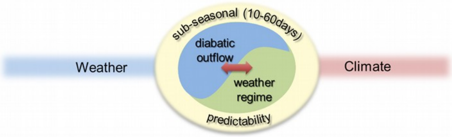
*Helmholtz Young Investigator Group VH-NG-1243: "**S**ub-seasonal **PRE**dict**A**bility: understanding the role of **D**iabatic **OUT**flow" (SPREADOUT)*



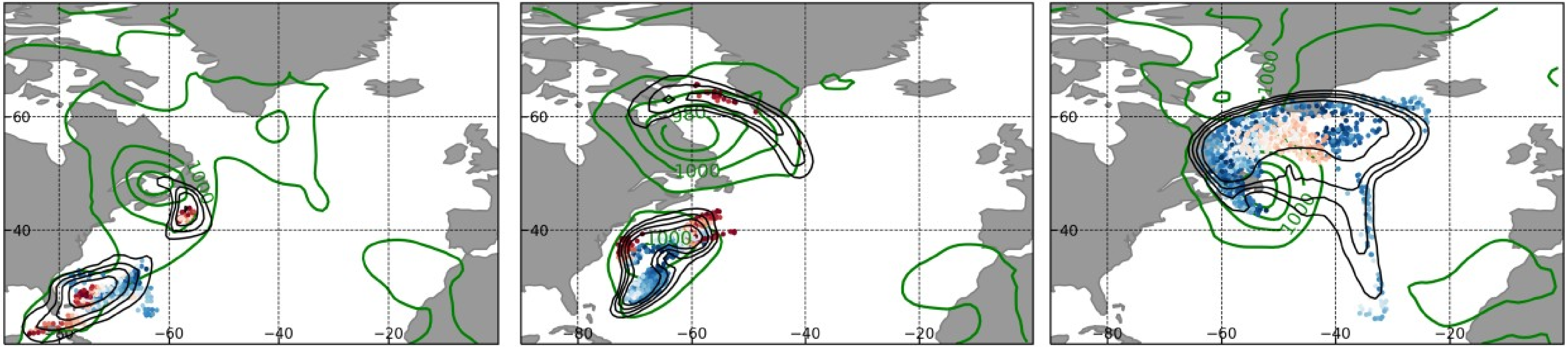
Karlsruhe Institute of Technology

HELMHOLTZ
RESEARCH FOR GRAND CHALLENGES

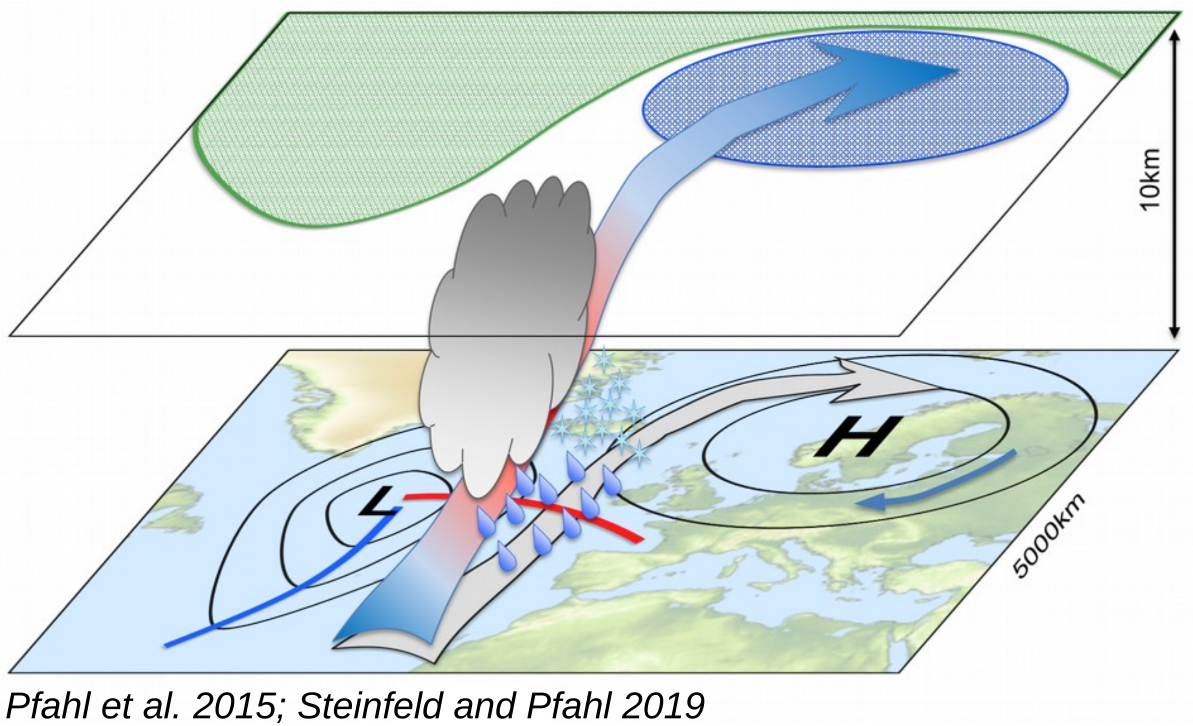
Deep Learning for the Verification of Synoptic-scale Processes in NWP and Climate Models

Julian F. Quinting[1] , Christian M. Grams[1] and Jan Wandel[1]

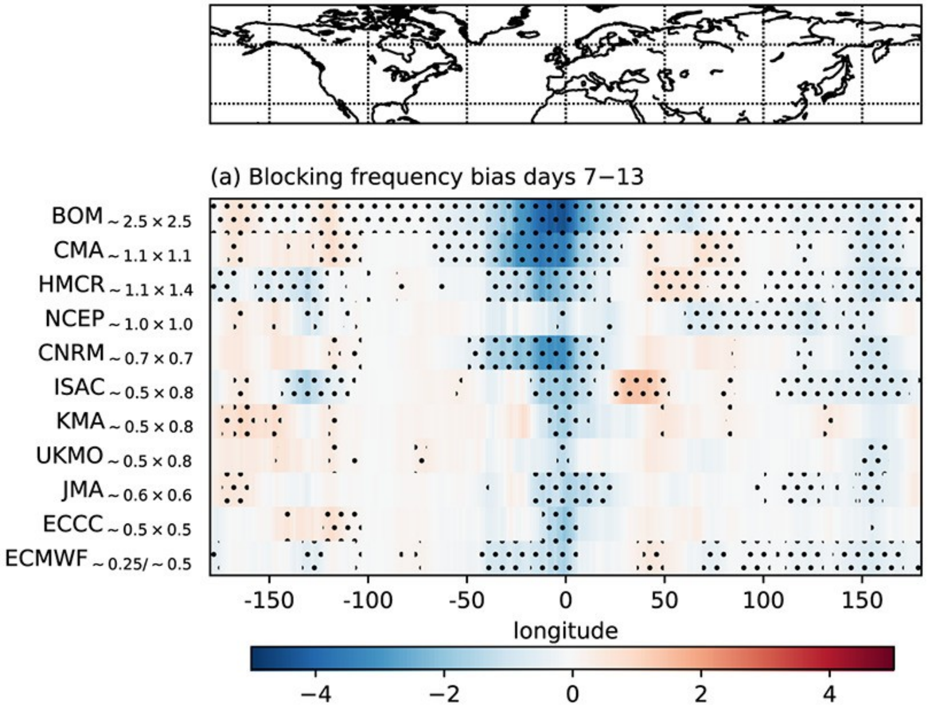
[1]Institute of Meteorology and Climate Research, Karlsruhe Institute of Technology, Germany (julian.quinting@kit.edu)



WCBs affect lifecycle of blocking and blocking regimes



Pfahl et al. 2015; Steinfeld and Pfahl 2019



Quinting and Vitart 2019

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

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

Data	**ERA-INTERIM**
amount	~ 58,400 time steps
availability	Grid: 1° at 61 vertical model levels Temporal availability: 6-hourly

Trajectory calculation

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: 1° at 61 vertical model levels Temporal availability: 6-hourly	Grid: 1.5° at 10 pressure levels Temporal availability: 24-hourly

Trajectory calculation ✅

Trajectory calculation ❌

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

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amount	~ 58,400 time steps	~ 6,439,356 time steps
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Trajectory calculation ✅

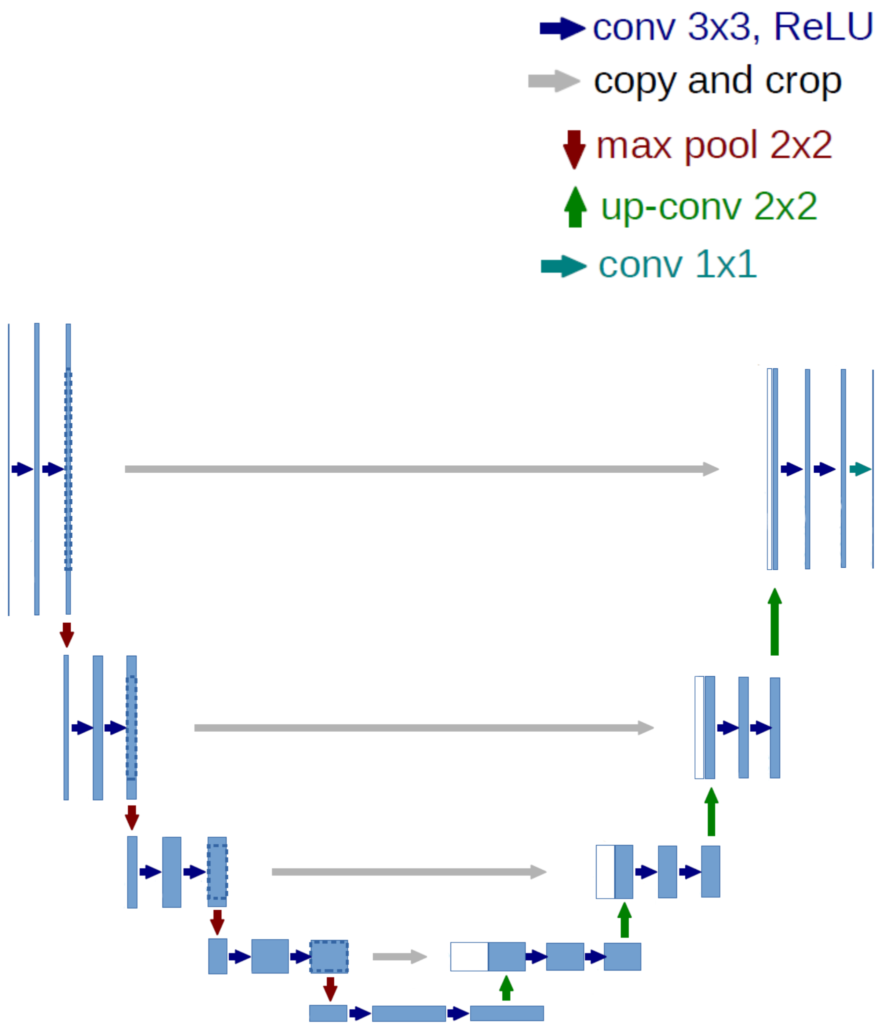
Trajectory calculation ❌

Train CNNs to identify WCB objects from routinely available fields!

UNet-type convolutional neural network

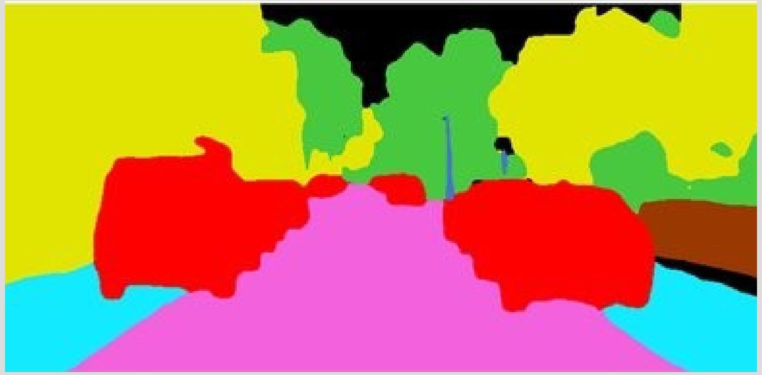
Input

RGB values of input image



Ronneberger et al. 2015

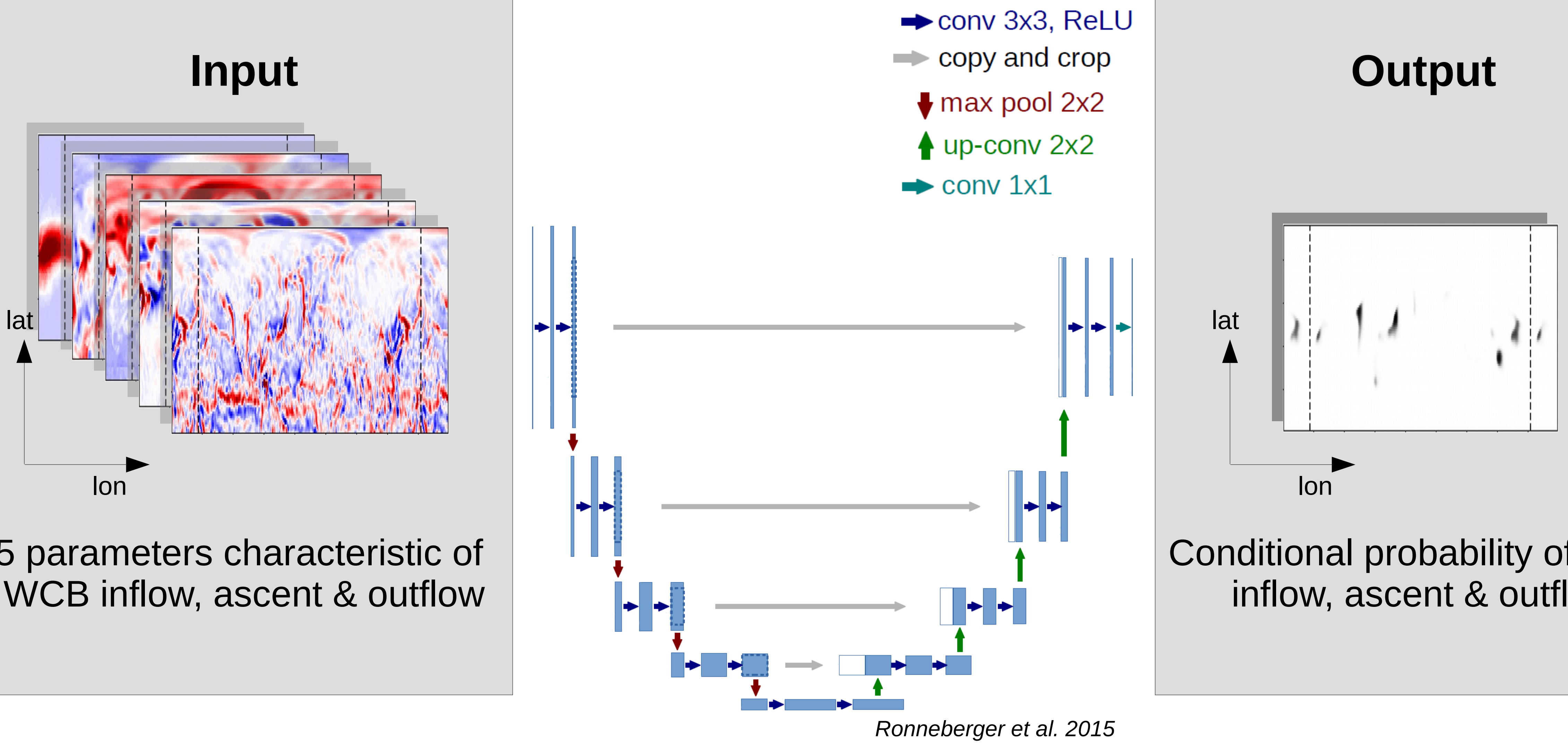
Output



Jeong et al 2018

Image partitioned into multiple image objects

UNet-type convolutional neural network



5 parameters characteristic of WCB inflow, ascent & outflow

Conditional probability of WCB inflow, ascent & outflow

Model development

- Predictand y: binary fields (0/1 flag) of WCB inflow, ascent and outflow based on ERA-I
  (*Madonna et al. 2014; Thanks to ETH Zurich Atmospheric Dynamics group for sharing the data.)*
- Predictors $x_1 ... x_n$: based on ERA-I of U, V, T, Z, Q on pressure level
  (Quinting and Grams 2020; JAS in revision)

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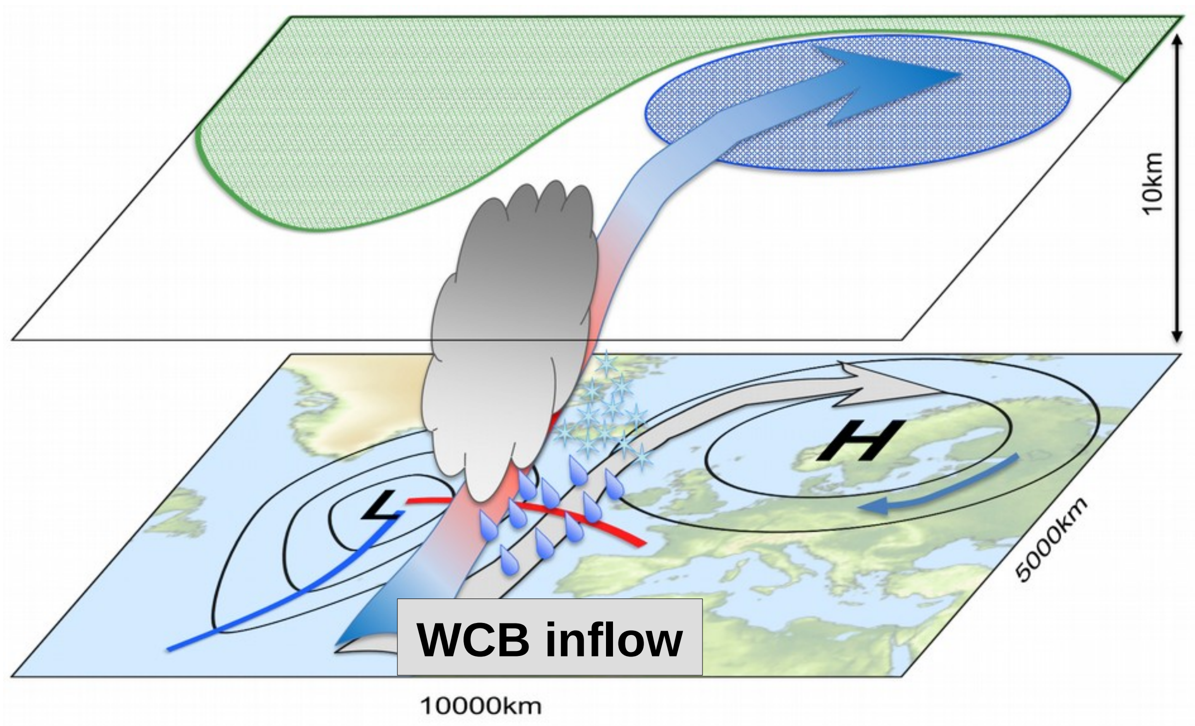

Predictors for WCB inflow
- thickness advection at 700 hPa
- meridional moisture flux at 850 hPa
- moisture flux divergence at 1000 hPa
- moist PV at 500 hPa
- climatological inflow frequency

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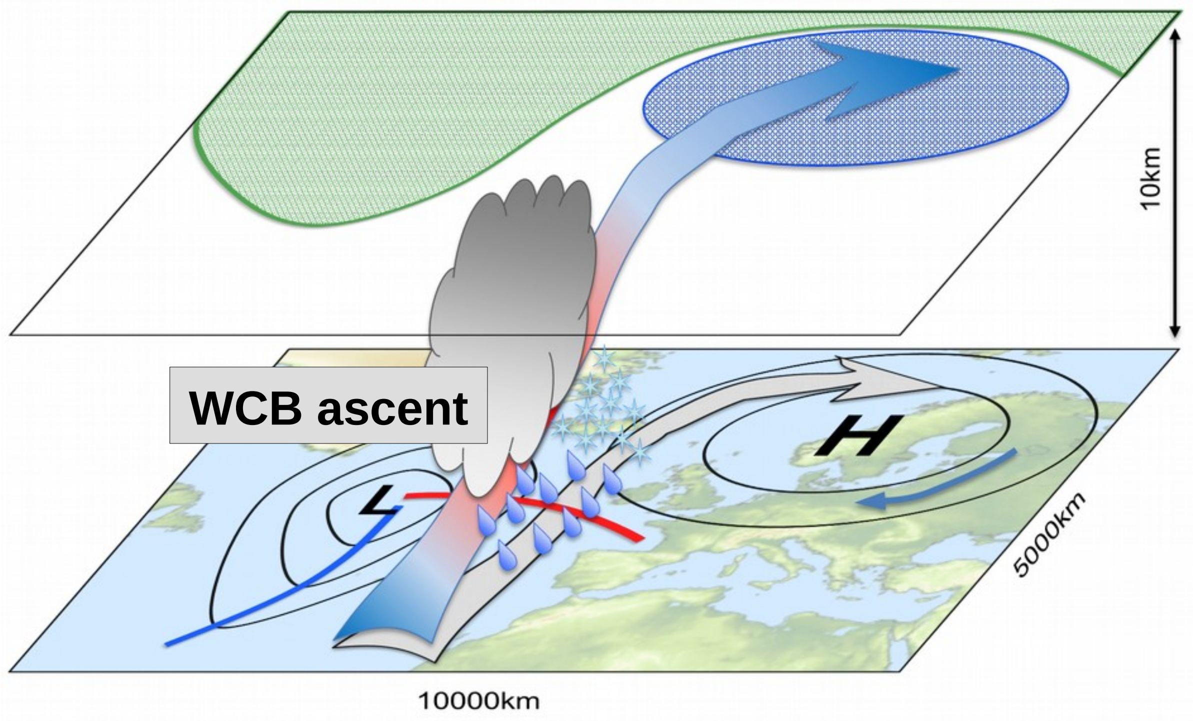
Predictors for WCB ascent
- rel. vorticity at 850 hPa
- rel. humidity at 700 hPa
- thickness advection at 300 hPa
- meridional moisture flux at 500 hPa
- climatological ascent frequency



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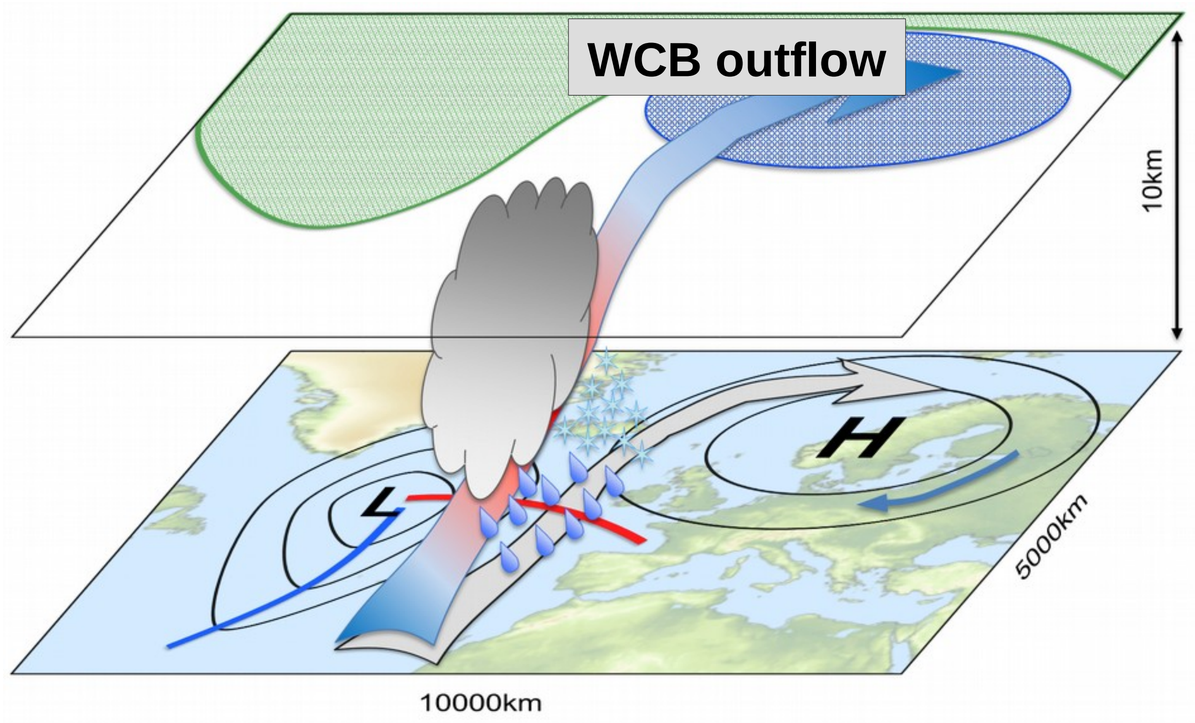
Predictors for WCB outflow
- irr. wind speed at 300 hPa
- static stability at 500 hPa
- rel. humidity at 300 hPa
- rel. vorticity at 300 hPa
- climatological outflow frequency



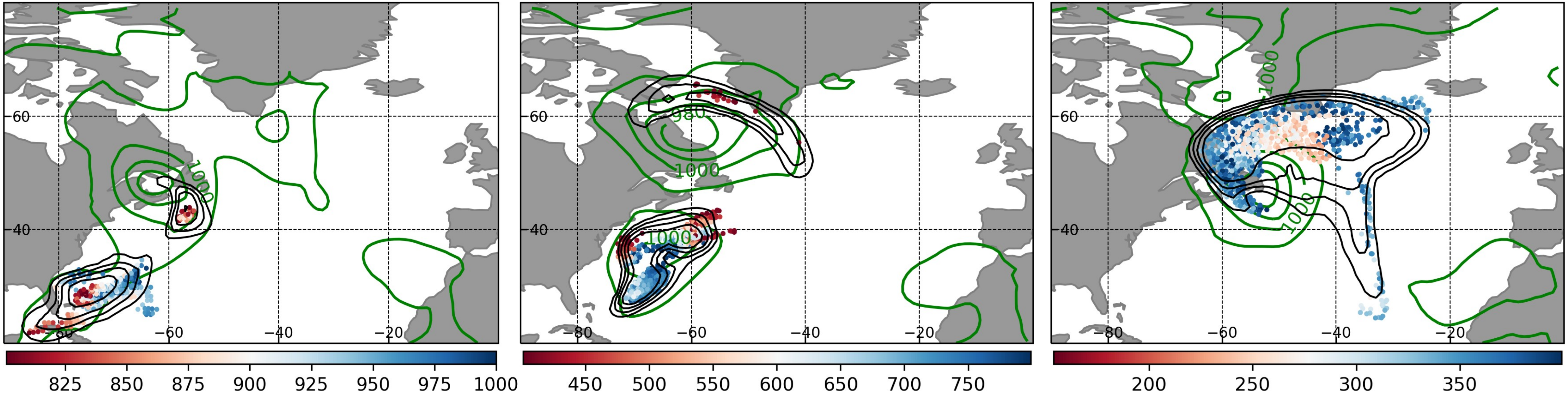
Model development

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

Testing of 72 hyperparameter concerning choice of number of filters, batch size, and dropout fraction to find the best CNN model.

Model evaluation – Case study

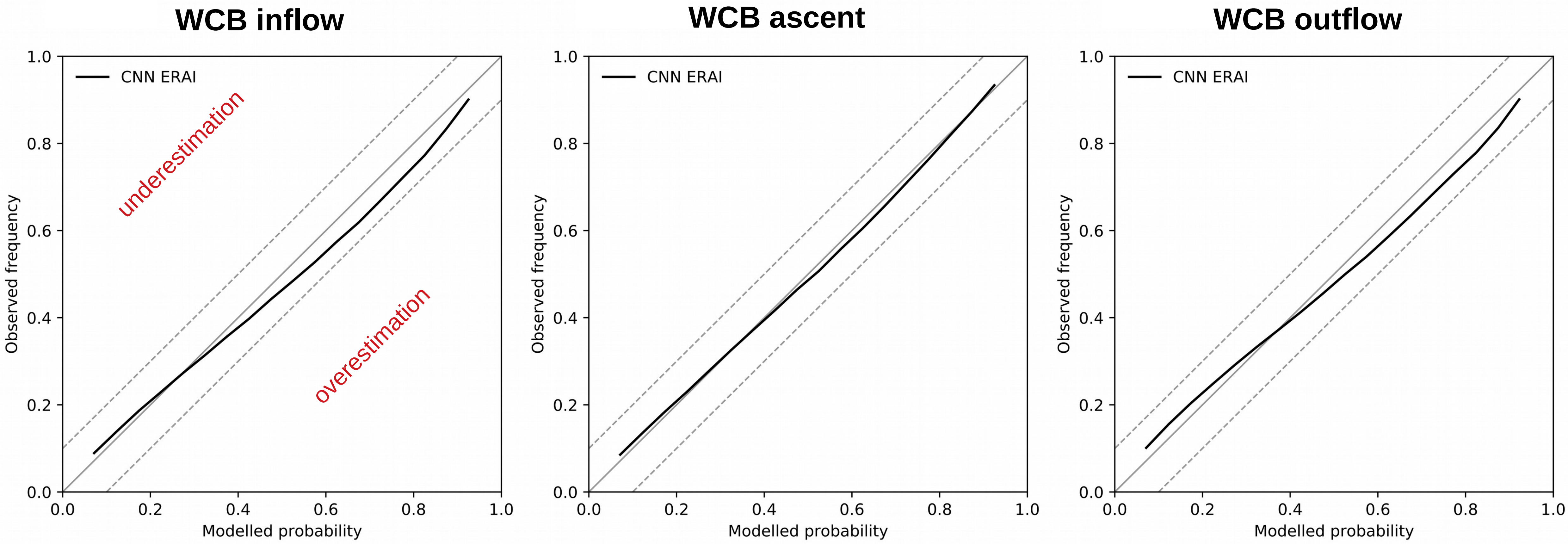
WCB inflow | **WCB ascent** | **WCB outflow**



22 January 2011 06 UTC | 23 January 2011 06 UTC | 24 January 2011 06 UTC

Sea level pressure [hPa]   WCB probability predicted by CNN   WCB air parcel locations colored by height [hPa]

Model evaluation – Reliability

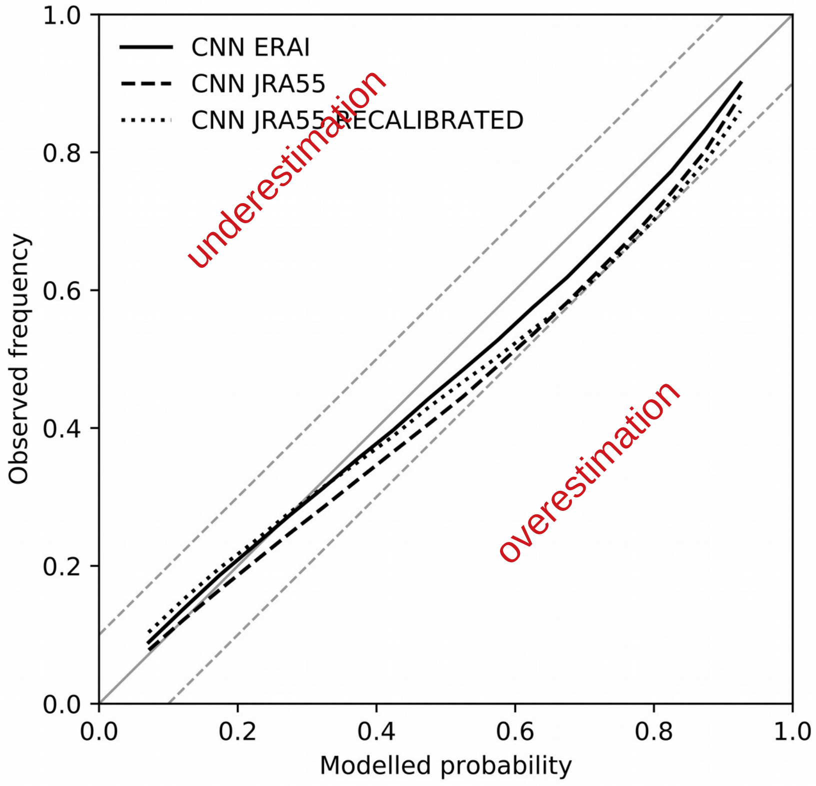


Model reliably predicts WCB frequency
Model slightly overestimates WCB frequency for probabilities > 0.4

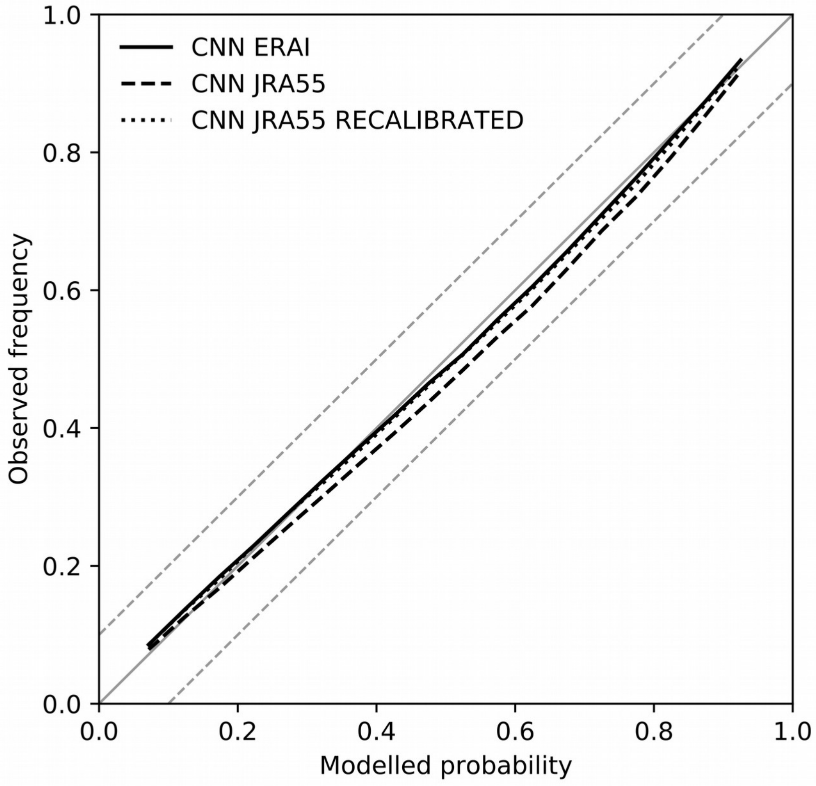
CNN ERAI = CNN model trained on ERA-I

Model evaluation – Reliability

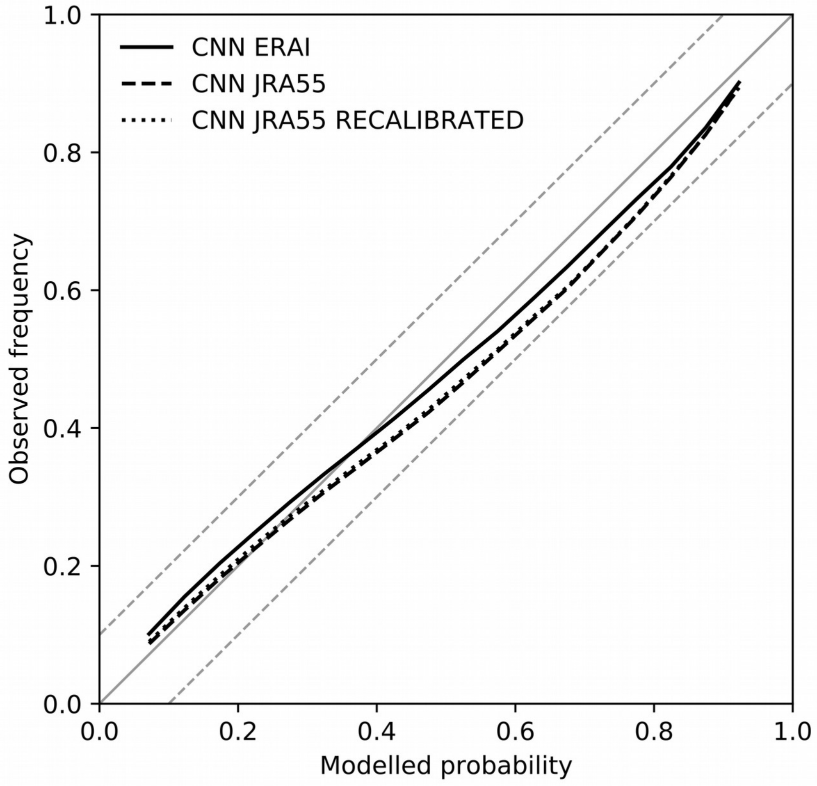
WCB inflow



WCB ascent



WCB outflow

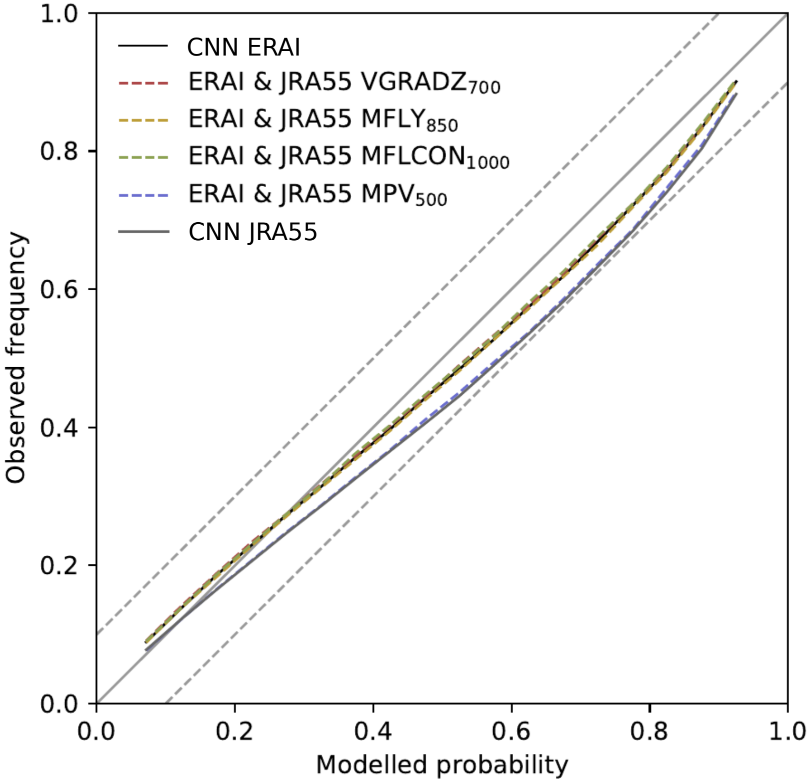


Differences in reanalysis data reduce reliability
Bias correction does not lead to improvement for inflow and outflow

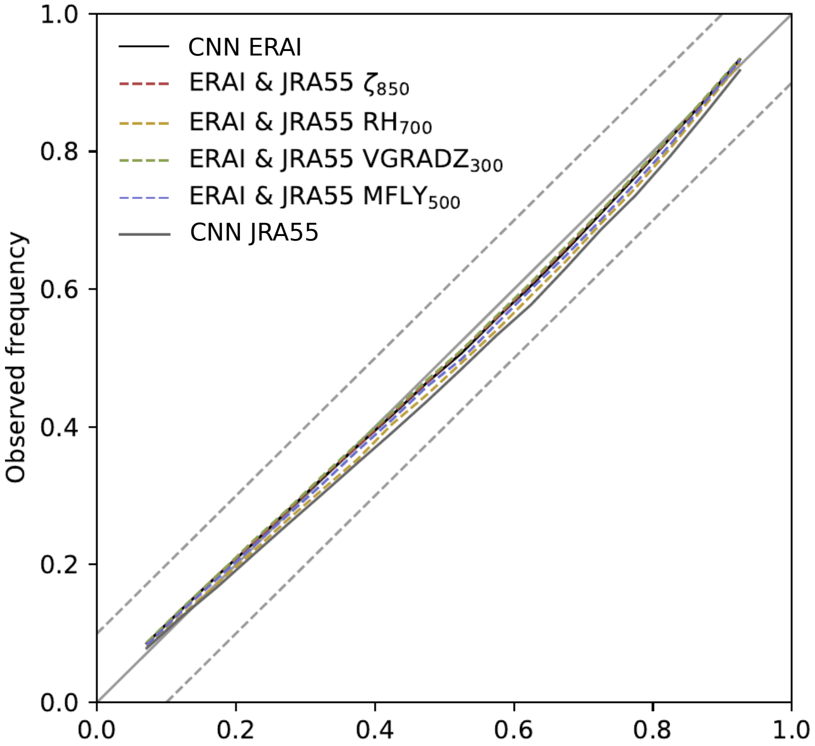
CNN ERAI = CNN model trained on ERA-I | CNN JRA55 = CNN ERAI applied to JRA55 reanalysis

Model evaluation – Reliability

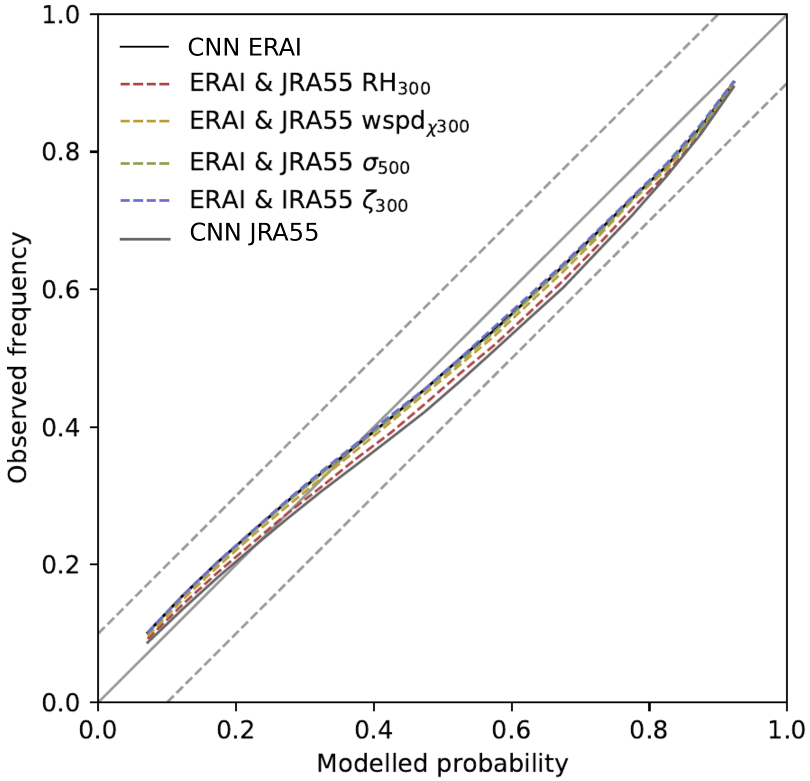
WCB inflow



WCB ascent



WCB outflow



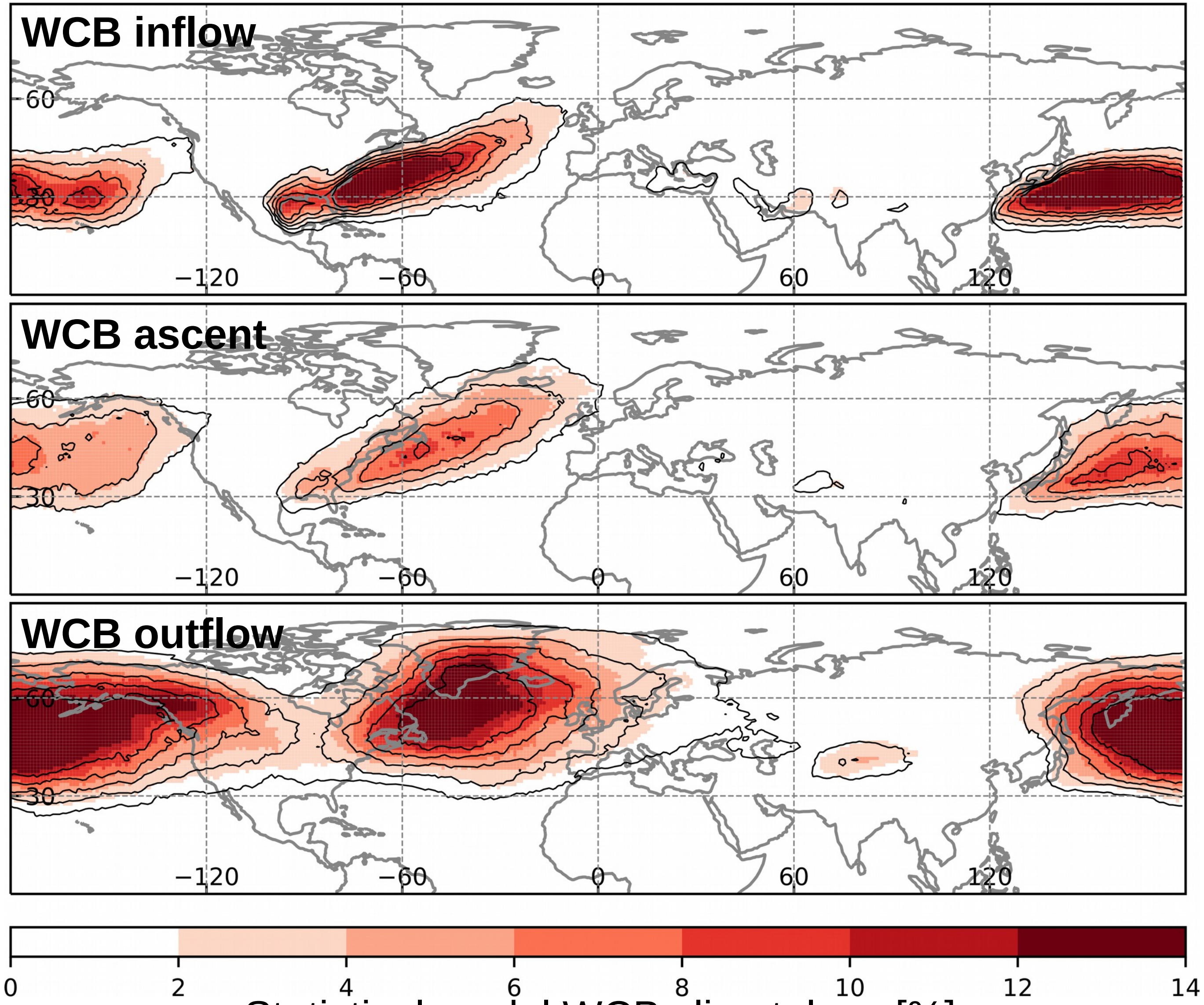
Sensitivity tests reveal predictor variables that deteriorate the reliability
The CNN model is not only a “black box”, it may be a useful error diagnostic

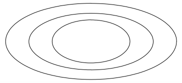
CNN ERAI = CNN model trained on ERA-I | CNN JRA55 = CNN ERAI applied to JRA55 reanalysis

Model evaluation – Climatology

Convert predicted probabilities to binary prediction by minimizing climatological bias.

By definition, climatology for WCB inflow, ascent and outflow is well reproduced.





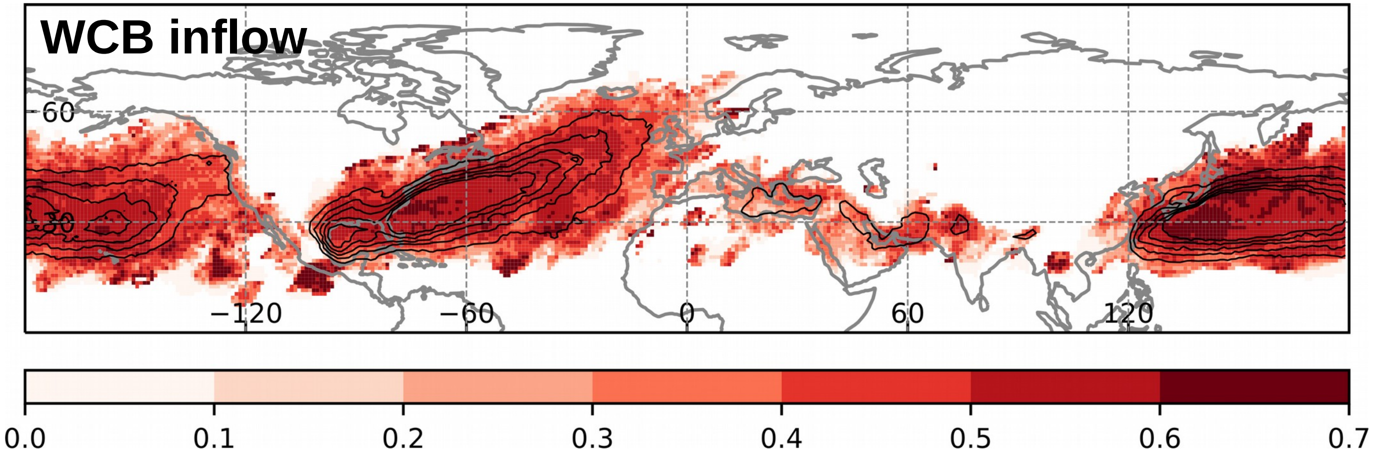
Lagrangian DJF WCB climatology

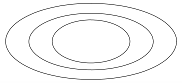
Statistical model WCB climatology [%]

Model evaluation – Matthews Correlation Coefficient

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$$

- MCC=+1 → perfect forecast
- MCC=-1 → total disagreement between forecast and observation
- useful for imbalanced data
- high score only if good results for TP, TN, FP, FN




Lagrangian DJF WCB climatology

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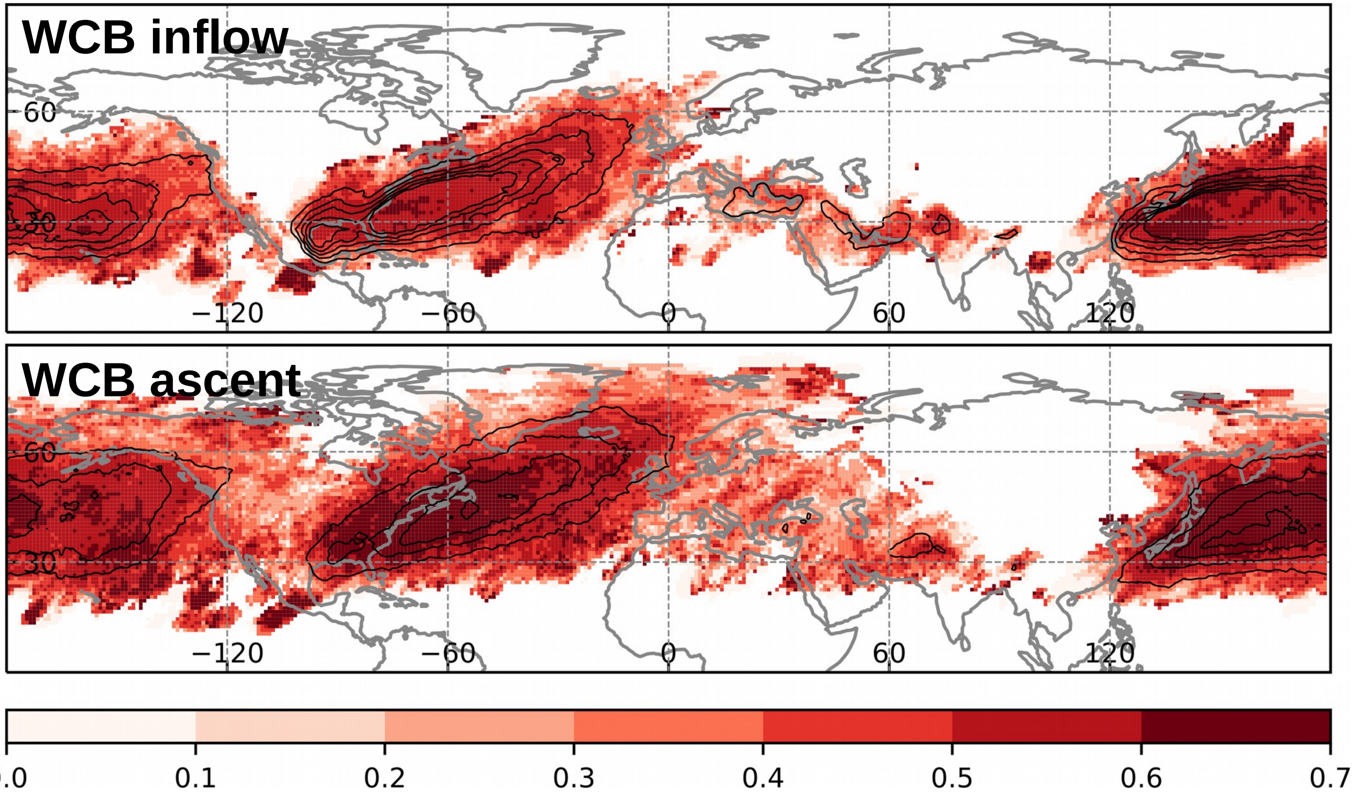

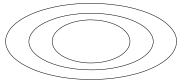

Lagrangian DJF WCB climatology

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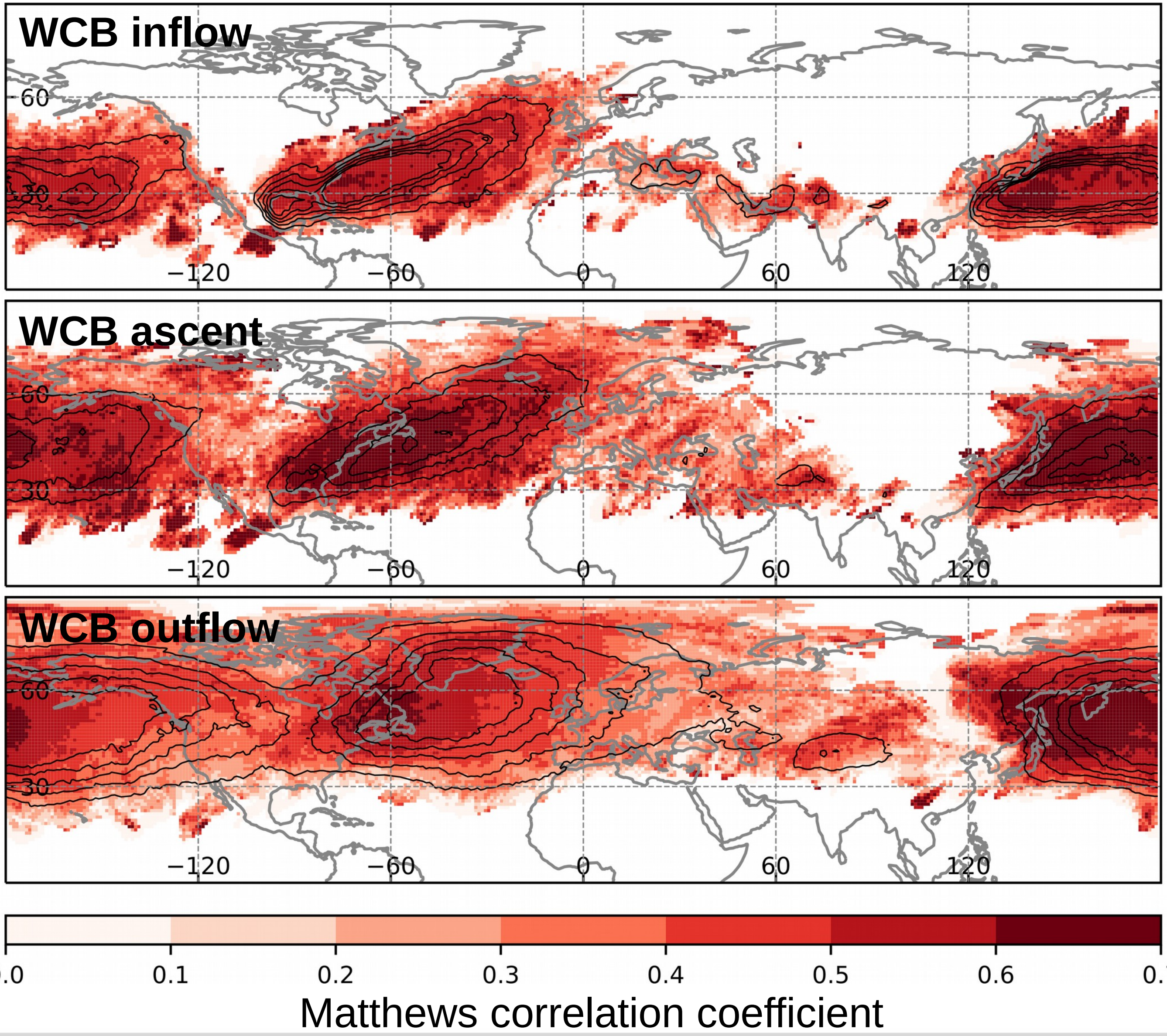

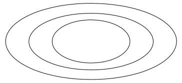

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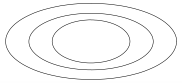
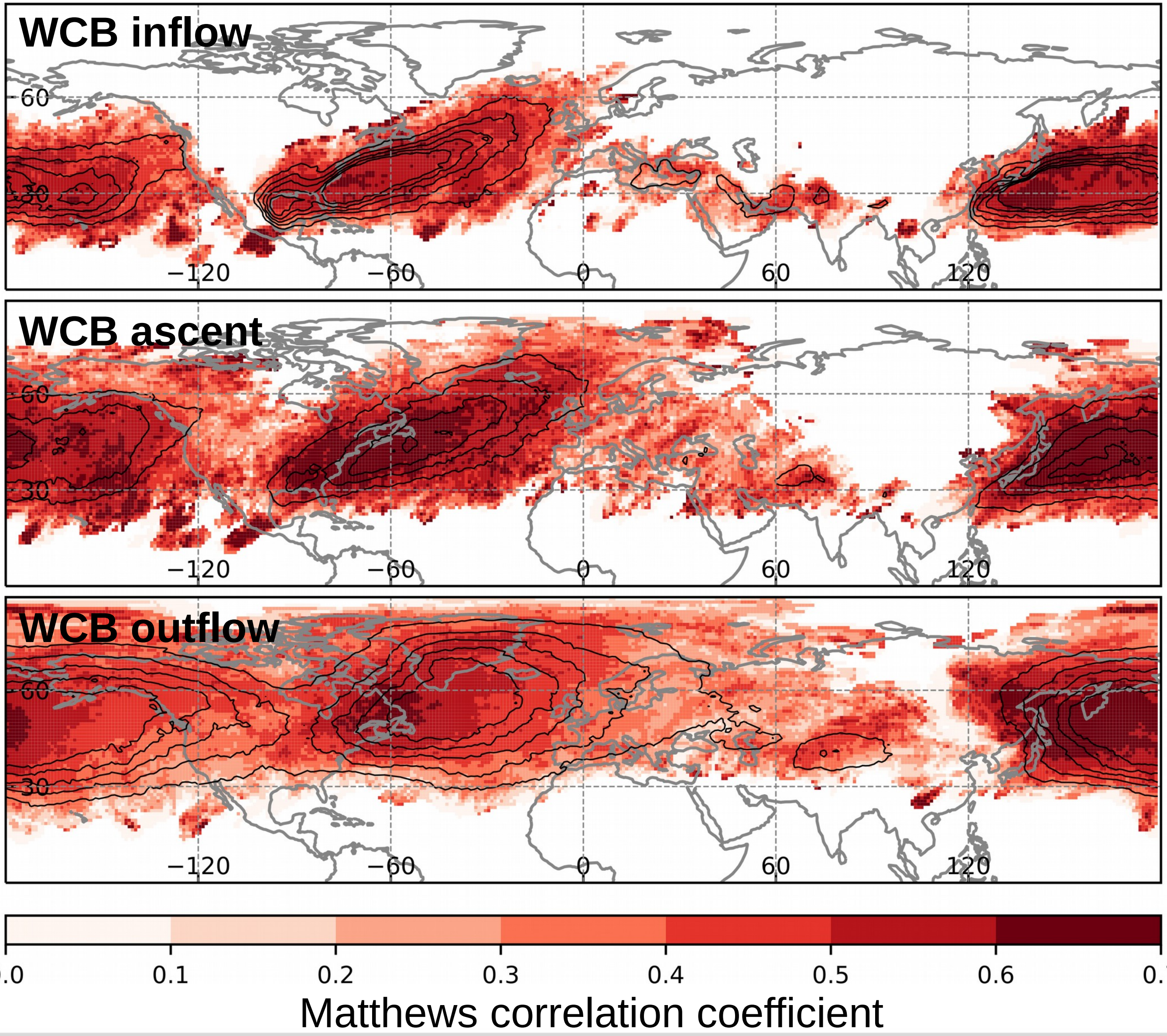
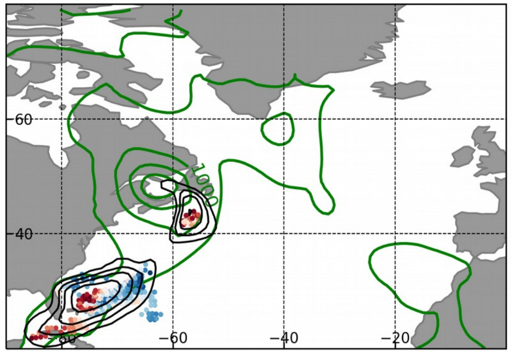
CNN Model skillfully predicts WCB occurrence in particular over the storm track regions.


Lagrangian DJF WCB climatology



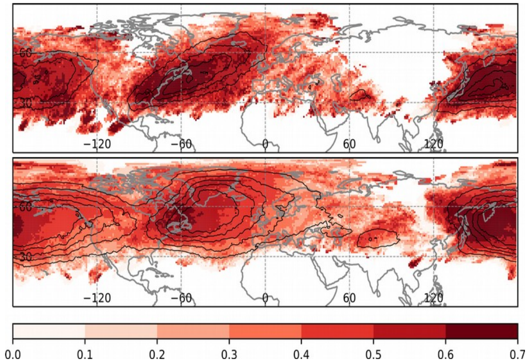
Take-home messages

First CNN-based diagnostic that identifies Lagrangian features. The approach reduces computational time by a factor of ~30.



Model skillfully identifies WCB inflow, ascent and outflow footprints.

CNN significantly outperforms previous logistic regression model.



The CNN model is not only a “black box”, it may be useful to advance process understanding