Preliminary application of machine learning in ensemble forecasting

Junjie Ma and Wansuo Duan

State Key Laboratory of Numerical Modeling for Atmospheric Sciences
and Geophysical Fluid Dynamics (LASG),
Institute of Atmospheric Physics (IAP),
Chinese Academy of Sciences (CAS)

CONTENT

1. Introduction

Chaos feature

Initial error

Model error

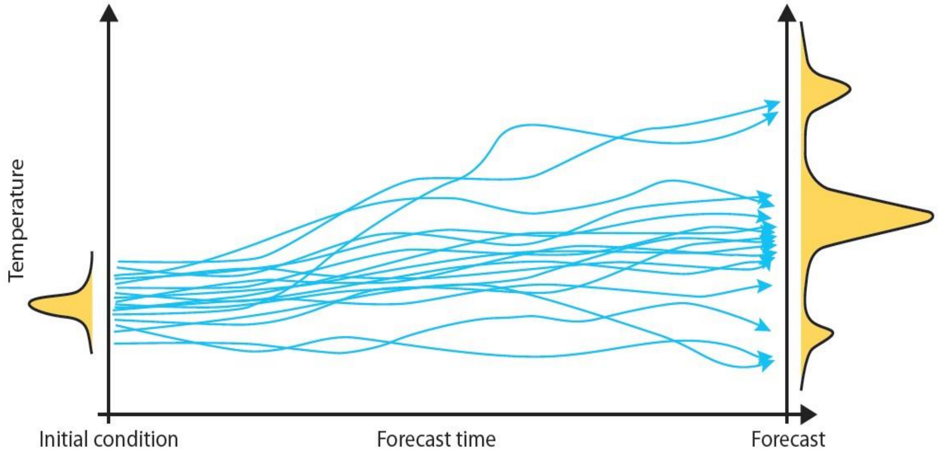
Deterministic prediction is only an estimation of the future state of the atmosphere, and there is uncertainty

Ensemble Forecast
(*Leith，1974*)

Ensemble mean

Spread

Probabilistic forecast



Ensemble Forecast（ECMWF,2012）

Table 1. TIGGE project partners.

Center	Country	Acronym
Bureau of Meteorology	Australia	BoM
China Meteorological Administration	China	CMA
Canadian Meteorological Centre	Canada	CMC
Centro de Previsão de Tempo e Estudos Climáticos	Brazil	CTPEC
European Centre for Medium-Range Weather Forecasts	Europe	ECMWF
Japan Meteorological Agency	Japan	JMA
Korea Meteorological Administration	Korea	KMA
Météo-France	France	MF
Met Office	United Kingdom	UKMO
National Center for Atmospheric Research	United States	NCAR
National Centers for Environmental Prediction	United States	NCEP
National Climatic Data Center	United States	NCDC

Richard Swinbank et al., 2016, BAMS

What and why?

1. Introduction

Methods

Compared with Linear singular Vectors (SVs) and forcing singular vectors (FSVs), orthogonal conditional nonlinear optimal perturbations (O-CNOPs) and orthogonal nonlinear forcing singular vectors (O-NFSVs) consider the influence of nonlinear physical process, and give more accurate ensemble average and more reasonable prediction uncertainty estimation.

(Duan and Huo, 2016; Huo and Duan, 2018)

But

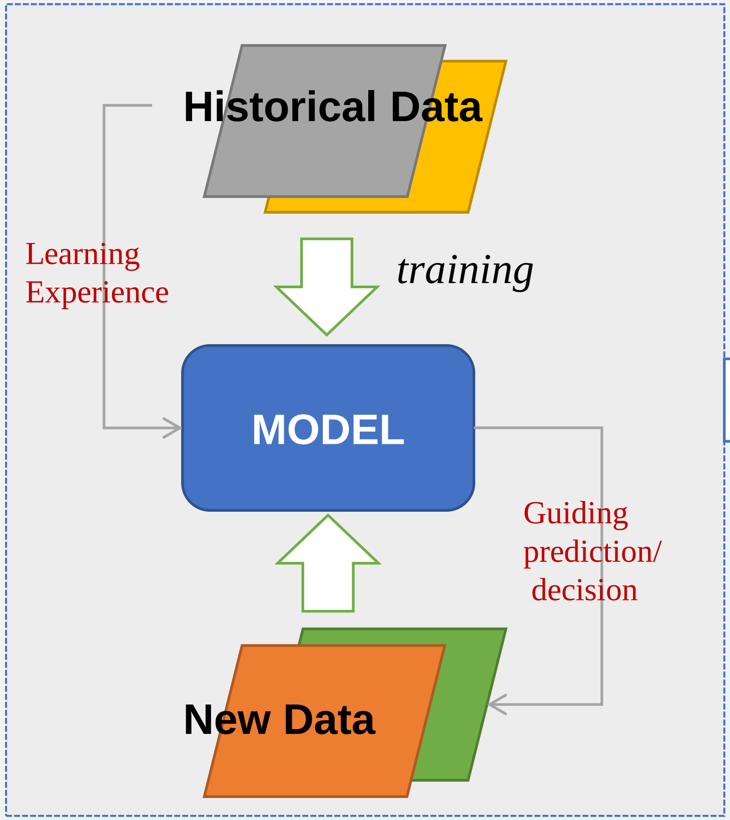
O-CNOPs and O-NFSVs have the drawback of high computational cost.
In practical weather prediction, the ensemble members usually need to be generated quickly.

So

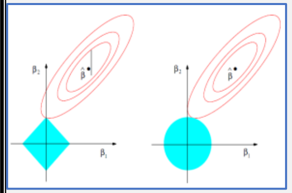
◆**How to model and benefit from O-CNOPs and O-NFSVs ?**

1. Introduction

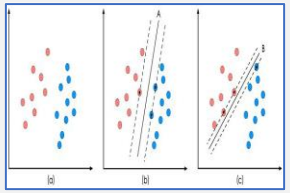
Machine Learning



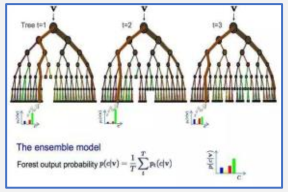
Classical Algorithm



Lasso/Ridge



SVM



Random Forest

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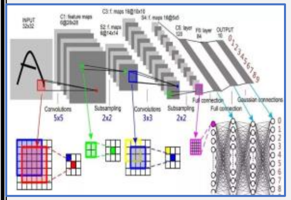
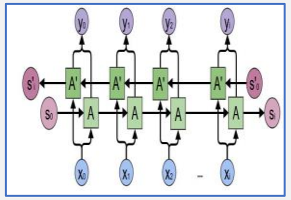
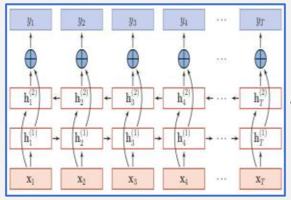
Deep Learning



CNN



RNN



LSTM

… …

Application

- **Image Classification**
- **Language Understanding**
- **Automatic Speech Recognition**
- **Automatic Drive**
- **...........**

◆ **Machine Learning provides some thoughts to solve the above problem.**

2.1 O-CNOPs and O-NFSVs

O-CNOPs

Forecast model with initial perturbation

$$\begin{cases} \dfrac{\partial(U+u)}{\partial t} = F(U+u), \\ U+u\Big|_{t=0} = U_0 + u_0. \end{cases}$$

prediction

$$U(x,\tau) = M_\tau(U_0 + u_0)$$

Prediction error

$$J(u_{0j}) = \left\| M_\tau(U_0 + u_{0j}) - M_\tau(0)(U_0) \right\|_2$$

$$J(u_{0j}^*) = \max_{u_{0j}\in\Omega_j^{(1)}} J(u_{0j})$$

$$\Omega_j^{(1)} = \begin{cases} \{u_{0j} \in R^n \,|\, \|u_{0j}\| \le \delta_u\}, j = 1 \\ \{u_{0j} \in R^n \,|\, \|u_{0j}\| \le \delta, u_{0j} \perp \Omega_k, k = 1, \dots, j-1\}, j > 1 \end{cases}$$

O-NFSVs

Forecast model with model perturbation

$$\begin{cases} \dfrac{\partial(U+u)}{\partial t} = F(U+u) + f(x), \\ U+u\Big|_{t=0} = U_0 + u_0. \end{cases}$$

prediction

$$U(x,\tau) = M_\tau(f)(U_0 + u_0)$$

Prediction error

$$J(u_{0j}, f_j) = \left\| M_\tau(f_j)(U_0) - M_\tau(0)(U_0) \right\|_2$$

$$J(f_j^*) = \max_{f_j\in\Omega_j^{(2)}} J(f_j)$$

$$\Omega_j^{(2)} = \begin{cases} \{f_j \in R^n \,|\, \|f_j\| \le \delta_f\}, j = 1 \\ \{f_j \in R^n \,|\, \|f_j\| \le \delta, f_j \perp \Omega_k, k = 1, \dots, j-1\}, j > 1 \end{cases}$$

2.2 Lorenz-96 model

The model is governed by the following differential equation:

$$\frac{dX_j}{dt} = \left(X_{j+1} - X_{j-2}\right)X_{j-1} - X_j + F$$

where $j = 1,2,\cdots m$, with cyclic boundary conditions ($X_{-1} = X_{m-1},\ X_0 = X_m, X_1 = X_{m+1}$).

Configuration: m=40, fourth-order Runge–Kutta scheme, 0.05 time units (6h)

The variables in the differential equation are nondimensional and can describe the main basic characteristics of atmospheric motion and be commonly used to simulate atmospheric dynamics over a single latitudinal circle, such as the dynamical behavior of vorticity, temperature, and gravitational potential.

(Lorenz and Emanuel, 1998; Basnarkov and Kocarev, 2012; Duan and Huo, 2016)

2.3 Machine learning in ensemble forecasting

Clustering Analysis :

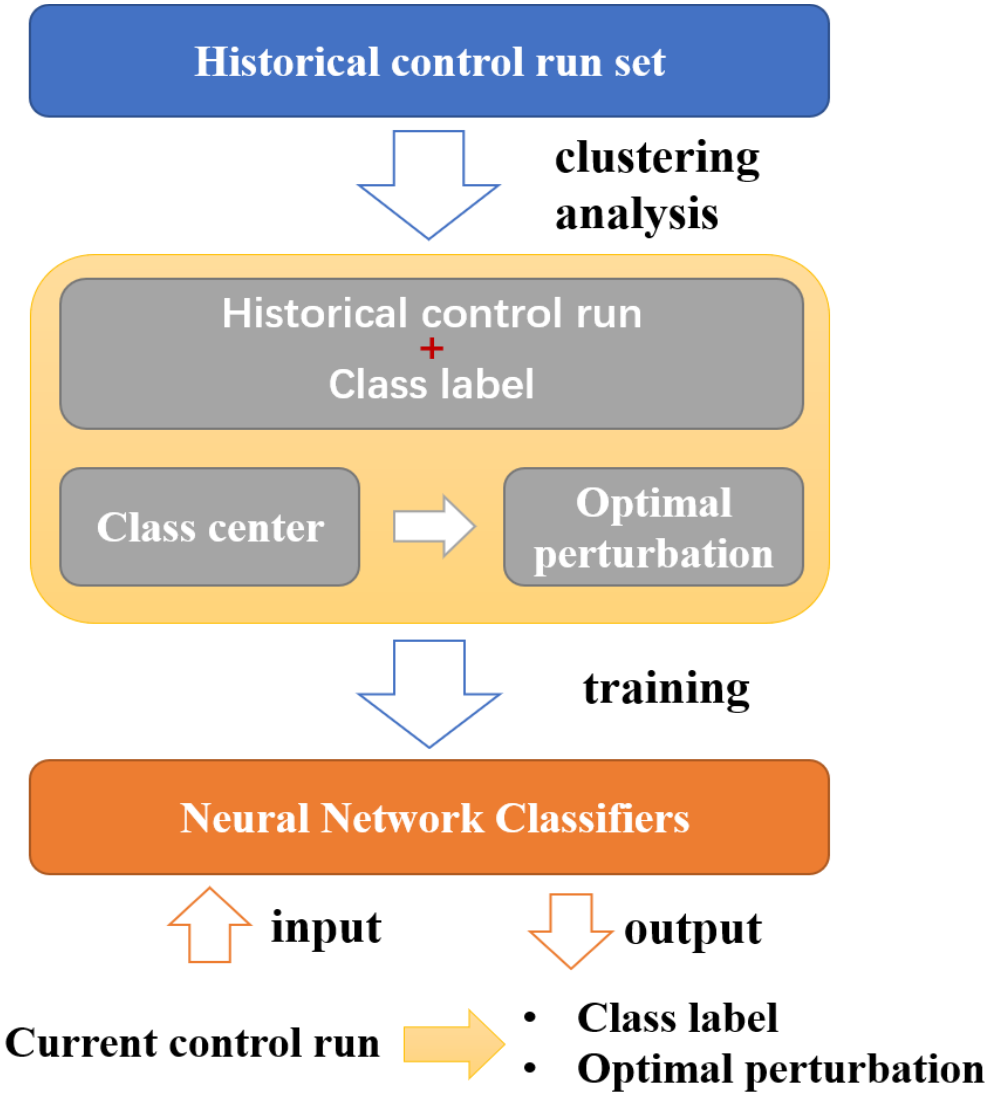
- Hierarchical clustering

Control Run:

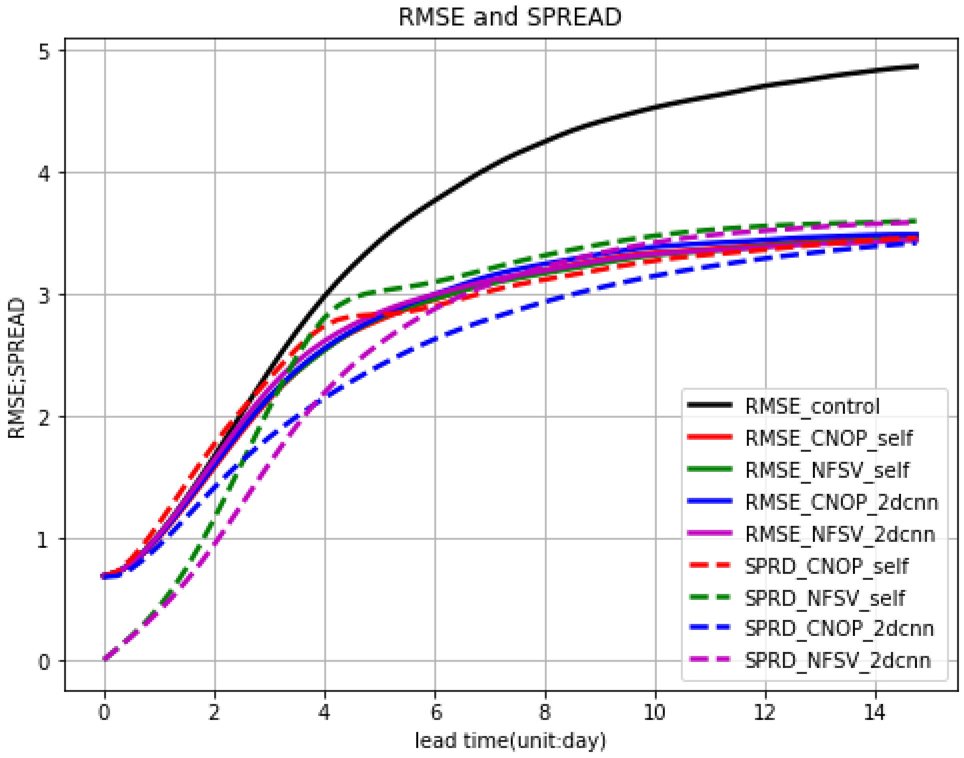
- Spatial data (~Image classification)
- Time series (~Language understanding)

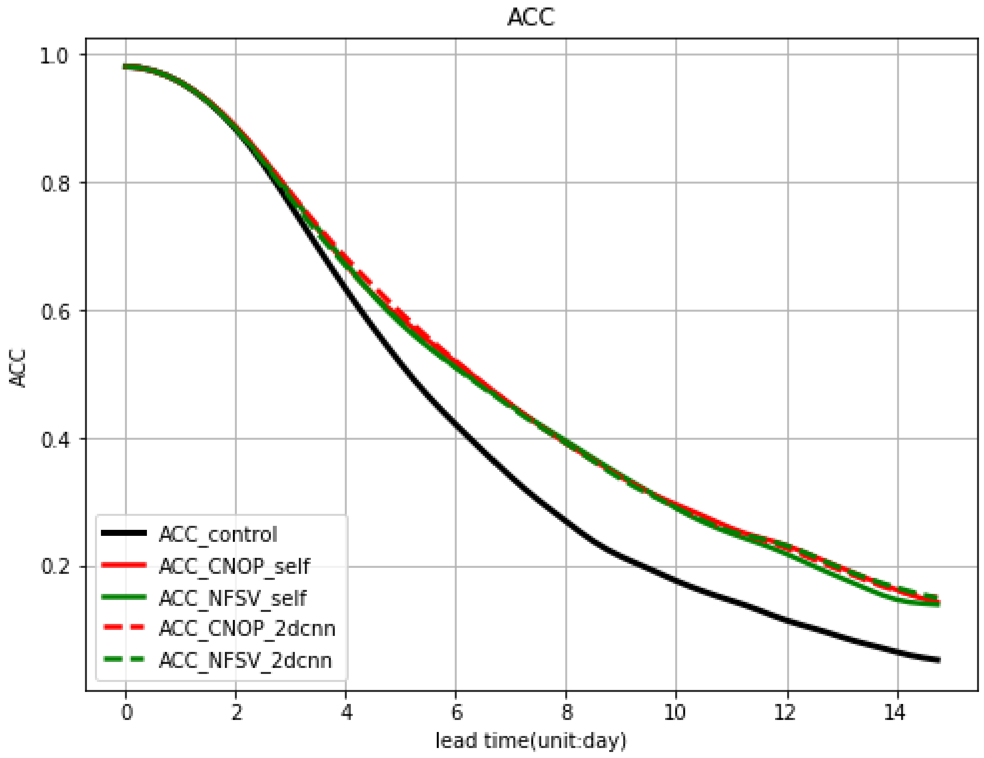
Neural Network Classifiers:

- Convolutional neural network (CNN)
- Recurrent neural network (RNN)



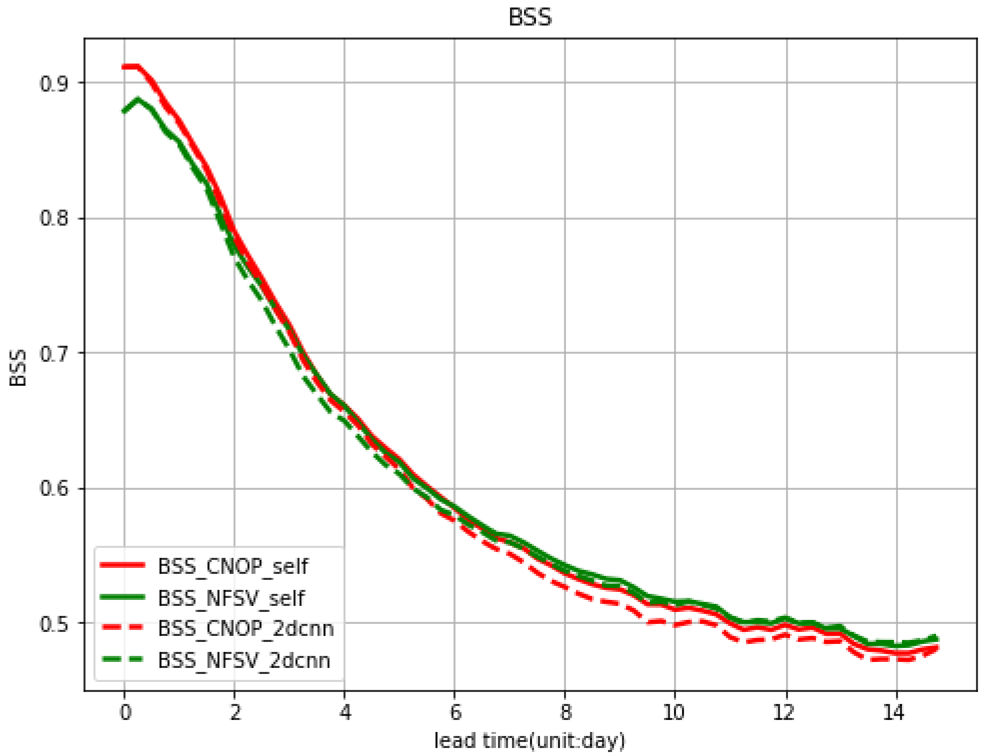
3.1 Results and comparison-CNN

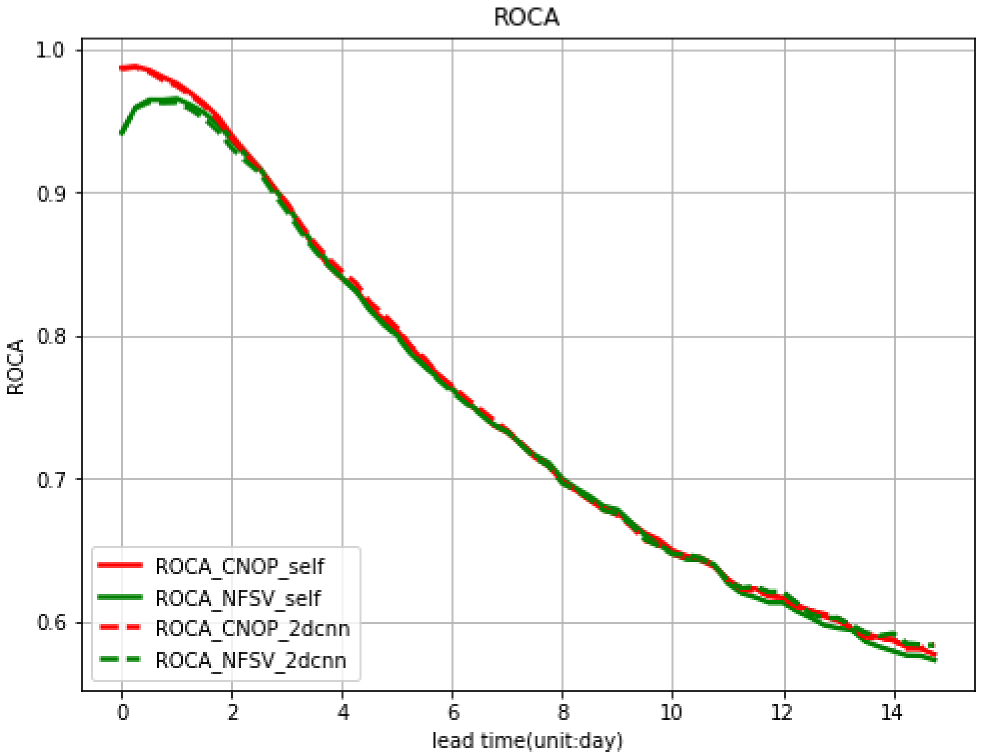




From the comparison of RMSE/SPRD, the O-CNOPs ensemble forecast with optimization algorithm is more reliable then ensemble forecast with CNN, but from the comparison of RMSE and ACC, the ensemble forecast with CNN is acceptable.

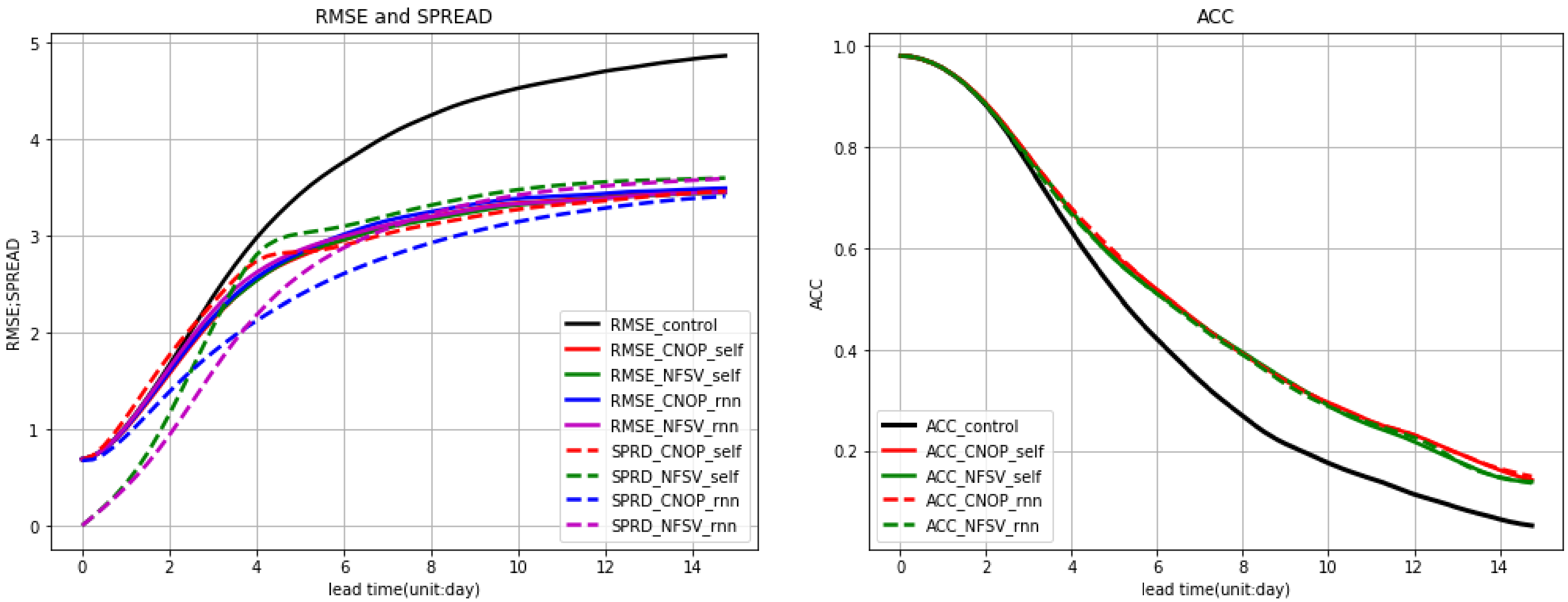
3.1 Results and comparison-CNN





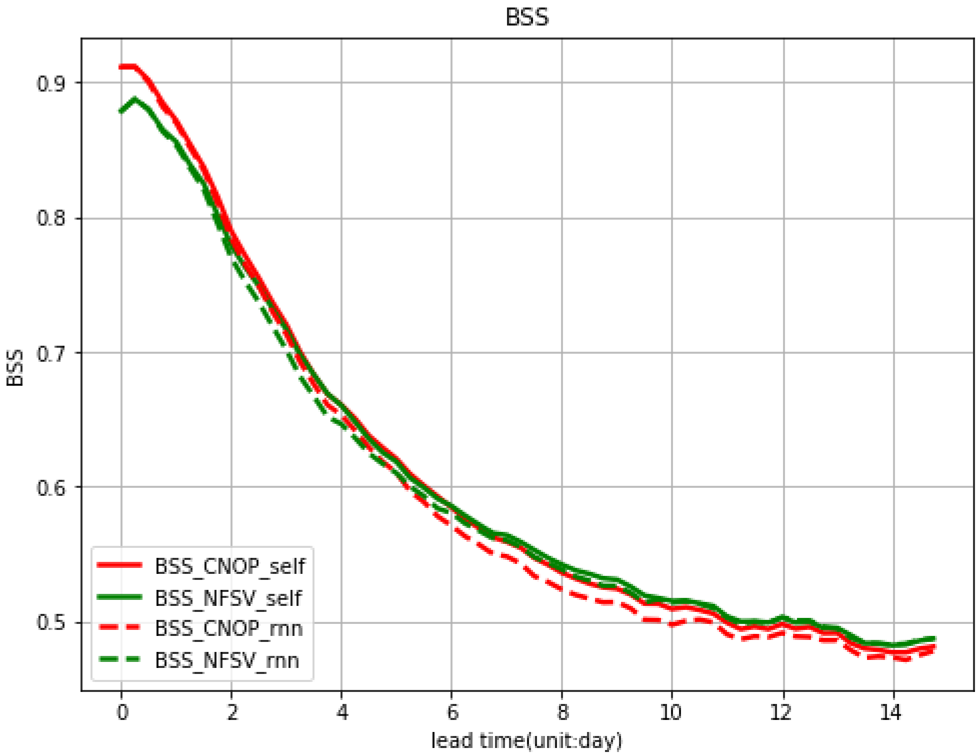
From the comparison of BSS and ROCA, the ensemble forecast with CNN is acceptable.

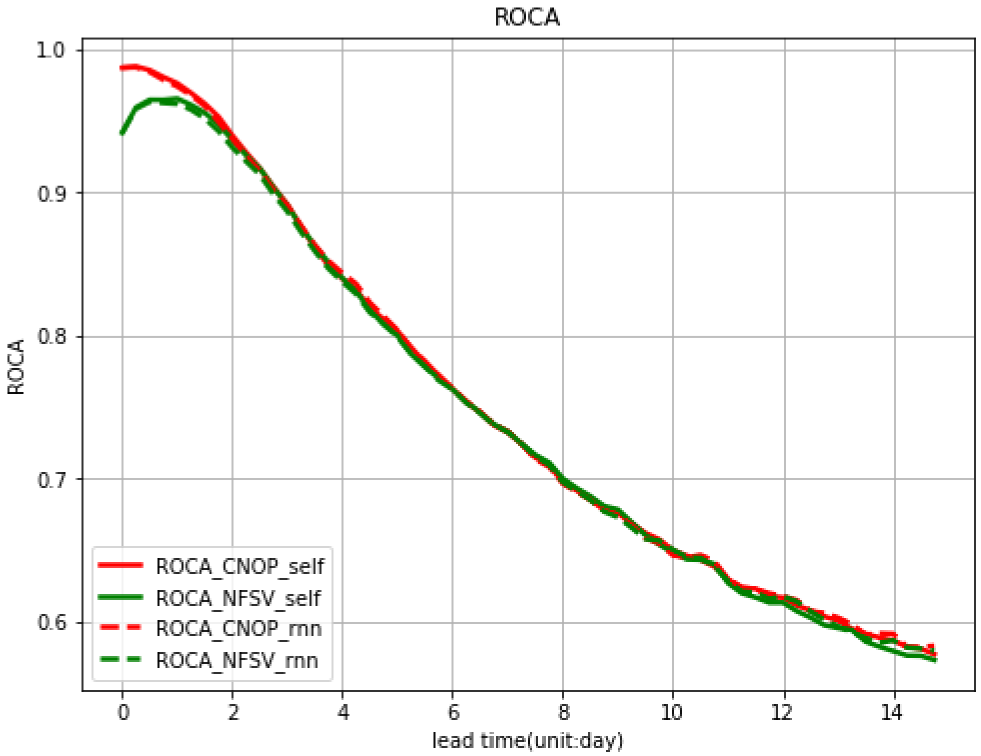
3.2 Results and comparison-RNN



From the comparison of RMSE/SPRD, the O-CNOPs ensemble forecast with optimization algorithm is more reliable then ensemble forecast with RNN, but from the comparison of RMSE and ACC, the ensemble forecast with RNN is acceptable.

3.2 Results and comparison-RNN





From the comparison of BSS and ROCA, the ensemble forecast with RNN is acceptable.

4. Summary

- From numerical simulation experiments, the application of machine learning in ensemble forecast is not good enough but it can make up for drawback of high computational cost of O-CNOPs and O-NFSVs, and the results is acceptable.
- To combine machine learning with ensemble forecasting is only a preliminary attempt in our study, and further research is needed.

References

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