Karlsruhe Institute of Technology WAVES TO WEATHER

Identifying high-wind features within extratropical cyclones using a probabilistic random forest

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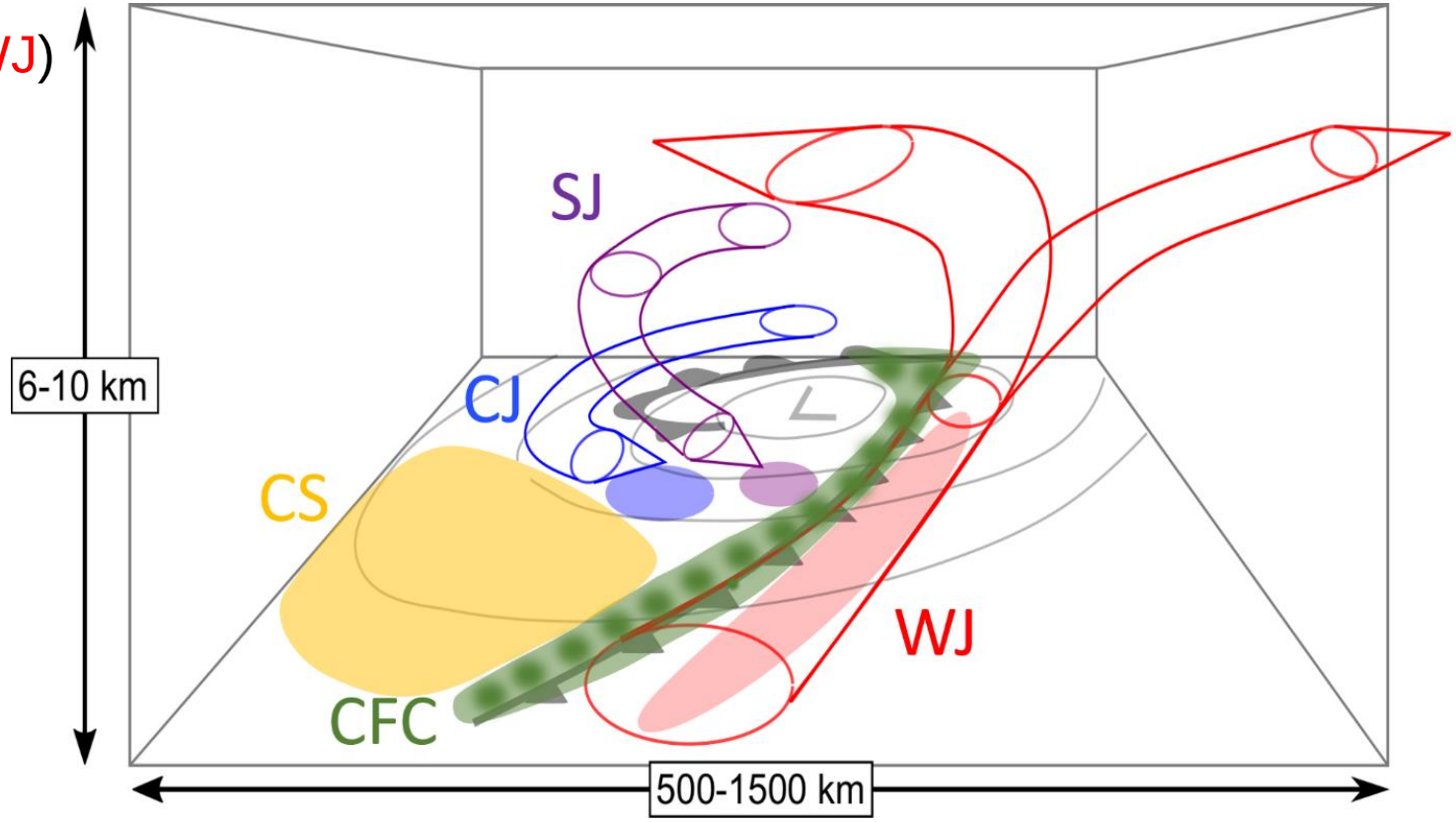
Causes of high winds

- Warm conveyor belt jet (warm jet, WJ)
- Cold conveyor belt jet (cold jet, CJ)
- Sting jet (SJ)
- Cold frontal convective gusts (CFC)
- Cold sector winds (CS)

Differ in location, timing and other characteristics (e.g. Hewson and Neu; 2015)

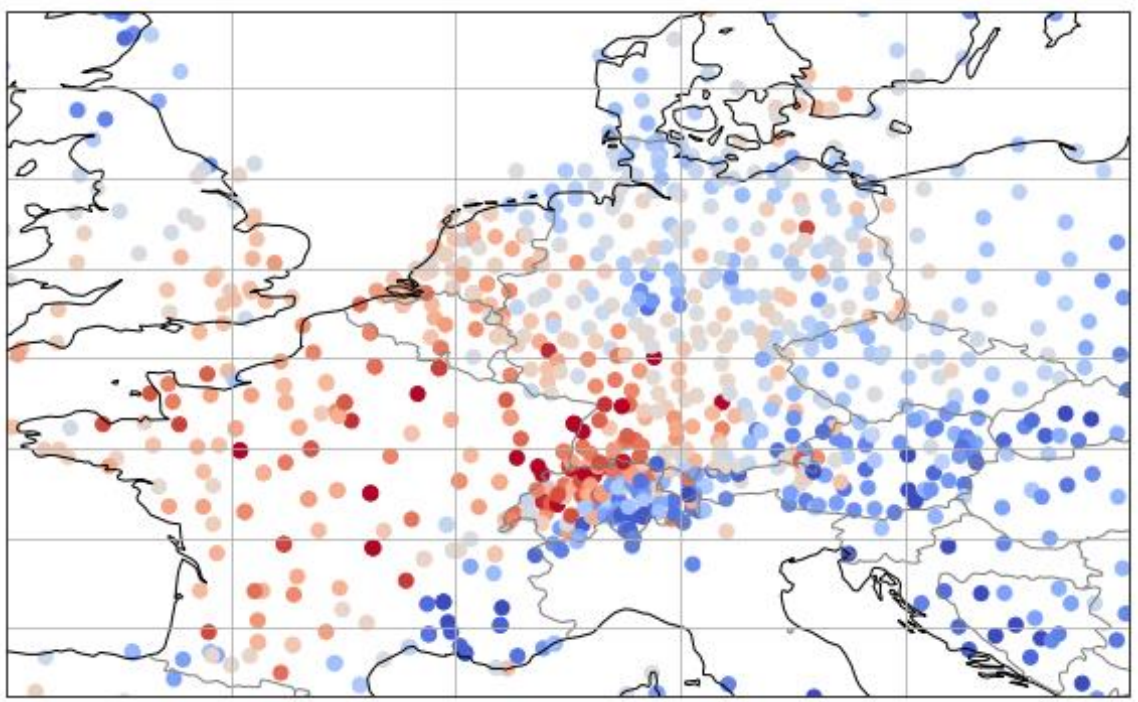
→Do forecast error also differ?

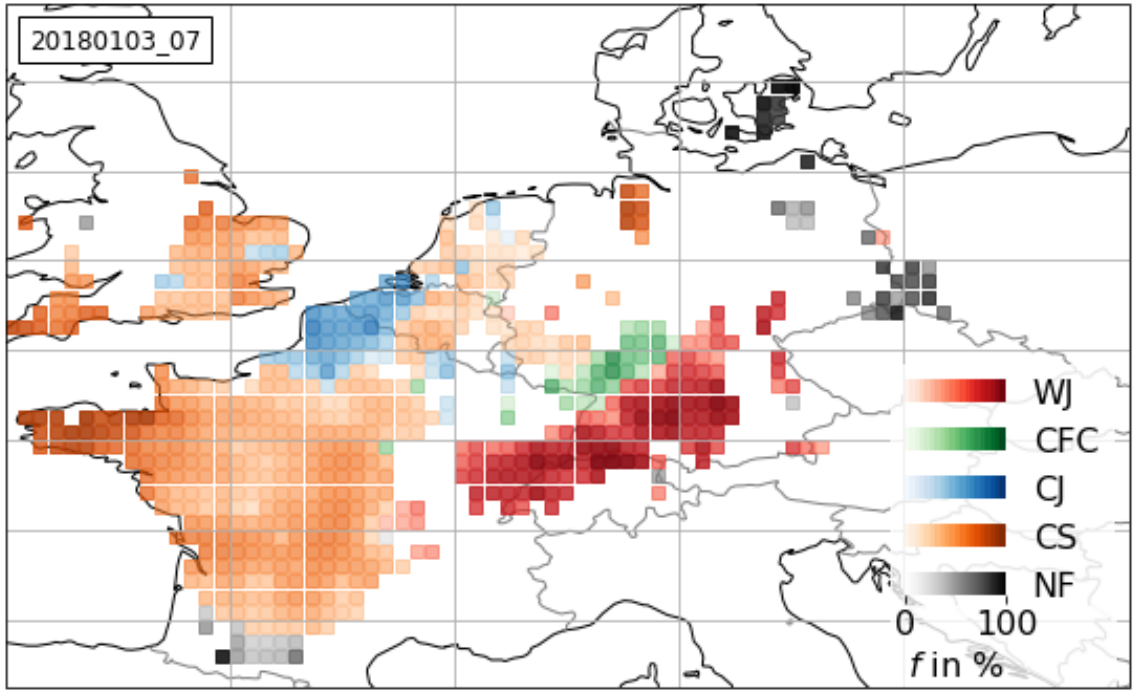
→Can feature-dependent post-processing improve the forecast?



Eisenstein et al. (2022) preprint, WCDD, Fig. 1; adapted from Clark and Gray (2018), Fig. 7

Goal





$v/v_{98} < 0.8$ $v/v_{98} \geq 0.8$

- Find the cause of high wind speeds at a single station at a given time step

  → independent of space (resolution, gradients, etc.) and temporal evolution (of more than 1h)

Subjective Identification → Probabilistic Random Forest → Kriging

Data

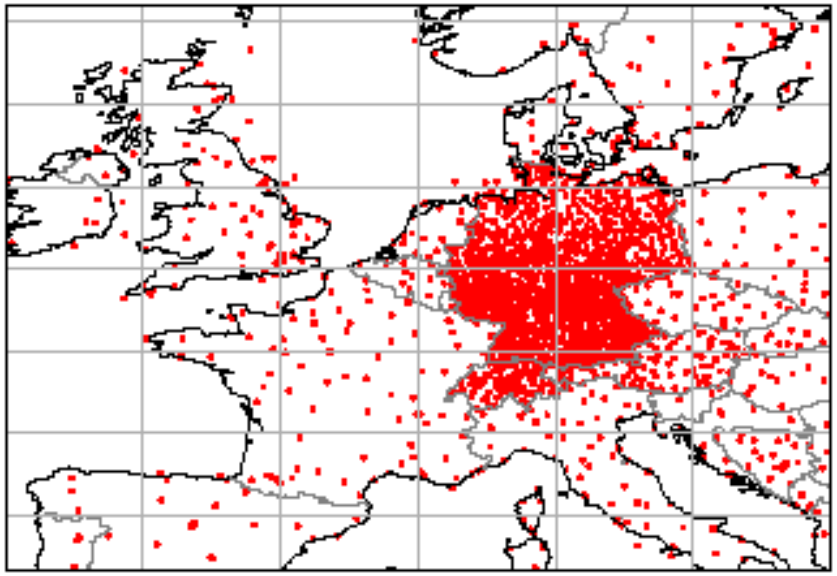
- Dataset of **hourly surface observations** (2001 – 2020):
  - Mean-sea level pressure (*p*), temperature, precipitation (*RR*), wind speed (*v*) and wind direction (*d*)

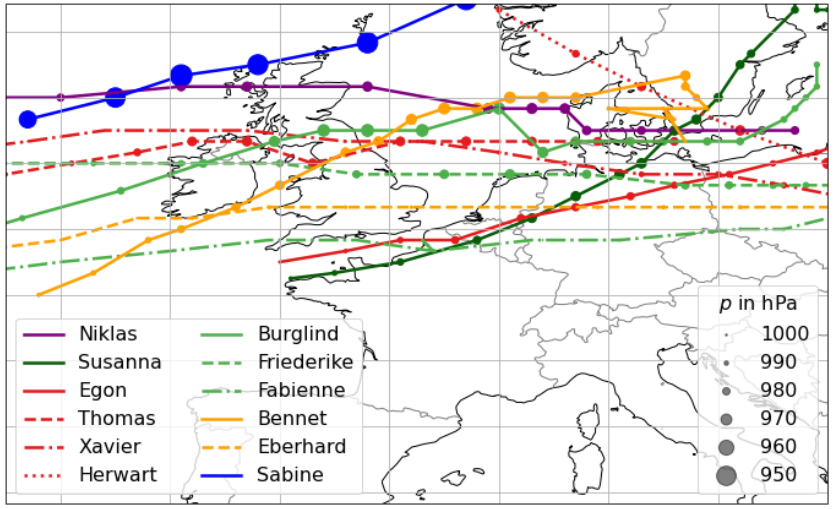
  →Computation of potential temperature θ

  →Normalising θ and v by the median and 98th percentile, respectively

  →Calculating tendencies ($\Delta x = x_0 - x_{-1h}$) for *p*, θ and *d*
- COSMO-REA6 (6km grid-spacing over Europe, 1995 – 2019)
  - Same parameters

→ 12 case studies (2015 – 2020)





Interactive identification

How does a meteorologist identify dynamical features with their synoptic knowledge?

→ Building an interactive tool to select feature areas by hand

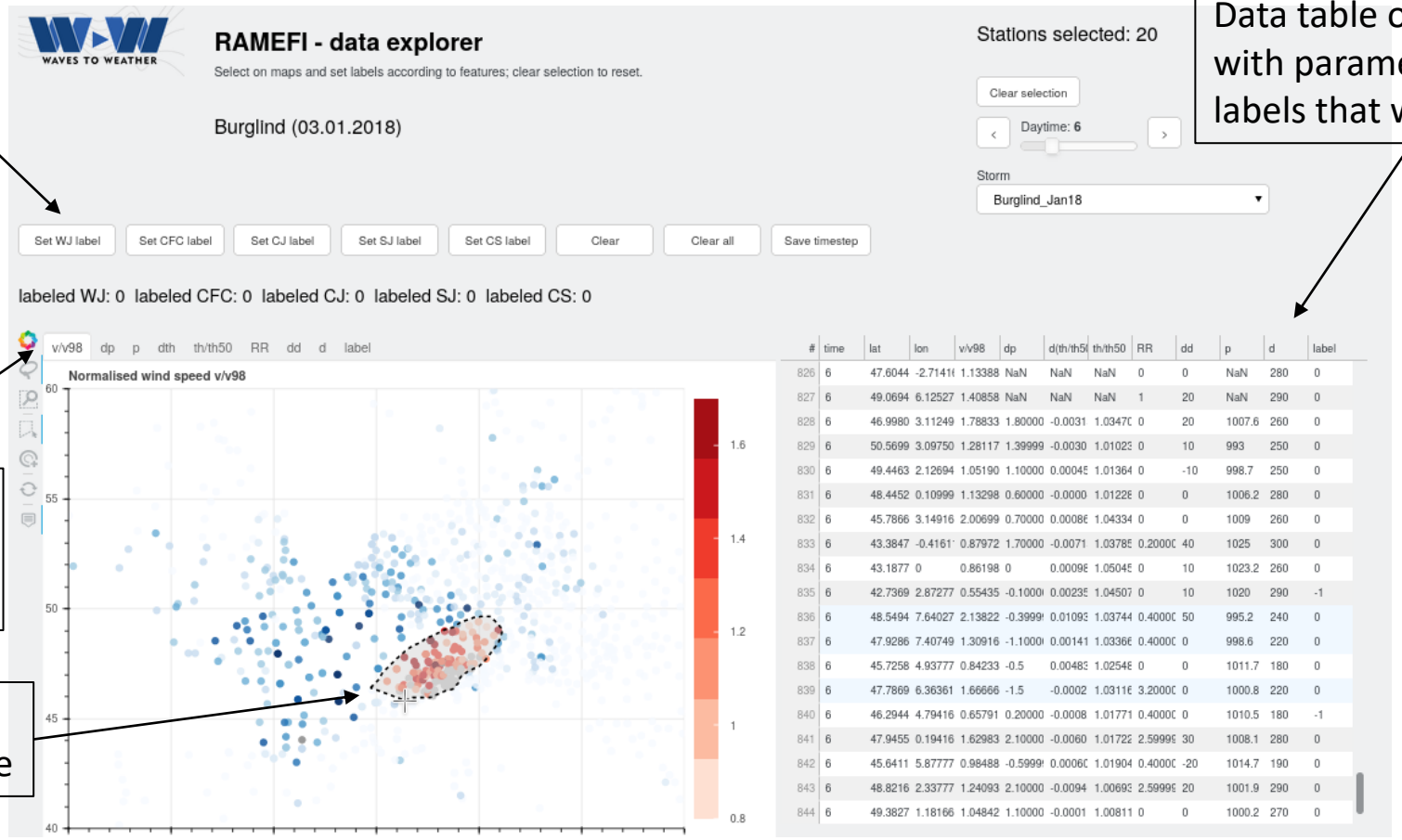
Set label of selected stations in the table to a specific feature

Data table of all stations with parameters and set labels that will be saved

Code available at
10.5281/zenodo.6541303

Choose which variable you want to see

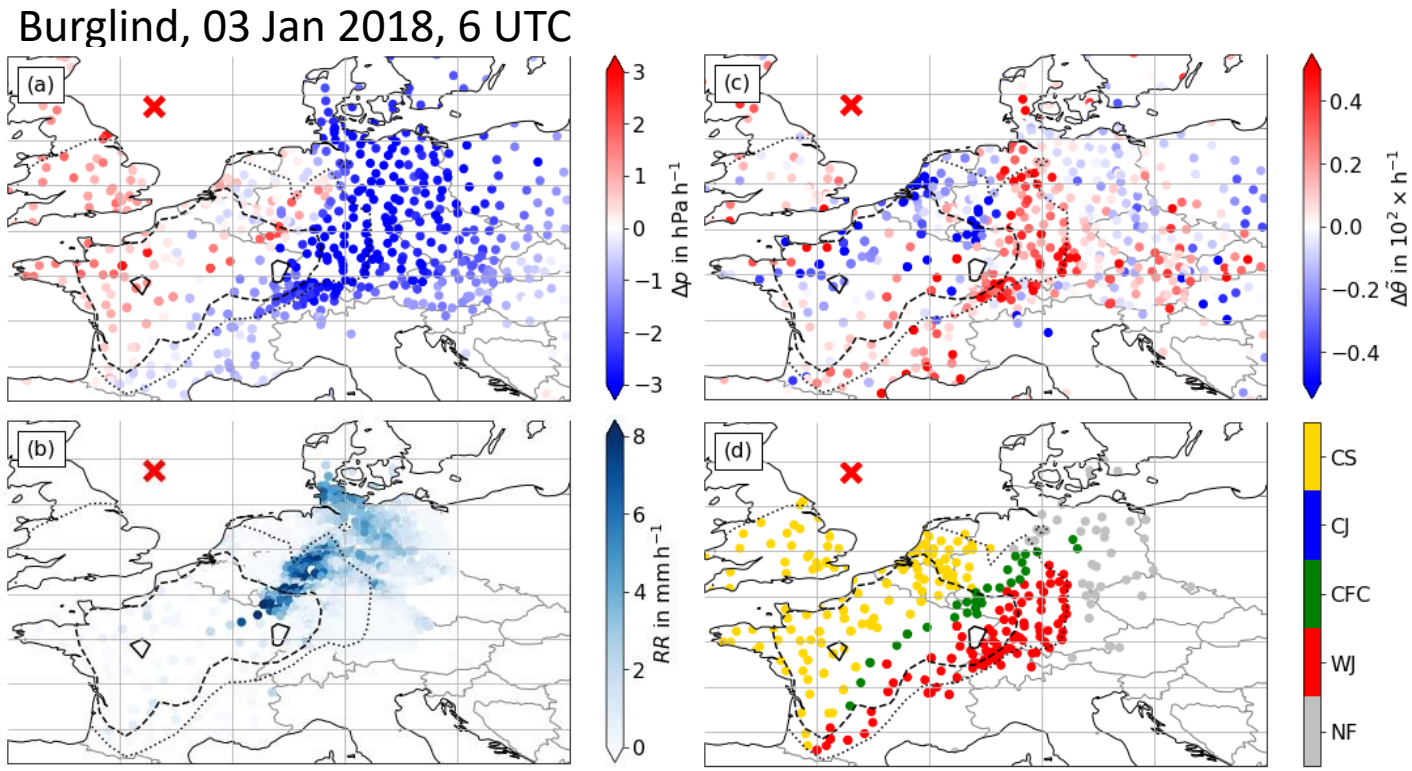
Select area with mouse



Adapted from Eisenstein et al. (2022), preprint, WCDD

Subjective labelling

- **MSLP** decreases ahead of the cold front, such that the tendency is $\lesssim 0$ for the WJ while it becomes positive when CFC arrives
- While CFC shows heavy **precipitation**, there is almost none ahead of the front, i.e. in the WJ region
- For CFC, **θ** decreases with the onset of precipitation
- The **wind direction** changes with arrival of the cold front, hence CFC

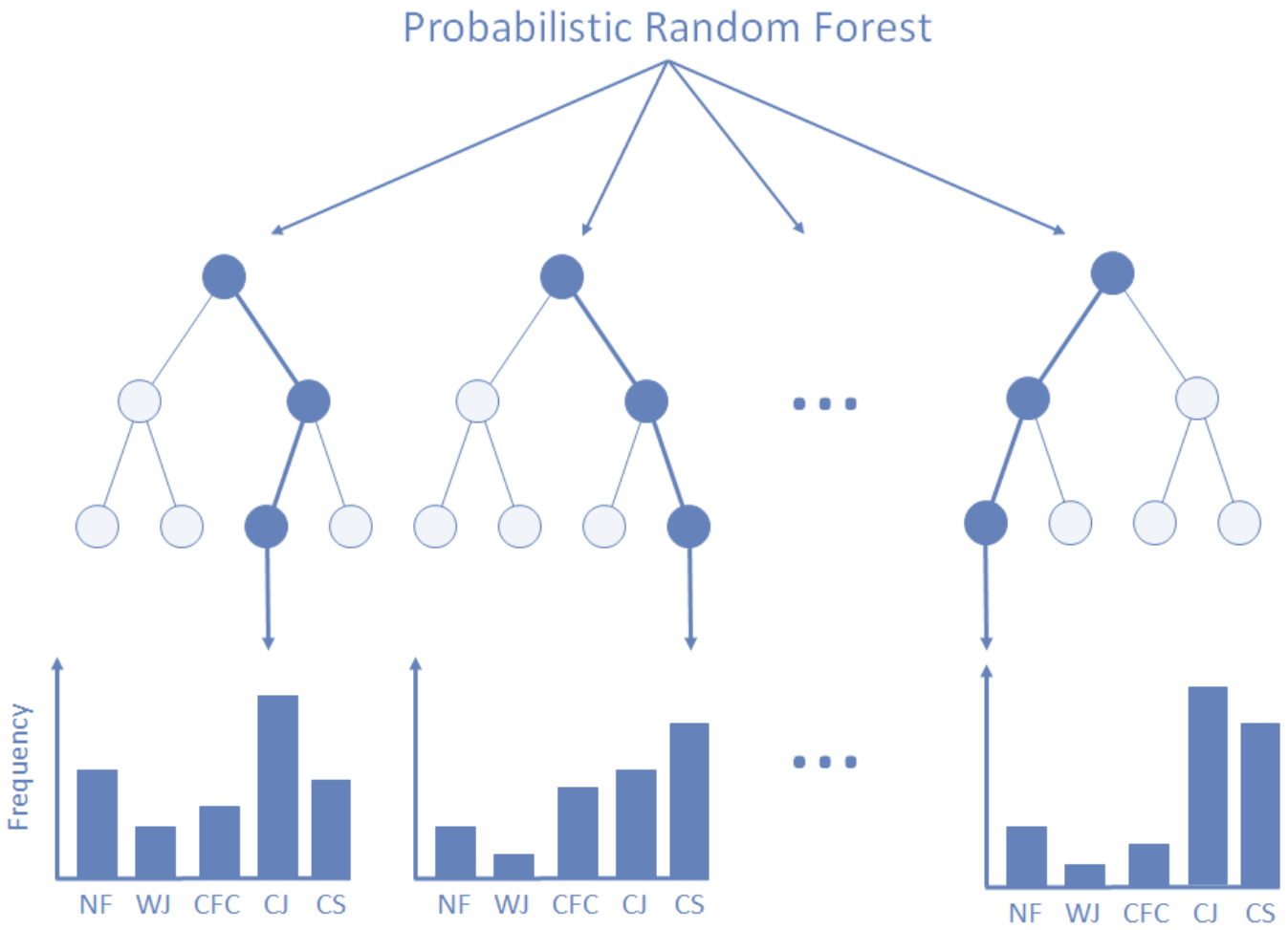


Eisenstein et al. (2022), preprint, WCDD, Fig. 3

- CJ usually noticable due to **hook-shaped** structure SW of cyclone center
- Everything behind CFC that is not CJ is labelled CS

Probabilistic Random Forest (RF)

- Use a random forest (RF) to generate **probability forecasts** for the wind features
- Predictor variables:
  - Normalised wind speed
  - Wind direction + tendency
  - Precipitation
  - Mean sea level pressure + tendency
  - Normalised potential temperature + tendency
- Training and prediction via **cross-validation** over 12 case studies (12 RF instances)

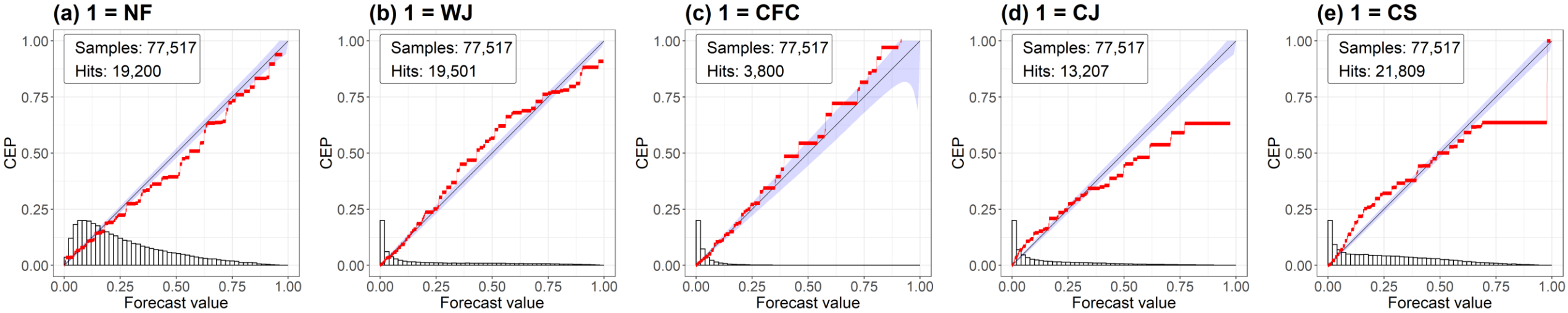


Calibration of RF forecasts

Overall improvement (Brier score) over Climatology: 24.7 %.

But: How well does the RF forecast the individual wind features?

➡ Use **reliability diagrams** to evaluate the probability forecasts. The forecasts are calibrated if the calibration curve follows the diagonal (meaning that if, for example, a 20%-forecast is issued 100 times, the event should occur ca. 20 times).

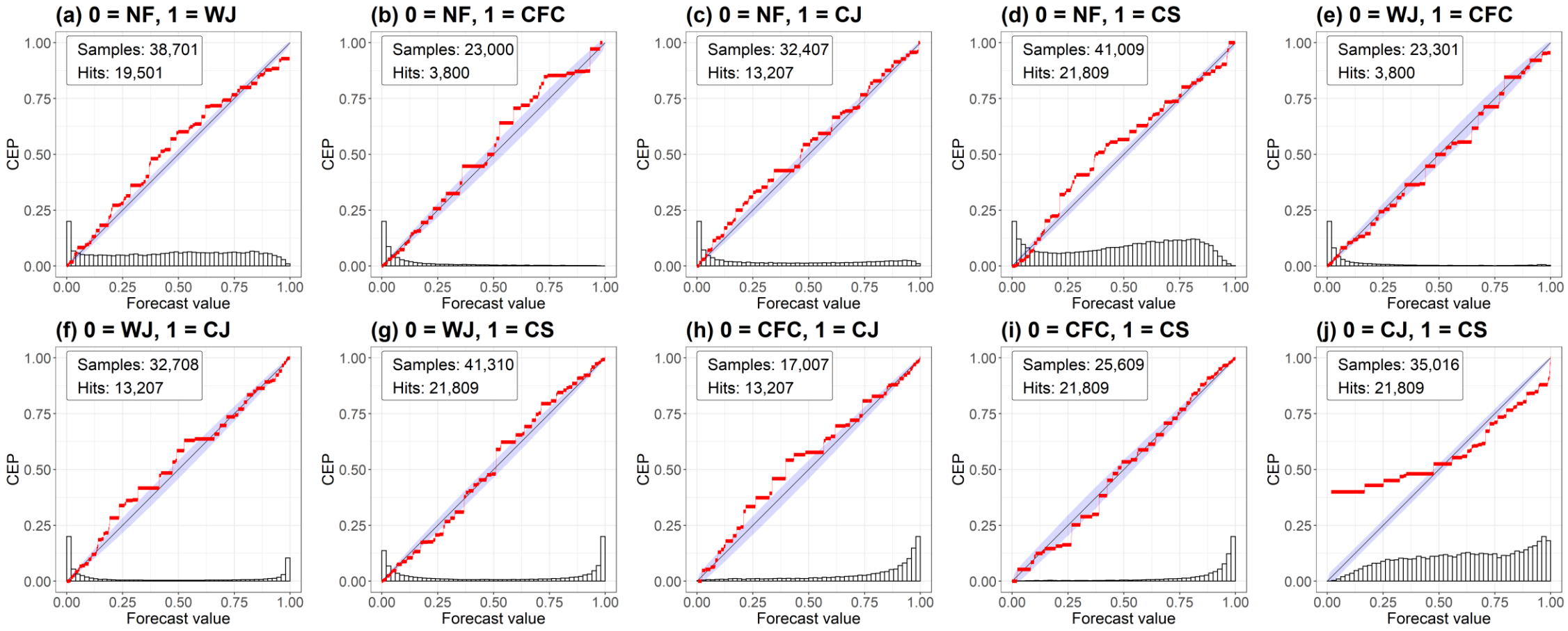


Eisenstein et al. (2022), preprint, WCDD, Fig. 6

The RF forecasts are (mostly) **well-calibrated**. Only for larger probabilities of the CJ and CS the forecasts miscalibration can be observed.

Distinction of wind features

How well does the RF **discriminate** two wind features?

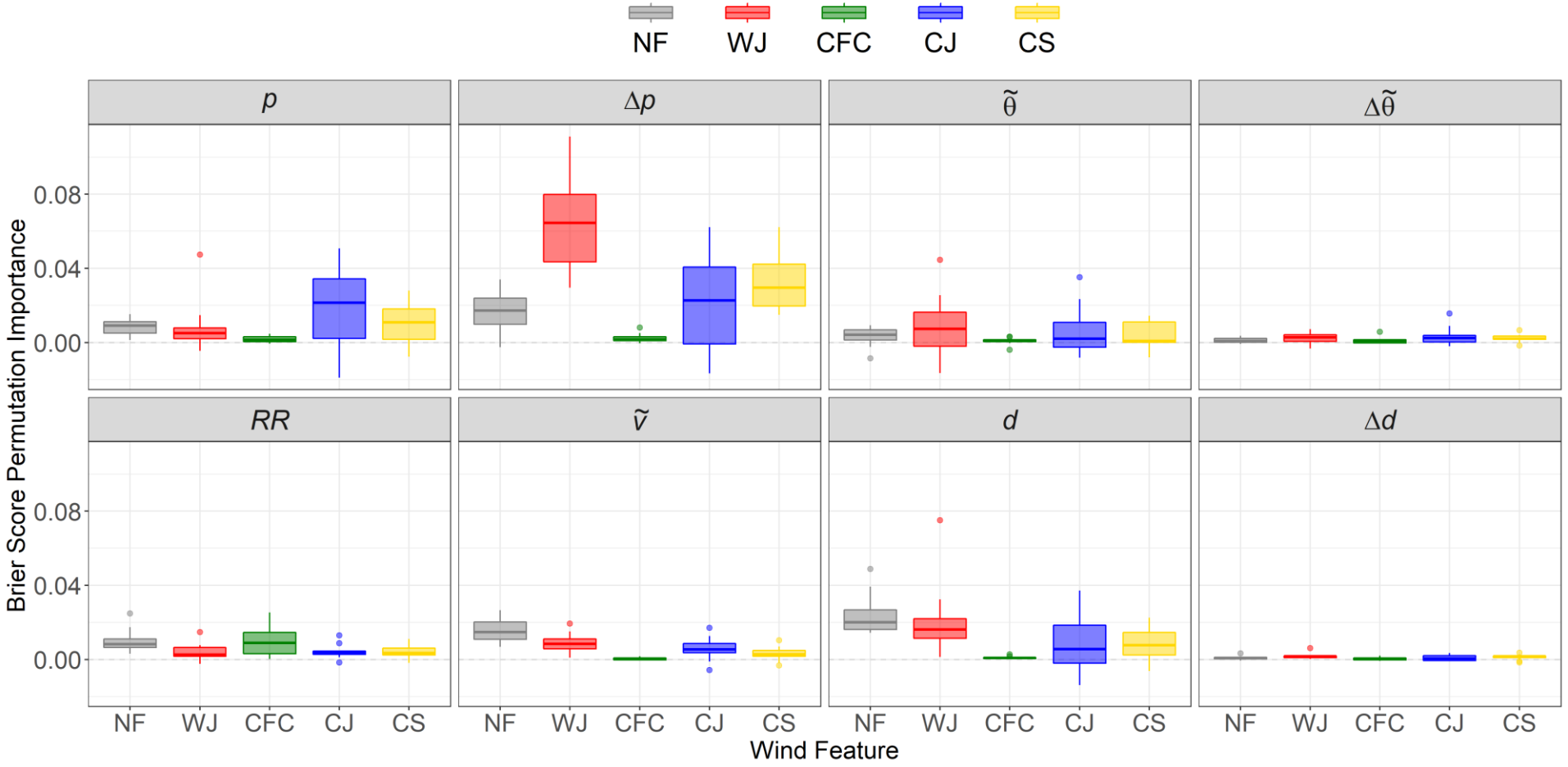


Eisenstein et al. (2022), preprint, WCDD, Fig. 7

The RF forecasts are **well-calibrated** besides the distinction of CJ and CS.

Predictor importance I

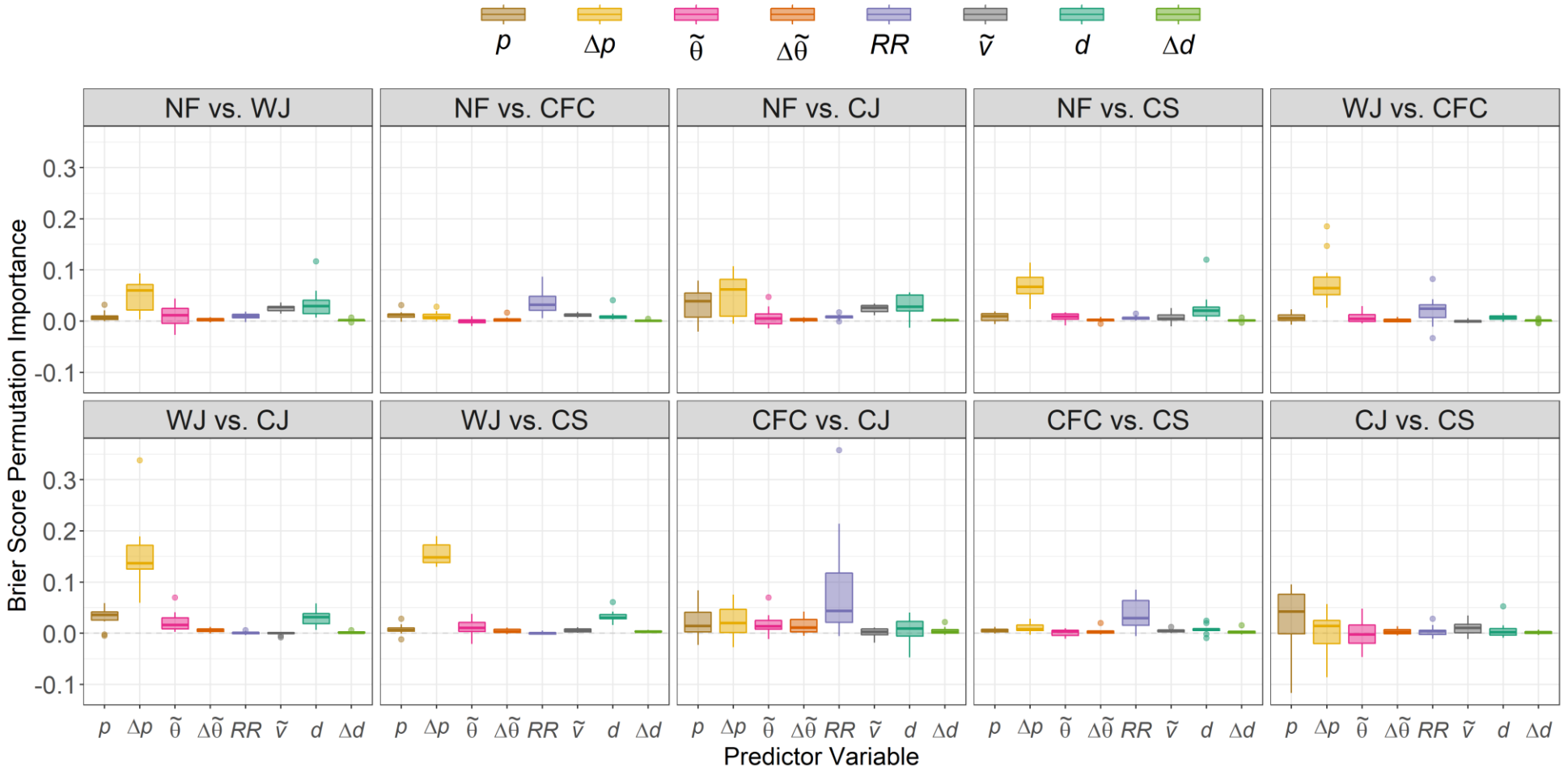
How important are the predictor variables for predicting the individual wind features?



Eisenstein et al. (2022), preprint, WCDD, Fig. 8

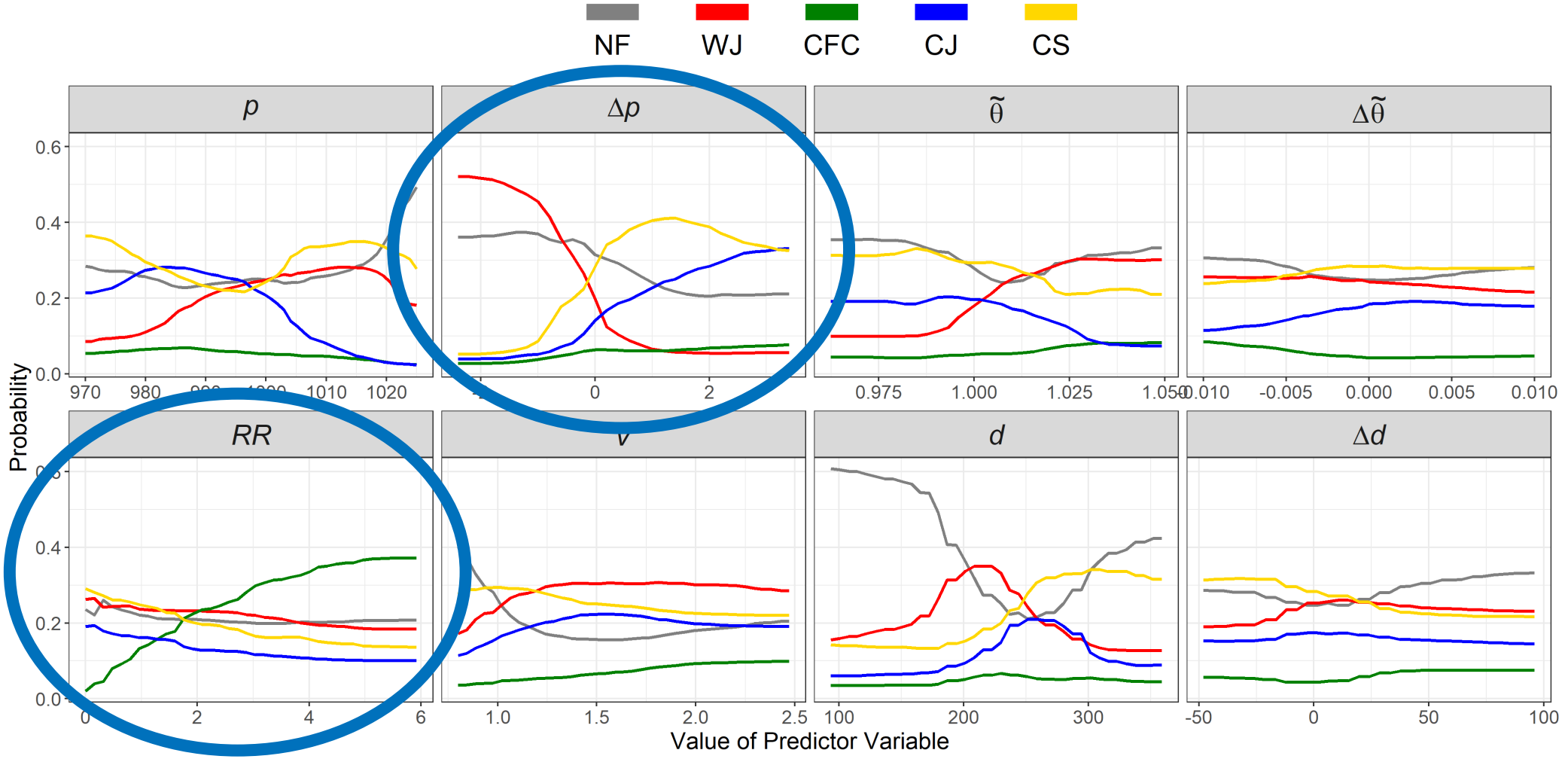
Predictor importance II

How important are the predictor variables for discriminating the wind features?



Eisenstein et al. (2022), preprint, WCDD, Fig. 9

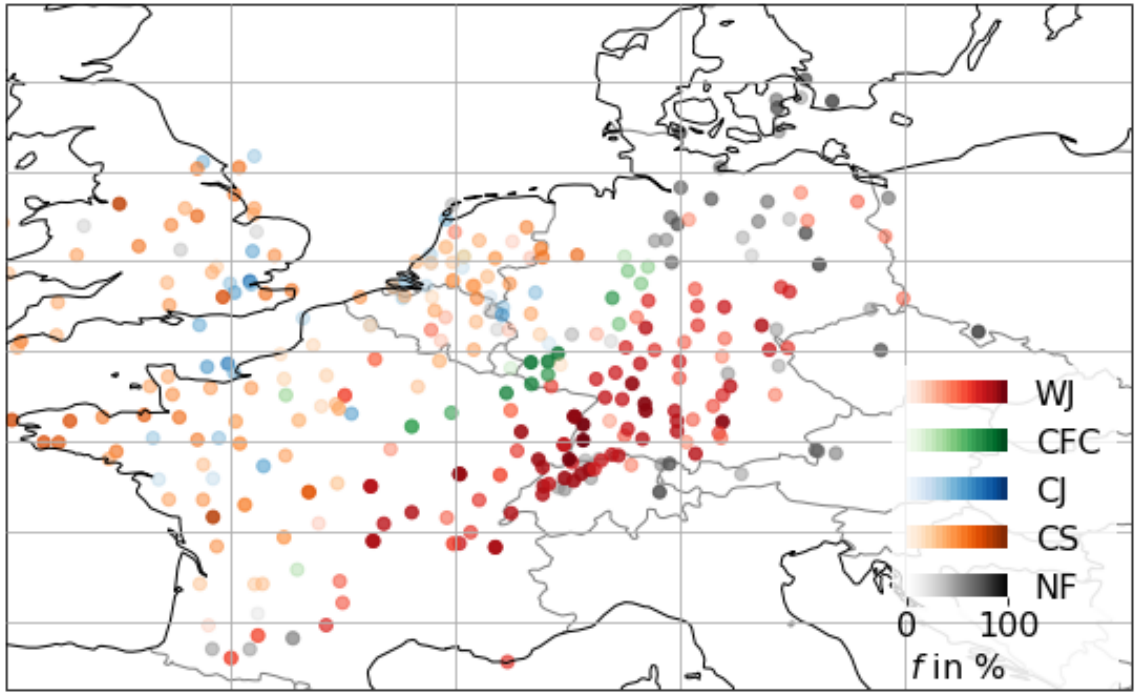
Predictor importance

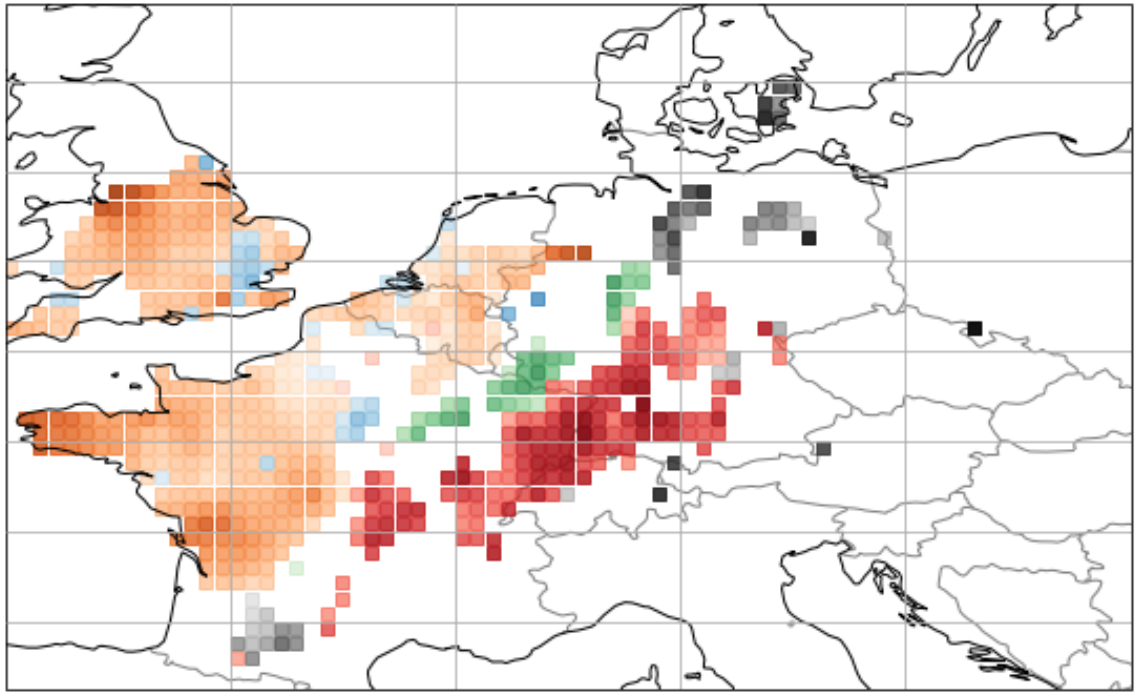


Eisenstein et al. (2022), preprint, WCDD, Fig. 10

Generation of probability maps

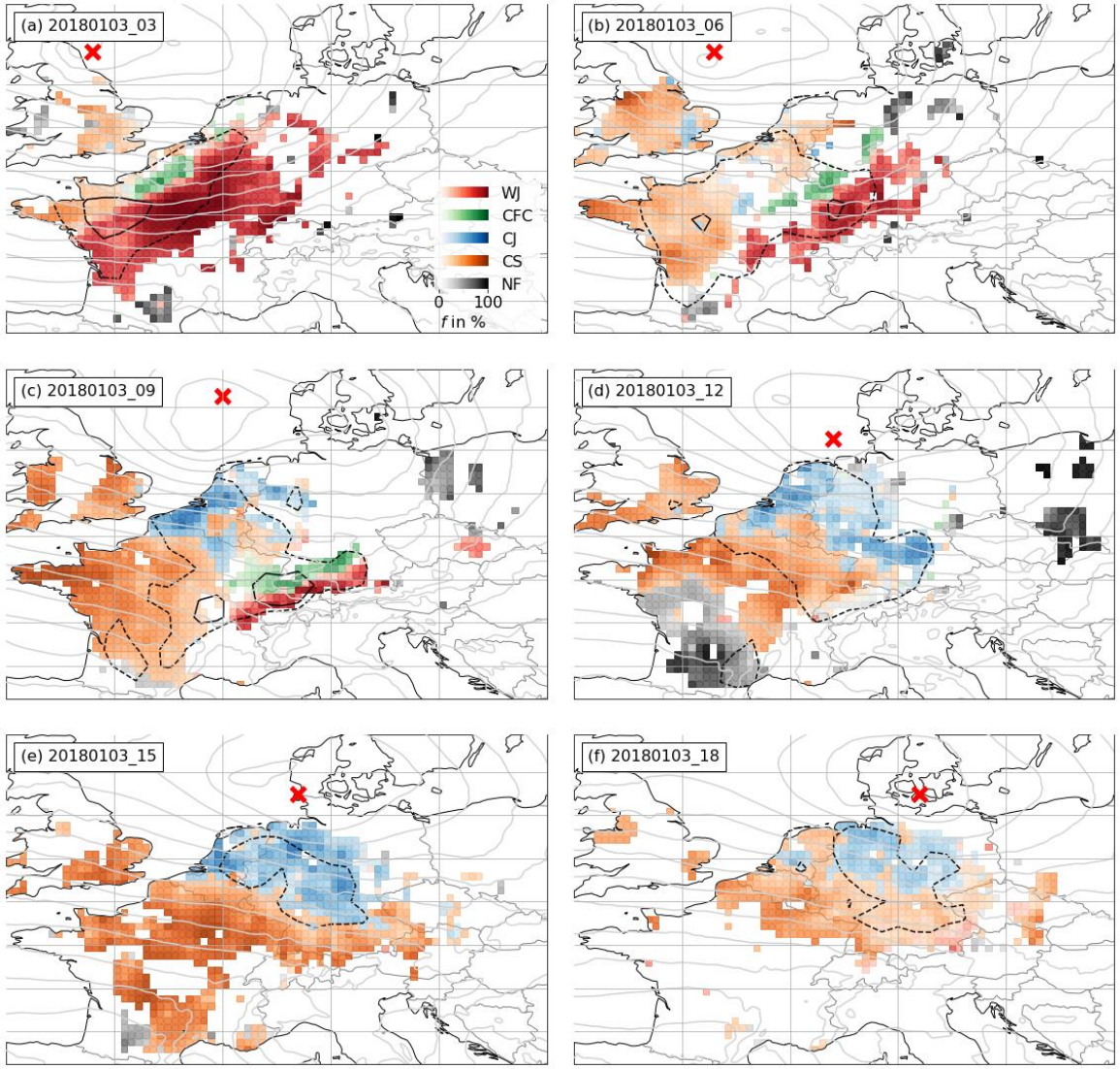
Use **Kriging** to spatially interpolate the forecasts from the stations to the grid

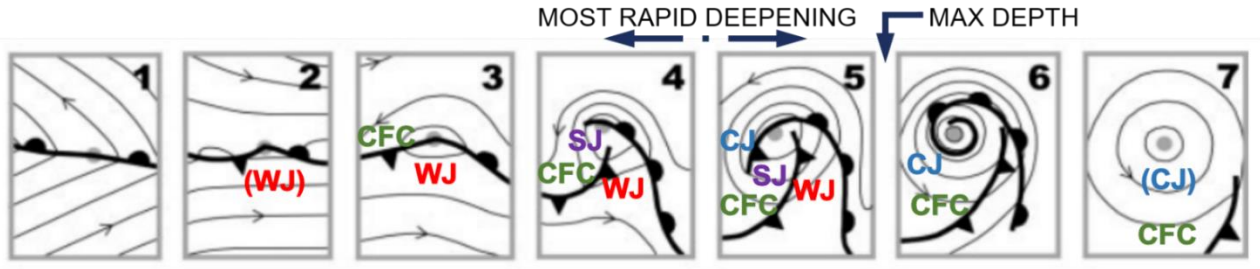




(in collaboration with Ghulam Qadir)

Burglind 03 Jan 2018



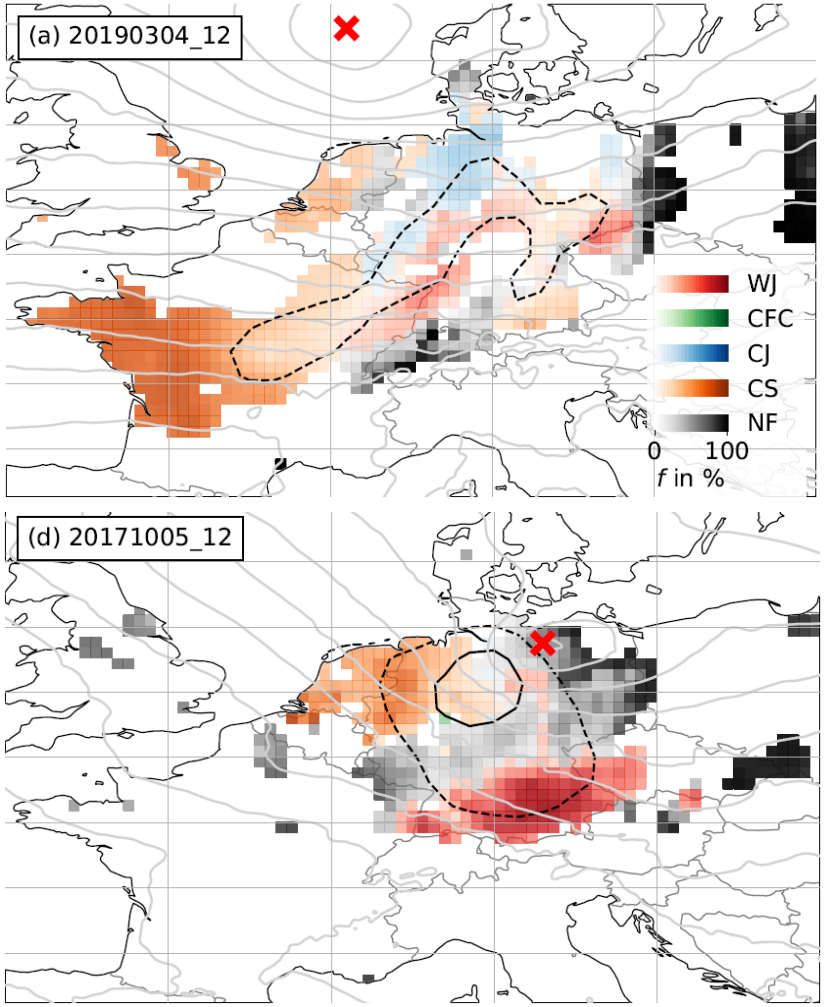


Adapted from Hewson and Titley (2010) and Hewson and Neu (2015)

Animations for this and more case studies available at:
10.5281/zenodo.6541277

Further examples and possible shortcomings

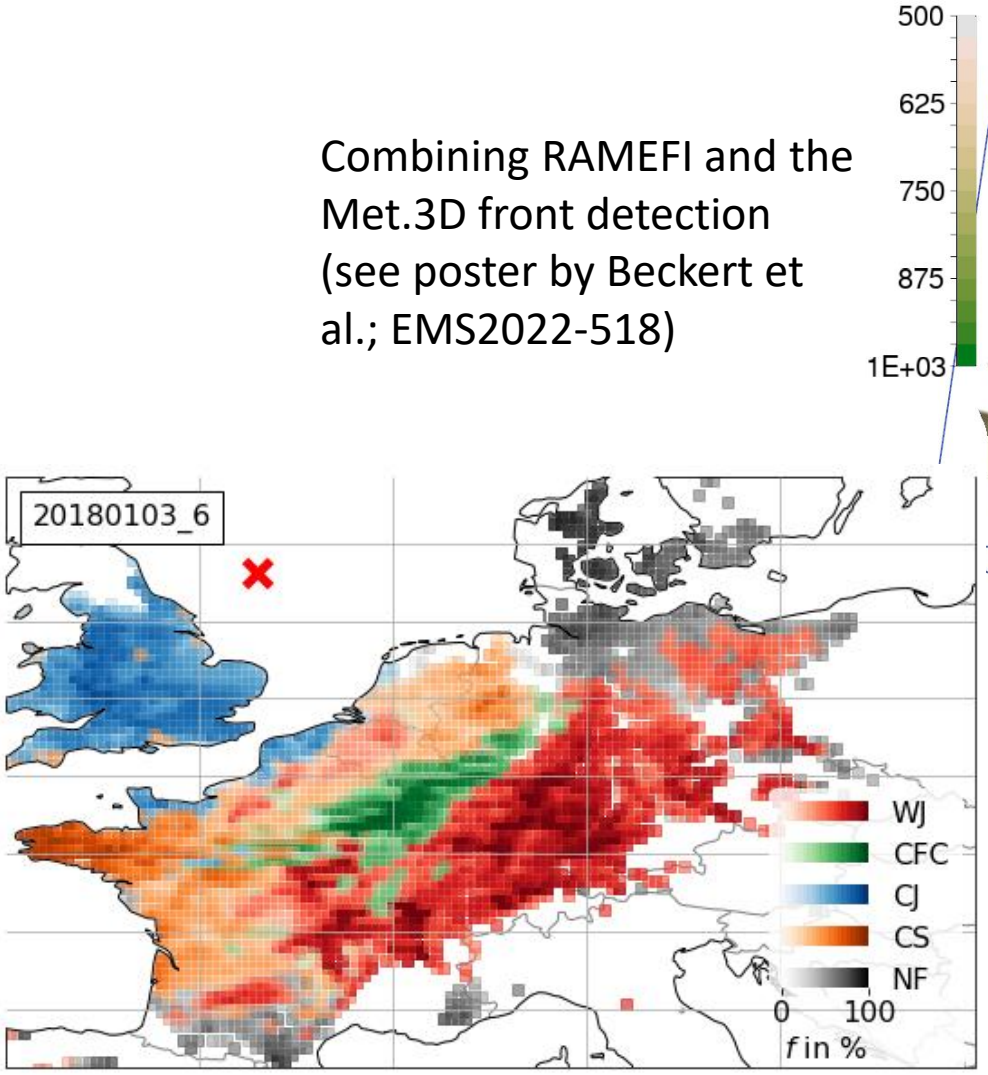
- Double fronts and convergence lines
  - →Area in between can show characteristics of both warm and cold sector
- Strong background pressure gradient
  - → May cause or enhance high wind speeds and make identification of features more difficult
- Shapiro-Keyser cyclones
  - → Differ in cyclone evolution and rarely show CFC
- Spatial independence
  - → No knowledge about intensity of the cyclone and more difficult to indentify warm sector

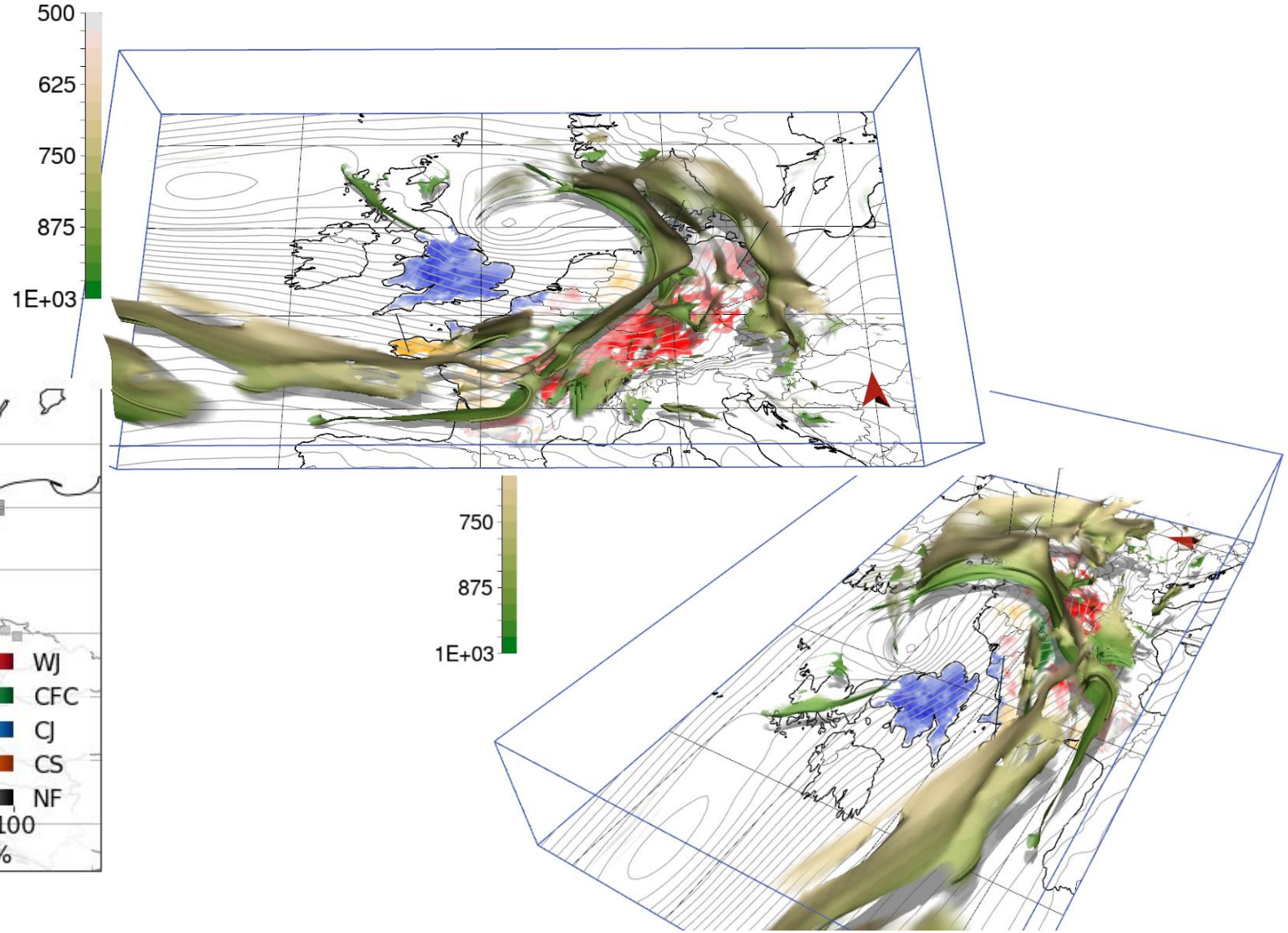


Eisenstein et al. (2022), preprint, WCDD, Fig. 11a,d

Gridded data

Combining RAMEFI and the Met.3D front detection (see poster by Beckert et al.; EMS2022-518)





Eisenstein et al. (2022), preprint, WCDD, Fig. 5

Summary and future plans

- Development of a tool to interactively identify wind features within European cyclones helped extracting their characteristics in surface observations and high-resolution gridded data.
- Training of probabilistic random forests based on subjective labels
- CJ, WJ, CFC and CS can be distinguished from precipitation, pressure and temperature fields.
- *Currently*
  – Feature climatology using observations & COSMO-REA6 (2000 – 2019, Oct – Mar)
- *Planned*
  – Feature-dependent forecast error analysis and post-processing
  – Distinguish CJ and SJ from gridded data without explicit use of Lagrangian trajectories

Eisenstein, L., Schulz, B., Qadir, G. A., Pinto, J. G. and Knippertz, P.: Objective identification of high-wind features within extratropical cyclones (RAMEFI): Part I: Method and illustrative case studies. *WCDD*. [preprint], doi: **10.5194/wcd-22-29**, in review, 2022

Sources

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- Hewson, T. and Titley, H.A. (2010) Objective identification, typing and tracking of the complete life-cycles of cyclonic features at high spatial resolution. *Meteorol. Appl.,* 17: 355-381. doi: 10.1002/met.204
- Hewson, T. and Neu, U. (2015) Cyclones, windstorms and the IMILAST project. *Tellus A*, 6, 1-33. doi: 10.3402/tellusa.v67.27128
- Eisenstein, L., Schulz, B., Qadir, G. A., Pinto, J. G., and Knippertz, P.: Objective identification of high-wind features within extratropical cyclones using a probabilistic random forest (RAMEFI). Part I: Method and illustrative case studies, *Weather Clim. Dynam. Discuss.* [preprint], doi: 10.5194/wcd-2022-29, in review, 2022
- Beckert, A. A., Eisenstein, L., Oertel, A., Hewson, T., Craig, G. C., and Rautenhaus, M.: The three-dimensional structure of fronts in mid-latitude weather systems as represented by numerical weather prediction models, Weather Clim. Dynam. Discuss. [preprint], doi: 10.5194/wcd-2022-36, in review, 2022.