

## Research questions (RQ)

1. Can windstorm characteristics be used to meaningfully classify windstorm events?
2. Can we quantify the influence of large- and small-scale atmospheric features on the classified windstorms using modern machine learning approaches?
3. Are there significant trends in windstorm characteristics within the observed period? (not shown)

## Data

Climate reanalysis - ERA5 and ERAINT:

- Horizontal resolution: 30km (ERA5), 80km (ERAINT)
- Period: 1981-2017, extended winter ONDJFM
- Temporal resolution: 6 hours
- ERAINT is only used for cyclone tracking!
- Matching following Nissen et al. (2010)

Identification & tracking:

- Windstorm tracking using the storm severity index (Leckebusch et al., 2008)
- Cyclone tracking following Murray and Simmonds (1991)
- Filter: EURO-CORDEX region (Fig. 1)

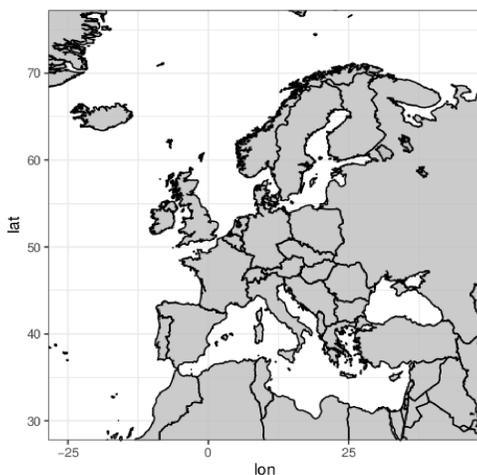


Figure 1: Study region, EURO-CORDEX (40.25°W–75.25°E, 25.25°N–75.75°N)

## Summary & conclusion

- Novel semi-supervised clustering method QSKM
- Method produces three windstorm classes of which one shows similar characteristics than the events from the XWS catalog
- Size and duration appear to play a greater role than wind speed in severe events
- Resulting classes can be described through a statistical model out of large scale predictors
- Although large-scale patterns can influence the occurrence of storms, they only have a small impact in our model
- The jet stream and the location and depth of the parent cyclone are determined for the type of event

## Outlook

- Dependences of individual windstorm characteristics
- Trends for clusters and characteristics
- Temporal structure and sequence of events

## References

- Leckebusch, Gregor C. et al. (2008). "Development and application of an objective storm severity measure for the Northeast Atlantic region". In: *Meteorol. Zeitschrift* 17.5, pp. 575–587.
- Murray, Ross J. and Ian Simmonds (1991). "A numerical scheme for tracking cyclone centres from digital data. Part I: development and operation of the scheme". In: *Aust. Meteorol. Mag.* 39.3, pp. 155–166.
- Nissen, K. M. et al. (2010). "Cyclones causing wind storms in the Mediterranean: characteristics, trends and links to large-scale patterns". In: *Nat. Hazards Earth Syst. Sci.* 10.7, pp. 1379–1391.
- Roberts, J. F. et al. (2014). "The XWS open access catalogue of extreme European windstorms from 1979 to 2012". In: *Nat. Hazards Earth Syst. Sci.* 14.9, pp. 2487–2501.
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## RQ1: Classifying windstorms

Quasi-supervised k-means (QSKM) clustering

- Novel clustering technique that partitions data w.r.t a reference (see Alg. 1)
  - + Allows for feature selection
  - + Produces relevant clusters
  - + Includes automatized processes for determining the optimal No. of cluster
- Reference is the XWS open access catalogue of extreme European windstorms from 1979 to 2012 (Roberts et al., 2014)
- Cluster No. 1 has multiple features close to the reference (Fig. 2)
- Most severe events are found over central Europe (Fig. 3b)
- Key characteristics are size, duration and travel speed/distance (Fig. 3a)

**Algorithm 1** Quasi-Supervised k-Means

- 1 Draw  $J$  subsets (with replacement)  $S_1^{n \times q}, \dots, S_J^{n \times q}$  from  $X^{n \times p}$  such that  $q < p$  and  $S_1 \neq \dots \neq S_J$ .
- 2 For  $j = 1 \rightarrow J$  do:
  - Enhanced k-means on  $S_j \Rightarrow C_{j,1}, \dots, C_{j,k}$
  - Calculate  $\gamma_j = \max[\text{count}(C_{j,1} \in R), \dots, \text{count}(C_{j,k} \in R)]$
  - Calculate  $\delta_j = \text{dist}(C_{j,p}, R)$  with  $C_{j,p}$  being the cluster where  $\text{count}(C_{j,p} \in R) = \gamma_j$
- 3 Select clustering result with the smallest  $\delta_j$  from the  $S_j$  with the largest  $\gamma_j$

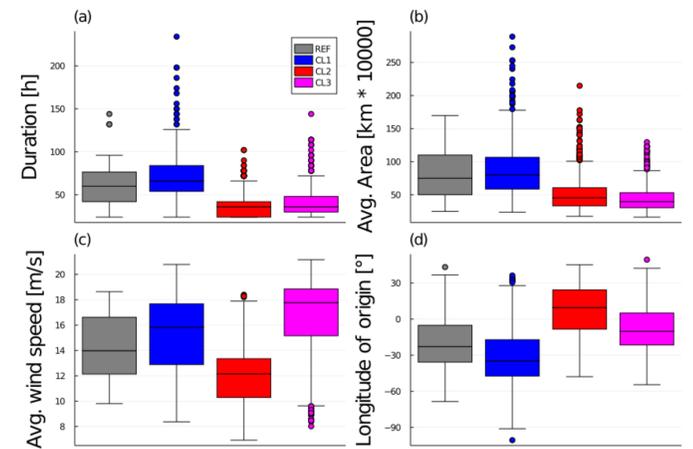


Figure 2: Comparison of the cluster against the reference for four different characteristics.

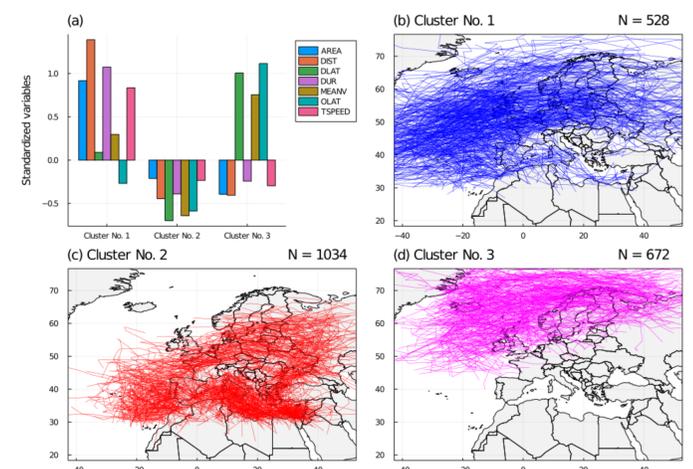


Figure 3: Clustering result after using QSKM where (a) shows the standardized characteristics and (b-d) the tracks for each cluster. Cluster No. 1 is closest to the reference.

## RQ2: Quantifying influences

- Random forest model to fit cluster against various predictors (see variable names in Fig. 4)
- The model shows high skill for Cluster No. 2 and 3, but struggles to predict Cluster No. 1 (Tab. 1)
- Evaluation of the feature importance and dependence using the Shapley value proposed by Shapley (1953)
- Latitude of minimum core pressure and strength of the jet stream are the two most important features (Fig. 4)
- The stronger the jet, the more likely a event is from Cluster No. 1 (Fig. 5, top left)
- Although core pressure is important, the relationship to the cluster is confuse (Fig. 5, bottom left)

Table 1: Confusion matrix for the trained random forests model.

Predicted	Ground Truth		
	1	2	3
1	64	15	15
2	23	254	12
3	30	18	135

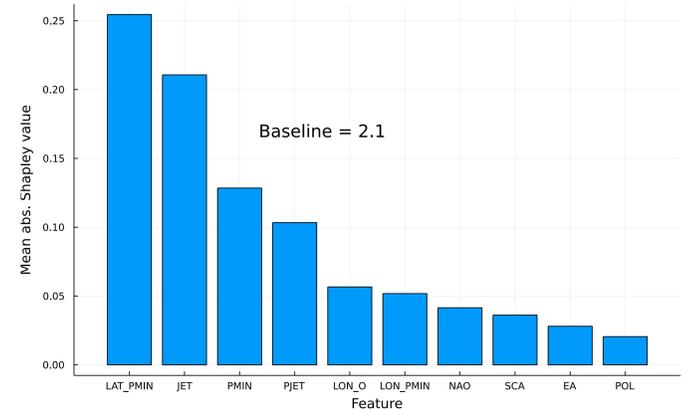


Figure 4: Feature importance derived from the random forests model using Shapley values. The base line is the average prediction of the model (here Cluster No. 2).

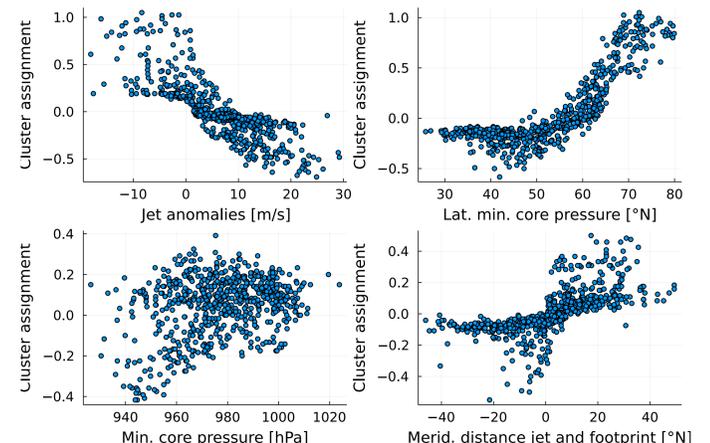


Figure 5: Feature dependence derived from the random forests model using Shapley values. Cluster assignments are added to the baseline of 2.1.