DL predicts ENSO

Problems

- **1.Datasets**
- 1)How to choose the variables (how much is enough);
- 2)Temporal resolution: daily or pentad;
- 3)Spatial resolution and coverage: 1deg/0.25deg; tropical or subtropical;

- **2.Experiment design**
- 1) Do we need/how to set the control experiment and discuss the addition of different factors;
- 2) Explain the evolution of the model in detail.

- **3.Results**
- 1) Why DL shows better performance over longer lead time (>9 mon);
- 2) Can DL learn the changing of the background before and after 2000yr;
- 3) Why TP shows better prediction skill than other index such as WWV;
- 4) How to explain clearly for the effective precursors such as TP300 and UVEL.

Suggestions of experiments from Prof. Tseng

- Algorithm type: ANN, CNN or ELM…
- Datasets and spatial resolution

Type	Spatial Resolution		
OISST	0.25°	1°	2°
GODAS	1°		

- Datasets and temporal resolution

Type	Temporal Resolution		
OISST	daily	5-day moving average	pentad
GODAS	pentad		

- Regional sensitivity: whole Pacific (60°S~ 60°N), subtropical tropical Pacific (30°S~ 30°N), tropical Pacific (10°S~ 10°N)
- Background influence: the background change before and after 2000yr.
- Test TP300 (GODAS), WWV, O-A index and EX-forcing

Studies on machine learning predicts ENSO

Method: maximum variance unfolding (MVU)

$$F(t+\tau) = \beta_{0,\tau,t} + \beta_{1,\tau,t}\cdot O(t) + \sum_{l=t-24}^{t} \beta_{2,\tau,l}\cdot Y_1(l) + \beta_{3,\tau,l}\cdot Y_2(l) + \beta_{4,\tau,l}\cdot Y_3(l) + \epsilon_\tau(t),$$

Data: thermocline depth at 20°C; *D*20 bounded by the region 26°N–28°S and 122°E–77°W (GODAS).

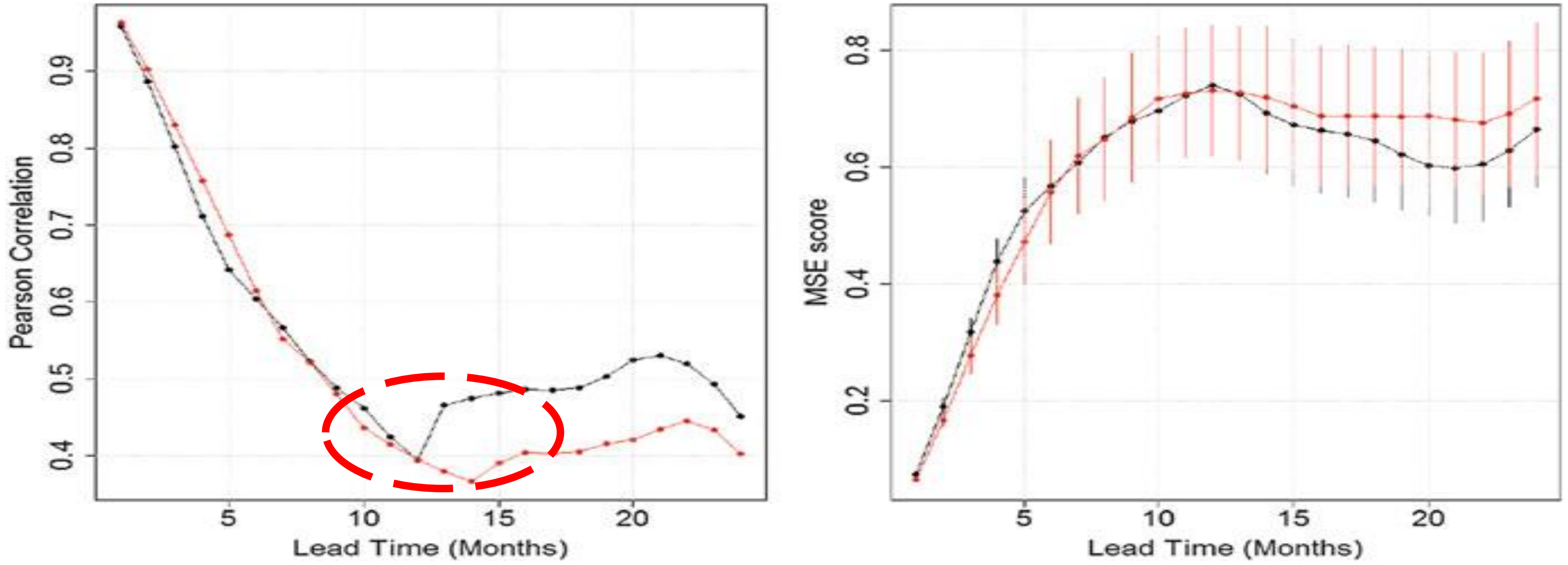

Fig. 2.2 Averaged cross-validated correlation (*left*) andMSE (*right*) skills for MVU- (*black*) and PCA (*red*)-based NINO3.4 forecast models. The *vertical bars* show ˙1 standard error for MSE based on the standard error in the tenfold cross-validation procedure

Lima, C. H. R., Lall, U., Jebara, T., & Barnston, A. G. (2015). Machine Learning Methods for ENSO Analysis and Prediction. Machine Learning and Data Mining Approaches to Climate Science.

Purpose for the study

- increase prediction skill at lags up to one year

Data and Methods

- The warm water volume (WWV), being the integrated volume above the 20°C isotherm between 5°N-5°S and 120°E-280°E,
- Combine ARIMA and ANN

Performance

- For predictions up to six months ahead, the results of the hybrid model give a better skill than the CFSv2 ensemble prediction by the National Centers for Environmental Prediction (NCEP). Moreover, results for a twelve-month lead time prediction have a similar skill as the shorter lead time predictions.

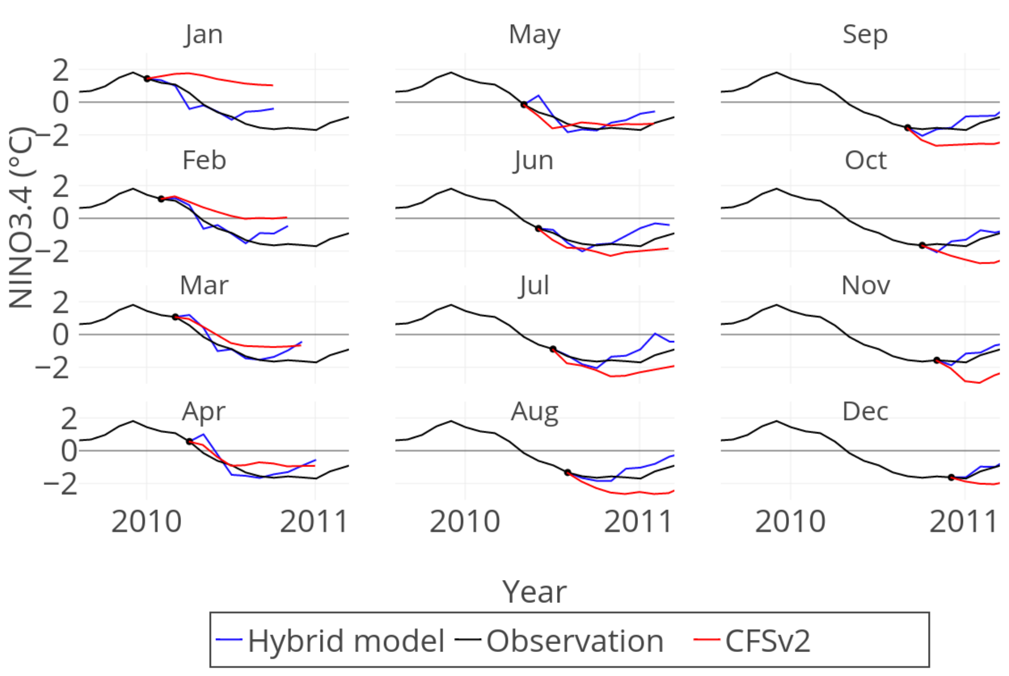

Figure 8. Nine-month ahead prediction starting from every month in the year 2010.

Nooteboom, P. D., Feng, Q. Y., López, C., Hernándezgarcía, E., & Dijkstra, H. A. (2018). Using network theory and machine learning to predict El Niño. Earth System Dynamics Discussions, 1-24.

Method: Extreme Learning Machine (ELM)

Conclusions: Compare results from ELM model with analytical solution. The results present a faster calculation speed and a satisfying accuracy. Consider introduces the ELM method and the ENSOphenomenon, and then adapts the ELM method to the ENSO model in the numerical experiments.

$$dT/dt = CT + Dh - \varepsilon T^3 \qquad (7)$$

$$dh/dt = -ET - R_h h \qquad (8)$$

$$T|_{t=0} = T_0,\ h|_{t=0} = h_0 \qquad (9)$$

Where T is the equatorial eastern Pacific SST anomaly and h is the thermocline depth anomaly. C, D, E, R_h and ε are the positive model parameters, the explicit definitions of which are explained in [8].

The nonlinear function above has the analytical solution of $T(t)$ at time t when $0 < \varepsilon \ll 1$[9-10]:

$$T(t) = [b + (1/T_o{}^2 - b)\exp(-2CT)]^{-1/2}, \qquad (11)$$

where $b = \varepsilon/C$. Eq. (10) described the discharge and recharge of equatorial heat content. In the warm phase of

Xing, D., Zhang, W., Huang, Q., & Liu, B. (2016). Research on Extreme Learning Machine Algorithm and Its Application to El-Niño/La-Niña Southern Oscillation Model. *International Conference on Intelligent Human-Machine Systems and Cybernetics* (pp.208-211). IEEE.

Explanations

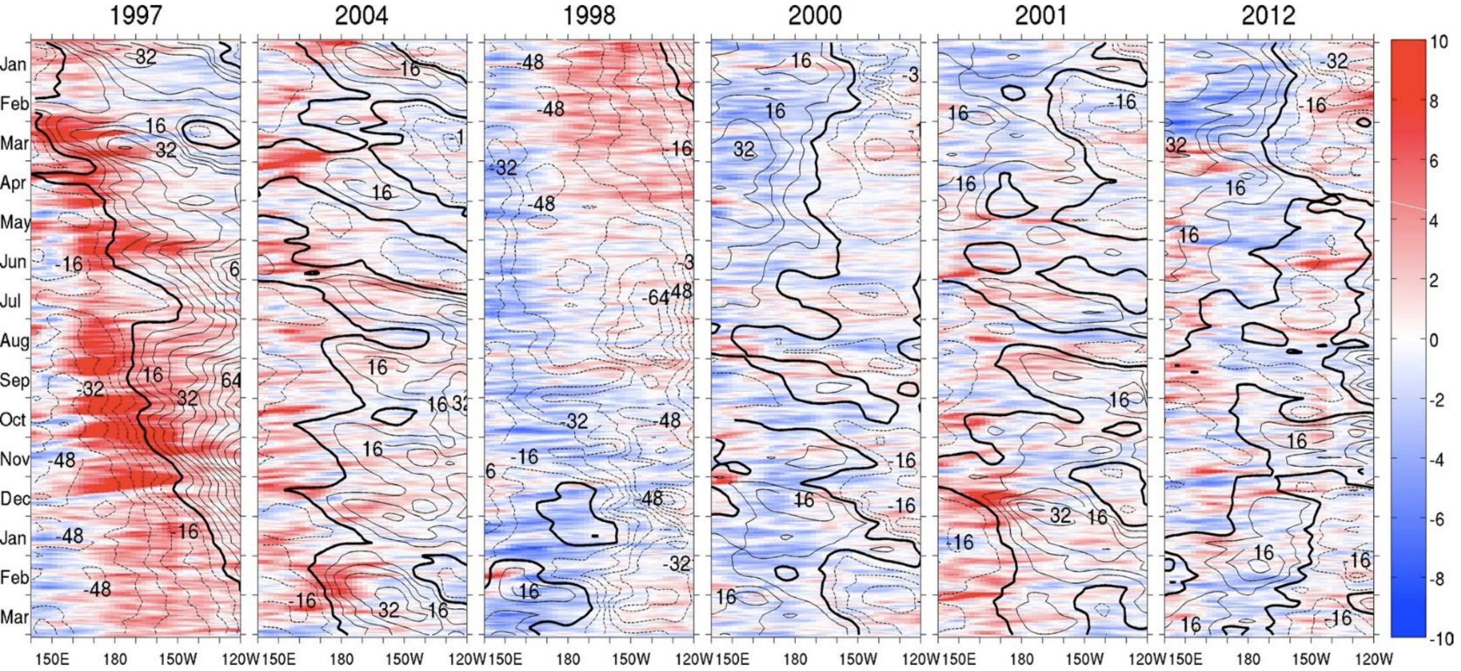

Fig. 9 Hovmöller diagram of D20a (contours) along the equator superimposed by the surface zonal wind anomalies (shaded) averaged between 2°S–2°N for two El Niños (strong: 1997, weak: 2004), two La Niñas (strong: 1998, weak: 2000) and two neutral years (2001 and 2012). Contour interval is 8 m and the zero contour is thick black.

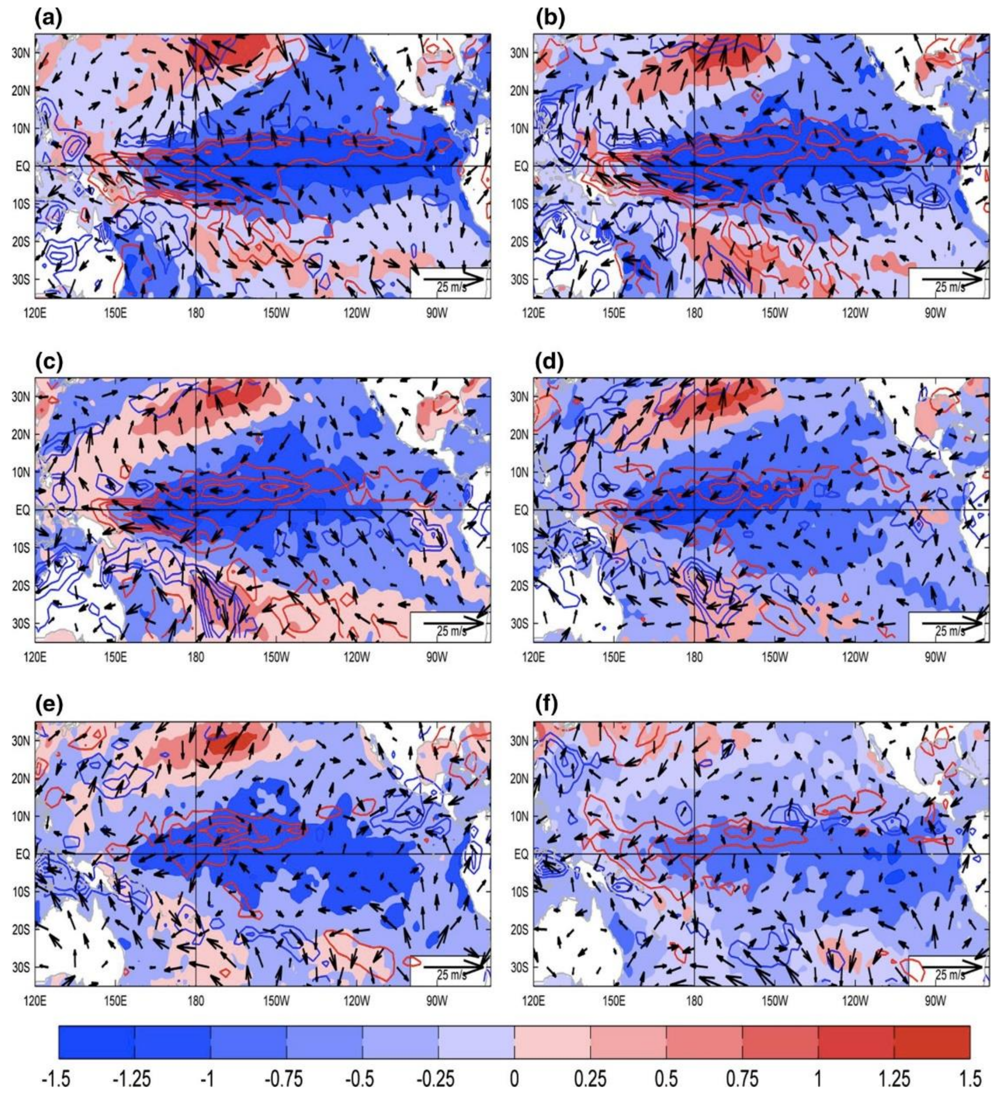

Fig. 10 Two-monthly averaged SSTa (shading), anomalous precipitation (contours), and the near-surface anomalous wind vector during 2000. The interval is 0.25 °C for SSTa, and 1.5 mm/day for anomalous precipitation (blue is positive and red is negative). The anomalous wind has the unit of m s^{-1}.

Tseng et al., 2017