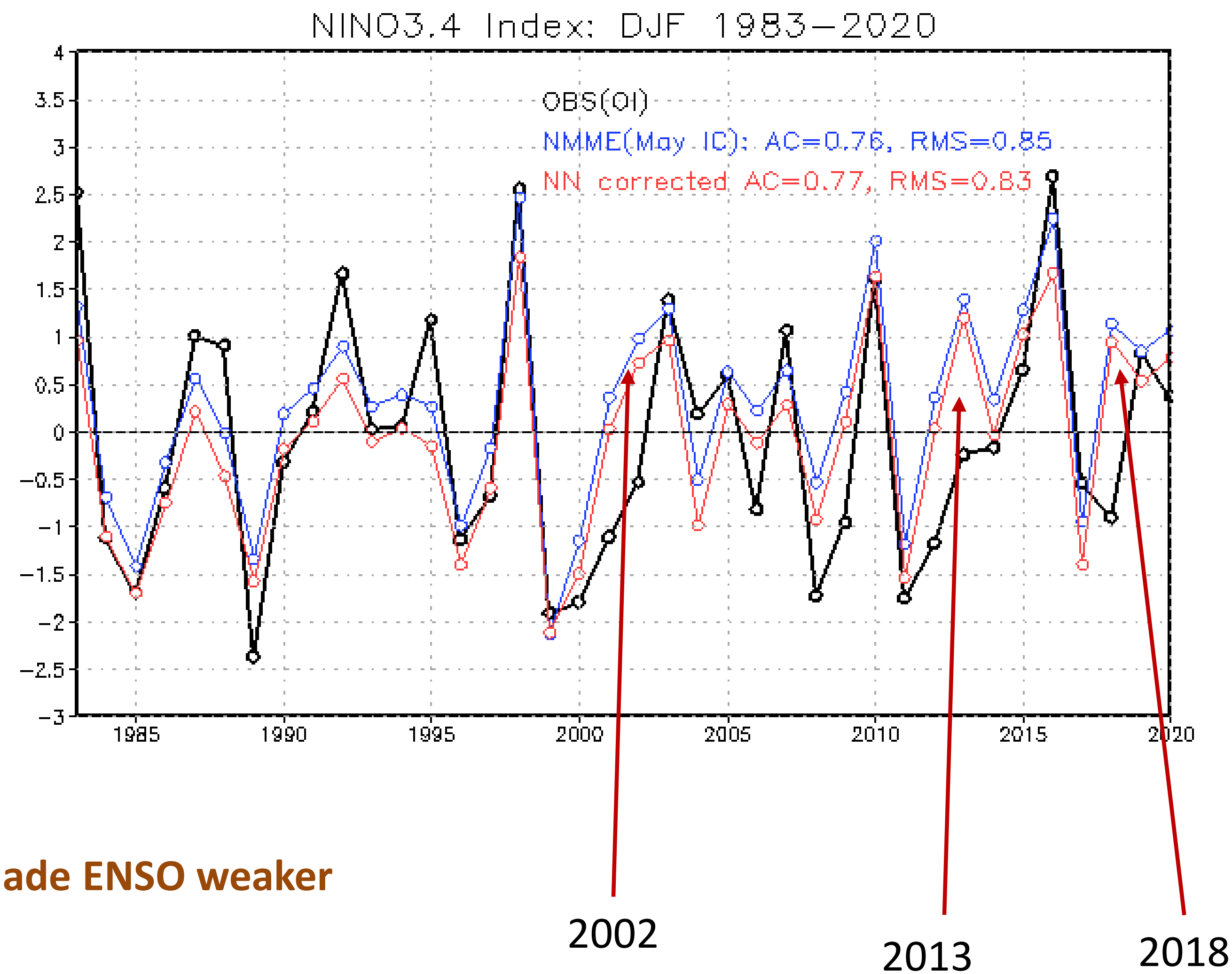


Use of NINO 3.4 Index alone leads to Small improvement

Use of Whole TP SST input results in Significant improvement

Local SST alone is not enough for a optimal correction

Result from NINO3.4 input: False alarms remained

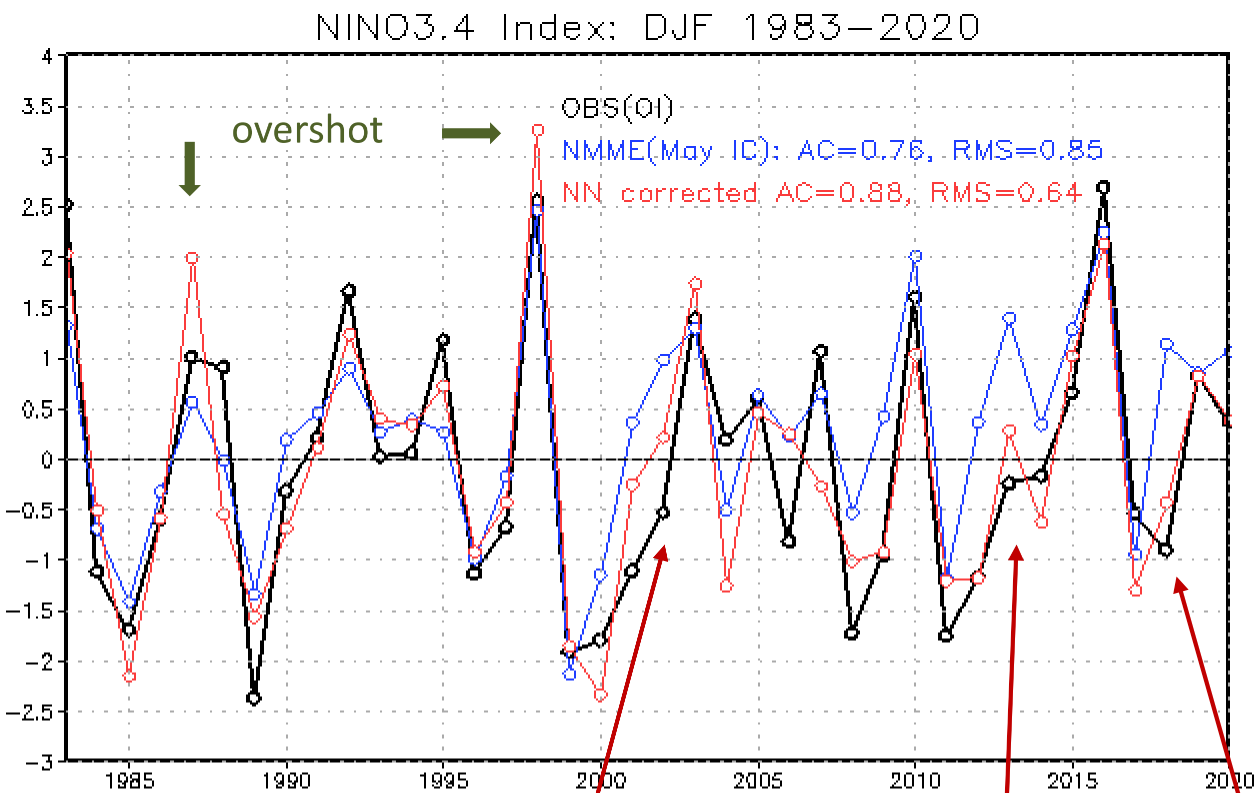


NN made ENSO weaker

False alarms remained

Using Nino3.4 index alone as input is not sufficient for removing forecast errors.

Result from TP SST input: False alarms silenced



False alarms significantly silenced

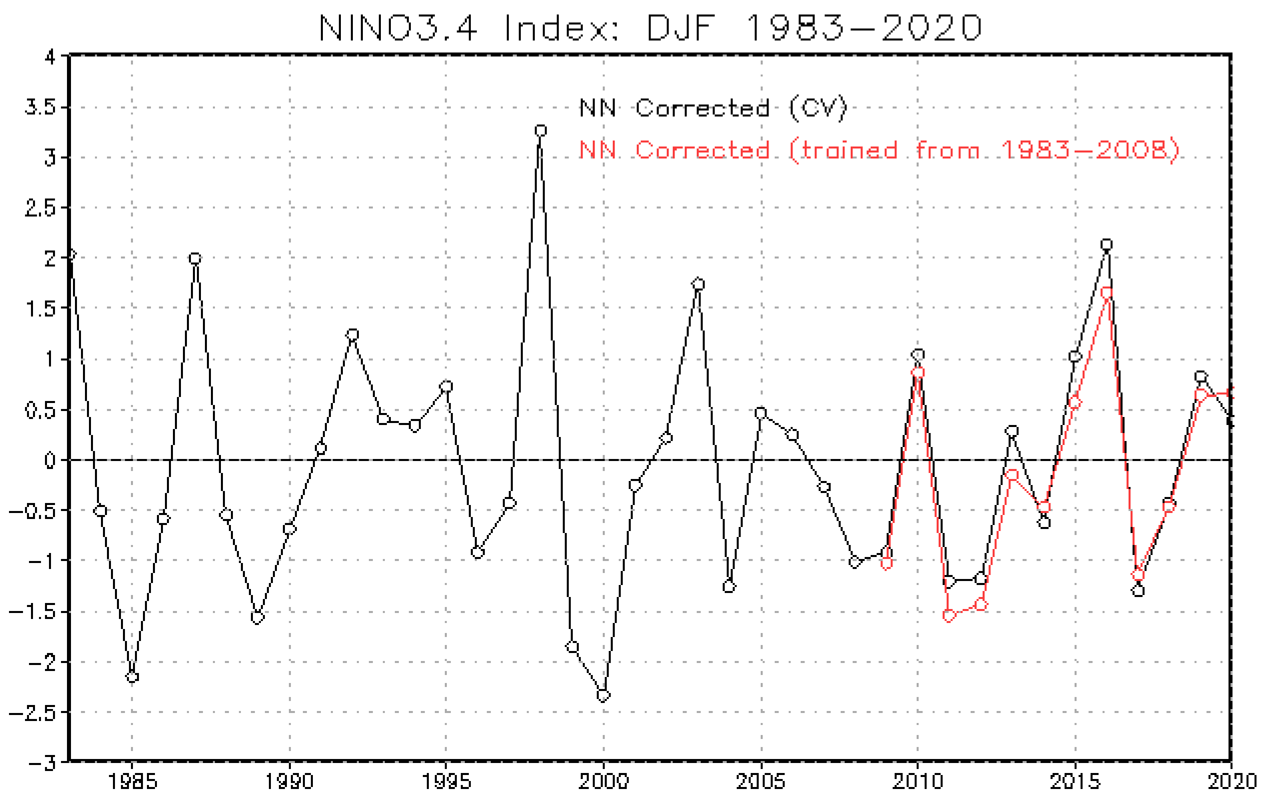
2002

2013

2018

Information outside Nino3.4 region is required to significantly remove forecast errors.

Result: Is the CV-1 result reliable? Yes!



CV-1 result is very close to that trained with earlier 2/3 data

INDICATION: parameters a&b are not sensitive to little changes in training data

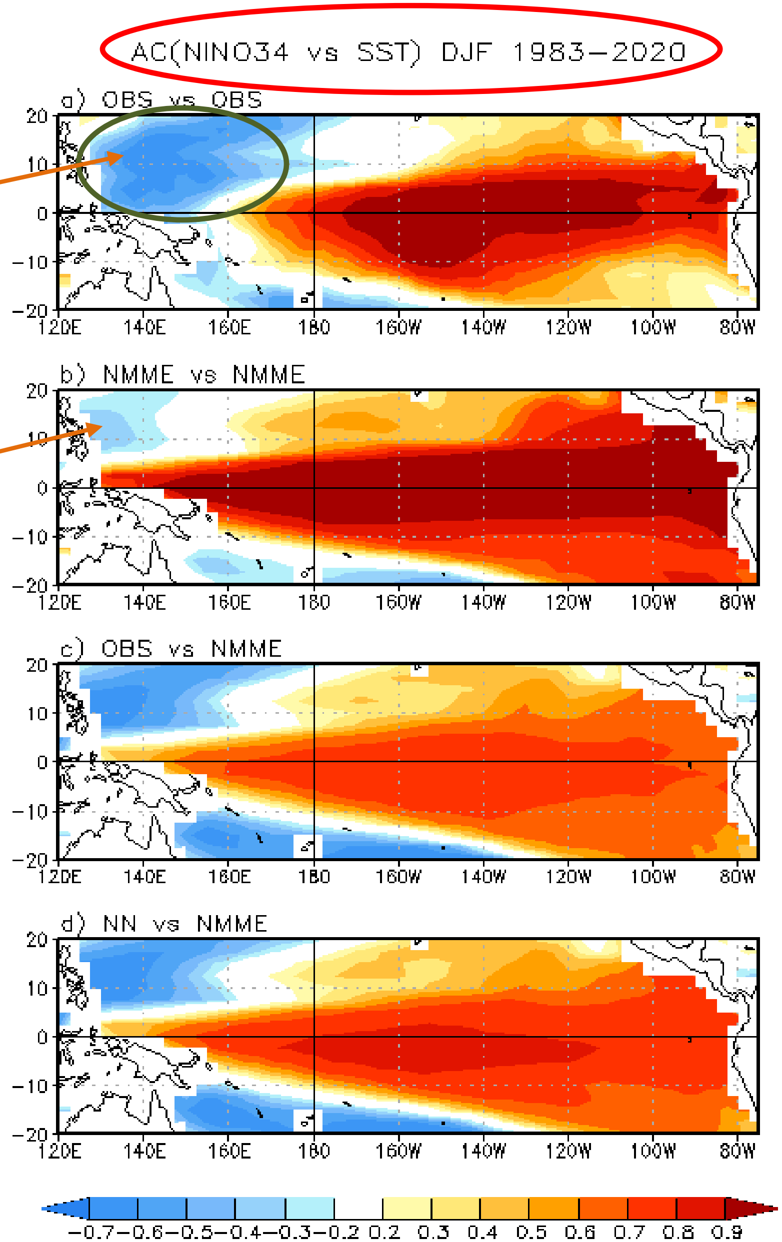
Result: why the correction works?

OBS: Nino3.4 index highly correlated with Northwestern Tropical Pacific (NWTP), indicating the importance of the information from there

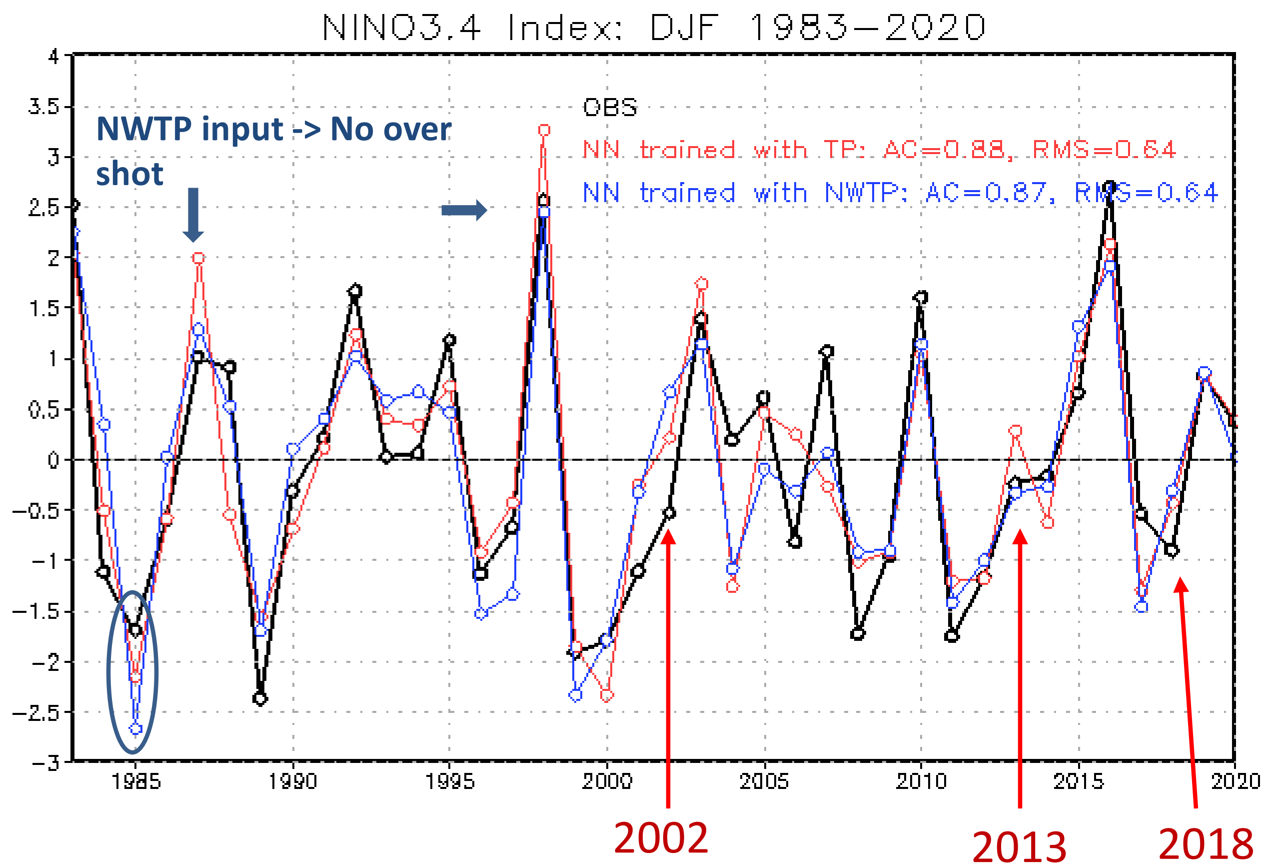
NMME: Nino3.4 index weakly correlated with NWTP, indicating model index is almost locally determined.

OBS Nino3.4 index equally correlated with local and NWTP SSTs, indicating model still has correct information in NWTP

NN-corrected Nino3.4 index gained information from NWTP



Result: Train NN with NWTP SST only

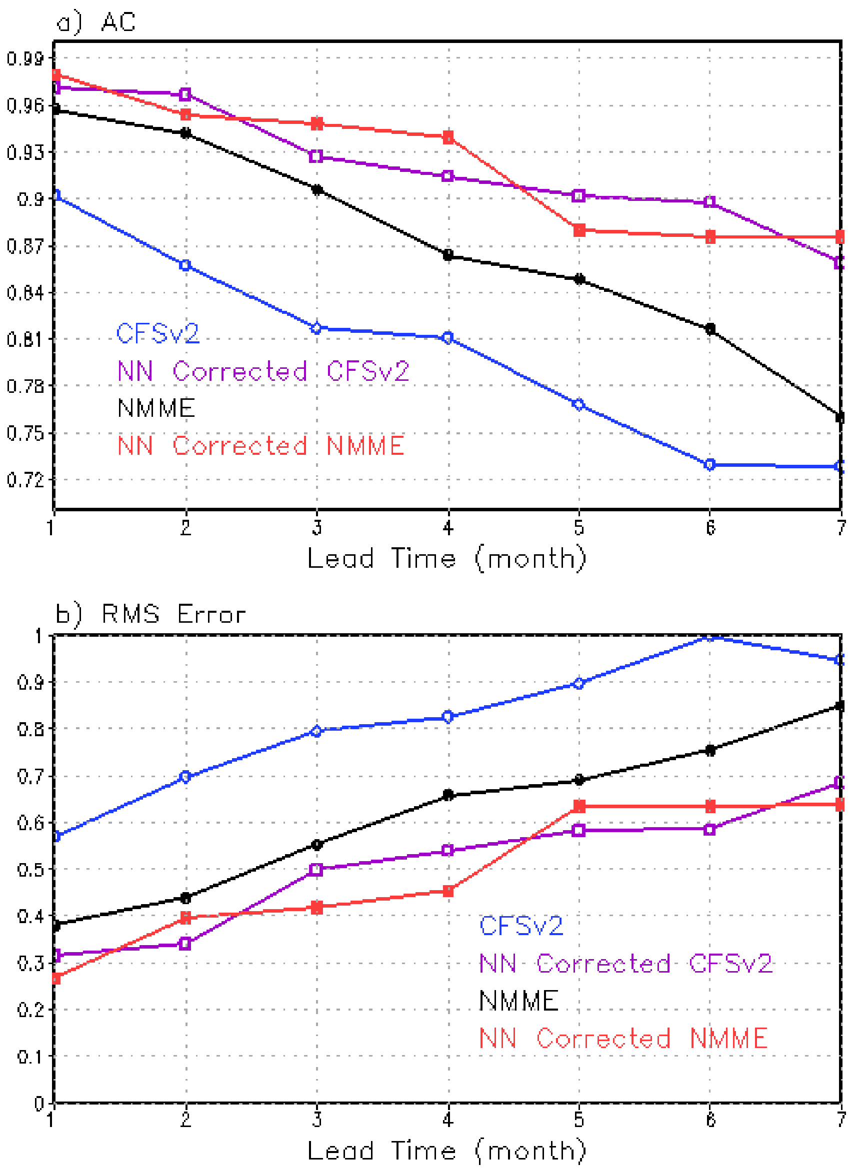


NWTP area: 120E - 160E, 0 – 20N
Data on the equator need to be included

NWTP area is critical for Nino3.4 index error correction.

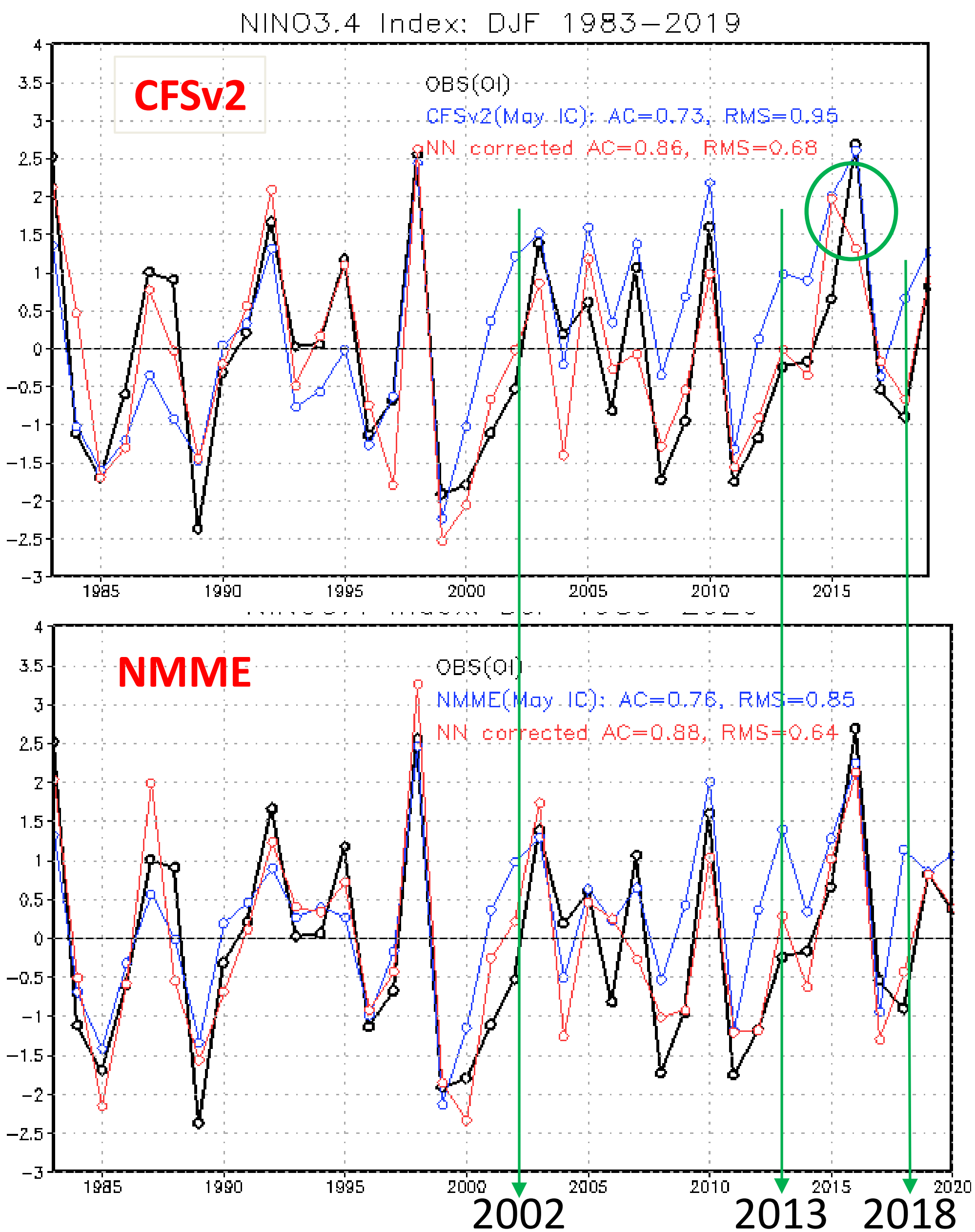
Results of NN Correction to CFSv2

Result: Compare to CFSv2: skill vs lead time



Skill of CFSv2 is obviously lower than that of NMME, but their NN corrected are very close

Result: Compare to CFSv2: forecast from May



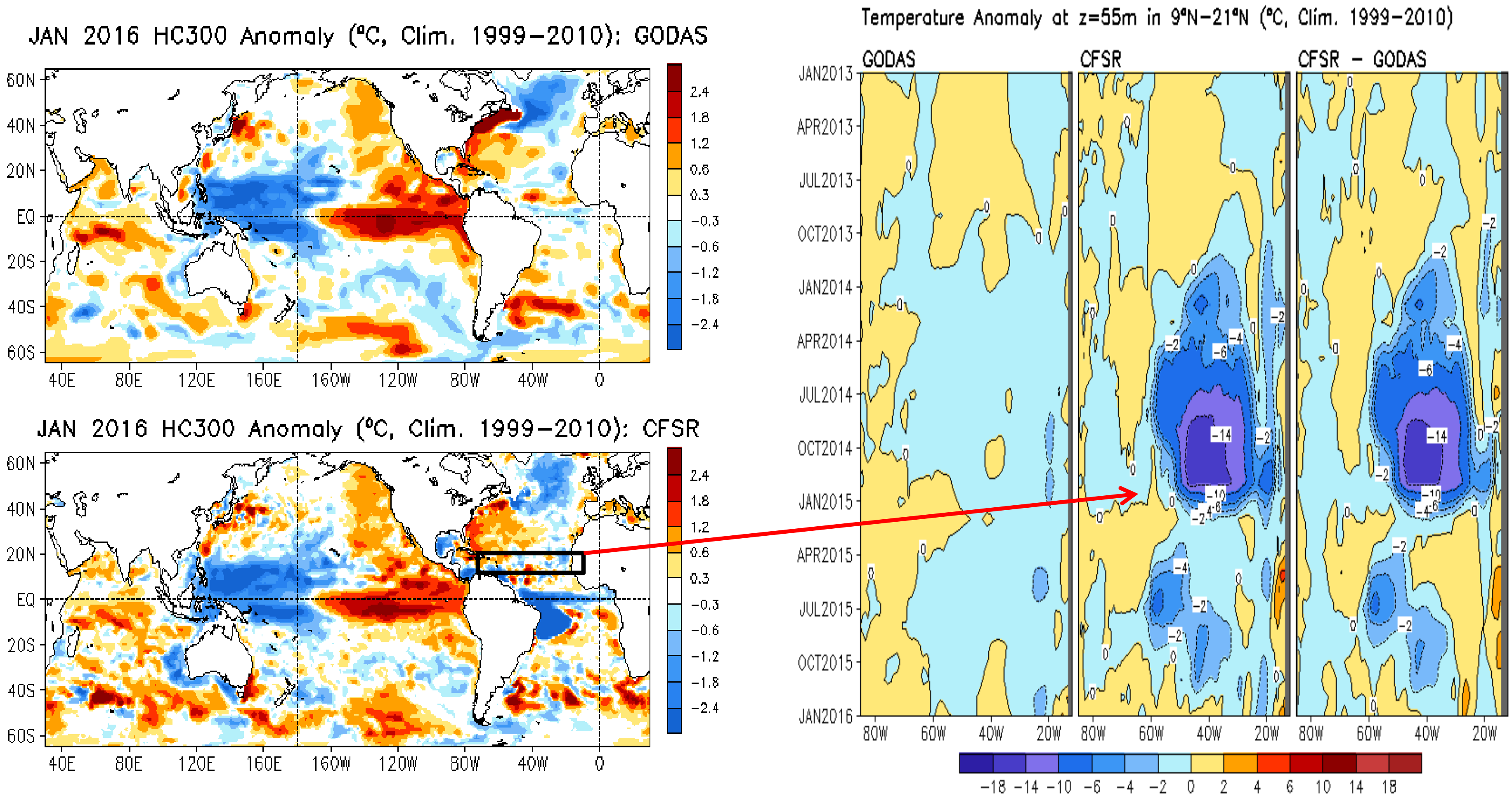
The NN method corrected NMME false alarms for 2002, 2013, 2015, and 2018, but with an overshot for 1987 & 1998

The NN method corrected CFSv2 false alarms for 2002, 2013 and 2018, but failed for 2015.

The failure for CFSv2 DJF 2015 correction may be related to initial significant error in CFSR oceanic initial conditions

Recent Cold Biases in Tropical North Atlantic

(updated on Feb 9, 2016)



- **A cold bias emerged in tropical North Atlantic around Nov 2013 and enhanced quickly with time.**
- **The cold bias was removed by the update in Jan 2015.**

Courtesy: Yan Xue (2016)

Summary

1. Dynamical ENSO forecast with NMME is of great skill, but false alarms existed in the forecast initialized in spring and early summer for some years.

2. Artificial Neural Network is effective in correcting the false alarms, leading to improved overall skill.

3. The skill improvement is due to the information taken from the model SST in the Northwestern Topical Pacific.

4. Individual model may have lower skill than NMME, but their corrected forecasts are very close.