Sub-seasonal Precursors of Cold Surges over North China & Dynamical Verification on AI Weather Prediction Model

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I. Introduction

- Cold surges, frequent winter extremes in mid-high latitudes of the Northern Hemisphere, often bring freezing disasters, endangering lives and economy. While weather-scale (about 2 weeks) forecasts have been advanced, sub-seasonal to seasonal (3-4 weeks) forecasts are still an international challenge.
- Dynamic numerical prediction is mainly used for sub-seasonal cold wave forecasting globally. However, traditional numerical models have issues such as long computing time and error accumulation, and predicting the atmospheric state for 3-4 weeks remains a global challenge. **FuXi-S2S**, the first ML-based prediction model for sub-seasonal atmospheric phenomena, is trained with multi-level and multi-variable data and outperforms the European Centre for Medium-Range Weather Forecasts (ECMWF) in some predictions.
- Ensemble forecasting can effectively address the uncertainties in sub-seasonal cold wave forecasting. Although FuXi-S2S has added perturbations implicitly in the model for ensemble forecasting *(Fig. 1)*. But these perturbations are lack of physical interpretation like a 'black-box'.
- This study identified the main precursor factors of sub-seasonal cold waves based on historical data. The mechanisms of these precursor factors were preliminarily examined through sensitivity experiments with FuXi-S2S.

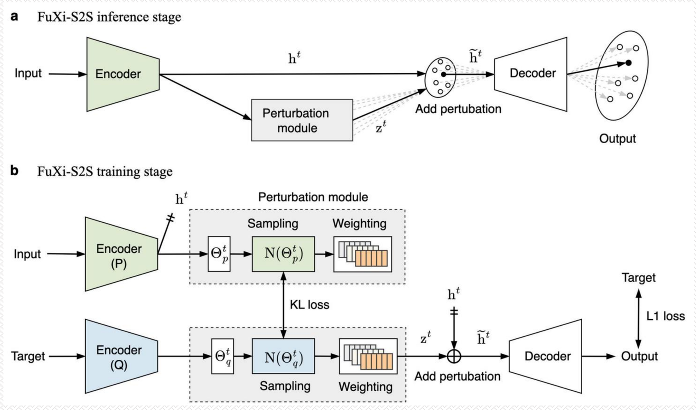

Fig. 1 Schematic of FuXi-S2S (Chen et al., 2024)

II. Data & Models

Model: FuXi-S2S
Data: ERA5 reanalysis data provided by ECMWF, including:
5 upper-atmosphere variables across 13 pressure levels & 10 surface variables – **75 variables in total.**
Temporal resolution: 1 day; Spatial resolution: 1.5°×1.5°. The same as the training data of FuXi-S2S

III. Methods

- To identify precursor factors of cold surges in North China *(Fig. 2)*, this study first applied a **threshold**-based method to select cold days in the region.

Cold days = { Days | when T2M ≤ 10% percentile of climatology for the same date}

For the **composite** features n days before cold days, calculate the average of the variables during Cold days $- n$. **t-test** of composite fields and climatological fields for the same date was adopted.

- For the dynamical verification of these precursors, an **iterative** method was adopted (Hakim & Masanam, 2024):

$$x(t+\Delta t) = M\big(x(t)\big) + \mathrm{d}\bar{x}$$
$$\mathrm{d}\bar{x} = M(\bar{x}) - \bar{x}$$

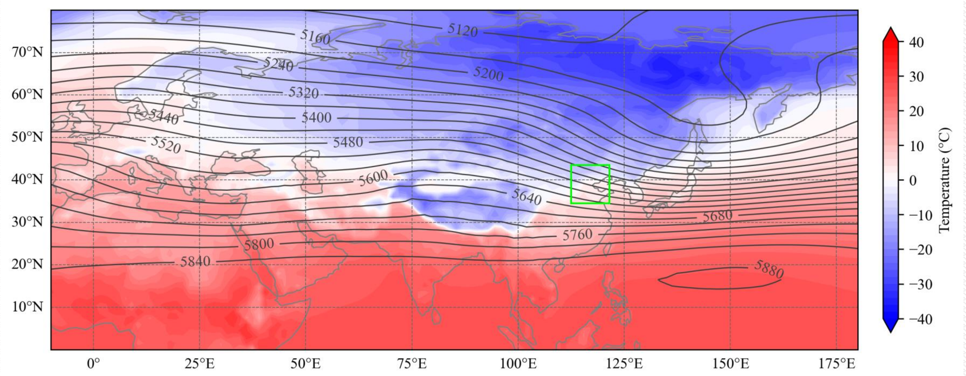

Fig. 2 Climatological T2M & H500 in winter, with the boxed area indicating North China

- $x(t)$ - The state fields at the time t
- $M(x(t))$ – The model result at the time $t+\Delta t$ derived from the inputs x
- $\bar{x}$ - winter climatology
- $\mathrm{d}\bar{x}$ - correction item, to reduce the errors caused by the model's response to the climate state itself during the iterative process

Empirically, $\Delta t = 4$ days

IV. Results

Sub-seasonal Precursors Analysis

- **Sub-seasonal signals:**
  Positive NAO (North Atlantic Oscillation)
  Azores low
  …
- **Synoptic-scale signals:**
  Ural blocking
  Siberian cold high
  …
- **Long-term signals:**
  Warm high-pressure anomaly around Barents-Kara Sea
  Remote signal around Antarctic
  …
- **Circulation features of Cold days:**
  The East Asian Trough deepens and moves southward
  Strong North wind at 850 hPa
  Cold low-pressure center appears in North China and its eastern side at 500 hPa
  Northwest Pacific and Ural-Siberia keeps high pressure at 500 hPa

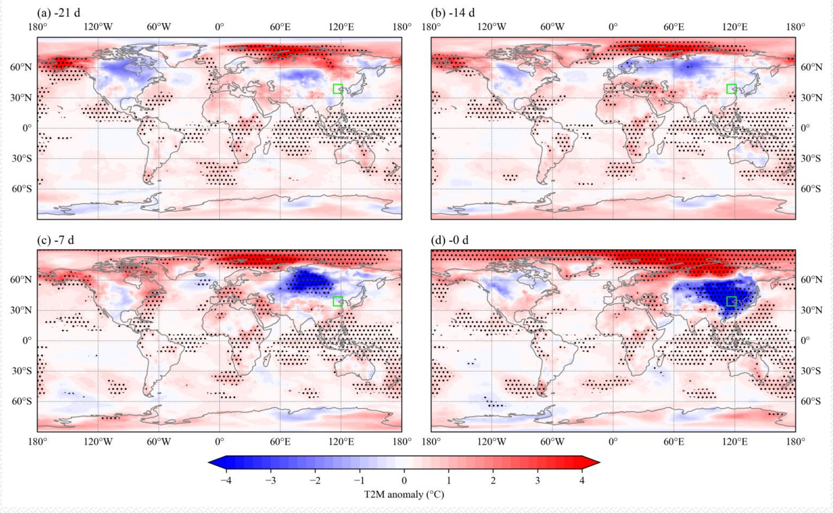

Fig. 3 T2M composite anomaly 21 days (a), 14 days (b), 7 days (c) and 0 days (d) prior to cold days (areas over 99% confidence level are spotted)

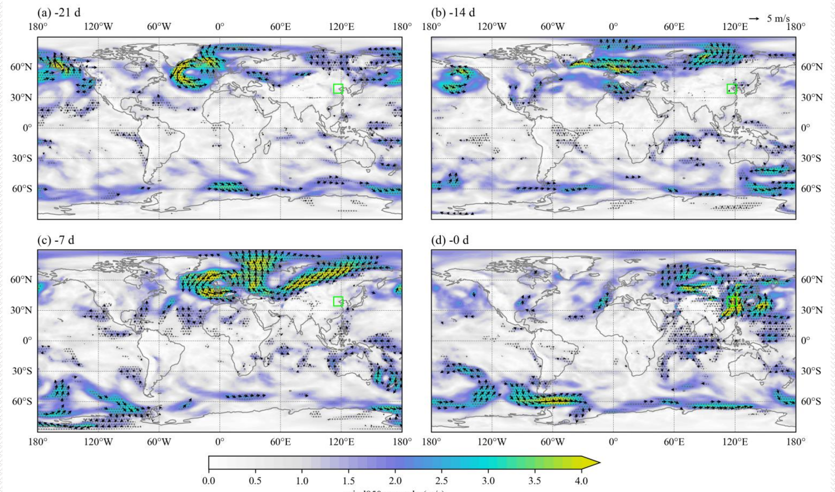

Fig. 4 Similar to Fig. 3, but for horizontal wind vectors at 850 hPa

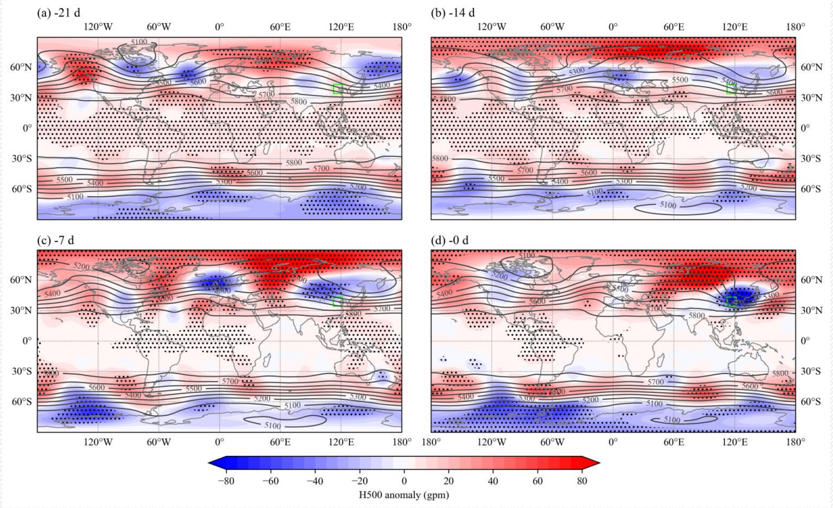

Fig. 5 Similar to Fig. 3, but for geopotential height at 500 hPa

Dynamical Verification

- **H500 simulation result:**
  - During integration, the warm high-pressure anomaly in the Arctic expands and intensifies, similar to the trend in the Arctic warm high-pressure anomaly.
  - Alternating positive and negative geopotential height anomalies emerge in the westerlies.
  - At the 21st day of simulation, negative H500 anomaly appears in North China and its northeast, with positive anomalies maintained in Northwest Pacific and central-western Siberia.

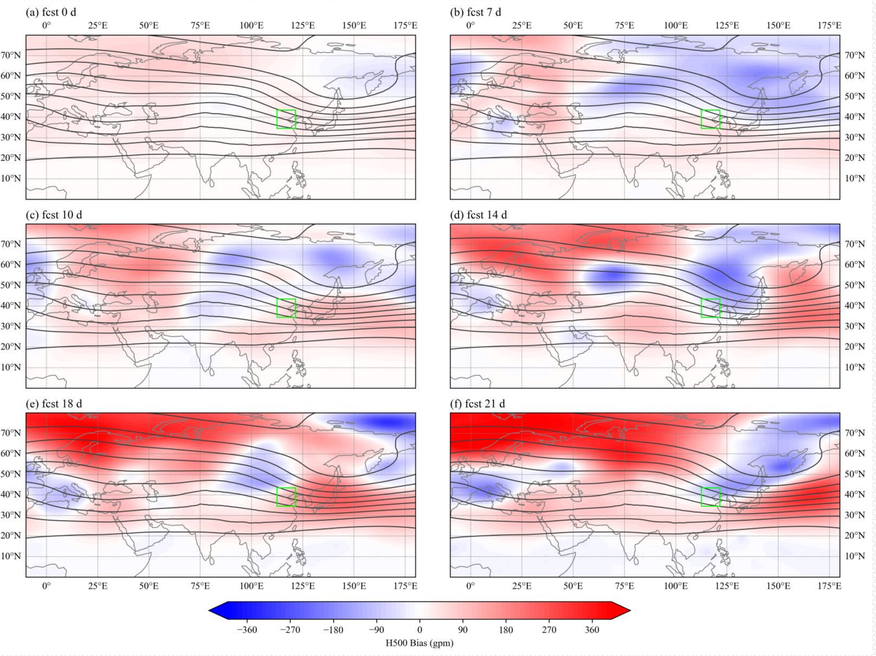

Fig. 6 Bias of the simulation results of H500 based on the composite field 21 days prior to cold days (Filling: Bias of H500 compared to the climatological state; Contour lines: Climatological state of H500) (a) Initial field; (b) 7-day forecast; (c) 10-day forecast; (d) 14-day forecast; (e) 18-day forecast; (f) 21-day forecast

- **T2M simulation result in North China:**
  - The results of the three experiments with a lead time of 21 days, 14 days, and 7 days before the cold days all showed a significant temperature drop in the period around Day = 0.
  - In the experiment with a lead time of 14 days before the cold days, the temperature dropped to a minimum of -14°C, while the temperature drop in the experiment with a lead time of 7 days was relatively small.
  - The shorter the lead time, the stronger the linearity of the temperature broken line.

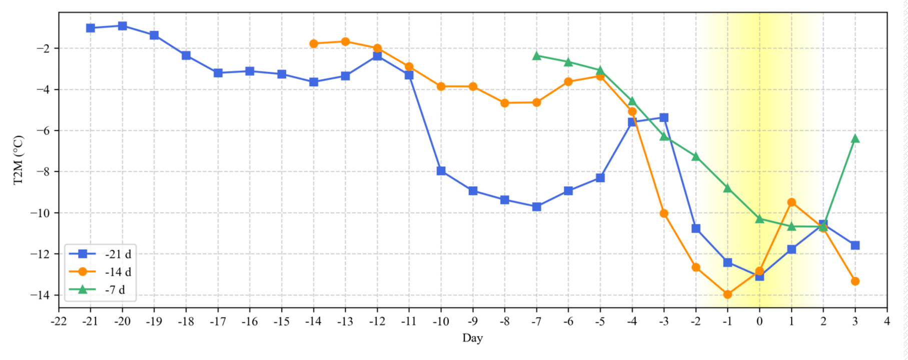

Fig. 7 Simulation results of T2M in North China based on the composite fields 21 days (blue broken line), 14 days (orange one), and 7 days (green one) prior to cold days. The initial forecast day is marked as Day = – lead days. The light yellow area highlights the period around Day = 0.

V. Discussion

- Based on the precursors of cold days in North China, FuXi-S2S is capable of generating a cooling process and circulation field whose features are similar to the true composite fields of a cold wave on the sub-seasonal scale.
- In the verification of the precursor mechanism, the selection of the iteration step size Δt and the amplitude of the initial perturbation x' are based on experience. More initial field sample experiments can be conducted to confirm the model's response to the precursors and improve the robustness of the results.

IV. Next Steps

- Conduct **ensemble forecast experiments** by integrating the precursors into actual cold wave cases. Try to construct different perturbation ensemble samples by adjusting the amplitude size and the perturbation area.
- Use indicators such as the Root Mean Square Error (RMSE). Compare the ensemble forecast results with the deterministic forecast result of FuXi-S2S.

Reference

Chen, L., Zhong, X., Li, H., et al., 2024: A machine learning model that outperforms conventional global subseasonal forecast models. *Nature Communications*, **15**(1), 6425.
Hakim, G. J., and Masanam, S., 2024: Dynamical tests of a deep learning weather prediction model. *Artificial Intelligence for the Earth Systems*, **3**(3), e230090.