EARLY PREDICTION OF WEAK STRATOSPHERIC POLAR VORTEX STATES

USING A CAUSAL PRECURSOR DETECTION SCHEME

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INTRODUCTION

Weak stratospheric polar vortex (SPV) states can cause extreme winter weather in the Northern Hemisphere mid-latitudes. Including stratosphere activity in seasonal model predictions therefore significantly improves skill. Though dynamical models have useful prediction skill of the SPV on synoptic time-scales of about one week, they poorly capture low-frequency processes and therefore have limited or no skill at longer lead-times [1]. Here we introduce a novel empirical prediction approach which builds upon response-guided community detection [2] and a causal discovery algorithm [3, 4].

DATA

We study half-monthly data (ERA-Interim) of linearly detrended climatological anomalies from 1979 – 2015.

	SPV Index	Precursor Fields
Variable	GPH at 10mb	SLP, SSTs, GPH at 500mb (Z500), poleward heat flux at 100mb (vT100), zonal wind at 50mb (u50)
Location	Polar cap mean, northward of 60° N	Gridded data, 20° S to 89° N
Time	November-March	Lead-lags up to four months (lag-8)

Tab.1: Table of considered data for the response variable and the precursors.

METHOD

We calculate correlation maps of the precursor fields with the SPV index for different lags (first panel in Fig.1). Grid-points with significant correlation indices of same sign are grouped to communities and their area-weighted mean is computed to create a time-series for each region (second panel in Fig.1).

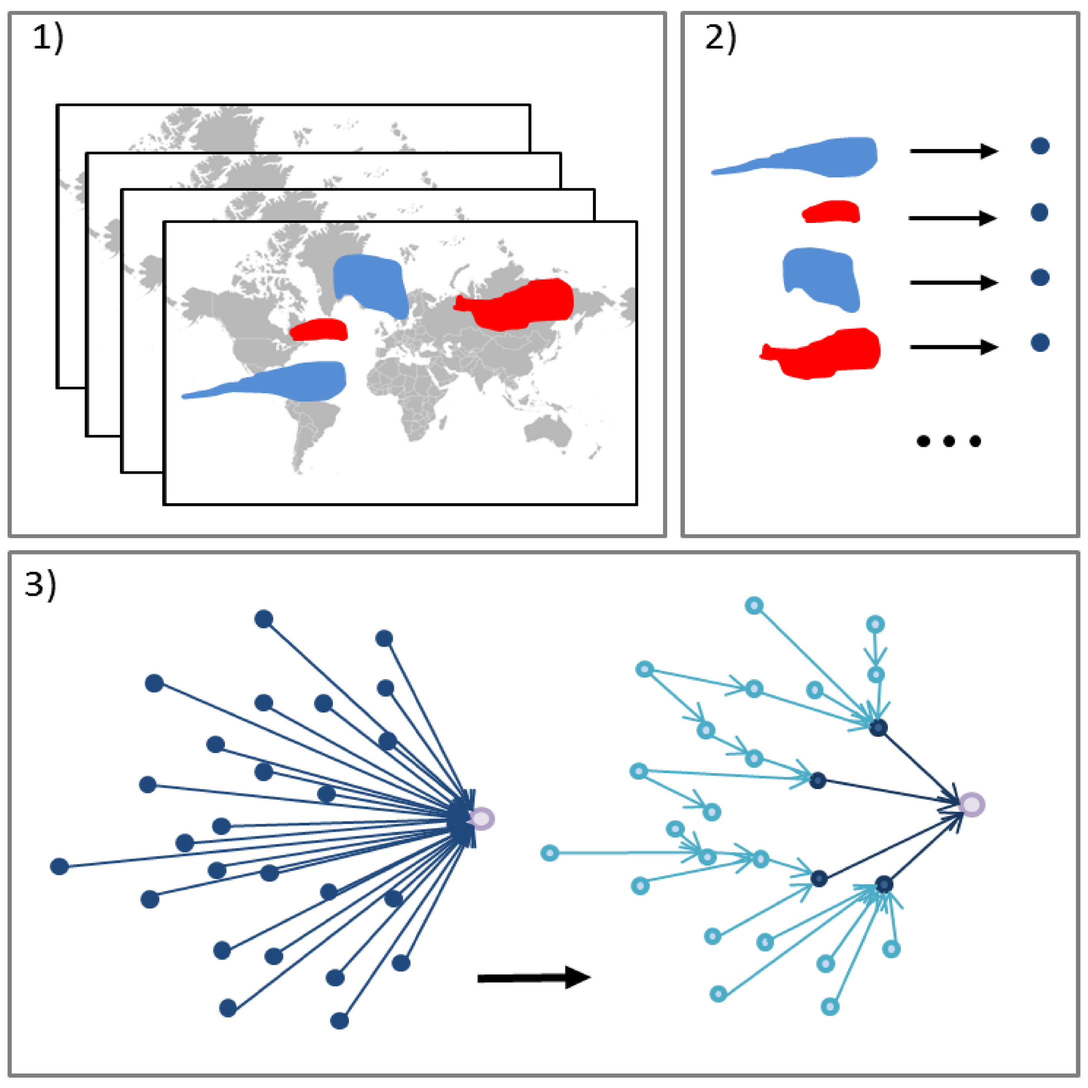

Figure 1: Schematic representation of the response-guided Causal Precursor Detection (CPD) scheme.

We then use a multivariate causal discovery algorithm to identify spurious correlations with the SPV due to auto-correlation, common drivers or indirect links (third panel in Fig.1). The remaining links (right part of third panel in Fig.1) are then interpreted as the causal drivers of the SPV.

RESULTS & DISCUSSION

- We identify 471 precursor communities composed of all fields: vT100 (72), SLP (40), SST (278), Z500 (49) and u50 (32)
- Only 4 causal precursors remain after applying the causal discovery algorithm:
  - the lag-1 auto-correlated SPV index
  - two lag-1 vT100 regions over Eurasia and the North Pacific
  - a lag-3 community of SSTs in the tropical Philippine Sea
- The identified causal precursors are physically interpretable and mostly robust for different parameter settings

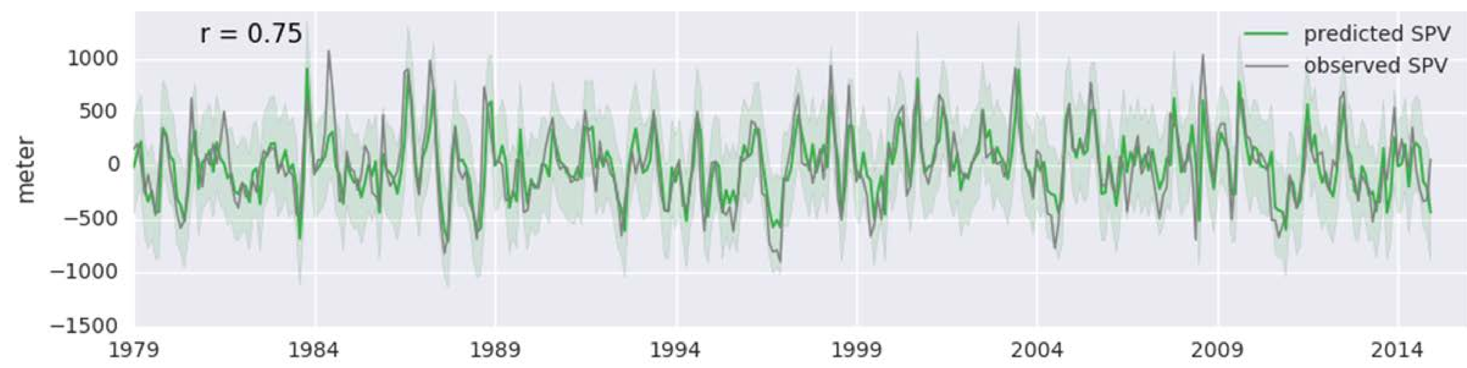

Figure 2: Cross validation of the regression model: One-step ahead predictions with the causal precursors as regressors. The regression models were build iteratively by leaving out data of the to predicted winter.

- A cross-validated multiple linear regression model of the causal precursors on the SPV can explain most of SPV variability (r^2=0.6)
- 64% of weak SPV states are accurately predicted with a false-alarm-rate of only ~4% (odds-ratio = 42.3)
- For longer lead-lags 42% (16-30 days ahead), 22% (31-45 days ahead) and 14 % (46-60 days ahead) of weak SPV events are still correctly predicted

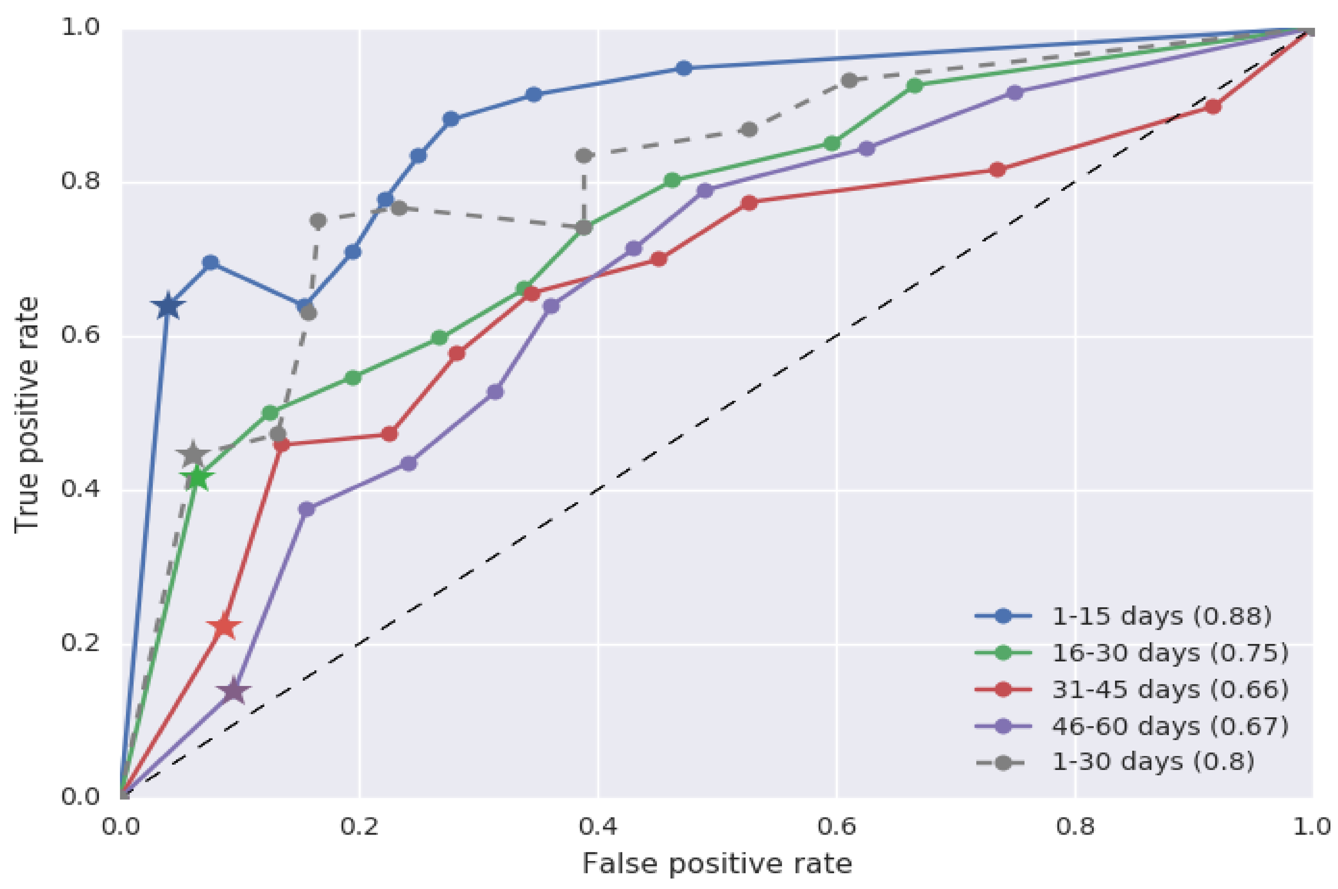

Figure 3: ROC scores for predictions based on different minimum lead-lags.

CONCLUSION

The presented data-driven algorithm proposes a way to objectively identify linear (causal) precursors of a variable of interest. It gives robust and physically interpretable results for the SPV with high prediction skills for lead-times up to two months. Our approach can be used for early warning directly but also to select individual members from ensembles of operational forecast models to improve (sub-)seasonal winter predictions. The approach is generic in nature and can be applied to other climate indices to predict and understand causal links of teleconnections.

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References: [1] Tripathi et al., 2015, *Q. J. R. Meteorol. Soc.* [2] Bello et al., 2015, *Machine Learning and Knowledge Discovery in Databases, Springer* [3] Runge et al., 2014, *Physical Review Letters* [4] Kretschmer et al., 2016, *Journal of Climate*

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