

Responses to Reviewers

Submission ID: EGUSPHERE-2024-2574

Title: Quantifying the local predictability of the 2021 sudden stratospheric warming event using a novel nonlinear method

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Responses to Reviewer 1

I-A: General comment

The authors apply a non-linear analytical assessment of the stratospheric state to assess the local predictability leading up to the 2012 Sudden Stratospheric Warming. The study provides an additional metric for assessing predictability alongside more conventional (linear) approaches and is therefore of merit for publication. However, I feel the manuscript needs substantial modification to enable readers to understand the applied method, the analysis carried out, and the comparison with other dynamical studies (see comments below).

Response: Thank the reviewer for sparing time to go through the manuscript, highlighting very important issues and providing helpful comments and valuable suggestions to improve the manuscript. According to the reviewer's suggestions, we have revised the manuscript seriously and carefully. More details and point-to-point responses to the reviewer's comments are listed as follows.

I-B: Specific comments

1. The methodology needs a clearer explanation – the authors have referenced previous papers, however more detail on the actual calculations and steps performed on the datasets within this study are needed for a reader to follow. As a minor example, line 181 refers to equations 9 and 10 however these are not found in the manuscript.

Response: Thanks for the good suggestions from the reviewer. We have rewritten the methodology and add more descriptions on the actual calculations and steps performed on the ERA5 reanalysis and S2S reforecast datasets in the revised manuscript (Lines 169-197).

The BaSIC technique used in our study aims to quantify the practical predictability limit of specific events from the perspective of forecast error growths. The criterion on how to estimate predictability limit includes three steps.

Step 1. We should determine a specific or target state, whose predictability limit is to be quantified. Because the predictability limit of target state estimated by the BaSIC method is based on the perspective of nonlinear growth of forecast errors.

Step 2. We need to investigate the nonlinear growth of forecast errors. Specifically, the

growth of initial forecast errors from different initialization date should be analyzed.

Step 3. After the analysis of initial forecast error growths, corresponding initial state (CIS) should be determined. Determining the corresponding initial state should follow a criterion. If the forecast error of an initial state prior to this target state grows with time and exceeds the threshold value at the time of the target state, then this initial state is the CIS which we need to find. After the determination of the CIS, the timespan between the corresponding initial state and the target state is defined as the predictability of the target state. It should be noted that the threshold value employed is the attractor radius, which is the standard deviation of a variable in a long time series. Above descriptions are the general procedure to quantify the practical predictability limit of specific events based on the BaSIC method. More details on how to apply the BaSIC method to practical predictability limit of the 2021 SSW event can be found in from lines 174 to 190.

In addition, Equations 9 and 10 now refer to equations A7 and A8 in the revised manuscript (Lines 703-705).

2. Apologies if I have misunderstood, but it appears the analysis performed here relates only to the zonal wind field at 10hPa, and is therefore missing the influence (and error growth) within the upper troposphere and lower stratosphere (which Cho et al 2021 suggest are important for this event)? The authors discuss the regional error growth within the forecast models in the stratosphere, however this is likely to be driven by the tropospheric wave activity, and will thus affect the resulting predictability limits?

Response: Thanks for the reviewer's suggestion. It is true that we only analyzed the zonal wind data at 10-hPa. And we agreed with the point from Cho et al. (2021). And the upper troposphere and lower stratosphere can modulate the predictability of 2021 SSW event. In fact, our study is not conflicted with that of Cho et al. (2021). Cho et al. (2021) aimed to find the important source of predictability of 2021 SSW event, and then determined its predictability. However, our study is not involved with the sources of the predictability of 2021 SSW event, and we directly estimated its predictability limit based on the reanalysis data and the reforecast data. Therefore, the research approach of our study is different from that of Cho et al. (2021).

From some previous papers, the observational data is directly analyzed, and then predictability limits of climate and weather events are quantified (Ding et al., 2010; Li and Ding, 2013; Ding et al., 2016). These studies don't need to find the sources of predictability, because they deemed that the observational data contained all the dynamical information from the external factors. We hold the same opinion as theirs. In this study, we think that the zonal wind data at 10-hPa contained the dynamical information both from stratospheric and tropospheric wave activities. Therefore, to obtain the practical predictability limit of the 2021 SSW event, we just directly need to analyze the reanalysis data and reforecast data.

We have added more explanations in the revised manuscript from lines 354 to 368, and from lines 501 to 508.

Ding, R., Li, J. and Seo, K.-H. Predictability of the Madden–Julian oscillation estimated using observational data. *Monthly Weather Review* 138, 1004-1013, <https://doi.org/doi.org/10.1175/2009MWR3082.1>, 2010.

Li, J. and Ding, R. Temporal-spatial distribution of the predictability limit of monthly sea surface temperature in the global oceans. *International Journal of Climatology* 33, <https://doi.org/doi.org/10.1002/joc.3562>, 2013.

Ding, R., Li, J., Zheng, F., Feng, J. and Liu, D. Estimating the limit of decadal-scale climate predictability using observational data. *Climate Dynamics* 46, 1563-1580, <https://doi.org/doi.org/10.1007/s00382-015-2662-6>, 2016.

3. Once again, apologies if I have misunderstood, but a key assumption within this methodology is that any state preceding the identified initial condition cannot, by definition, predict the event state? Given the importance of tropospheric conditions driving the stratospheric flow, by only focusing on the 10hPa winds, surely multiple tropospheric states could precede the event (at lead times earlier than the identified initial condition) and would not be captured within this analysis? A practical example of this is that you may find one member predicts the event at a very long lead time (earlier than those utilised here), possibly by chance, but this still represents a physical state leading to the SSW.

Response: Thanks for the good comment from the reviewer. This methodology firstly needs to find a corresponding initial condition, which is prior to the target condition. In this study, the target condition is the reversal of westerly zonal-mean zonal wind to easterly at 10-hPa (that is the onset of 2021 major SSW event). After determining the corresponding initial condition, the timespan between the corresponding initial condition and the target condition is defined as the predictability limit of the 2021 SSW event. A criterion on how to determine the corresponding initial condition is that the corresponding initial condition is the most distant condition to predict the target condition. That is, any state between the corresponding initial condition and the target condition can predict the target condition. This clarification can be found in from lines 169 to 197 of the revised manuscript.

We think that the influence of both the stratospheric and tropospheric process will reflect in the reanalysis and reforecast data. Therefore, directly analyzing the zonal wind at 10-hPa can estimate the predictability limit of the onset of the 2021 SSW event, whose predictability is affected by both the stratospheric and tropospheric wave activities.

In this study, we are more concerned with the ensemble mean of all members of reforecasts, not the single member. Because the ensemble mean result will eliminate the effects on predictability from some bad members. In addition, a single good member may have a certain degree of randomness. That is this member performs well in this forecast, but bad in other forecasts. Therefore, we don't analyze the single member, but use the ensemble mean result to study the predictability.

I-C: Minor comments

1. Suggest adding “practical” to the article title (i.e. “quantifying the practical local predictability...”

Response: We have added “Practical” to the article title.

2. Please can sub-headings be used to separate out the different sections of the results?

Response: We have divided the results into three parts in the revised manuscript.

3. How does this approach compare or with other statistical approaches e.g. Finkel et al 2023 (Revealing the Statistics of Extreme Events Hidden in Short Weather Forecast Data)?

Response: Thanks for the comment. Finkel et al. (2023) presented an effective approach to reveal statistics of extreme events. This method can extract climatological information from these short weather simulations, and then characterize sudden stratospheric warming (SSW) events with multi-centennial return times. In addition, the estimates of the frequencies and seasonal distributions of SSW can be also obtained. The BaSIC method used in this work investigates the practical predictability of the 2021 SSW event from the nonlinear perspective. This method focuses on the dynamics of forecast errors to quantitatively estimate the upper practical predictability limit of the 2021 SSW event. Both two methods are effective tools to study the predictability of SSW events.

We have added the discussion of the work of Finkel et al (2023) in the introduction section (Lines 89-95).

4. If understood correctly, the analysis depends upon the ensemble mean RMSE; can the authors add discussion regarding the regional growth of the ensemble spread, which is also important for understanding predictability barriers (e.g. Sanchez 2020: Linking rapid forecast error growth to diabatic processes)?

Response: We have added more analysis of the regional growth of the ensemble spread (Fig. 5, Lines 286-299; Figs. 11 and 12, Lines 472-497). It is showed that the spread of reforecasts in both ECMWF and CMA models is lower than the root-mean-square error (RMSE). And the spread of ECMWF is higher than that of CMA. The differences in spread arise from different ensemble numbers and different initialization schemes in two numerical centers. Generally, the spread is an indicator of forecast skills. The closer the Spread is to the RMSE, the higher the forecast skills.

5. It is also useful to note that new dynamical methodologies demonstrating causality are now available and have been used for SSWs (Kent et al 2023: Identifying Perturbations That Tipped the Stratosphere Into a Sudden Warming During January 2013)

Response: We have added the discussion of the work of Finkel et al (2023) in the introduction section (Lines 82-88).

6. There are several acronyms which need defining (e.g. WN1, ES, CIS)

Response: WN1 refers to zonal-wavenumber 1. And the ES and CIS refer to extreme state and corresponding initial state, respectively. The extreme state and ES have been replaced with target state and TS in the revised manuscript, respectively.

7. In the abstract the authors state that the surface response is around two weeks following SSWs (Line 11), however the surface impact can be 30-60 days for the downward coupling to influence the troposphere.

Response: We have fixed it in the revised manuscript (Lines 12-13).

8. A few spelling errors also need addressing (e.g. "middel")

Response: We have revised it (Line 403).