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Model uncertainty, ensemble reanalysis data (EDA) and North Atlantic flow regimes

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Sharing is

encouraged

1: Ensemble Data Assimilation (EDA)

- Estimates assimilation uncertainty
- Used in the production of reanalysis data (ERA5; [1])
- Ensemble member perturbation scaled by observation uncertainty (instrument-dependent)
- Perturbation propagated by model uncertainty (state-dependent)
- Ensemble spread = assimilation

2: Change Points in Observation Uncertainty

Abrupt changes in the observation system introduce discontinuities. Change Point (CP) detection is a standard method in statistics [2]. Predicted: logarithmic ensemble variance, predictors: year and season. The following CPs minimize the Bayesian Information Criterion (BIC; 99% confidence intervals shaded).

North Atlantic monthly mean g500 ensemble variance



uncertainty = observation uncertainty + model uncertainty

Can we isolate model uncertainty (short timescales) from observation uncertainty (long timescales)?

• Focus on North Atlantic g500 since observational record is long and synoptics well-researched

3: Grid-Point-Wise Observation Uncertainty

- Using change points from \rightarrow 2
- •One set of coefficients (year and season) for each segment
- One linear statistical model per grid point [3] • Daily data

Statistical models account for substantial amount of variability. Uncertainty used to be largest in Arctic/Northern Atlantic, now rather evenly spread.



4: Weather Regimes Uncertainty



- •Weather Regimes from [4]; green contours show z every 100 gpdm
- Red-blue shading shows composite mean residual (model uncertainty) obtained from the statistical models from \rightarrow 3
- •Only grid points with false discovery rate (FDR)-adjusted [5] pvalue < 5% according to 10,000 permutation tests on the regime life cycle series are shown



High pressure/blocked regions are associated with decreased model uncertainty. Increased model uncertainty especially at large gradients and jet exits.

5: Outlook

- Understand patterns and find processes responsible for higher/lower model uncertainty
- Investigate other variables and other layers; especially w.r.t. moist processes • Estimate model uncertainty using more complex (smooth) statistical models • Understand (regionally varying) seasonal cycle of observation uncertainty

References

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