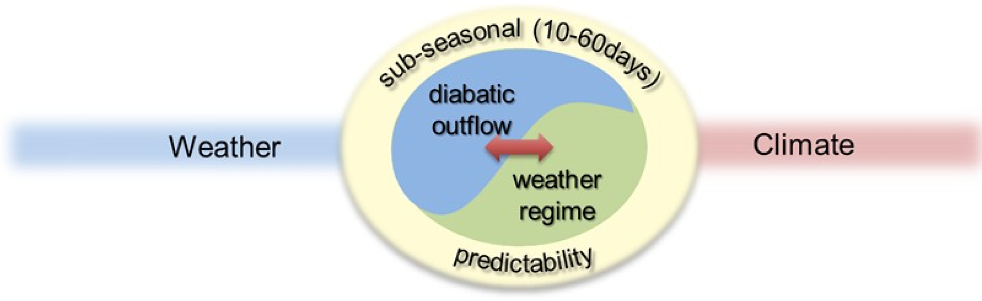
Helmholtz Young Investigator Group VH-NG-1243: "**S**ub-seasonal **PRE**dict**A**bility: understanding the role of **D**iabatic **OUT**flow" (SPREADOUT)



HELMHOLTZ
RESEARCH FOR GRAND CHALLENGES

Deep Learning for the Verification of Warm Conveyor Belts in NWP and Climate Models

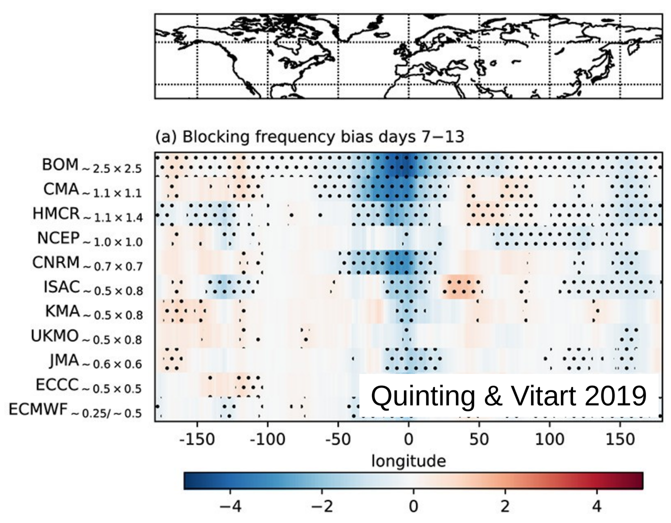
Julian F. Quinting[1] and Christian M. Grams[1]

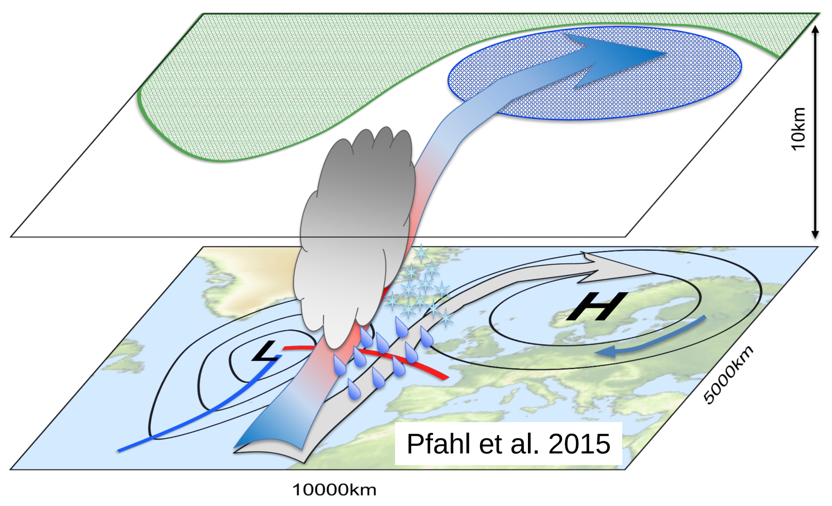
(1) Institute of Meteorology and Climate Research, Department Troposphere Research (IMK-TRO), Karlsruhe Institute of Technology

MOTIVATION

- blocking over Atlantic-European sector underestimated in NWP and climate models
- diabatic heating in warm conveyor belts (WCBs) affects life cycle of blocking

Does a misrepresentation of WCBs explain blocking biases in NWP and climate models?





PROBLEM

How to verify WCBs systematically in NWP and climate models?

WCB identification requires trajectory calculations based on data at a high spatio-temporal resolution.

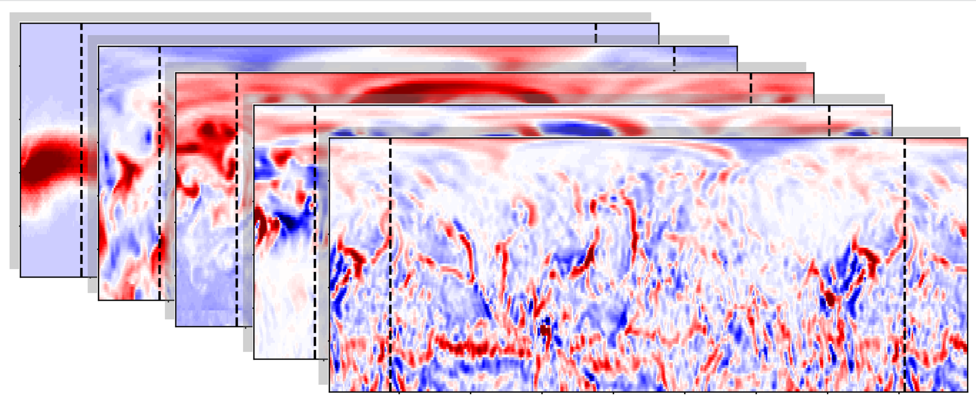
Data	ERA-INTERIM	S2S data base
- amount	~ 58,400 time steps	~ 6,439,356 time steps
- availability	Grid spacing: 1° at 61 vertical model levels Temporal availability: 6-hourly	Grid spacing: 1.5° at 10 pressure levels Temporal availability: 24-hourly

Trajectory calculation ✓ | Trajectory calculation ✗

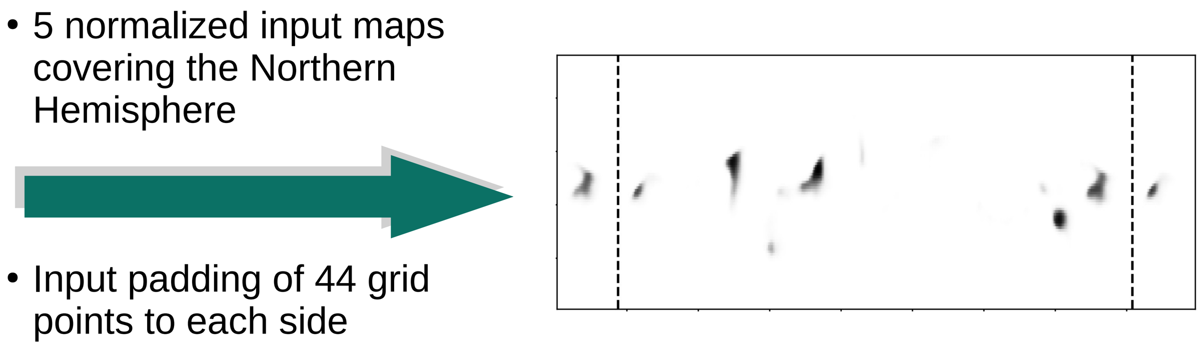
Use CNN image segmentation to identify WCB objects from Eulerian fields!

MODEL DEVELOPMENT

- UNET-CNN (Ronneberger et al. 2015) with ReLu activation, Adam optimization, binary cross entropy loss and hyperparameters in Table 2
- predictand y: binary fields (0/1 flag) for WCB inflow, ascent and outflow derived from Lagrangian WCB climatology (Madonna et al. 2014)
- predictor x: dynamical quantities on pressure levels; optimal predictors are due to Quinting and Grams (2020)



- 5 normalized input maps covering the Northern Hemisphere
- Input padding of 44 grid points to each side

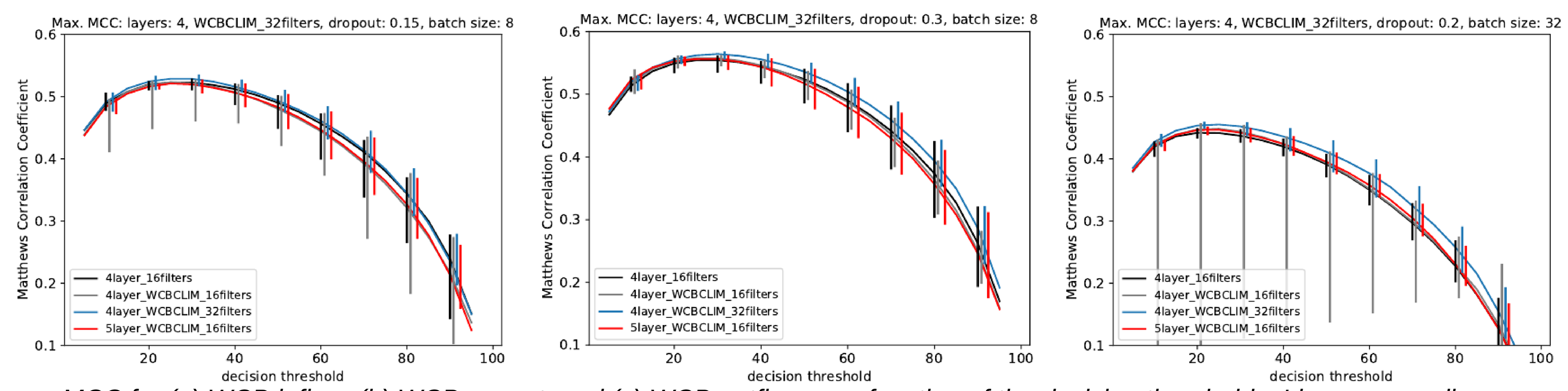


Dataset	Time period
Training	1 Jan 1980 – 31 Dec 1999
Validation	1 Jan 2000 – 31 Jan 2004
Testing	1 Jan 2005 – 31 Dec 2016

Table 1. Temporal coverage of training, validation and testing data for CNN.

Hyperparameter	Values
Number of filters/layers	16/4, 16/5, 32/4
Batch size	8, 16, 32, 64
Dropout fraction	0.05, 0.1, 0.15, 0.2, 0.25, 0.3

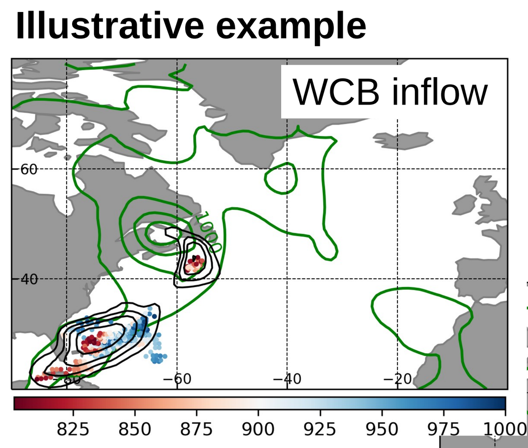
Table 2. Parameters that are used to find the best model setup according to the average Matthew's Correlation Coefficient.



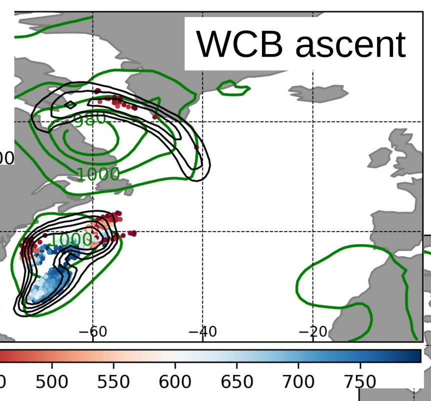
MCC for (a) WCB inflow, (b) WCB ascent, and (c) WCB outflow as a function of the decision thresholds. Lines are median over all experiments with varied dropout fraction and batch size, error bars denote their minimum and maximum values.

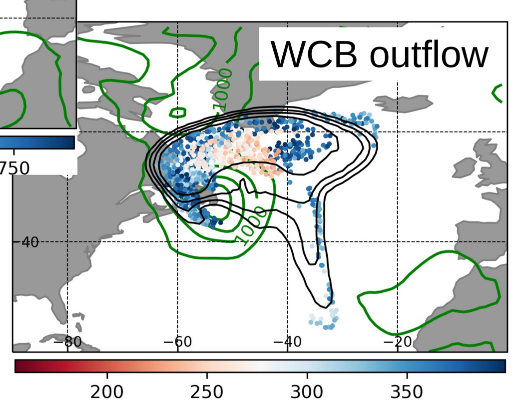
MODEL EVALUATION

Illustrative example



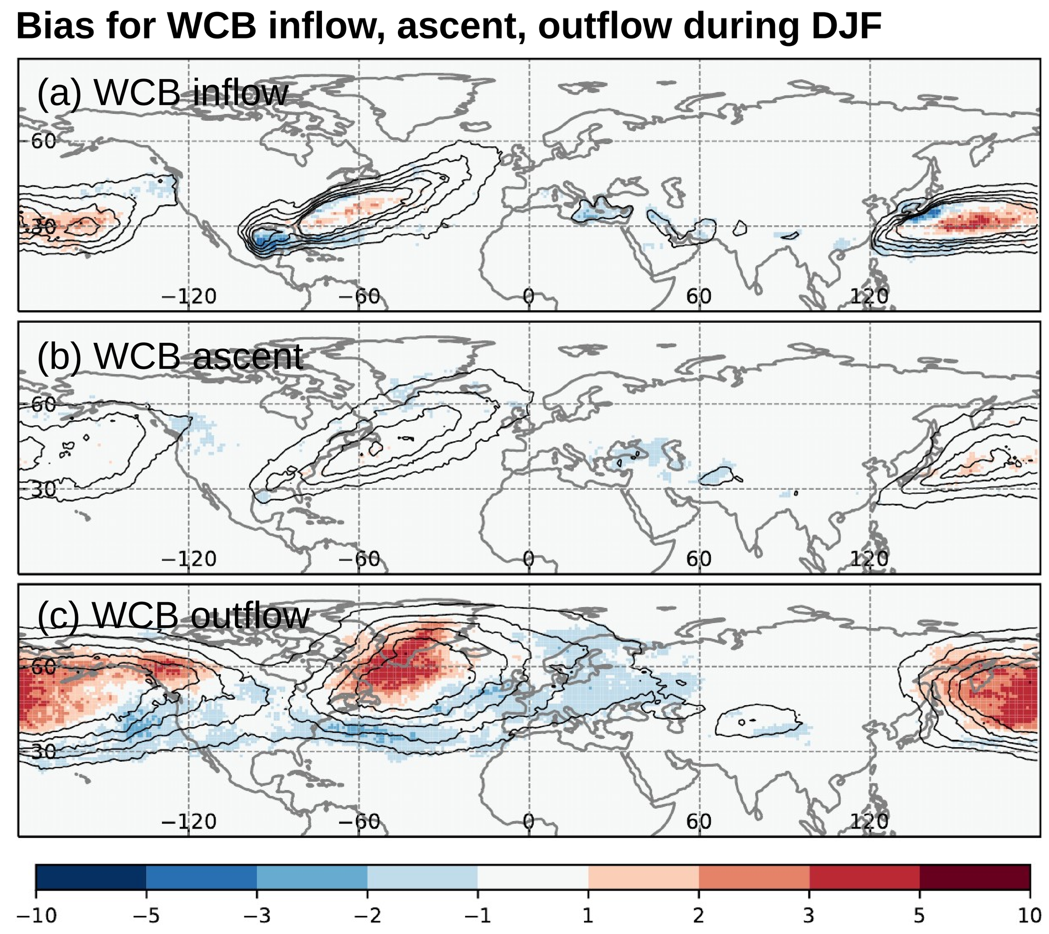
CNN-based models skillfully identify trajectory-based footprints of WCB inflow, ascent and outflow. Using fewer data and less computational time, the models can be applied to large data sets such as ensemble reforecast and climate projections).





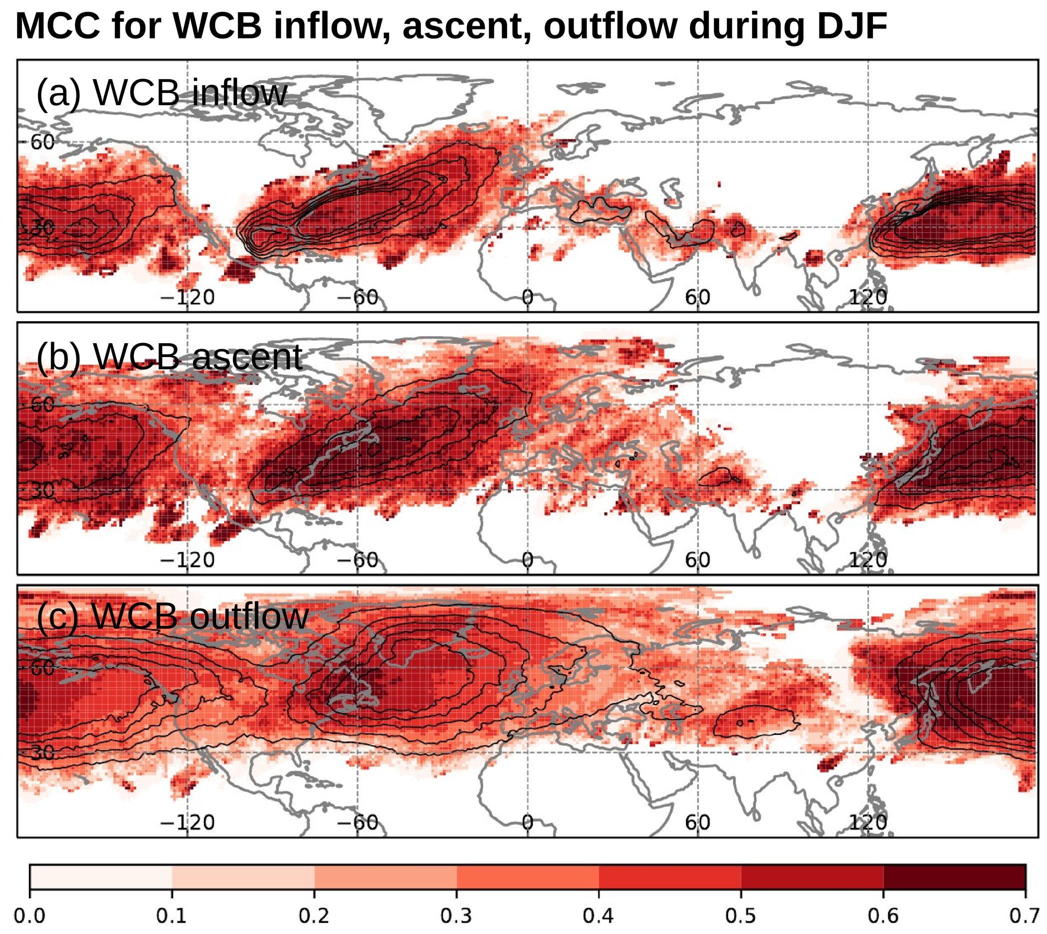
- Sea level pressure
- WCB probability predicted by CNN
- WCB air parcel locations colored by height (hPa)

Bias for WCB inflow, ascent, outflow during DJF



Climatological bias (shading) for (a) WCB inflow, (b) ascent, and (c) outflow. Contours denote climatological WCB frequency at intervals of 2%.

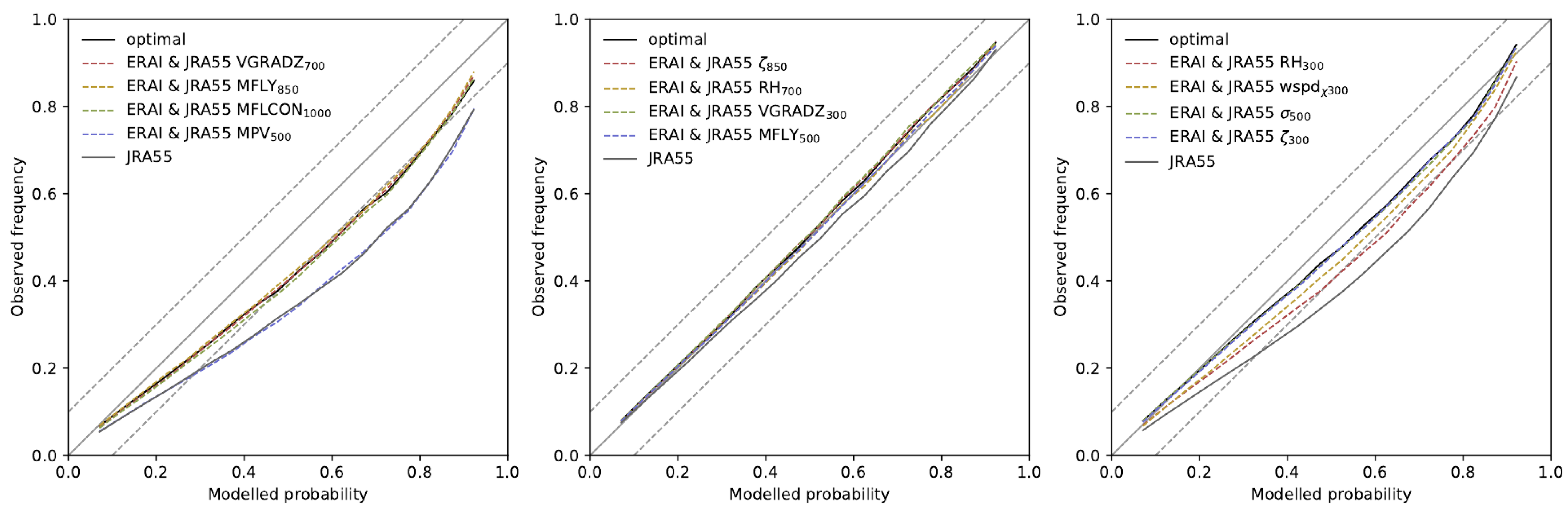
MCC for WCB inflow, ascent, outflow during DJF



MCC (shading) for (a) WCB inflow, (b) ascent, and (c) outflow. Contours denote climatological WCB frequency at intervals of 2%.

PROCESS UNDERSTANDING

Reliability of CNN models deteriorates considerably when being applied to JRA55 reanalysis data. Permutation feature importance helps to identify predictors that cause the lower reliability. **Could this approach be used to identify erroneous predictors in NWP systems?**



Reliability diagrams for (a) WCB inflow, (b) ascent, and (c) outflow. Black curve denotes ERA-Interim based reliability, gray curve JRA55 based reliability.

OUTLOOK

- use models as a diagnostic to verify the representation of WCB inflow, ascent, and outflow in NWP and climate models
- develop error framework to identify erroneous predictor variables in NWP models
- linkage of WCB and blocked weather regimes

References: Madonna et al. (2014). Warm Conveyor Belts in the ERA-Interim Dataset (1979–2010). Part I: Climatology and Potential Vorticity Evolution. J. Climate | Pfahl et al. (2015). Importance of latent heat release in ascending airstreams for atmospheric blocking. Nat. Geosci. | Quinting & Vitart (2019). Representation of synoptic-scale Rossby wave packets and blocking in the S2S prediction project database. GRL | Ronneberger et al. (2015). U-net: Convolutional networks for biomedical image segmentation. MICCAI | Quinting & Grams (2020). Towards a systematic evaluation of warm conveyor belts in NWP and climate models. Part I: Predictor selection and logistic regression model. JAS (in revision)

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