



Use of deep learning (CNN) in predicting ENSO & IOD

Jing-Jia Luo (jjluo@nuist.edu.cn)

Institute for Climate and Application Research (ICAR) Nanjing Uni. of Information Science & Technology (NUIST)

Collaborators:

Fenghua Ling, Yoo-Geun Ham, Jeong-Hwan Kim

Ham, Y.-G., J.-H. Kim, and J.-J. Luo, 2019: Deep Learning for multi-year ENSO forecasts. *Nature*, **573**, 568–572



- 1. Current skill in predicting ENSO using dynamical models
- 2. The principal of CNN machine learning
- 3. Prediction skill of CNN model
- 4. Perspective

Extremes induced by ENSO

Yangtze flooding in 1998



South China drought in 2011 spring



Impact of ENSO on global crop yields



Iizumi, Luo et al. (Nature Comm. 2014)

Seasonal-multiyear prediction of ENSO

Prediction of Nino3.4 SSTA (1982-2001)



Prediction of DJF Nino3.4 SSTA (1982-2019)



Prediction of SON Nino3.4 SSTA (1982-2019)



2-year prediction of ENSO 0.8 Ensemble mean 0.6 0.4 0.2 0 -0.2 12 18 20 22 6 8 0 14 6 24 lead time (month)

Luo et al. 2008

Monthly updated real time forecasts of ENSO and IOD up to 2 years ahead (https://icar.nuist.edu.cn/) From 1 Jan 2019 Nino3.4 SSTA(190-240E,55-5N) forecast (NUIST CFS1.0)









From 1 Oct 2019 eIOD SSTA(90-110E,10S-0) forecast (NUIST CFS1.0) 1.5 1 0.5 0 -0.5 - 1 -Observation ensemble mean each member -1.5 anomaly calculated relative to climatology of 1983-2011 -2JAN 2019 JÚL JÚL JÁN 2020 JÜL JAN 2021

Monthly updated real time forecasts (1-24 months lead)

(https://icar.nuist.edu.cn/)



Including: El Niño index, El Niño-Modoki index, IOD index Sea Surf Temp Anomaly, Precipitation Anomaly, 2m Temp Anomaly ZUV 200/500/850 hPa Anomaly, etc.

ENSO real time forecasts using multiple models and methods

https://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/



Convolutional Neural Network (CNN)





▲ Artificial Intelligence Algorithm Mimicking Human Decision Making Process

How CNN works :

1. Convolutional Layers + threshold function







Image

Convolved Feature

2. Pooling Layers





Popular use of CNN



• Face Recognition (Facebook)



Autonomous Car (self-driving car)

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Image Recognition



CNN method is good to finding pattern of predictor for predictand.

Structure of CNN for ENSO Prediction





	Data	Period		
Turburg	CMIP5 historical run	1861-2004		
Training dataset	Reanalysis (SODA)	1871-1973		
Validation dataset	Reanalysis (GODAS)	1984-2017		

Correlation Skill of 3-month-averaged Nino3.4 forecast

Prediction of SON Nino3.4 SSTA (1982-2019)

Prediction of DJF Nino3.4 SSTA (1982-2019)





Forecast skill of Feed-forward Neural Network (FFNN) model



Skill of El Nino-type (CP, EP, mixed) forecasts



Year	OBS	CNN	SINTEX-F	CanCM3	CanCM4	CCSM3	CCSM4	GFDL- aer04	GFDL- FLOR- A06	GFDL- FLOR- B01
1976	EP	EP		-	-	-	-	-	-	-
1977	CP	СР	-	-	-	-	-	-	-	-
1979	MIX	MIX		-	-	-	-	-	-	-
1982	EP	EP		-	-	-	-	-	-	-
1986	MIX	MIX	MIX	MIX	MIX	MIX	MIX	EP	CP	CP
1987	MIX	CP	MIX	EP	EP	EP	СР	EP	EP	EP
1990	CP	MIX	MIX	МІХ	MIX	СР	МІХ	MIX	MIX	MIX
1991	MIX	CP	CP	MIX	MIX	MIX	EP	EP	EP	EP
1994	МІХ	MIX	EP	EP	EP	EP	EP	EP	EP	EP
1997	EP	EP	MIX	MIX	MIX	MIX	MIX	MIX	MIX	MIX
2002	МІХ	MIX	MIX	EP	MIX	MIX	EP	MIX	MIX	MIX
2004	CP	СР	MIX	EP	СР	EP	EP	EP	СР	СР
2006	MIX	MIX	MIX	MIX	MIX	MIX	MIX	MIX	MIX	MIX
2009	MIX	MIX	EP	MIX	MIX	MIX	MIX	MIX	MIX	MIX
2014	CP	CP	MIX	МІХ	МІХ	МІХ	MIX	СР	MIX	MIX
2015	МІХ	CP	CP	MIX	MIX	EP	EP	CP	MIX	MIX
Hit rate (%)	-	66.67 (75.00)	33.33	41.67	58.33	50	25	33.33	41.67	41.67

a Hit rate of 12-month lead prediction of El Niño type (1984-2017)

2021 "AI ENSO prediction competition" (2849 teams from worldwide participated)



Accurate weather and climate forecasts are essential for disaster preparedness, socio-economic

CNN prediction of SON IOD index

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Rapidly blooming of AI application to ES studies



ARTICLES

Experimental forecasts of El Niño

Mark A. Cane, Stephen E. Zebiak & Sean C. Dolan

Lamont-Doherty Geological Observatory of Columbia University, Palisades, New York 10964, USA

Experimental forecasts of El Niño events occurring since 1970, made with a deterministic model of the coupled oceanatmosphere system, indicate that El Niño is generally predictable one or two years ahead. A forecast for 1986 is also presented.

THE devastating climatic events of 1982-83 were the most recent extreme phase of the irregular cycle of atmospheric and oceanographic changes known collectively as El Niño and the Southern Oscillation (ENSO)¹⁻⁵. If forecasts could provide sufficient warning of an impending episode, appropriate planning could reduce human suffering and economic loss^{6,7}. In 1982 the state of information gathering and forecasting activities was clearly inadequate: the event was well under way before it was recognized. Statistical procedures reported more recently^{8,9} could have forecast it in the spring of 1982, a few months in advance of the peak warming.

Forecasts of El Niño at longer lead times could be impossible

phere and oceans, allowing his original framework to be bolstered and elaborated. Our theory and model design draw on this collective progress^{1,14}, only a brief sketch of which is possible here.

Ocean-atmosphere interaction

Work on equatorial ocean dynamics following the pioneering sea-level studies of Wyrtki^{15,16} established that changes in the eastern equatorial Pacific could be caused by remote wind changes to the west, with the signal propagating through the ocean along the equatorial wave guide¹⁷. Others explored the wave in which ocean dynamics^{13,18-20} not surface heating

CNN mimics Human Visual System (David Hubel, Torsten Wiesel)



Difference with multiple linear regression



Linear model y = wx

CNN model $y = \varphi(wx)$

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- 1st training : CMIP5 archives (number of samples : about 2,700)
- 2nd training : Reanalysis from 1871 to 1973
- Initial weighting for 2nd training is final weighting of 1st training

CNN real time prediction of ENSO up to 2-year lead



CNN prediction of SON IOD index

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Summary

ENSO prediction

Machine deep learning (CNN) outperforms most dynamical models' prediction of ENSO and IOD at seasonal to multi-year lead.

Perspective

- Develop ML for Earth Science
- Help extract complex teleconnections and causality of climate signals
- Help improve model parameterizations
- Help reduce biases in model predictions
- > Help downscaling of the large-scale products