

SINTEX-F seasonal prediction system and its application A brief review of my recent activities

1Application Laboratory (APL)/Research Institute for Value-Added-Information Generation (VAiG)/Japan Agency for Marine-Earth Science and Technology (JAMSTEC), Japan

Acknowledgements:

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Takeshi Doi





Predicted FMA2022 precip from 1jan2022 (ALL,36member) 90N TR Sizes

60

mm/dc

What is seasonal prediction? Seasonal prediction



Predicted FMA2022 precip from 1jan2022 (ALL, 36member) 90N FR Szzer

mm/dc





Weather prediction

Seasonal prediction







Weather prediction

A snapshot of atmospheric conditions

Target

Seasonal prediction

A statistical summary of the weather events occurring in a given season.





Weather prediction

A snapshot of atmospheric conditions

Tomorrow's daily maximum temperature

Target

Example

Seasonal prediction

A statistical summary of the weather events occurring in a given season.

June-July-August averaged temperature





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A snapshot of atmospheric conditions

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Lead time

Tomorrow's daily maximum temperature

up to approximately 10 days because of a chaotic system

Seasonal prediction

A statistical summary of the weather events occurring in a given season.

June-July-August averaged temperature

a few seasons ahead





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> Q. Why is seasonal prediction possible despite the chaotic nature of the atmosphere?

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A statistical summary of the weather events occurring in a given season.

June-July-August averaged temperature

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Weather prediction

A snapshot of atmospheric conditions

Tomorrow's daily maximum temperature

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> Q. Why is seasonal prediction possible despite the chaotic nature of the atmosphere?

Potential source of predictability

Target

Example

Lead time

Atmospheric initial conditions

Seasonal prediction

A statistical summary of the weather events occurring in a given season.

June-July-August averaged temperature

a few seasons ahead

Atmospheric boundary conditions (e.g. SST, sea-ice concentration, soil moisture, stratosphere, etc)





Prediction of the Indian Ocean Dipole Mode (IOD) is crucial for seasonal prediction over the Indian Ocean rim countries, Europe, and East Asia (including Japan)

Positive Dipole Mode



(Saji et al. 1999; Yamagata et al. 2004)

AGCM OGCM	Sea Ice Ensem model size	nble Initialization	Reforecast every mont 1983-prese
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F2-3DVAR (Doi et al. 2017, JC)	ECHAM5 T106L31	ECHAM5 T106L31	LIM2	12	SST-nudging with 3DVAR ocean assimilation	24-mo lead

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The pIOD occurrence was predicted a few seasons ahead by overcoming the so-called winter predictability barrier, which is related to the success in predicting the El Niño Modoki and its atmospheric connection (Doi et al. 2020a, GRL)

Doi, T., Behera, S. K., & Yamagata, T. (2020). Predictability of the super IOD event in 2019 and its link with El Niño Modoki. Geophysical Research Letters, 47, e2019GL086713. https://doi.org/10.1029/2019GL086713

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2.5

4.5

4

3.5

2.5

3.5 4 4.5

140W 120W 80E 120E 140E 160E 180 160W 60E 100E 40E 4.5 2.5 3.5 4

3.5 4 4.5

2.5

The anomalies among the ensemble members (defined as deviations from the ensemble mean) may provide useful insights into possible precursors and teleconnection patterns related to a climate event [Ma et al., 2017; Ogata et al., 2019; Doi et al., 2020].

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In some of those previous studies, a way of sampling was not only in the ensemblespace, but also in the time-dimension by ignoring event-to-event diversity of climate events. In this study, however, our sampling is only in the ensemble-space to explore the inter-member co-variability while maintaining event-to-event diversities. This is because IOD events display a diverse range of amplitudes, spatial patterns, life cycles, and developing mechanisms and its combination with ENSO diversity [e.g. Tozuka et al., 2016; Tanizaki et al., 2017; Verdon-Kidd, 2018].

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We calculate inter-ensemble correlation: correlation coefficient between a target index (e) and a horizontal map of a variable (x, y, e) for each grid point among 108-members of ensemble prediction in a particular month. In this analysis, the conventional time dimension is replaced by the ensemble phase space.

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Scatter plot of ensemble members

-0.45 -0.4

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-0.45 -0.4 -0.35 -0

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1) The higher SST anomaly in the WIO enhance the convective activity locally and excite stationary Rossby waves,

-0.3 -0.25 0.25 0.3 0.35 0.4 0.45

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A zonal dipole is also seen in the correlation maps for the temperature and the OLR anomalies in the tropical Indian Ocean, confirming the link with the super IOD of 2019.

In this study, we have explored the potential source of the unusually warm 2019-2020 winter in East Asia by analyzing the co-variability of inter-member anomalies in the 108-members ensemble of the SINTEX-F prediction system.

We have found a possible teleconnection pattern related to the meander of the subtropical jet, which was excited by the atmospheric processes due to the abnormally warm SST in the western Indian Ocean.

The anomalous SST is due to the long-lasting super IOD in 2019.

For the present purpose, the ensemble prediction system with 108-members has an advantage in finding possible teleconnection patterns influencing the mid-latitude climate with the large stochastic internal variability.

Doi, T., Behera, S. K., & Yamagata, T. (2020). Wintertime impacts of the 2019 super IOD on East Asia. Geophysical Research Letters, 47, e2020GL089456.

Summary

Application Ex. 1

with SINTEX-F2 to predict worldwide yields for four major crops

The daily outputs from the SINTEX-F2 seasonal prediction system were used as the inputs to the crop model

Doi, T., G. Sakurai, and T. lizumi. 2020. Seasonal Predictability of Four Major Crop Yields Worldwide by a Hybrid System of Dynamical Climate Prediction and Eco-Physiological Crop-Growth Simulation. Frontiers in Sustainable Food Systems. 4: https:// doi.org/10.3389/fsufs.2020.00084

Application Ex. 2

Malaria predictions in South Africa based on our seasonal climate forecasts: A time series distributed lag nonlinear model

Kim, Y., and Coauthors (2019), Malaria predictions based on seasonal climate forecasts in South Africa: A time series distributed lag nonlinear model, Scientific Reports, Article No. 17882

