

Identification and climatology of high-wind features within European winter storms

Lea Eisenstein, Benedikt Schulz, Joaquim G. Pinto, Peter Knippertz

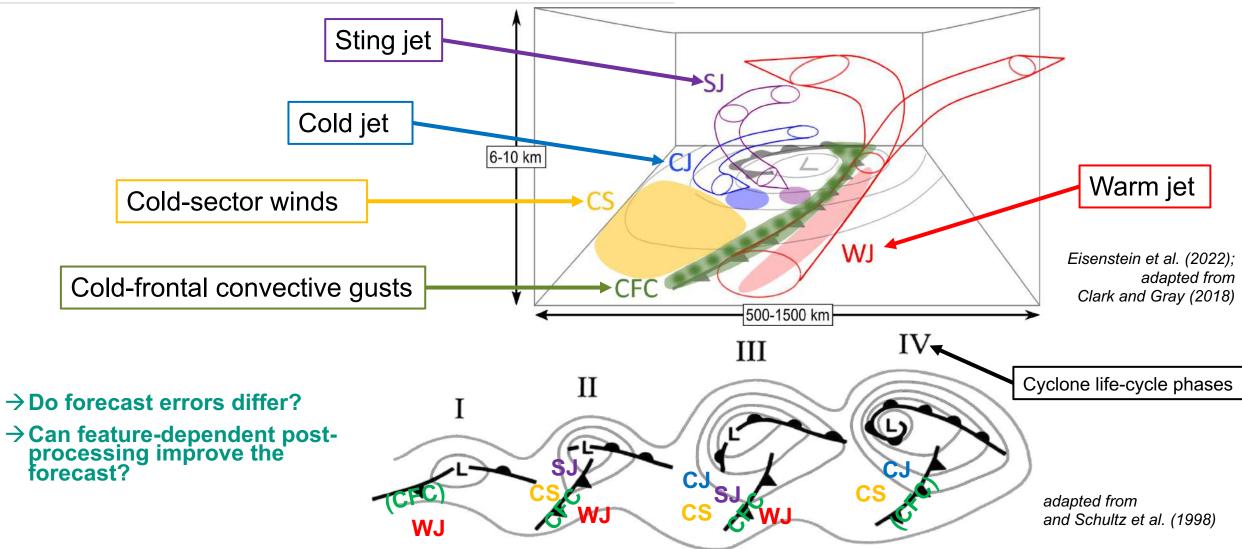
Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research



www.kit.edu



CAUSES OF HIGH WINDS





Dataset of hourly surface observations (2001 – 2020):

- Mean-sea level pressure (p), temperature, precipitation (RR), wind speed (v) and wind direction (d)
- \rightarrow Computation of potential temperature θ
- \rightarrow Normalising θ and v by the median and 98th percentile, respectively
- \rightarrow Calculating tendencies ($\Delta x = x_0 x_{-1h}$) for *p*, θ and *d*

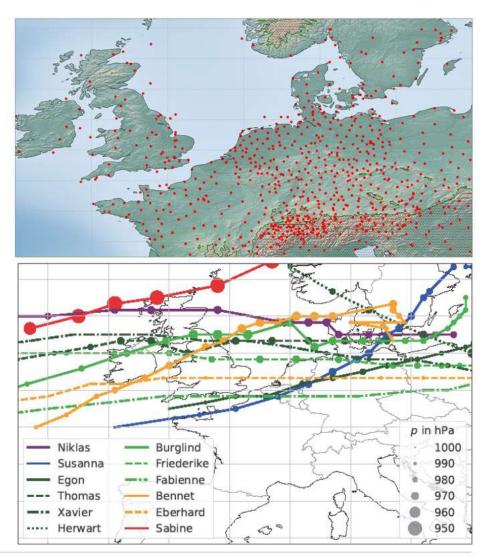
COSMO-REA6 (CORDEX area, 1995–2019)

Same parameters + gust speed (v_{gust}), relative humidity (RH), specific humidity (q) and total cloud cover (cc)

 \rightarrow Calculating gust factor $g_v = v_{gust}/v$

→ 12 case studies (2015 – 2020)

June 29, 2023





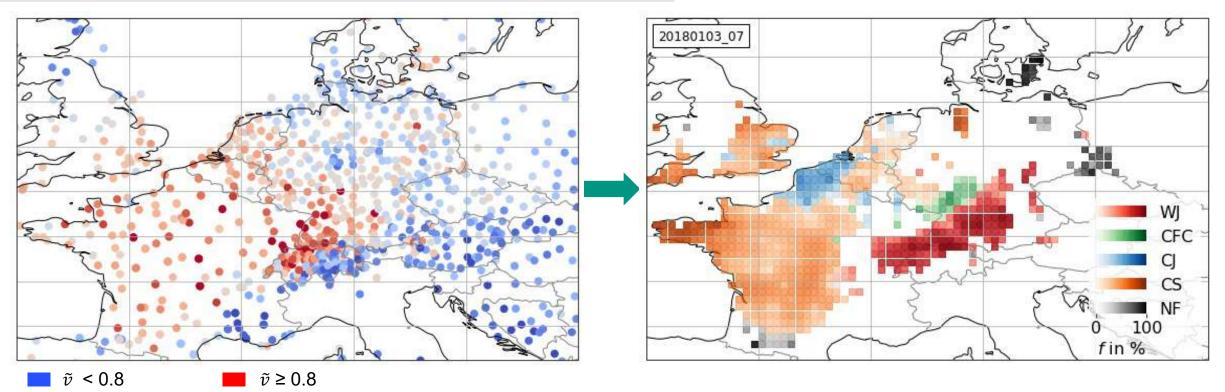


Eisenstein, L., Schulz, B., Qadir, G. A., Pinto, J. G. and Knippertz, P. (2022): Identification of high-wind features within extratropical cyclones using a probabilistic random forest – Part 1: Method and case studies. *Weather and Climate Dynamics*, **10.5194/wcd-3-1157**.

9th European Storm Workshop

GOAL





Find the cause of high wind speeds at a single station or grid point at a given time step

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

Subjective Identification

Probabilistic Random Forest

Kriging

RANDOM-FOREST-BASED MESOSCALE WIND FEATURE IDENTIFICATION (RAMEFI)



- Subjective labelling of 12 case studies including ,no feature' (NF) category
 - Training of a probabilistic random forest independent of spatial distribution
- 8 surface predictor variables:
 - Normalised wind speed
 - Wind direction + tendency
 - Precipitation
 - Mean sea level pressure + tendency
 - Normalised potential temperature + tendency

→ Once trained, RAMEFI can also be used on gridded data!

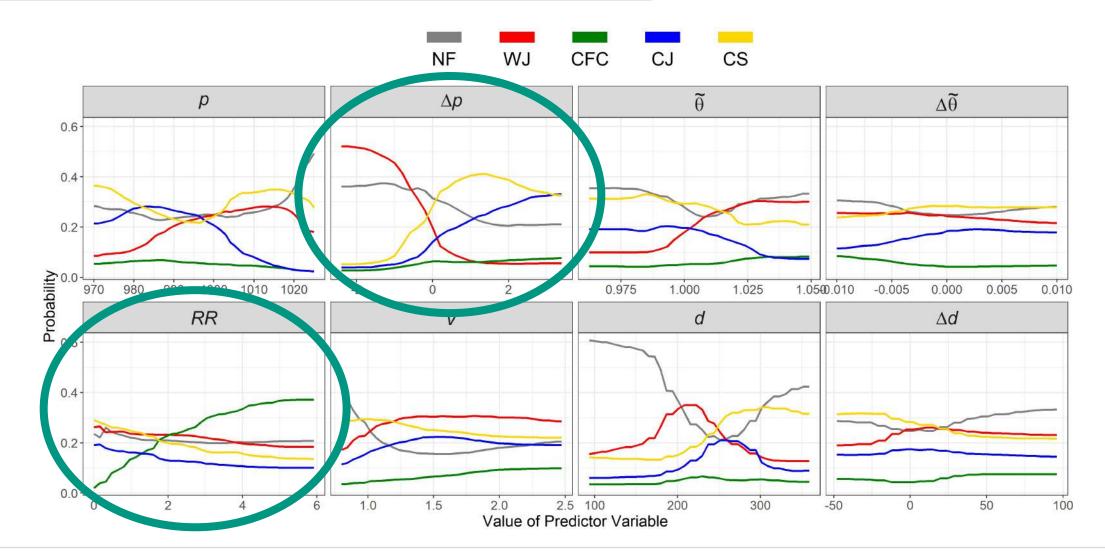


Code available at 10.5281/zenodo.6541303



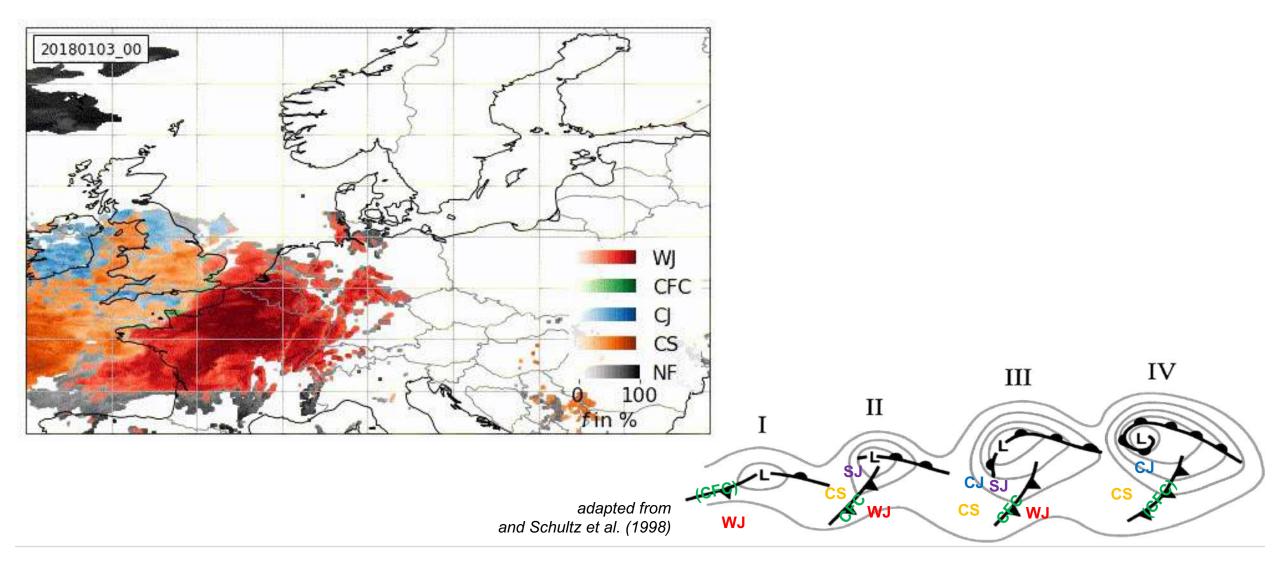
PREDICTOR IMPORTANCE





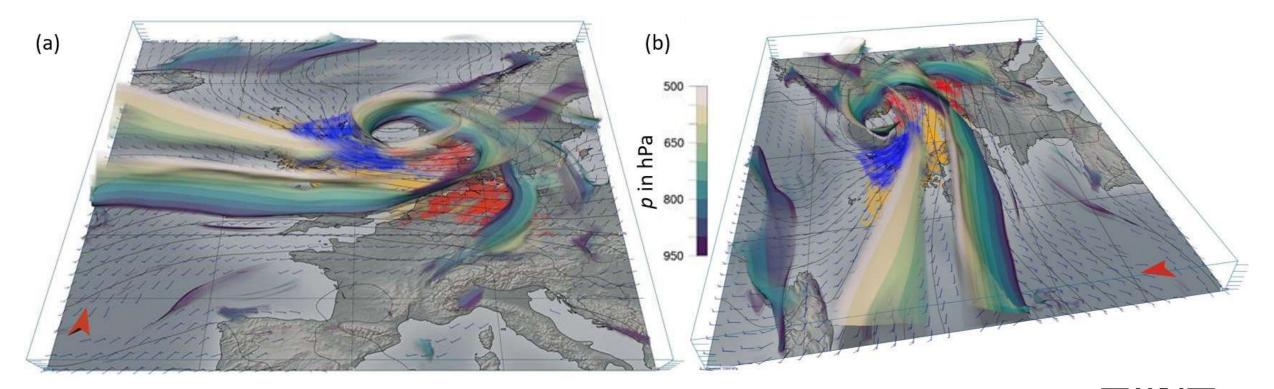
BURGLIND (03 JANUARY 2018)





NEAR-REAL-TIME PRODUCT





Combining RAMEFI with the 3D front detection of Met.3D (Beckert et al., GMD, 2023)



Coming soon to www.kit-weather.de !





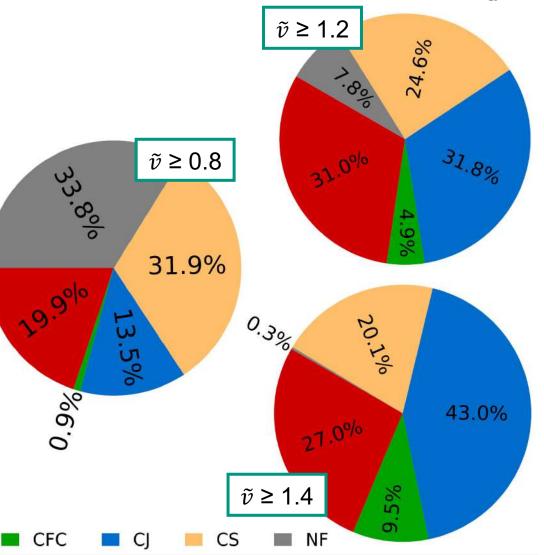
Eisenstein, L., Schulz, B., Pinto, J. G. and Knippertz, P. (2023): Identification of high-wind features within extratropical cyclones using a probabilistic random forest – Part 2: Climatology [preprint]. *Weather and Climate Dynamics Discussions*, **10.5194/wcd-2023-10**.

9th European Storm Workshop

RELATIVE OCCURRENCE

- CS: most frequent cause of high winds affecting a large area
- CFC: small-scale and less frequent
- NF: very high proportion but mostly situated in the outskirts of a cyclone area and decreases for higher wind speeds
- CJ and CFC proportion increase substantially for higher wind speeds





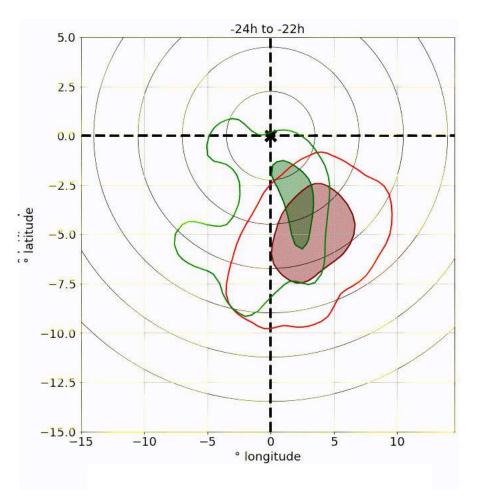
Lea Eisenstein et al. (lea.eisenstein@kit.edu)

WJ

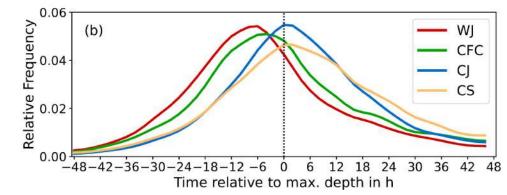
9th European Storm Workshop

SYSTEM-RELATIVE COMPOSITE





- WJ: mostly in **south-eastern** quadrant and **first** to occur
- CFC: high case-to-case variability and occurring shortly after the WJ
- CS: mostly in south-western quadrant and usually the last feature to vanish
- CJ closer to cyclone centre and peak occurrence around time of maximum depth



CHARACTERISTICS



- CJ: highest wind and gust speeds → low gust factor
- CFC: highest gust factor
- WJ and CS similar wind characteristics

- CFC: highest humidity levels
- CS: large cloud cover distribution due to spotty convection in otherwise quite sunny conditions

10.5194/wcd-2023-10

RAMEFI enables a probabilistic identification of WJ, CFC, CS and CJ+SJ ...

- independent of spatial distribution and temporal evolution (of more than 1h)
- using only surface parameters based on temperature, pressure, wind, precipitation
- suitable for a near-real-time product

RAMEFI was used to compile a 19-year climatology over Europe

- CS: most common cause of high winds
- CJ: causes highest wind speeds
- CFC: less frequent, high case-to-case variability, but highest gust factor



9th European Storm Workshop



SUMMARY

INTERACTIVE IDENTIFICATION



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

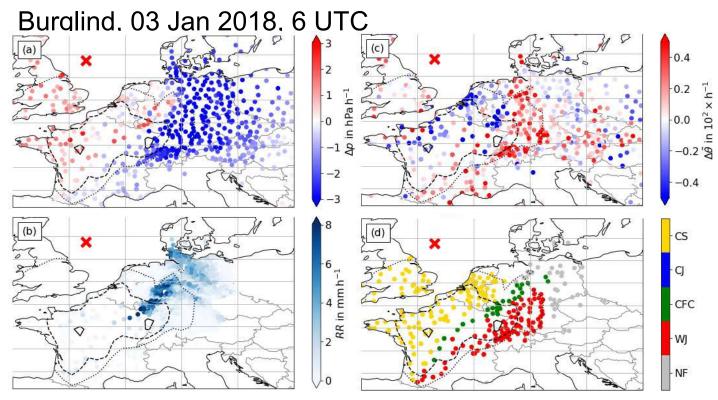
 \rightarrow Building an interactive tool to select feature areas by hand

	Set label of selected stations in the table to a specific feature	RAMEFI - data explorer Select on maps and set labels according to features; clear selection to reset. Burglind (03.01.2018)					Stations selected: 20 Clear selection Clear selection Daytime: 6 Storm Burglind_Jan18	Data table of all stations with parameters and set labels that will be saved	
		Set WJ label Set CFC label	Set CJ label Set SJ labe	Set CS label	Clear Cle	ear all Save timest	ep		
Code available	at	labeled WJ: 0 labeled CFC	: 0 labeled CJ: 0 labele	d SJ: 0 labeled CS	0				
10.5281/zenod		🞐 v/v98 dp p dth th/th5) RR dd d label			# time	lat ion v/v98 dp d(th/th5(th/th50 RR	dd p d label	
10.5201/261100	0.0041000	Normalised wind speed v/	/98			826 6	47.6044 -2.7141(1.13388 NaN NaN NaN 0	0 NaN 280 0	
		P 60]				827 6	49.0694 6.12527 1.40858 NaN NaN NaN 1	20 NaN 290 D	
┍═┑╴▃┎╺╷┍═					1 N N	828 6	46.9980 3.11249 1.78833 1.80000 -0.0031 1.03470 0	20 1007.6 260 0	
المتراجع المتراجع				•		1.6 829 6	50.5699 3.09750 1.28117 1.39999 -0.0030 1.01023 D	10 993 250 0	
		0.4		1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1	- · · ·	830 6	49.4463 2.12694 1.05190 1.10000 0.00045 1.01364 0	-10 998.7 250 0	
76.00° 7.780-87	Choose which	O 55 -				831 6	48.4452 0.10999 1.13298 0.60000 -0.0000 1.01228 0	0 1006.2 280 D	
2790 L 1949 ST 27			11 C			832 6	45.7866 3.14916 2.00699 0.70000 0.00086 1.04334 0	0 1009 260 0	
	L variable you		1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1		8 C C 4	1.4 833 6	43.3847 -0.4161 0.87972 1.70000 -0.0071 1.03785 0.20000	40 1025 300 0	
			·		11. N. N.	834 6	43.1877 0 0.86198 0 0.0009E 1.0504E 0	10 1023.2 260 0	
	want to see	50 - 0 0				835 6	42.7369 2.87277 0.55435 -0.1000 0.00235 1.04507 0	10 1020 290 -1	
					CSS - 22	836 6	48.5494 7.64027 2.13822 -0.3999! 0.01093 1.03744 0.40000	50 995.2 240 0	
lait, u fa' ist		· · · · ·		3.9.5		837 6	47.9286 7.40749 1.30916 -1.1000 0.00141 1.03366 0.40000	0 998.6 220 0 0 1011.7 180 0	
=						635-0	45.7256 4.93777 0.84233 -0.3 0.00482 1.02346 0	0 1000.8 220 0	
	Select area				2.5.1	840 6	46.2944 4.79416 0.65791 0.2000 -0.0008 1.01771 0.40000	0 1010.5 180 -1	
						1 841 6	47.9455 0.19416 1.62983 2.10000 -0.0060 1.01722 2.59995	30 1008.1 280 0	
	with mouse					842 6	45.6411 5.87777 0.98488 -0.5999! 0.0006C 1.01904 0.4000C		
	with mouse	,				843 6	48.8216 2.33777 1.24093 2.10000 -0.0094 1.00693 2.59995	20 1001.9 290 0	
			- a - Y	1.0		0.8 844 6	49.3827 1.18166 1.04842 1.10000 -0.0001 1.00811 0	0 1000.2 270 0	
		40 +			1 1				



SUBJECTIVE LABELLING

- MSLP decreases ahead of the cold front, such that the tendency is ≤ 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



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

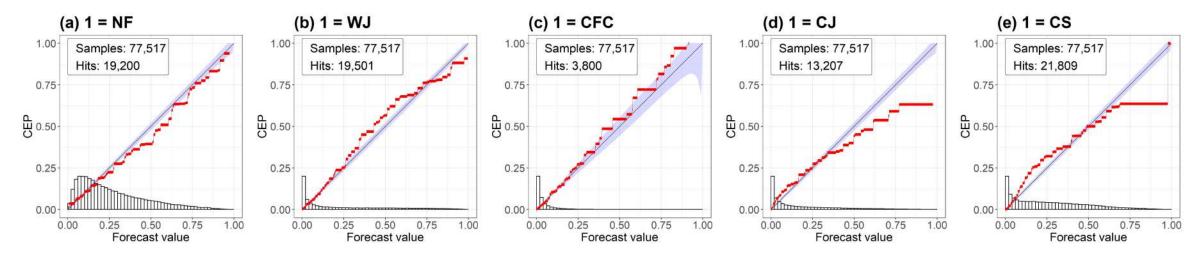
CALIBRATION OF RF FORECASTS



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).

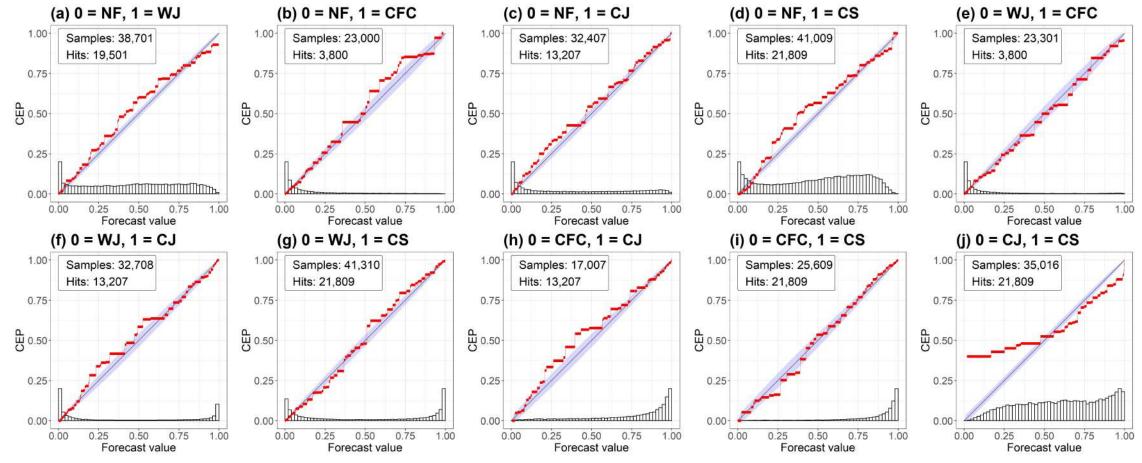


The RF forecasts are (mostly) **well-calibrated**. Only for larger probabilities of the CJ and CS the forecasts miscalibration can be observed.

DISTINCTION OF WIND FEATURE



How well does the RF discriminate two wind features?

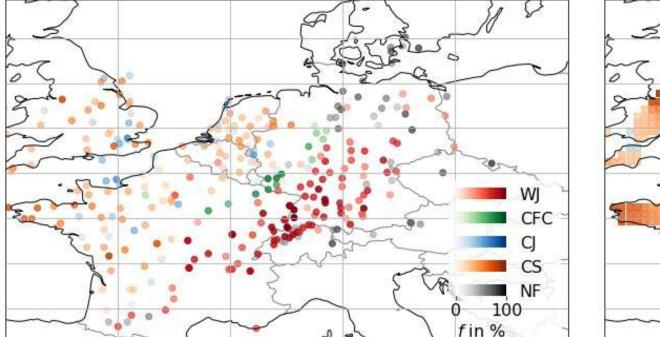


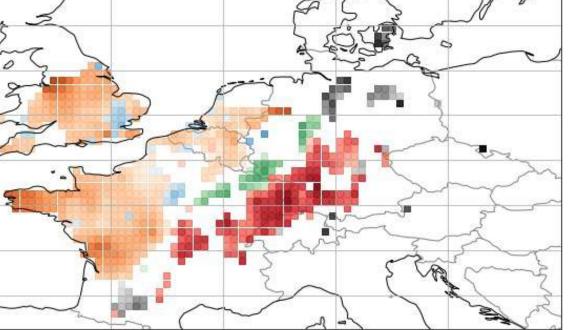
The RF forecasts are well-calibrated besides the distinction of CJ and CS.

GENERATION OF PROBABILITY MAPS



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





(in collaboration with Ghulam A. Qadir)

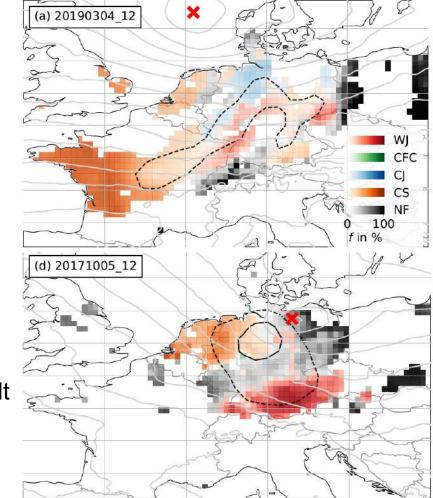
EXAMPLES & POSSIBLE SHORTCOMINGS

- 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
 - \rightarrow Differ in cyclone evolution and rarely show CFC
- Spatial independence

→ No knowledge about intensity of the cyclone and more difficult to indentify warm sector











- Clark, P.A. and Gray, S.L. (2018): Sting jets in extratropical cyclones: a review. Q J R Meteorol Soc., 144, 943–969. doi: 10.1002/qj.3267
- Schultz, D. M., Keyser, D. and Bosart, L. F. (1998): The Effect of Large-Scale Flow on Low-Level Frontal Structure and Evolution in Midlatitude Cyclones, *Monthly Weather Review*, 126(7), 1767–1791. doi: 10.1175/1520-0493(1998)126<1767:teolsf>2.0.co;2.
- Eisenstein, L., Schulz, B., Qadir, G. A., Pinto, J. G., and Knippertz, P. (2022): Identification of high-wind features within extratropical cyclones using a probabilistic random forest Part 1: Method and case studies, Weather Clim. Dynam., 3, 1157–1182, https://doi.org/10.5194/wcd-3-1157-2022.
- Eisenstein, L., Schulz, B., Pinto, J. G., and Knippertz, P. (2023): Identification of high-wind features within extratropical cyclones using a probabilistic random forest Part 2: Climatology, Weather Clim. Dynam. Discuss. [preprint], https://doi.org/10.5194/wcd-2023-10, in review.
- Beckert, A. A., Eisenstein, L., Oertel, A., Hewson, T., Craig, G. C., and Rautenhaus, M. (2023): The threedimensional structure of fronts in mid-latitude weather systems as represented by numerical weather prediction models, Geosci. Model Dev. Discuss. [preprint], https://doi.org/10.5194/gmd-2022-278, in review.