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Using Dynamical Precursors for Statistical SSW Prediction

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CONTEXT

- From previous SSW lifecycle and composite studies, we know that **Eliassen-Palm flux (F_z)** peaks and polar vortex sharpens prior to SSW onset[1-15]
- Linear wave theory: waves propagate towards higher **refractive index**[1,16]

$$n^2 = \frac{\bar{q}_\phi}{(\bar{u}-c)/a} - \left(\frac{k}{\cos\phi}\right)^2 - \left(\frac{af}{2NH}\right)^2$$

- First term is the only dynamical term. **Potential vorticity gradient** is most sensitive to changes (proportional to second derivatives)

$$\bar{q}_\phi = 2\Omega\cos\phi - \left[\frac{(\bar{u}\cos\phi)_\phi}{a\cos\phi}\right]_\phi + \frac{af^2}{R_d}\left(\frac{p\theta}{T}\frac{\bar{u}_p}{\bar{\theta}_p}\right)_p$$

- We analyze CM2.1 data from a 10k-year coupled high-top simulation from *Horan and Reichler (2017)*.

AIMS

- We invert the usual approach of first detecting all SSWs and then compositing
- Instead, we detect certain **events *E*** known to be precursors of SSWs and compute the probability that an SSW occurs within a given lead time
- Like this, the events become statistical predictors for the onset of SSWs in the future
- We want to quantify the information gain from using precursors as a function of lead time
- Precursor events are defined as the crossing of the 5th or 95th percentiles of
  - F_z: upward EP flux at 100hPa (**"F event"**)
  - q_{phi}: meridional potential vorticity gradient at 30hPa (**"Q event"**)

RESULTS

- Anomalously strong F_z increases short-term SSW probability ~5x
- Anomalously weak F_z decreases short-term SSW probability >10x
- Anomalously strong q_{phi} decreases short-term SSW probability >10x
- Anomalously weak q_{phi} increases short-term SSW probability ~5x (first week)
- It also decreases long-term SSW probability ~2x (3-6 weeks)
- Anomalously strong F_z and weak q_{phi}
  - **increase immediate SSW probability ~10x (first week)**
  - **decrease long-term SSW probability 2-5x (3-10 weeks)**

1. SSW ➡ E

First, we check the standard approach of compositing SSWs around the onset date.

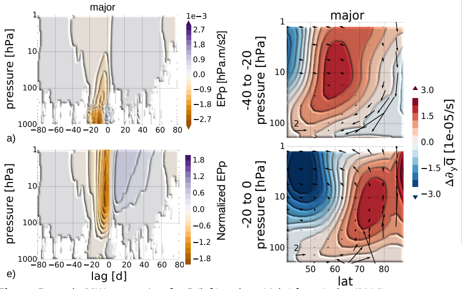


Figure: Example SSW composites for F_z (left) and q_{phi} (right) from *Jucker (2016)*.

This gives both a validation of the model data and an indication for relevant lead times for future prediction. We look for composite evolutions of F_z and q_{phi}, similar to previous work, such as from *Jucker (2016)* above.

Indeed, our composites (right, w/ 1σ and 5th/95th percentiles) show that our GCM data agrees well with such composites:

- Strong increase of F_z (100hPa) within ~2 weeks, w/ peak ~1 week prior to onset (top).
- Weak but significant increase in q_{phi} (30hPa) ~1 month, and strong decrease ~1 week prior to onset (bottom).

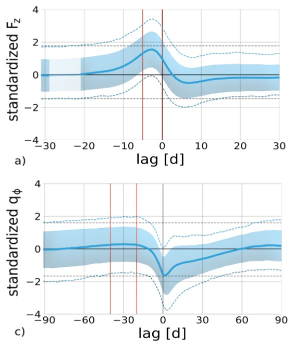


Figure: SSW composites for F_z (top) and q_{phi} (bottom) from CM2.1: composite mean (thick continuous), 1σ (shaded), 5th/95th percentiles around SSWs (blue dashed) and all days (black dashed). From *Jucker & Reichler (2018)*.

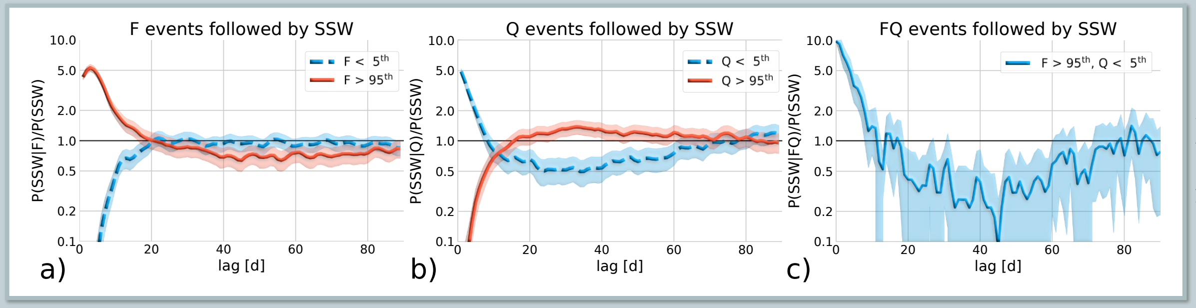


Figure: Conditional probabilities of SSW occurrence given an event *E* has happened, *P(SSW|E)*, divided by the climatological mean probability *P(SSW)* = 0.49%/day. At long lead times, events and SSWs decouple, and *P(SSW|E)* = *P(SSW)*.

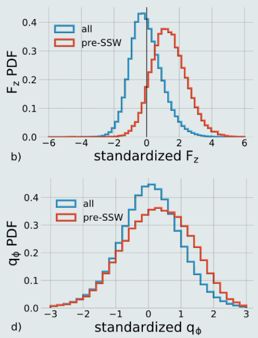
Strong upward EP flux at 100hPa increases the ~1 week SSW probability 5-fold, and strong negative EP flux anomaly reduces it ~10-fold (red/blue, left). Anomalously strong F_z also indicates slightly reduced *P(SSW)* between ~1-3 months.

Anomalously weak meridional PV gradient also increases immediate *P(SSW)* 5-fold, and strong q_{phi} decreases it ~10-fold. In contrast to F_z, q_{phi} also carries information about SSW occurrence out to ~60 days ahead, with *P(SSW)* about half the climatological value (blue dashed, middle).

Combining F_z and q_{phi}, immediate *P(SSW)* increases ~10-fold, and decreases ~2-5 times on the monthly time scale all the way to ~10 weeks (right).

2. E ➡ SSW

If we construct histograms of individual days rather than compositing all SSWs, we get one step closer to estimating how "generic" composite evolution really is.



The left figure shows histograms of all days (blue) or only the days within the lag intervals of any SSW marked with the red vertical lines on the far left (red).

The F_z distribution prior to SSWs is clearly different to the total distribution (top), with a strong shift towards positive (upward) values and a slight re-shaping of the tails (more Gaussian).

The q_{phi} distribution ~1 month before onset is also shifted towards positive numbers (sharper polar vortex edge, bottom). Note that while the PDF differences are much less pronounced than for F_z, the averaging period (lags -40 to -20) is also much longer (lags -40 to -20 for q_{phi} vs. -5 to 0 for F_z).

Figure: Histograms of daily F_z (top) and q_{phi} (bottom) from CM2.1: All winter days (blue) vs. days associated with SSWs (red). For F_z, the red line includes days within lags -5 to 0, for q_{phi} lags -40 to -20 prior to onset. From *Jucker & Reichler (2018)*.

Pushing the inversion further, we can also compare the fraction of SSWs preceded by a given event *E* (thick lines below) to the expected fraction of SSWs preceded by the same event, assuming *E* and SSWs are independent (thin lines). The difference between the two curves (shaded) gives a measure of the influence of event E on the occurrence of SSWs.

A much larger-than-random fraction of SSWs is preceded by strong F_z (top left), as well as weak q_{phi} (bottom left). 80% of all SSWs are preceded by F_z > 95th percentile within 25 days, and q_{phi} < 0 within 16 days.

q_{phi} < 5th percentile provides the strongest long term signal (purple, dashed).

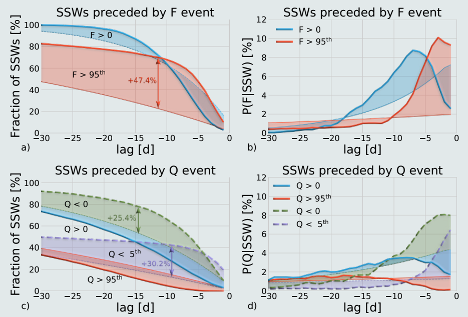


Figure: (left) Fraction of SSWs preceded by events defined by the F_z (top) and q_{phi} (bottom) thresholds indicated by black text. (right) Derivatives of the plots from the left column. Colored percentage numbers show the maximum differences between the actual and theoretical (if independent) SSW fractions. From *Jucker & Reichler (2018)*.

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This work:
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