Intra-seasonal variability of spatial clustering of severe European winter windstorms

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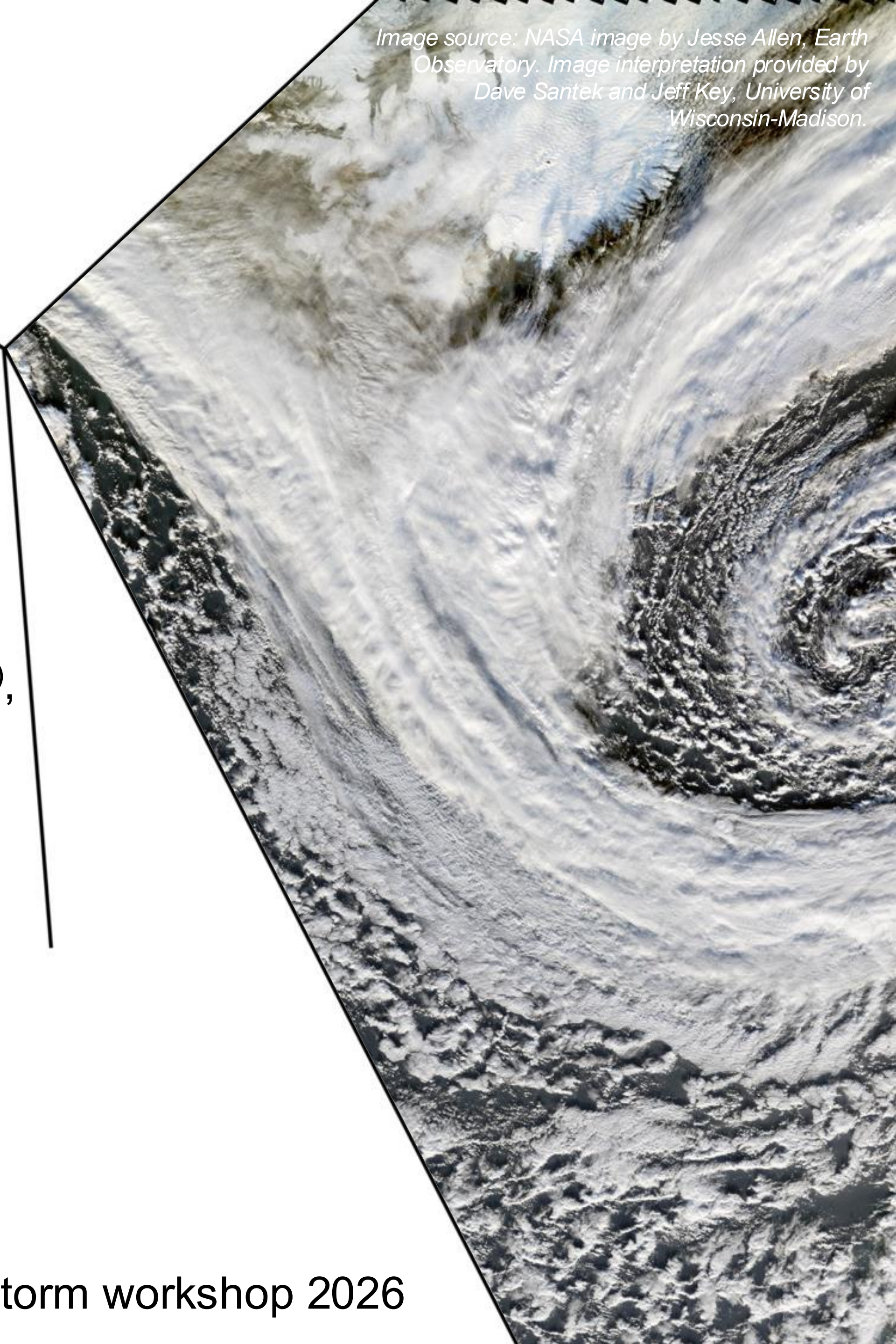
Gallagher Re



European storm workshop 2026

Introduction – Temporal storm clustering

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- **Storm clustering** can be defined as irregular occurrences of events, i.e., leading to **multiple events in quick succession** over the same location over a given period of time (e.g., Mailier et al., 2006)

- Storms *Dudley, Eunice and Franklin* (February 16-21, 2022)

  ➔ Accumulated European economic losses of over £4bn (Gallagher Re, 2023).

Image source: theguardian.com
https://images.app.goo.gl/eXadRyEyYBYv37N48

Introduction – Temporal storm clustering

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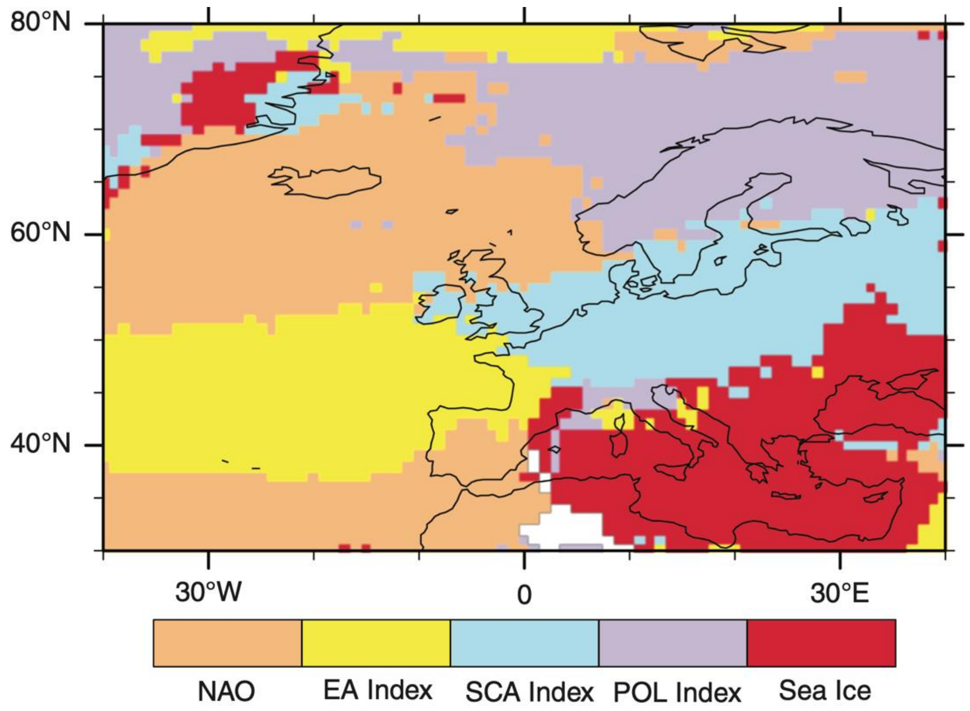
- Previously Clustering was investigated on either:

  Synoptic timescales: e.g., cyclone families (Bjerknes and Solberg, 1922; Priestley et al., 2020)
  or
  Inter-annual timescales: e.g., climatological clustering (Mailier et al., 2006, Vitolo et al., 2009, Economou et al., 2015, Walz et al., 2018).

- **Large-scale modes**, North Atlantic Oscillation, Scandinavian pattern and the East Atlantic have been found to be **good predictors** (Degenhardt et al., 2023) and clustering of windstorms (Vitolo et al., 2009; Walz et al., 2018) **on intra-annual timescales**.



Most dominant teleconnection patterns explaining the inter-annual variability of windstorm counts (Walz et al. 2018)

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➔ Intraseasonal temporal storm clustering

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London 15-day <u>time</u> clustering development – ERA5

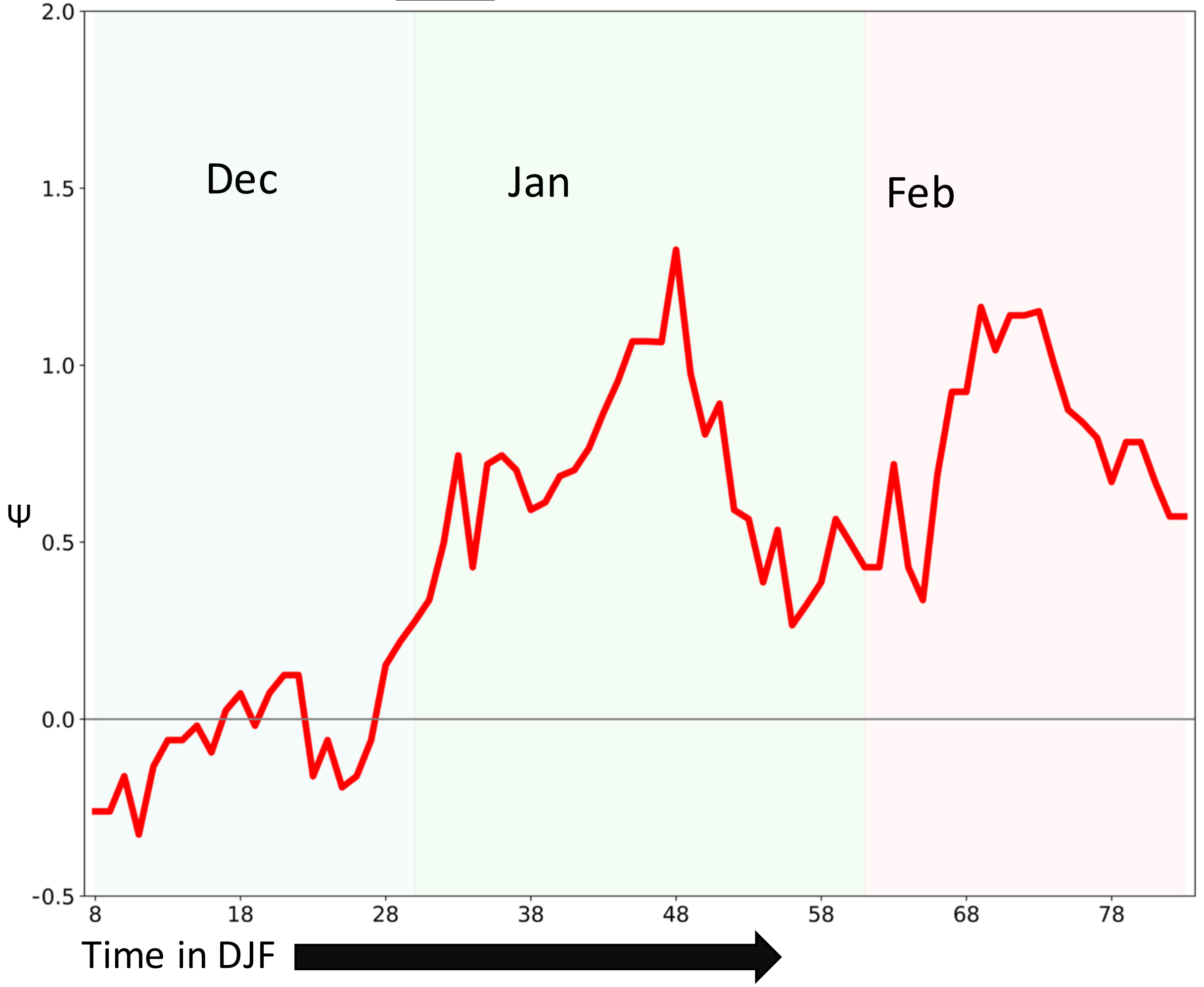

Figure 1. Centred 15-day moving window of the dispersion statistic (Ψ) windstorms footprints (1979/80-2024/25). The x-axis refers to the start day of the moving window, e.g. (a.) 8 = is centred on the 8th Dec and includes data from 1st Dec – 15st Dec for London (51.5°N, 0°W).

Methods

Clustering metric ➔

Dispersion statistic $\Psi = \left(\frac{\sigma^2}{\mu}\right) - 1$

Derived from the Poisson distribution, Variance (σ^2)

Mean (μ) (Mailier et al., 2006)

Windstorm tracking ➔

Impact-oriented wind-based tracking algorithm WiTRACK (Leckebusch et al., 2008a) using 6-hour 10m wind speeds > local 98th percentile.

Key takeaways

Our latest research highlights distinct intra-seasonal variability of windstorm footprints:

➔ **Greater magnitude of clustering in the later part of the season.**

➔ **Specifically, two distinct periods of enhanced clustering**

Feltz et al., 2026, in Review GRL

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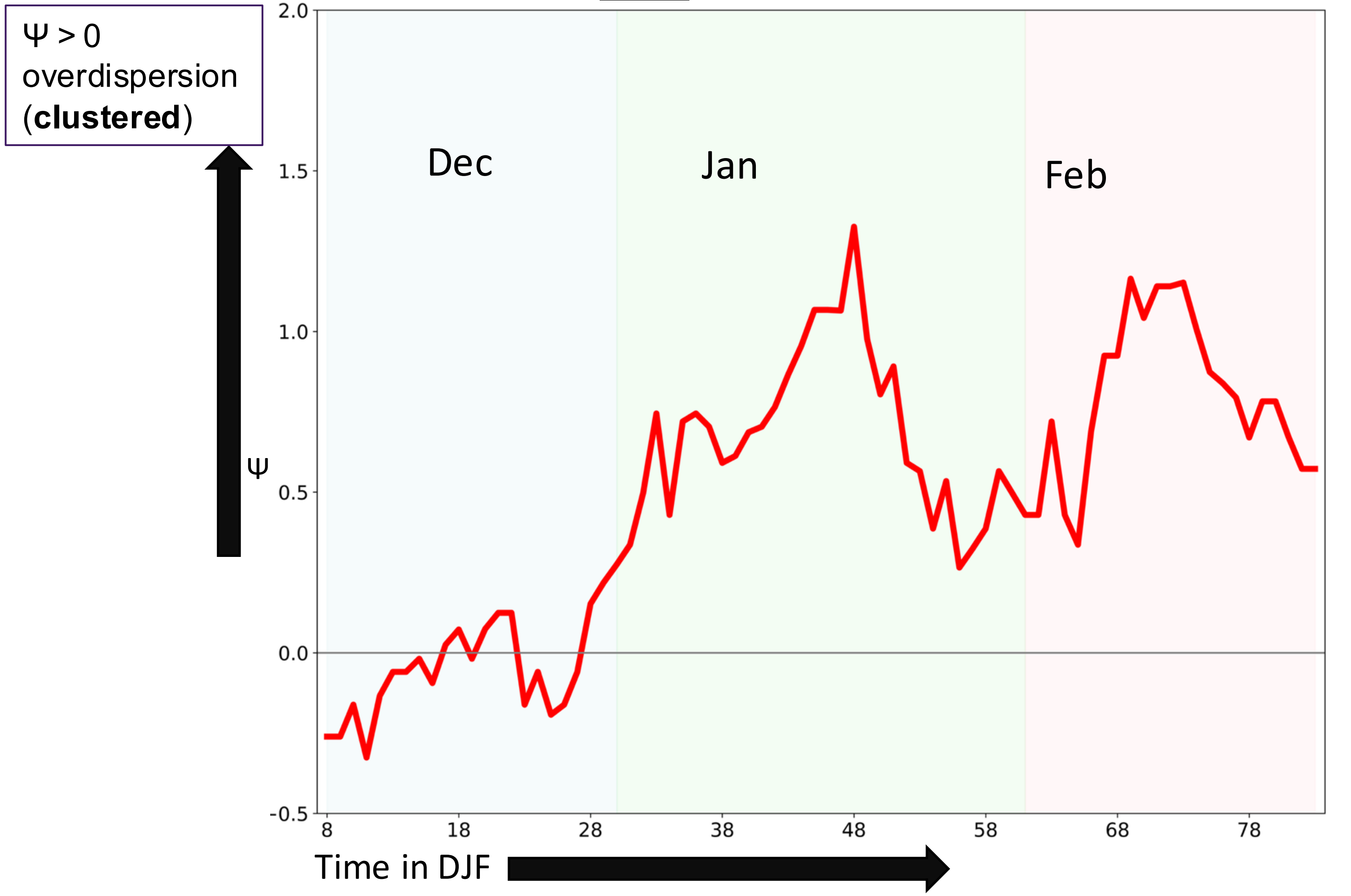

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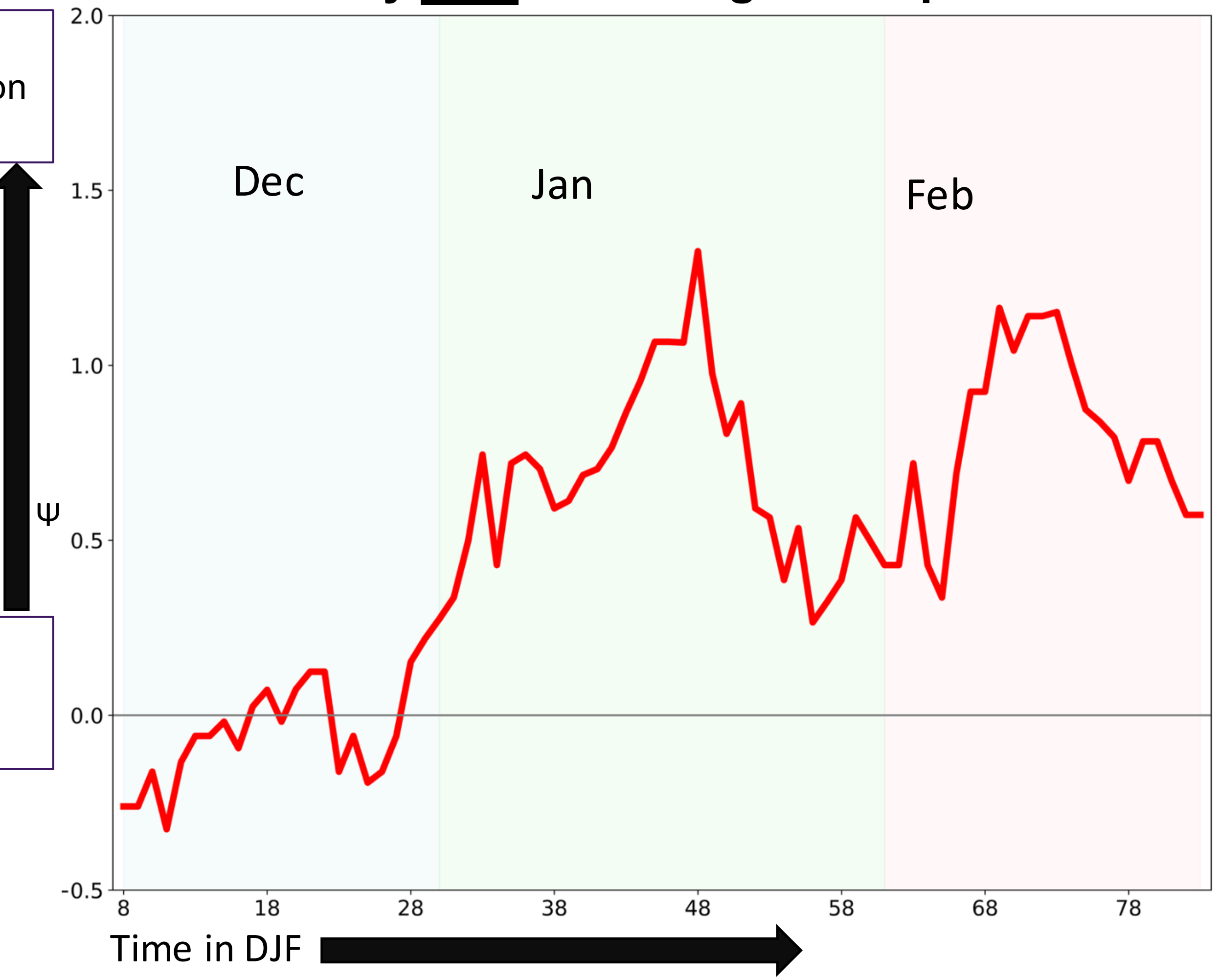
London 15-day time clustering development – ERA5

Ψ > 0
overdispersion
(**clustered**)

Ψ = 0
randomly
distributed



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$\Psi > 0$ overdispersion (**clustered**)

$\Psi = 0$ **randomly** distributed

$\Psi < 0$ under dispersion (**regular**)

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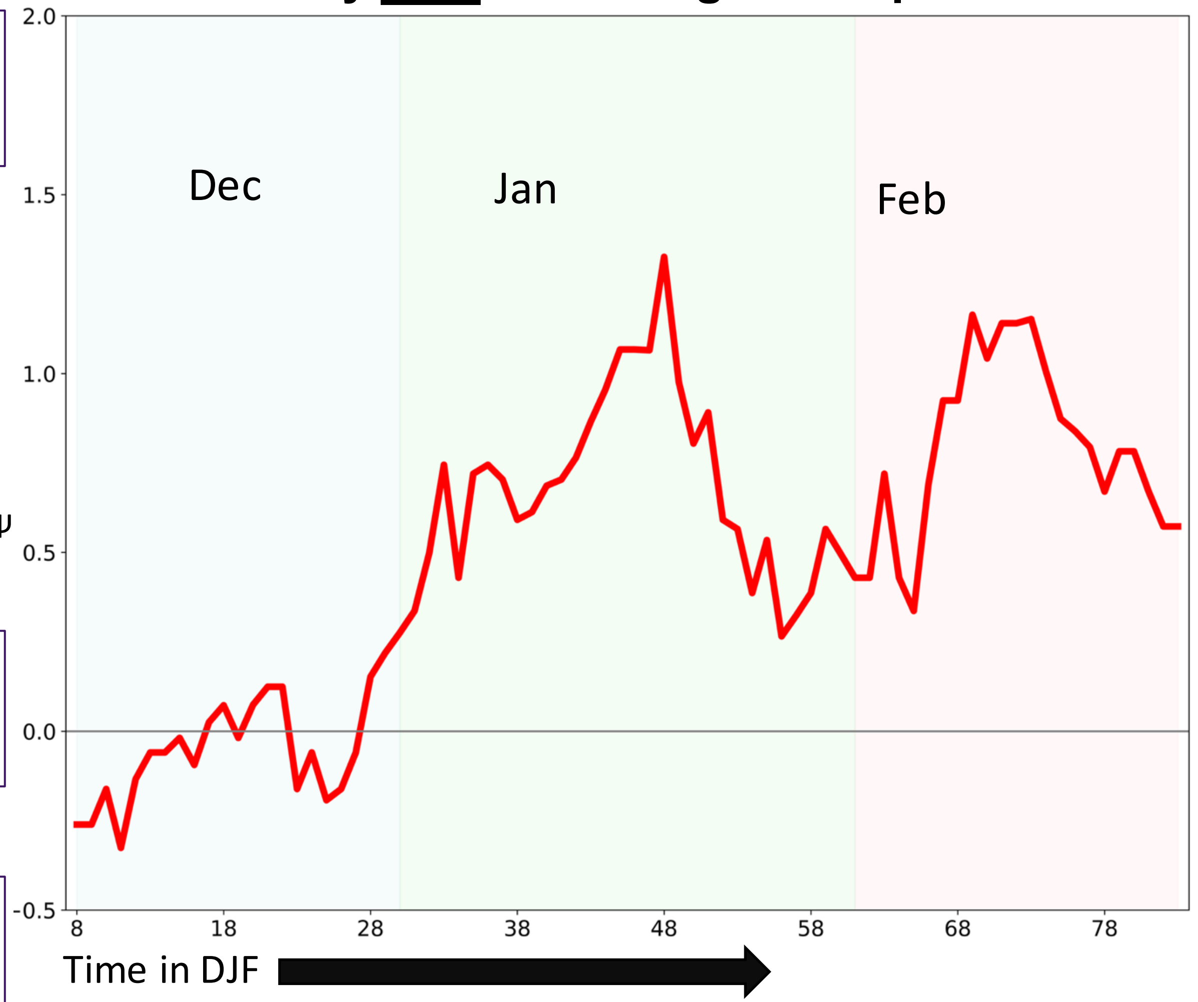

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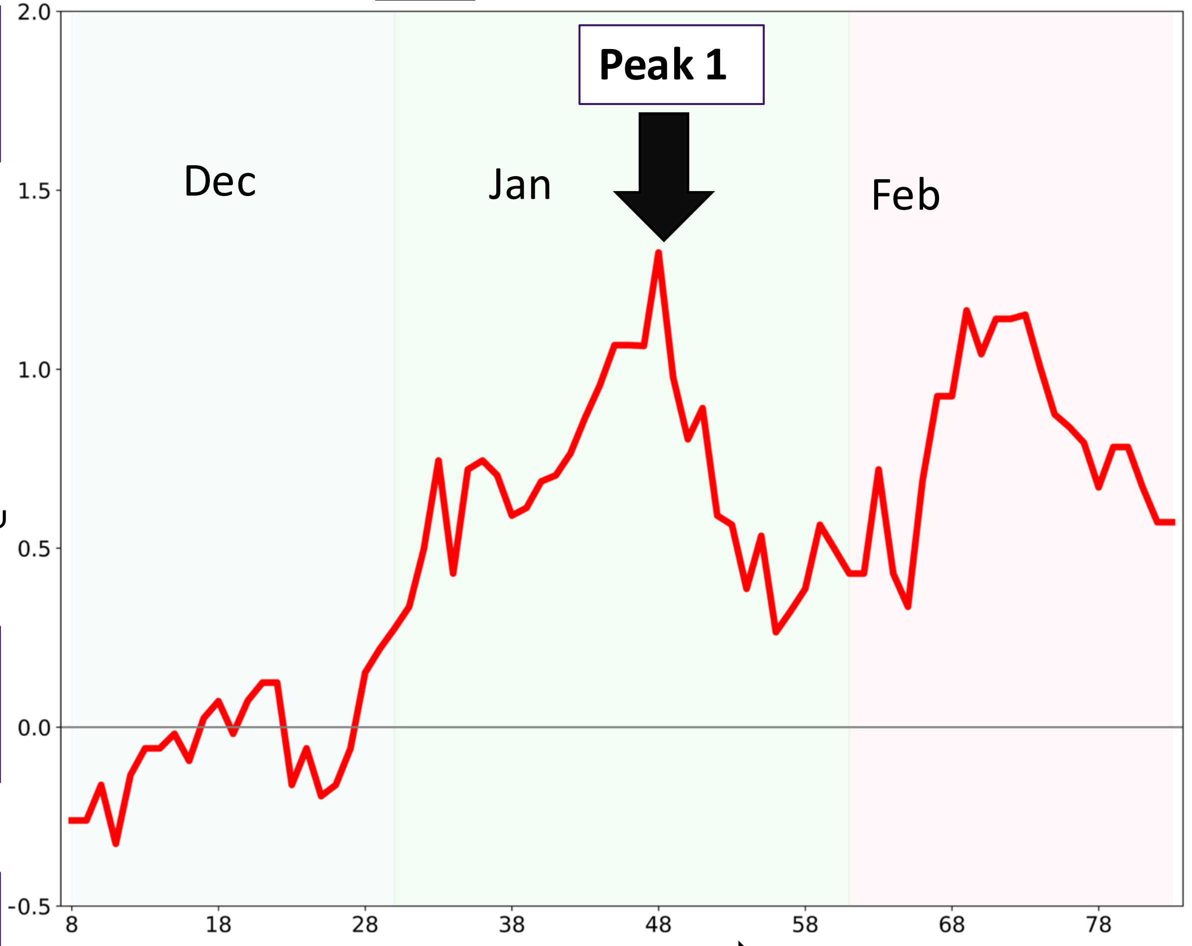

Time in DJF

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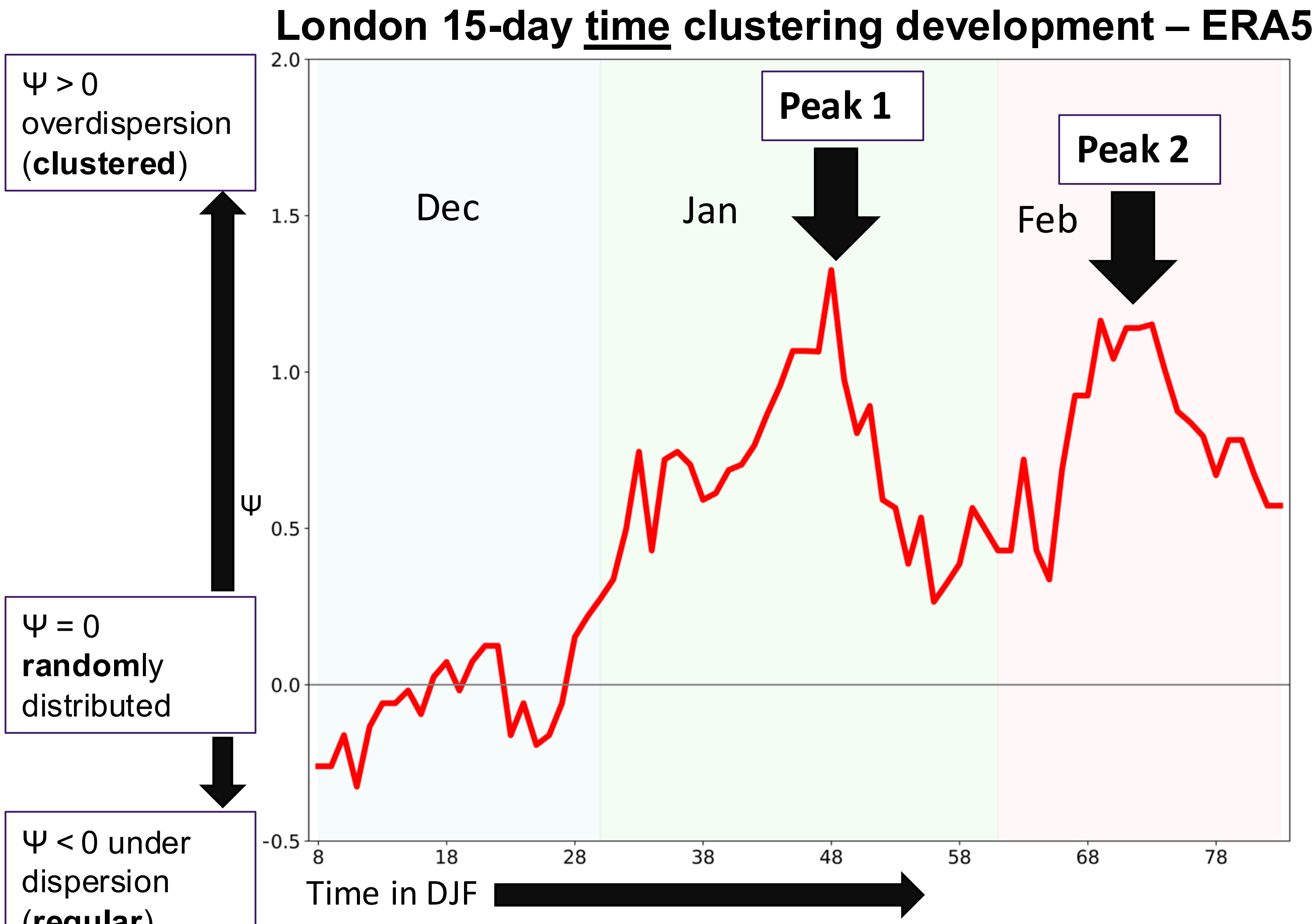

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Introduction Results1.2
➔ Intraseasonal temporal storm clustering

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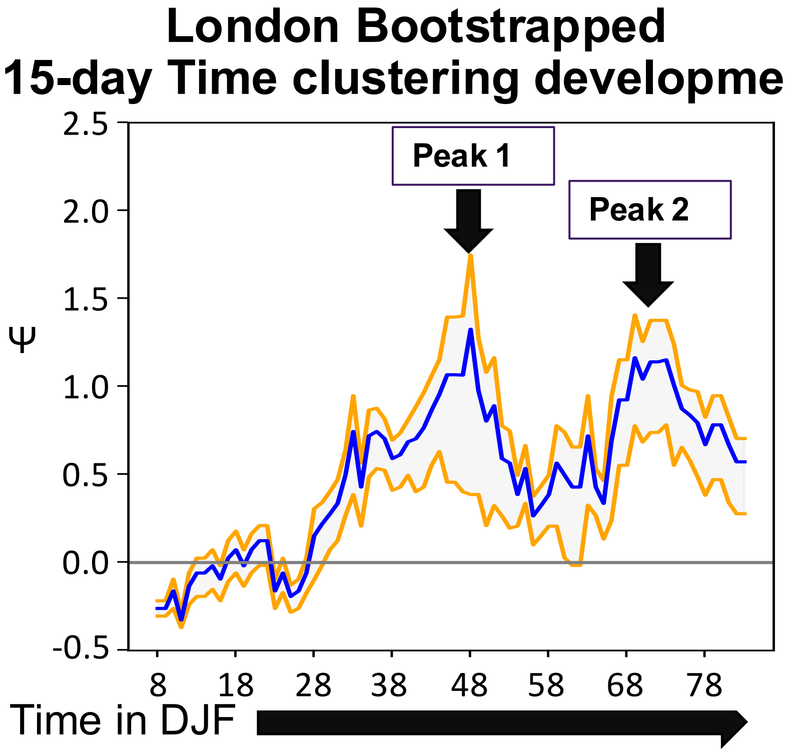
We also highlighted:
- ➔ **Two-peak structure seems robust** in extreme windstorm climatology through bootstrapping 10,000 times with replacement
- ➔ **Spatial coherency** of the intra-seasonal variability of clustering



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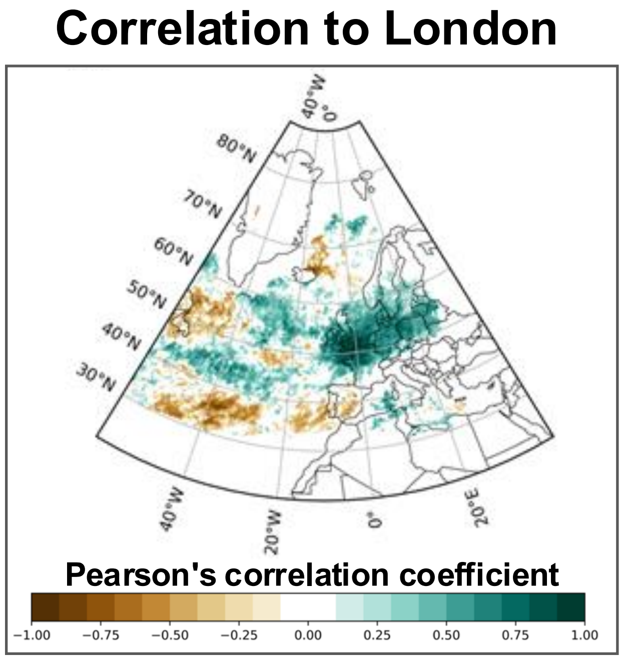

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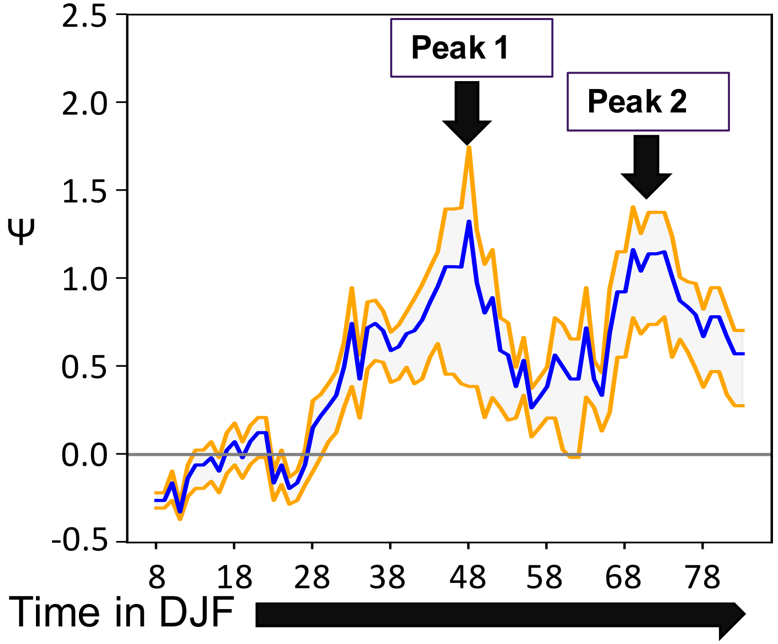
Also proven for:

London Bootstrapped 15-day Time clustering development



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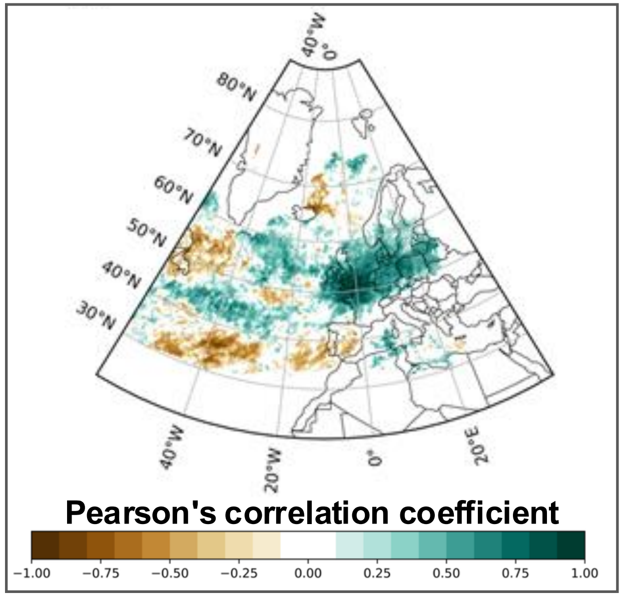
Correlation to London



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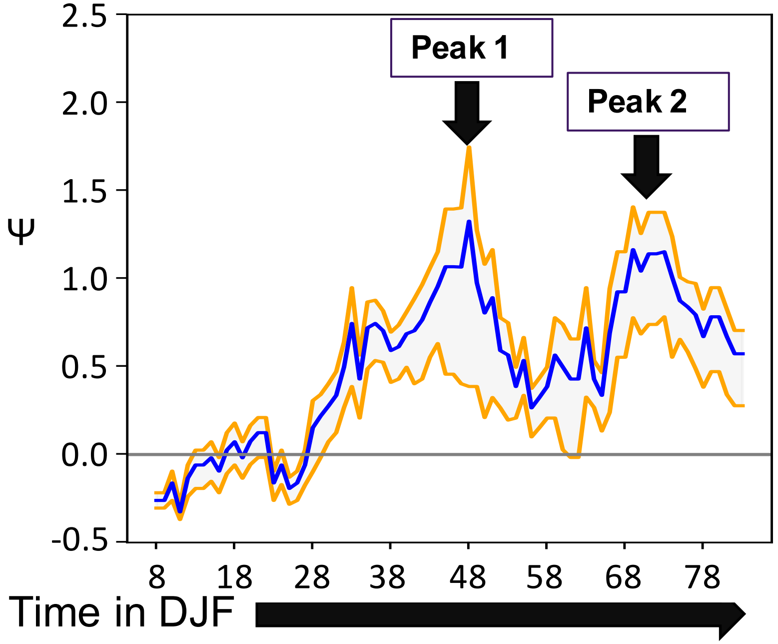

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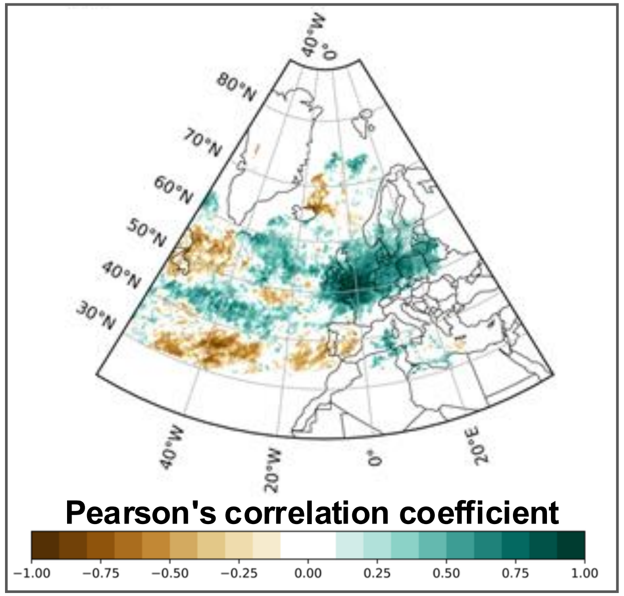

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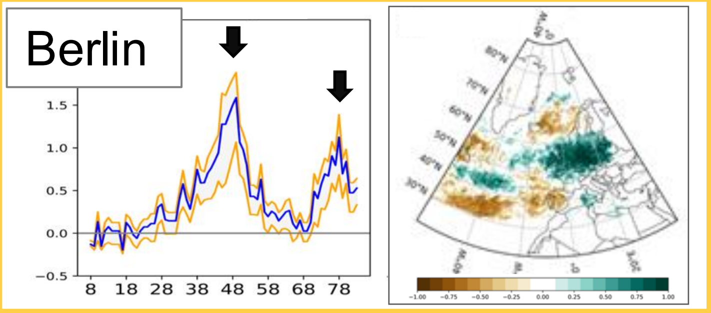

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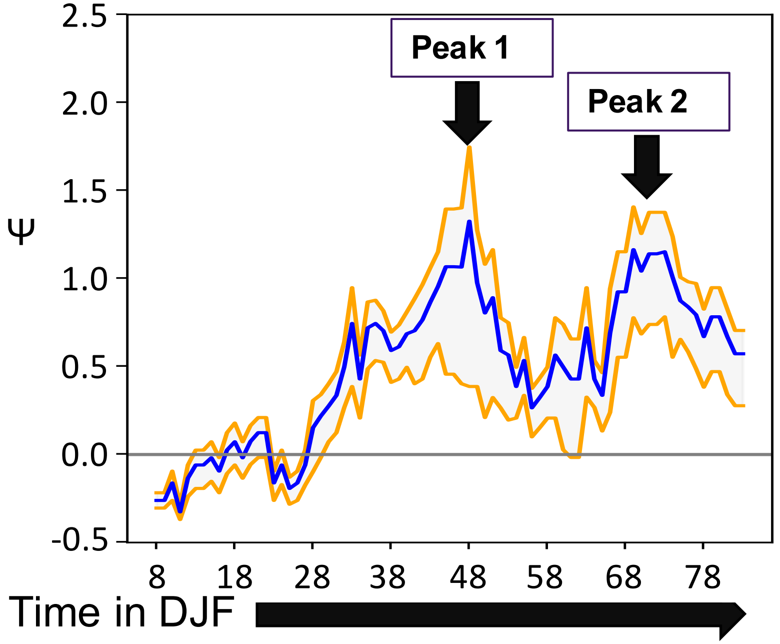

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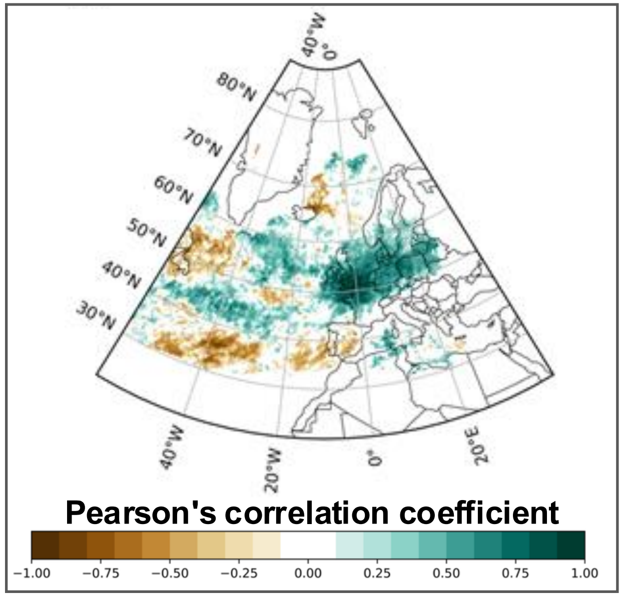

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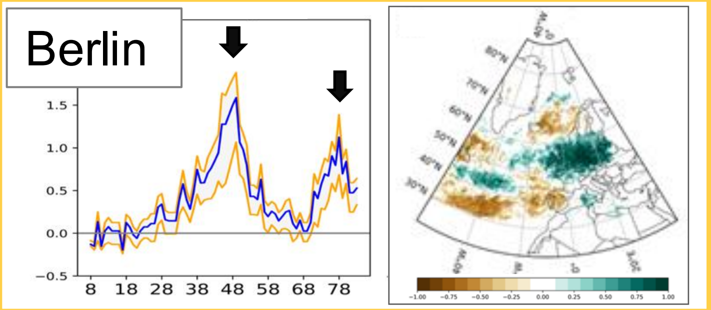

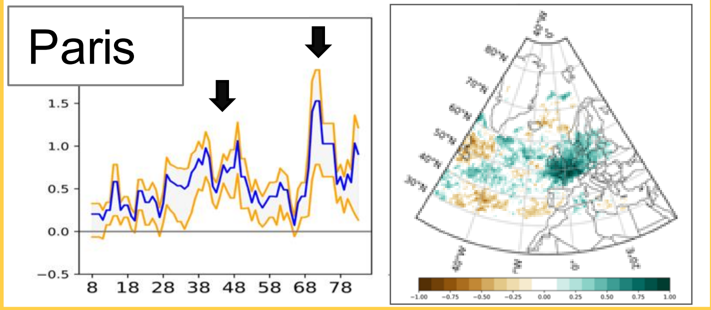

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Introduction Results1.3: Large-scale modes ➔ Definition

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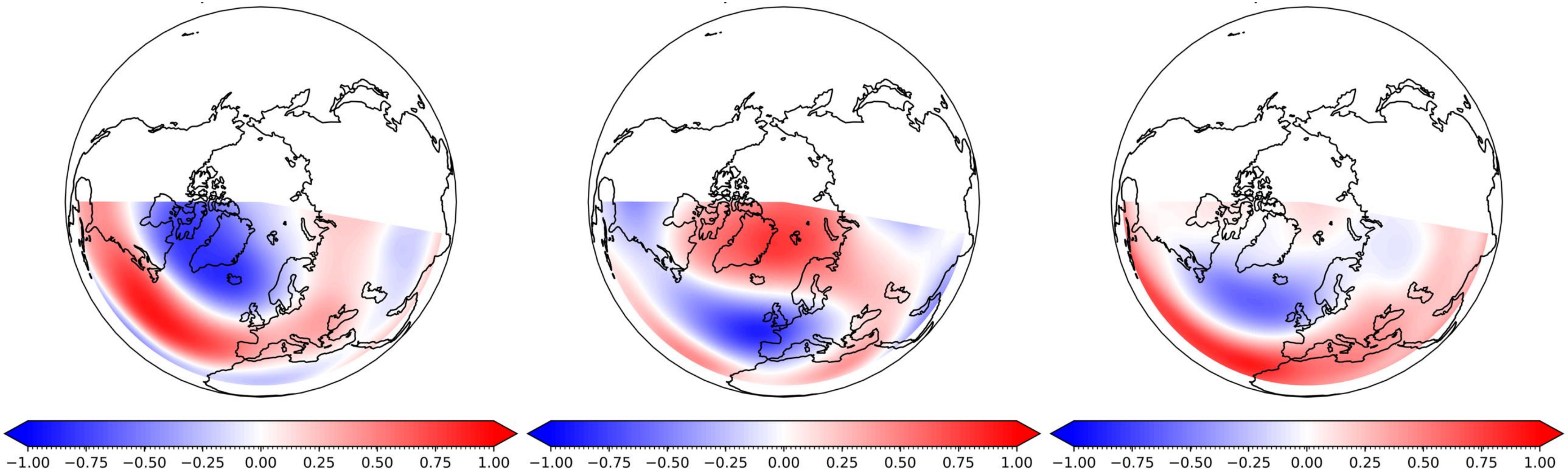
EOF1: North Atlantic Oscillation (**NAO)**

EOF2: Scandinavian pattern (**SCA)**

EOF3: East Atlantic (**EA)**



EOF loadings positive phase (following NOAA's definition)

Top 3 leading modes of Varimax rotated EOF performed over 20N°-90N°, 90W°-80E°- using 500-hPa geopotential height standardized anomalies. Plotted as correlation to their respective pc timeseries where (a) EOF1 explains 12.42% of the variance and is identified as the North Atlantic Oscillation (NAO), (b) EOF2 explains 10.29% of the variance and is identified as the Scandinavian pattern (SCA) and (c) EOF3 explains 9.74% of the variance and is identified as the East Atlantic (EA).

Introduction Results 1.3: Large-scale modes
➔ Intraseasonal temporal storm clustering

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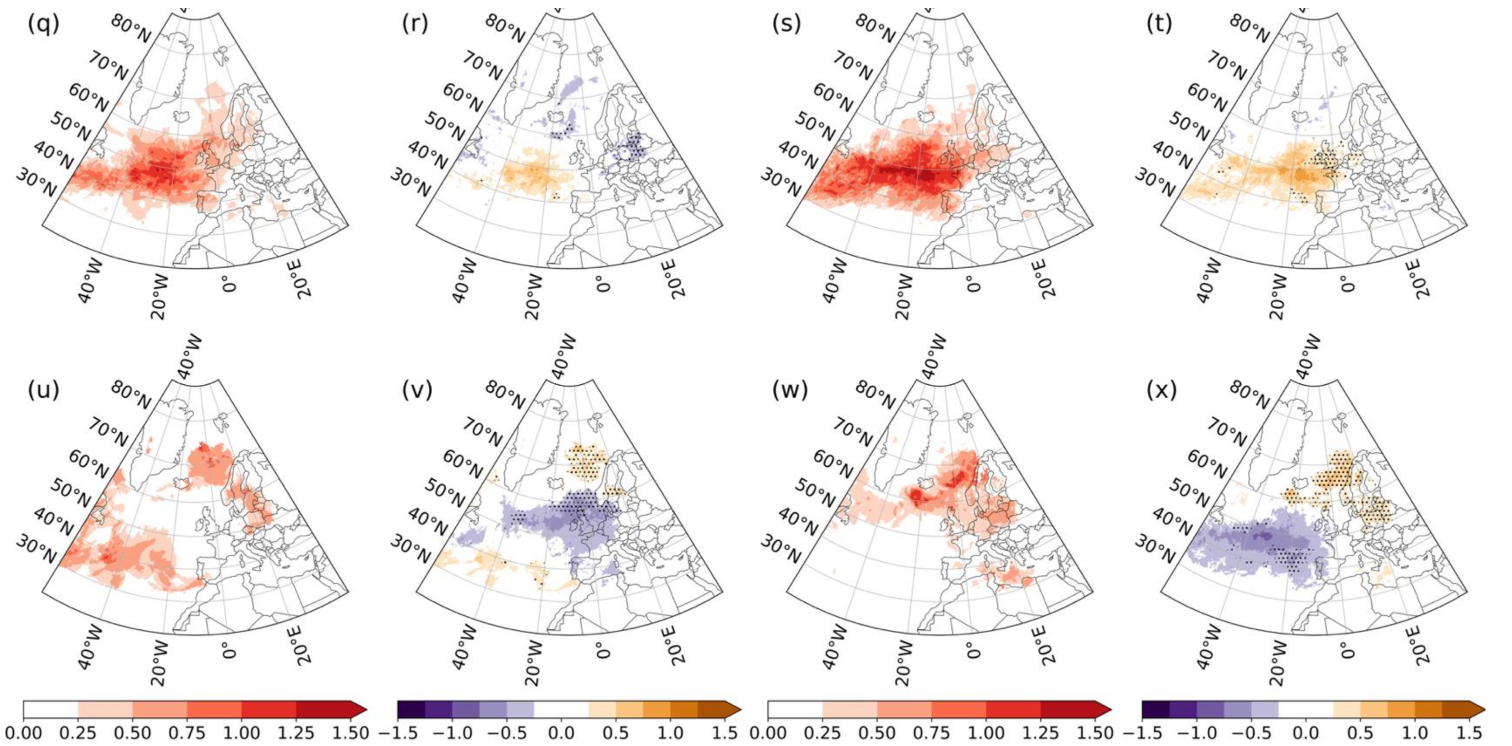
East-Atlantic pattern

Peak 1 composite **Peak 1 anomaly** **Peak 2 composite** **Peak 2 anomaly**

EA+

EA-



Footprint density composites and anomalies during London's 15-day Ψ moving window 1st peak (columns 1-2) and 2nd peak (columns 3-4) for positive (+) and negative (-) phases of EA. The time interval for the 1st peak is 10th Jan – 24th, and the 2nd peak is 31st Jan – 14th Feb (15-day perspective). Results are only shown where the footprint density is > 1.1. Dots show results of a one-sample t-test between the composite and climatology, where significance is P < 0.1.

→ **Large-scale modes reveal variations in their intra-seasonal influence**, specifically in their association with windstorms between the 1st and 2nd peak.

→ More research is needed to discern their roles to clustering on intra-seasonal timescales

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Introduction Results 1.3 : Large-scale modes
→ Intraseasonal temporal storm clustering

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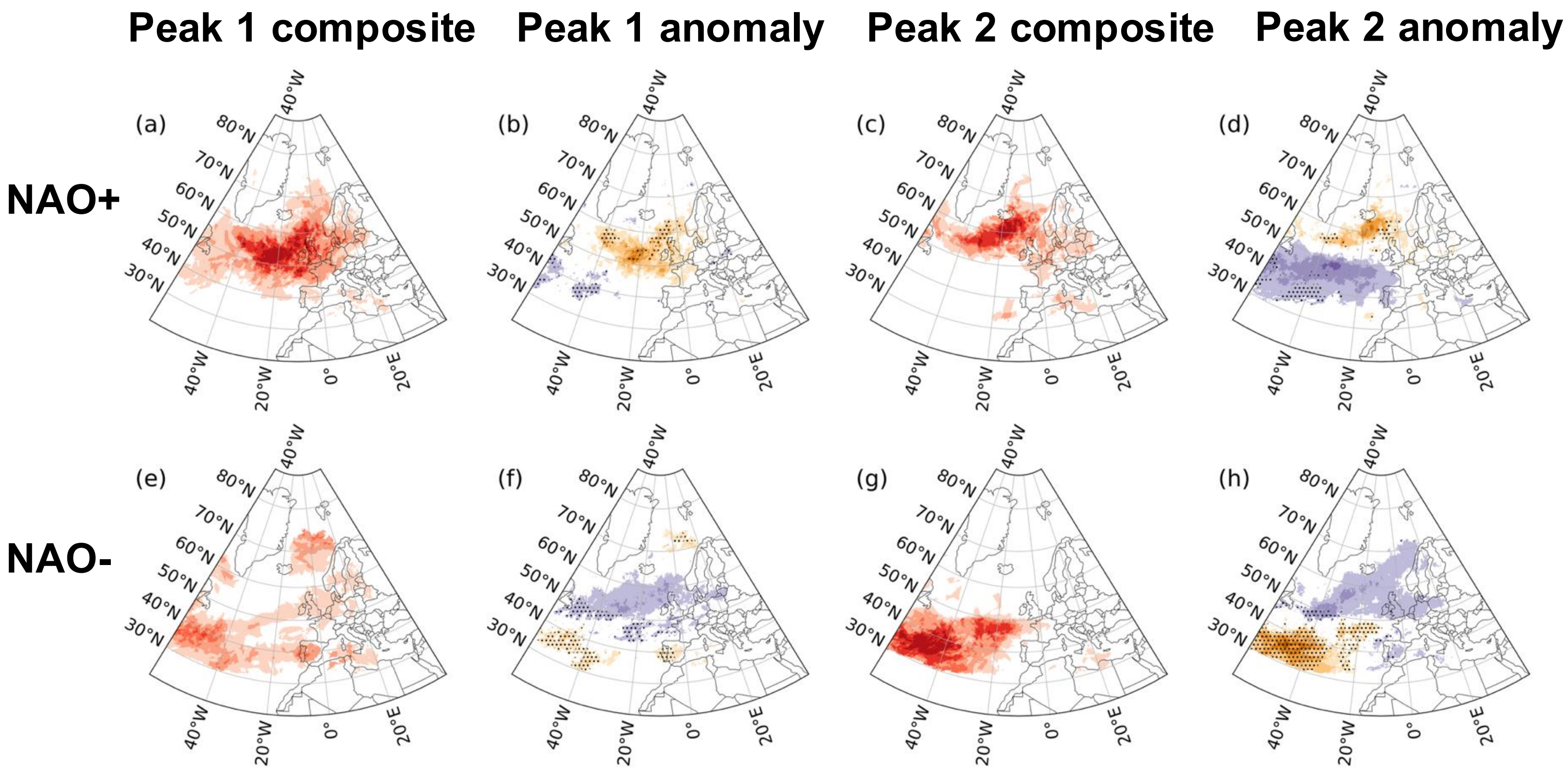
North Atlantic Oscillation



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Introduction Results 1.3 : Large-scale modes
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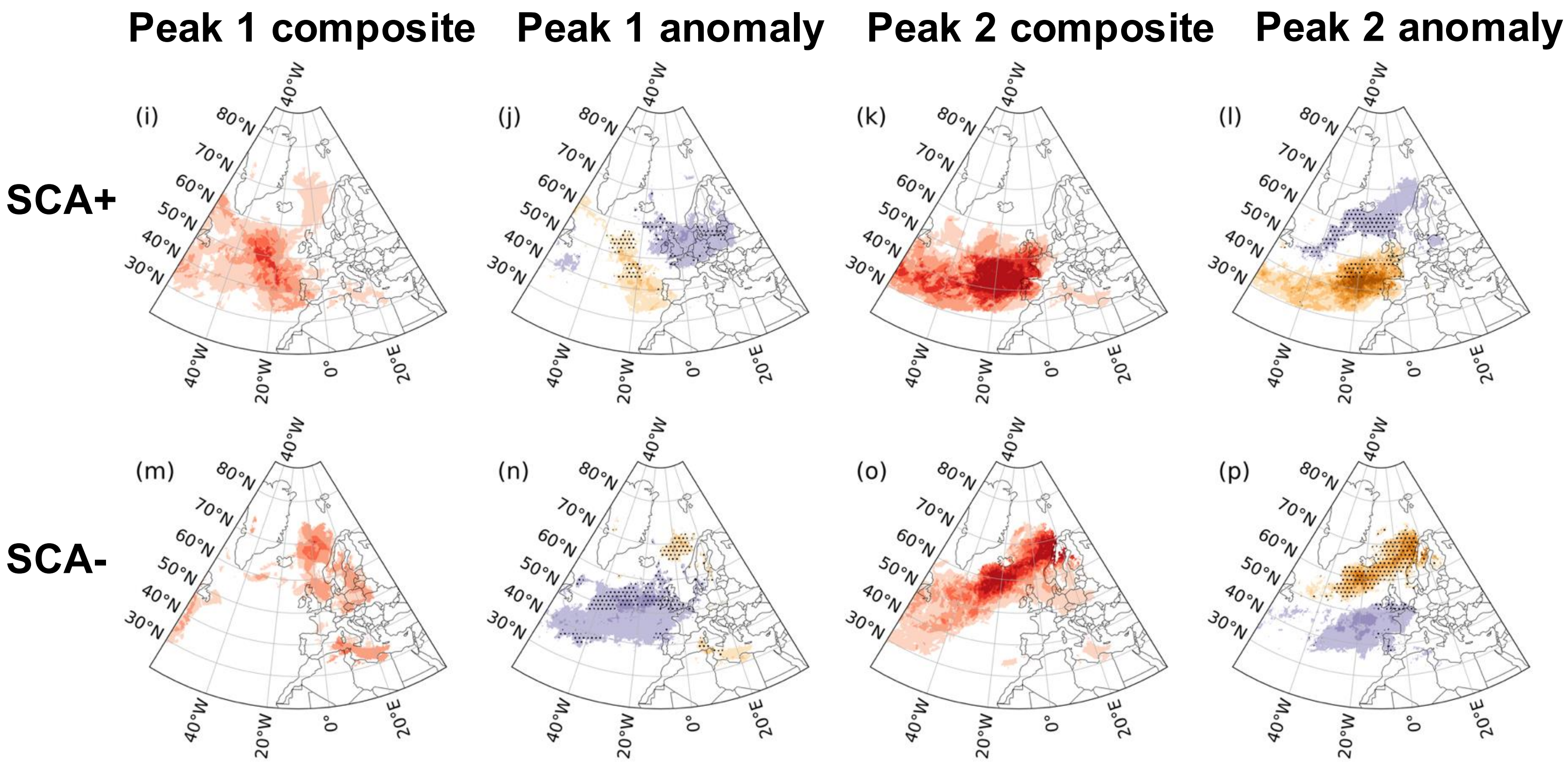
Scandinavian pattern



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Primary research questions:

➔ Can we group similar Geopotential height 1000hpa development fields (equivalent to mslp)?

➔ Are some more common at certain times of the winter season?

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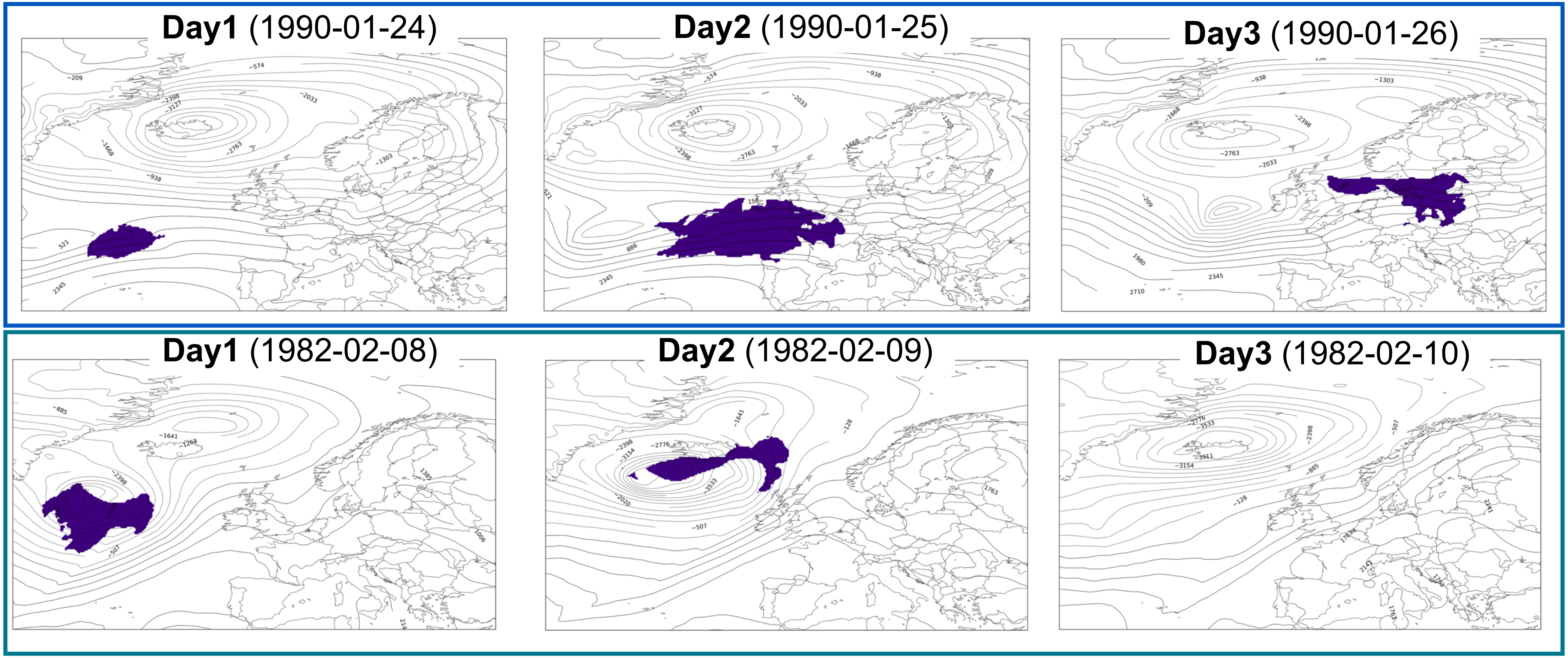
Windstorm footprint



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Spatial clustering method via PCA + K-means (Leckebusch et al., 2008b): DOI: 10.1127/0941-2948/2008/0266

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Data:
Core winter season (DJF), 1979/80-2024/25 ERA5 reanalysis.

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PCA on 12-hourly Geopotential height 1000hpa

Data reduced by retaining the first 6 PCs that explained the most variance.

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PCA on 12-hourly Geopotential height 1000hpa

Data reduced by retaining the first 6 PCs that explained the most variance.

Slice the 6 PC's timeseries' into 3-day episodes

Obtained the 3-day development fields.

$$\begin{bmatrix} pc1\_day1 & \cdots & pc1\_day3 \\ \vdots & \ddots & \vdots \\ pc6\_day1 & \cdots & pc6\_day3 \end{bmatrix}$$

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PCA on 12-hourly Geopotential height 1000hpa ➔ Slice the 6 PC's timeseries' into 3-day episodes ➔ n * 36-dimentional vector's

Data reduced by retaining the first 6 PCs that explained the most variance.

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$$\begin{bmatrix} pc1\_day1 & \cdots & pc1\_day3 \\ \vdots & \ddots & \vdots \\ pc6\_day1 & \cdots & pc6\_day3 \end{bmatrix}$$

Each 3-day episode in the form:

[Pc1_day1
⋮
Pc6_day3]

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PCA on 12-hourly Geopotential height 1000hpa

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Slice the 6 PC's timeseries' into 3-day episodes

Obtained the 3-day development fields.

$$\begin{bmatrix} pc1\_day1 & \cdots & pc1\_day3 \\ \vdots & \ddots & \vdots \\ pc6\_day1 & \cdots & pc6\_day3 \end{bmatrix}$$

n * 36-dimentional vector's

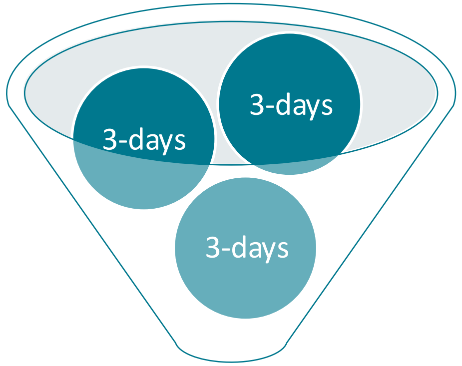
Each 3-day episode in the form:

[Pc1_day1

⋮

Pc6_day3]

K-means →20 spatial-groups

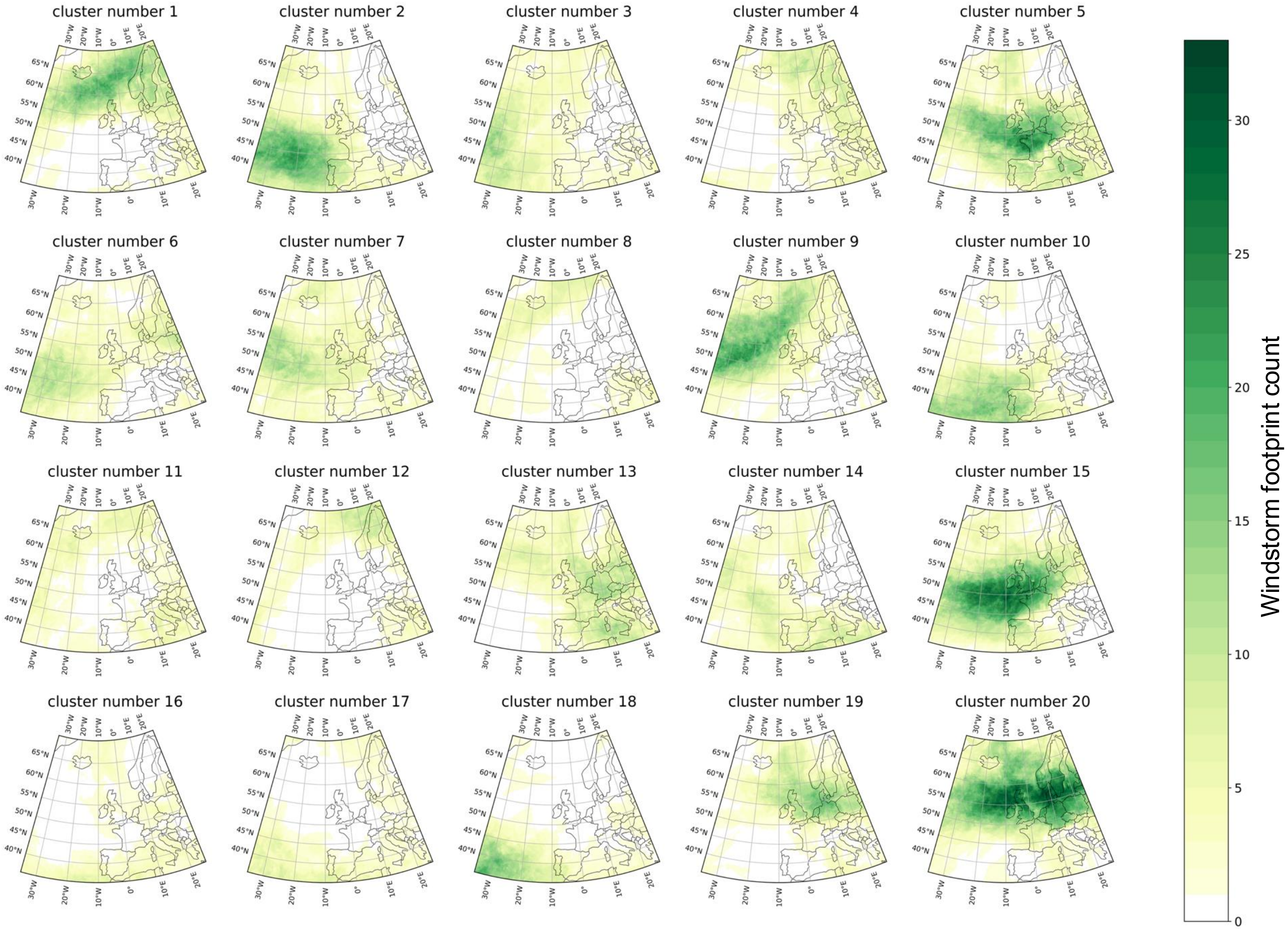


20 spatial-groups

Results part 2.1 : Spatial clustering → Windstorm spatial-group occurrence

➔ Clear storm clusters can be identified

➔ Different 3-day development fields have led to spatially varying windstorm footprint occurrences



Number of windstorm footprint occurrences per spatial-group. (Number of times a spatial-group has occurred when there have been at least 1 or more windstorm footprints in the 3-day period)

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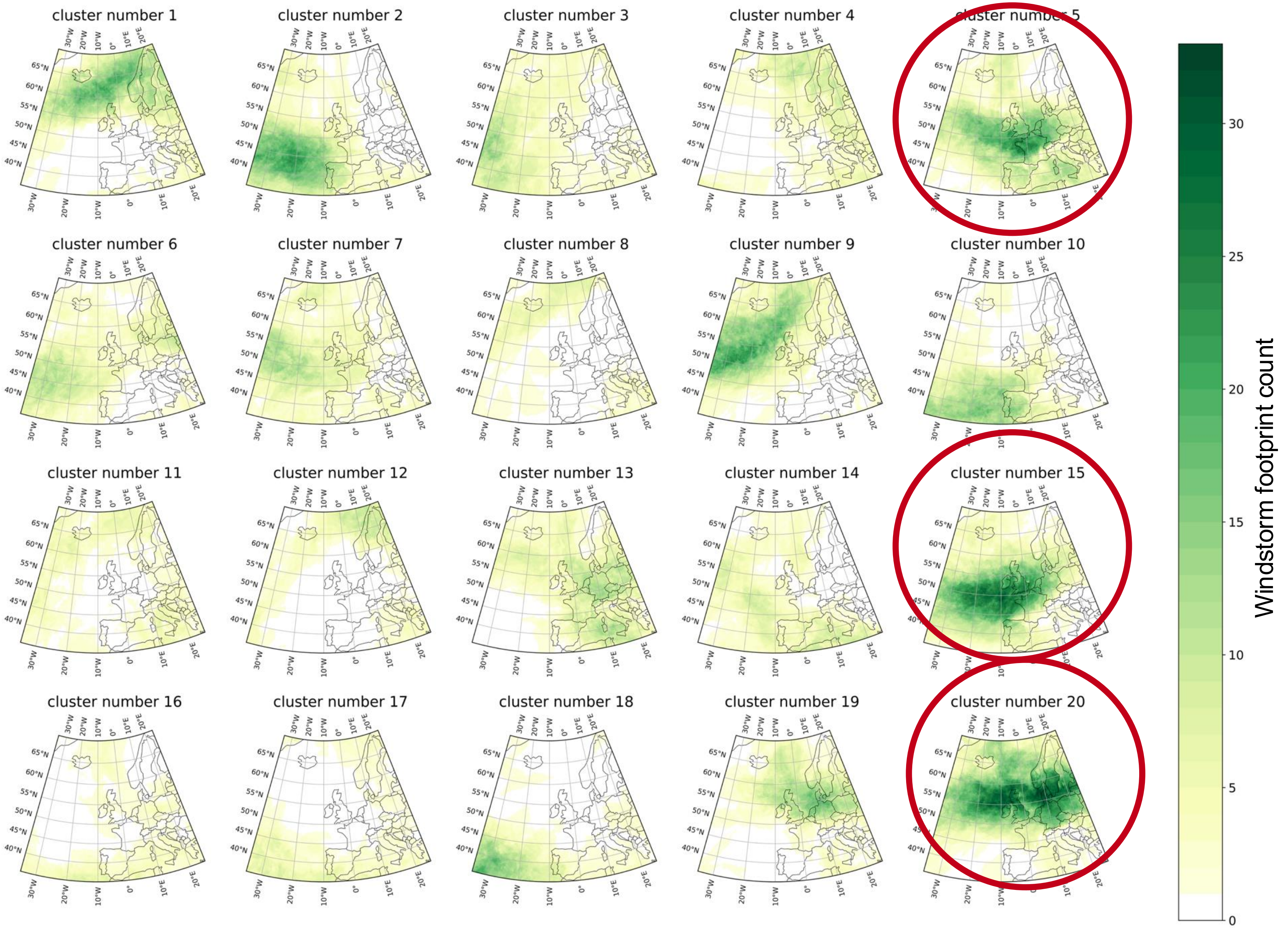

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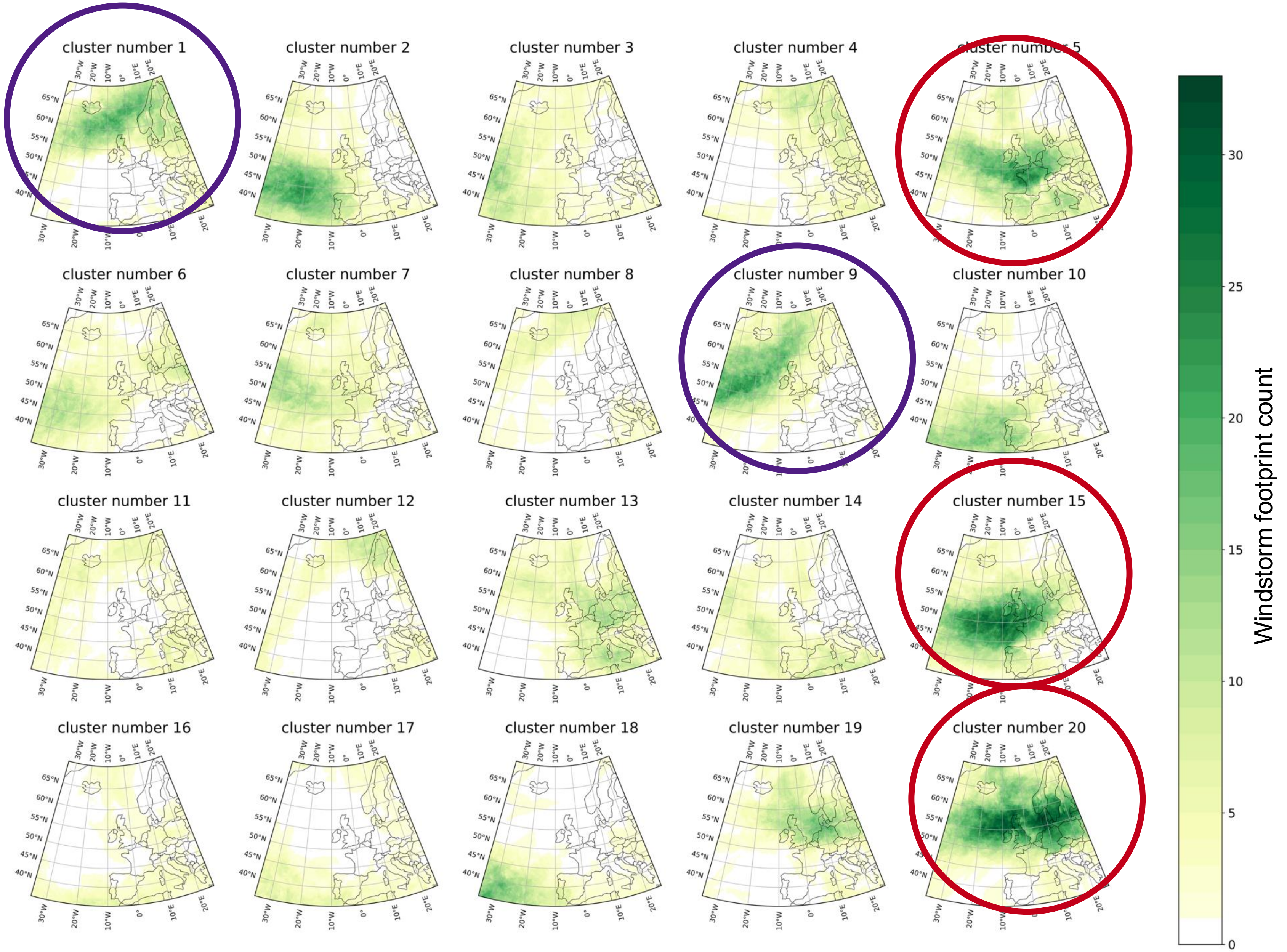

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Results part 2.1: Spatial clustering → Intraseasonal 15-day Windstorm spatial-group occurrence

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➔ Spatial and time clustering are linked
➔ Certain clusters contribute more than others, depending on the time within the season

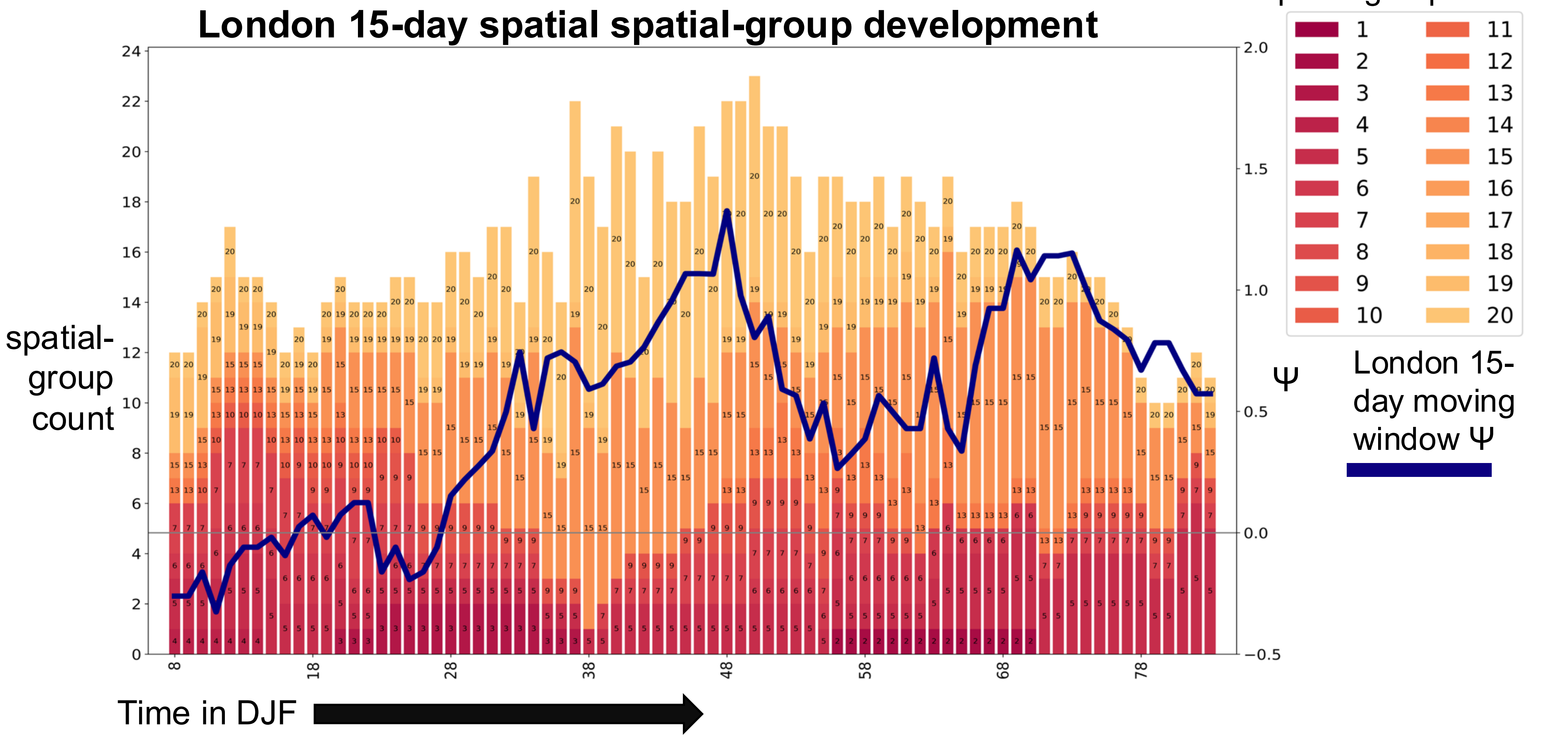

Figure 5. The spatial-group number of a given windstorm footprint on a Centred 15-day moving window (1979/80-2024/25). The x-axis refers to the start day of the moving window, e.g. (a.) 8 = is centred on the 8th Dec and includes data from 1st Dec – 15st Dec for London (51.5°N, 0°W). Blue line is the 15-day moving window dispersion (Ψ) statistic for London.

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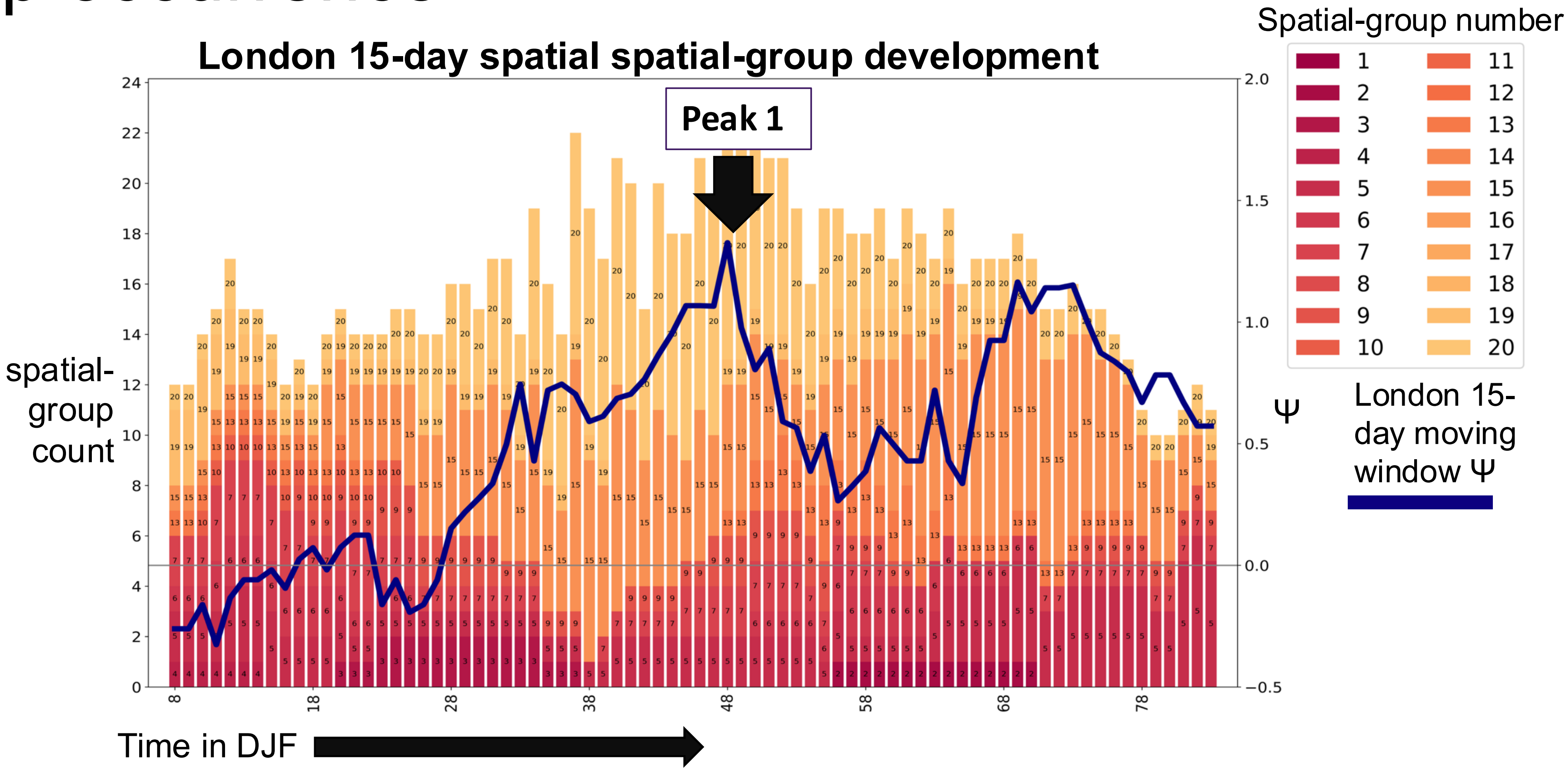

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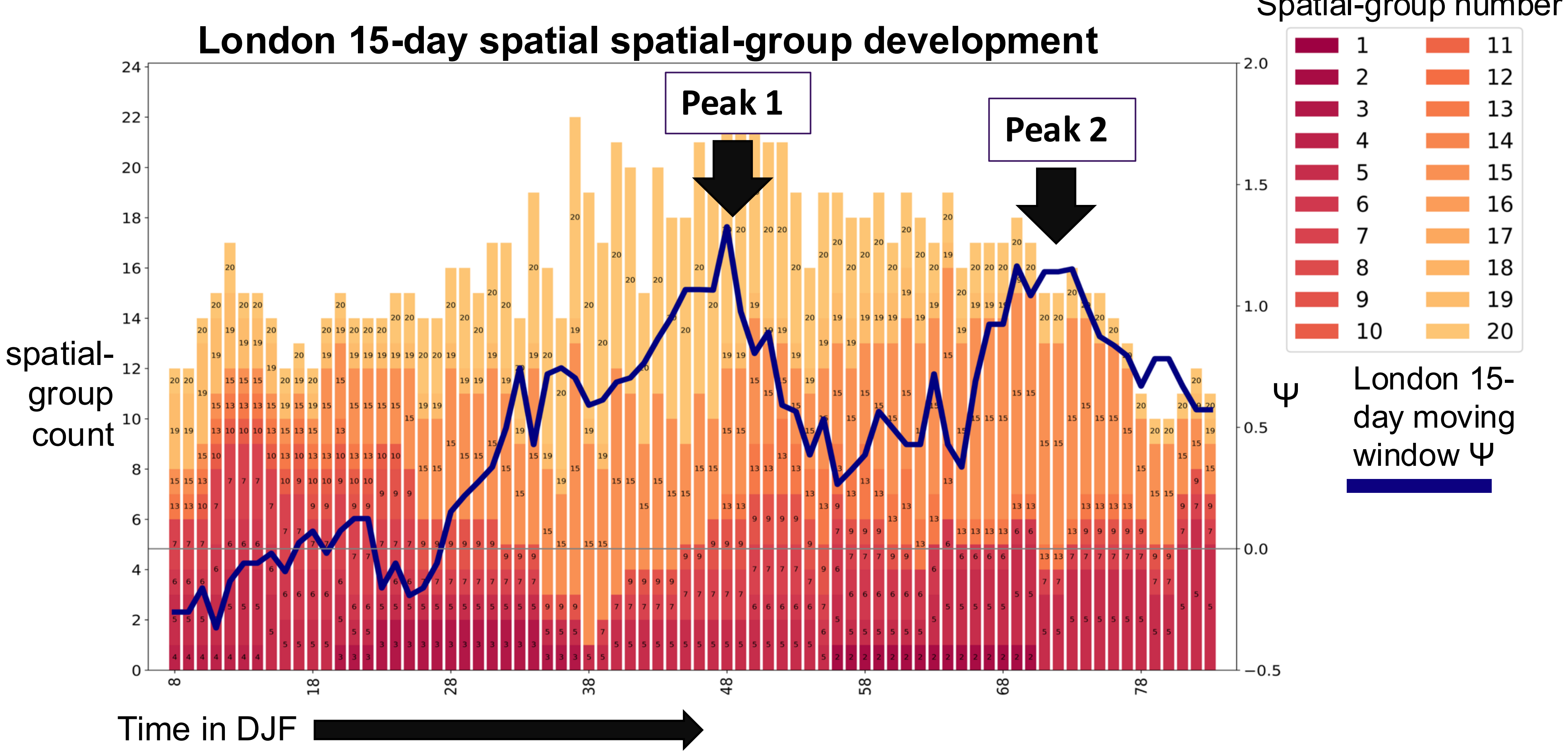

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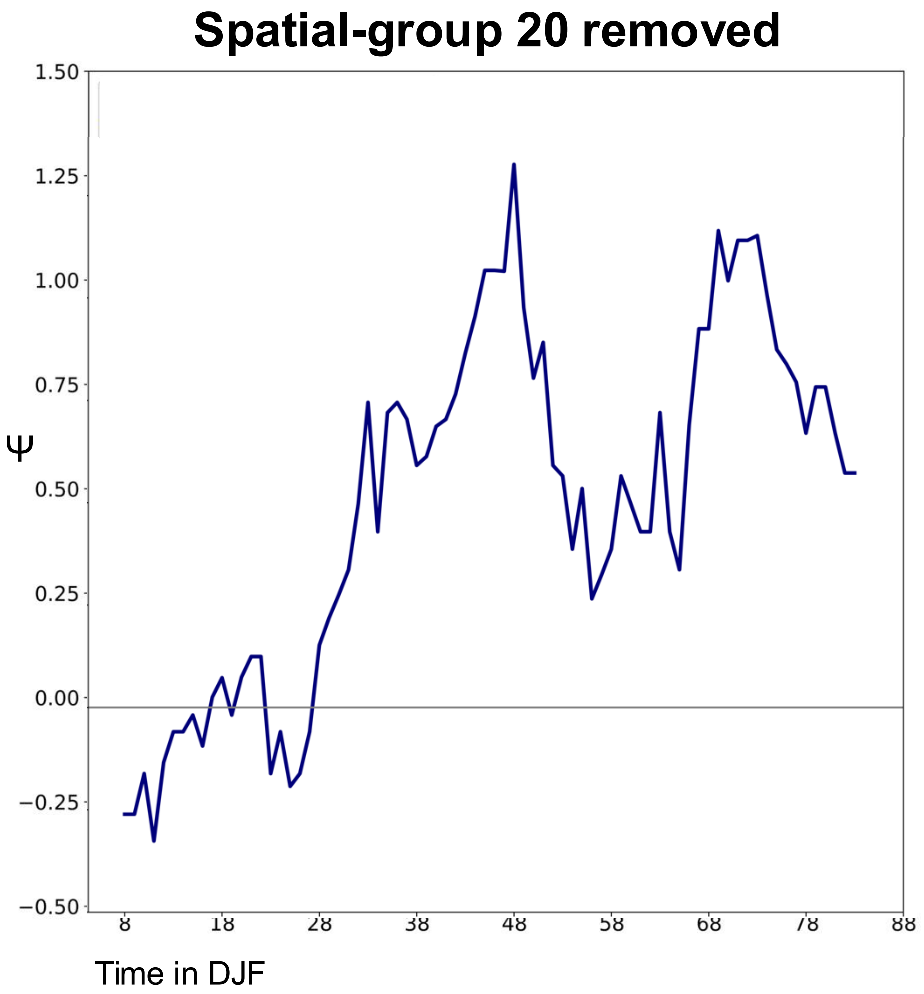
Results part 2.1: Spatial clustering → intraseasonal Ψ 15-day moving window London leave one out

→ Removal of storms from **spatial-group 20 removes peak 1**

→ Removal of storms from **spatial-group 15 removes peak 2**

Measure of temporal clustering Ψ
Ψ > 0 ➔ over dispersion (clustered)
Ψ = 0 ➔ randomly distributed
Ψ < 0 ➔ under dispersion (regular)



For each spatial-group when there is a storm, it is set to 0. E.g. for spatial-group 20, when a storm occurs during a 3-day episode with spatial-grouping 20, the storm count is set to 0

Results part 2.1: Spatial clustering → intraseasonal **Ψ** 15-day moving window London leave one out

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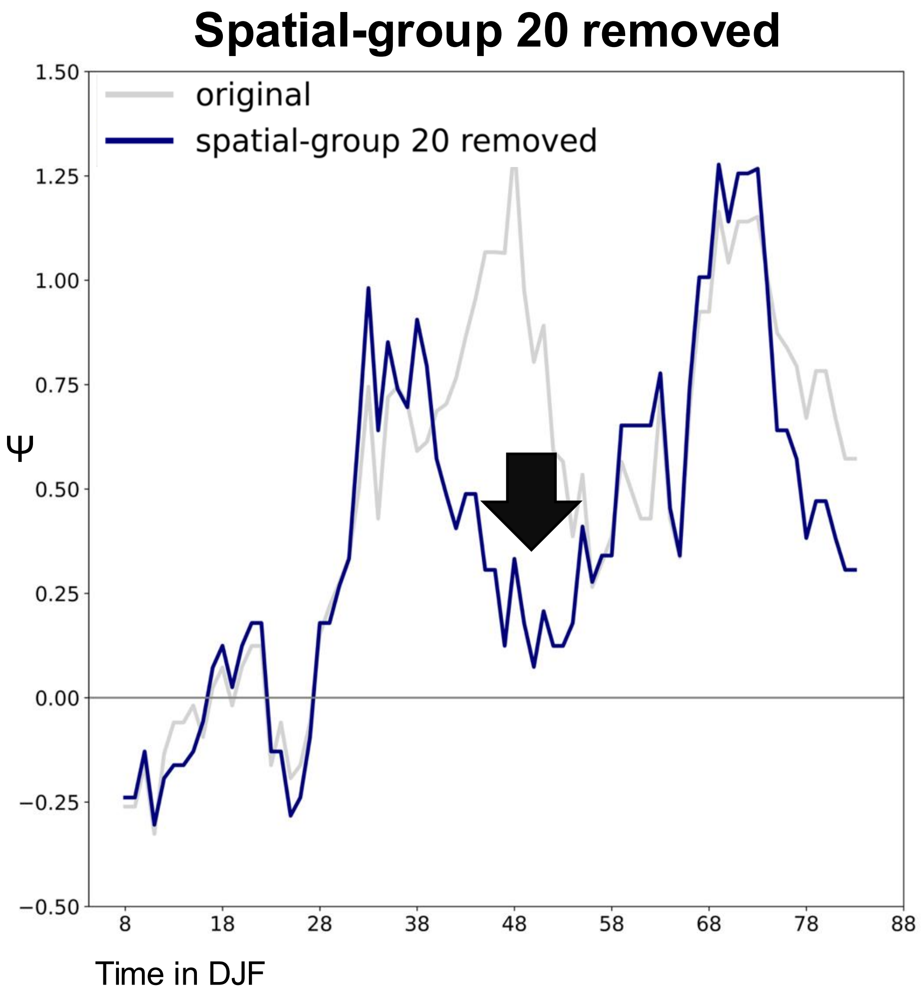

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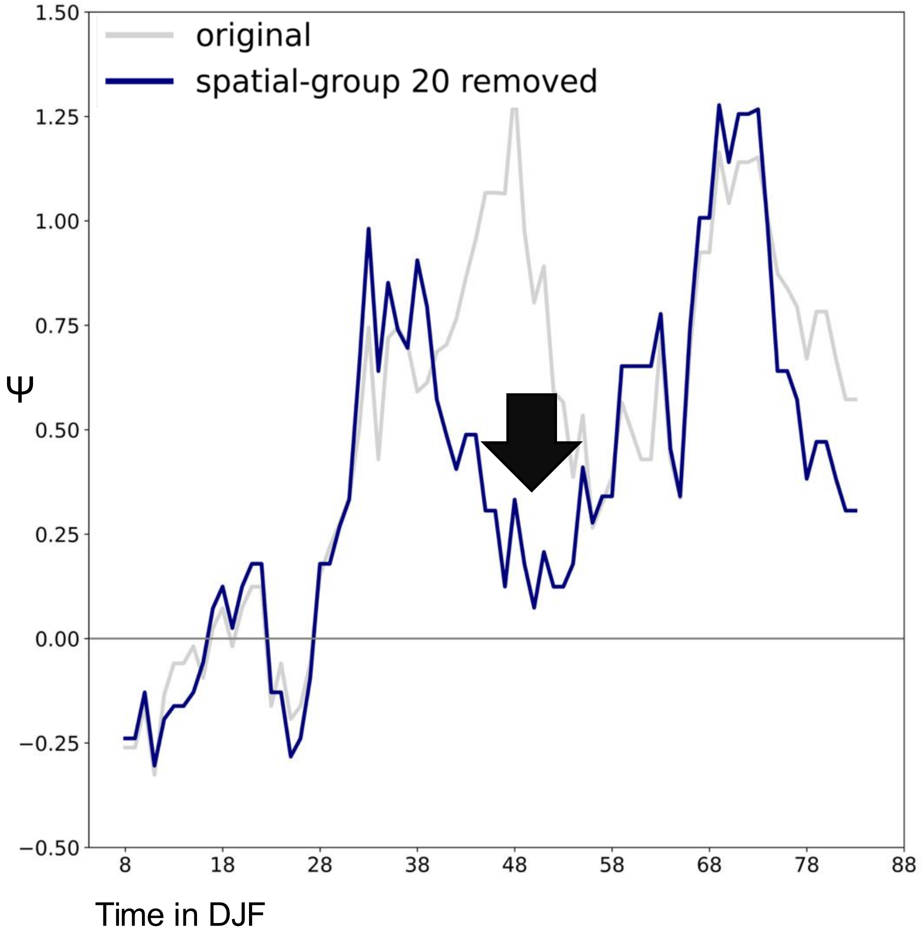
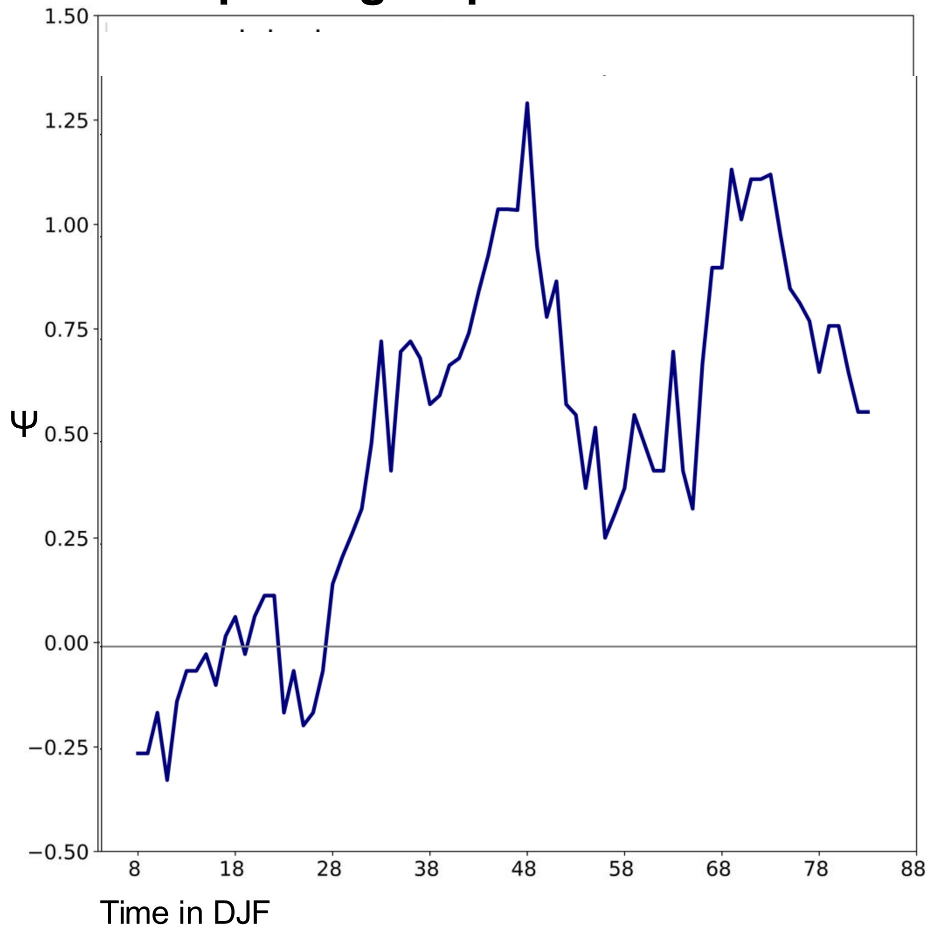
Spatial-group 20 removed



Spatial-group 15 removed



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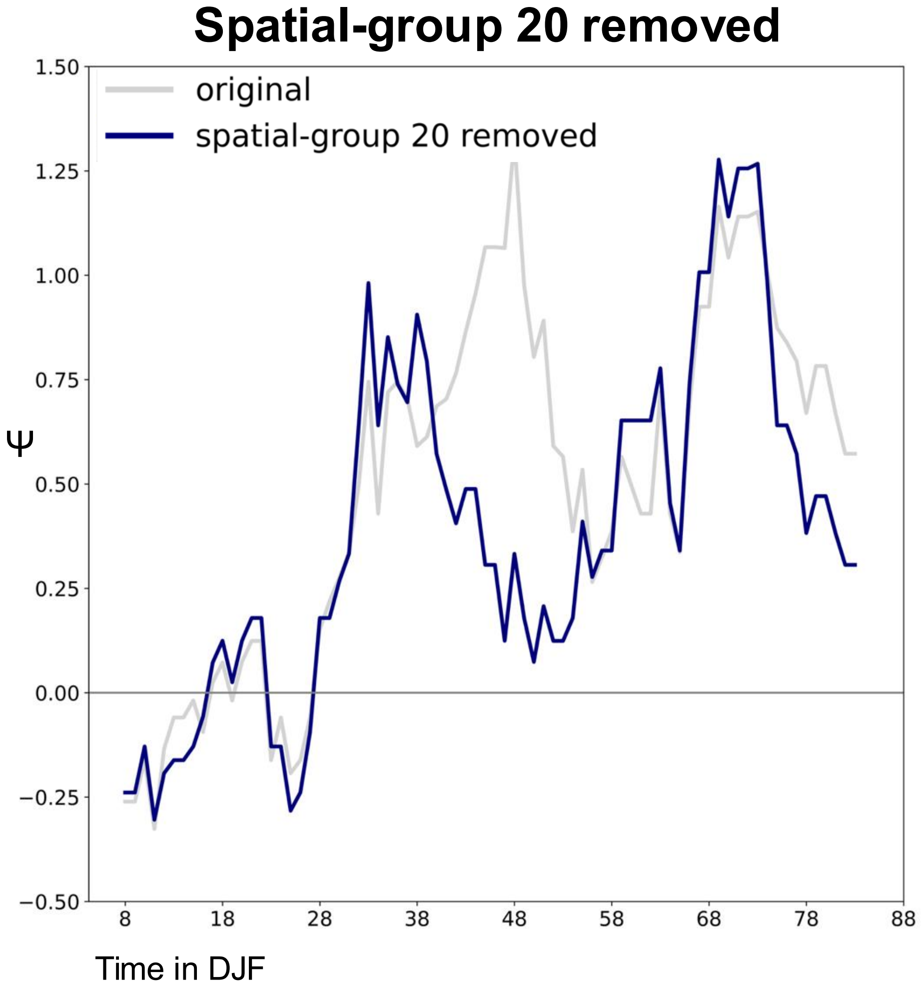
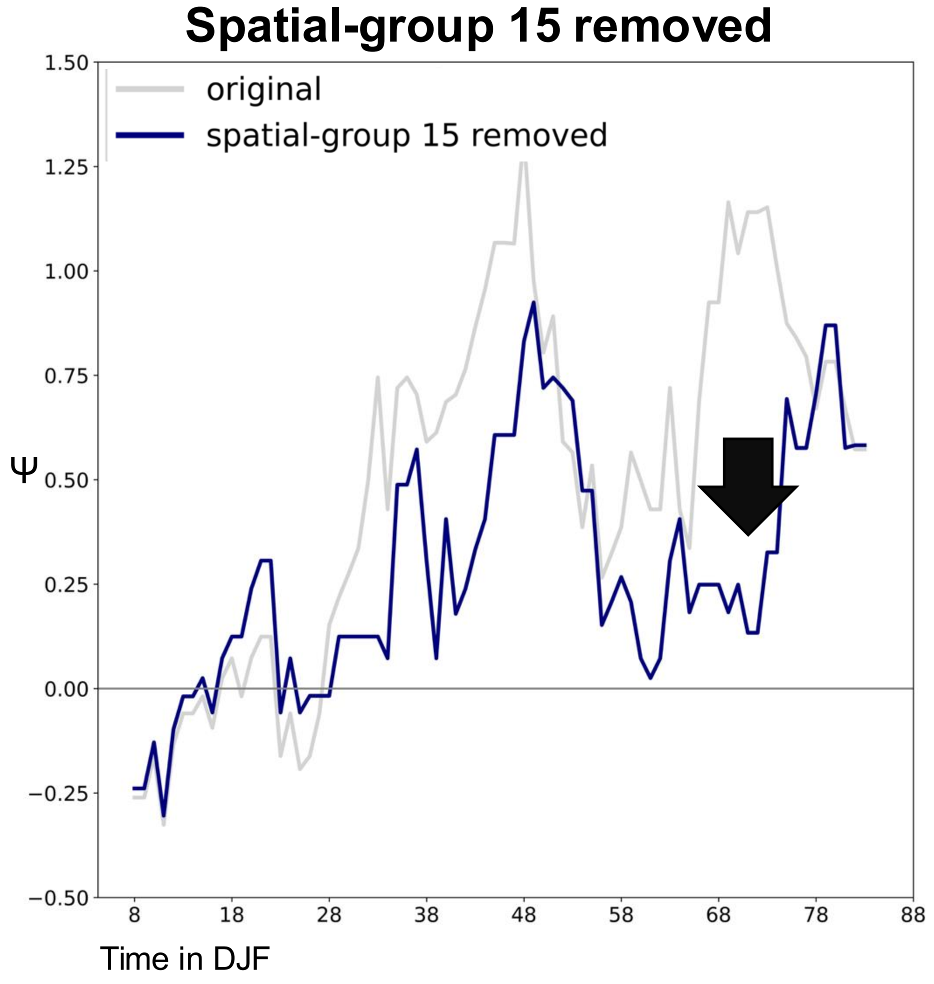
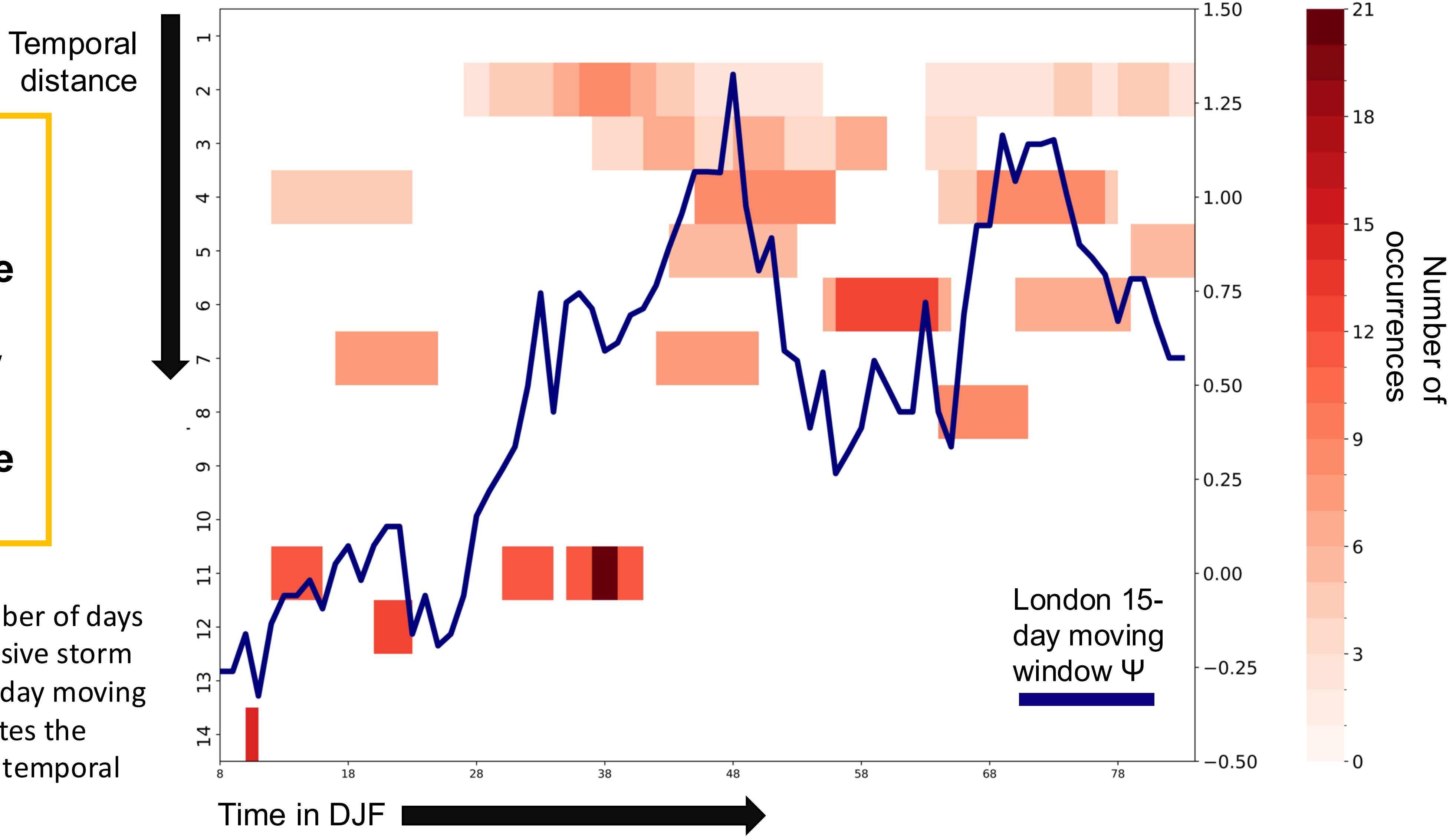




For each spatial-group when there is a storm, it is set to 0. E.g. for spatial-group 20, when a storm occurs during a 3-day episode with spatial-grouping 20, the storm count is set to 0

Results part 2.1: Spatial clustering → intraseasonal 15-days temporal distance

- → **Dip shows an increase in temporal distance of storms**
- → **Both peaks show a decrease in temporal distance of storms**

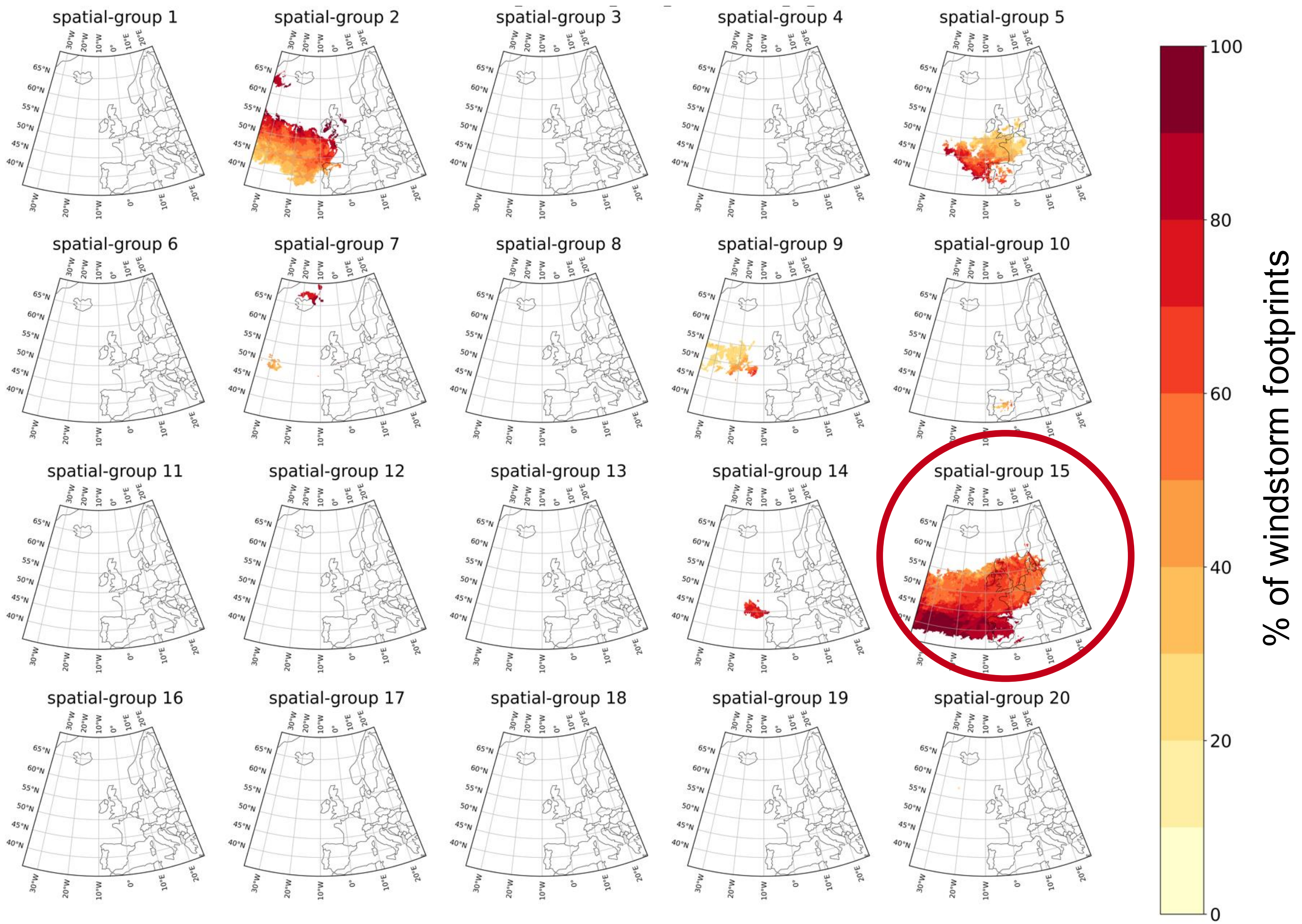


Left y-axis represents the number of days between a storm and a successive storm that hit London within the 15-day moving window. The colour bar indicates the number of occurrences of the temporal distance.

Results part 2.1
➔Large-scale modes spatial-group intra-seasonal 15-day occurrence

EA+,SCA+,NAO+

→ **Spatial-group 15**: High chance of storm occurrence when 15-day index EA+,SCA+,NAO+



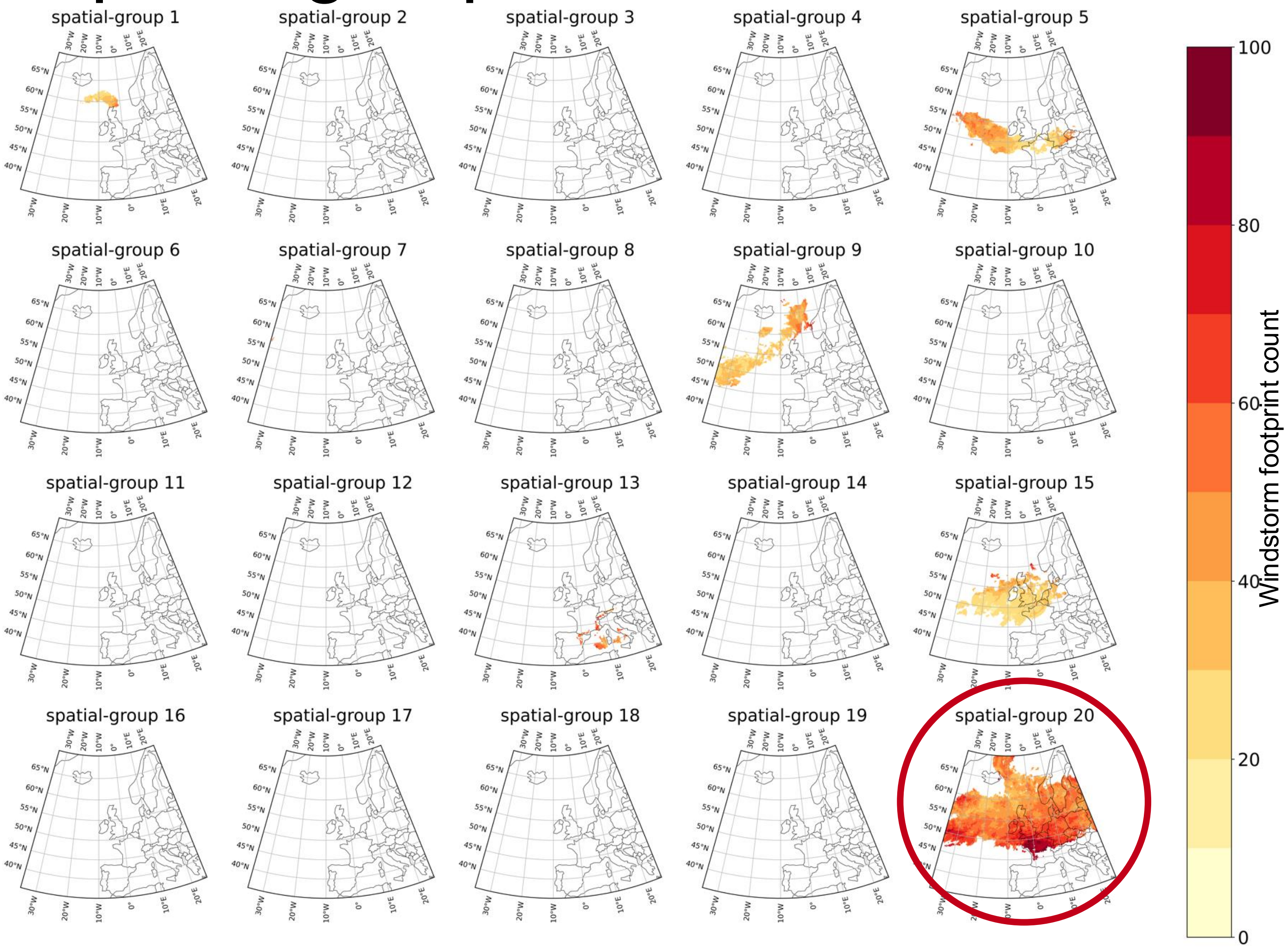
Percentage of windstorm footprint occurrence per spatial group based on a 15-day EA+,SCA-,NAO+ index. (Number of storms in subset / total number of storms in a given spatial-group). Only shown where the total number of storms is > 5.

Results part 2.1
➔Large-scale modes spatial-group occurrence intra-seasonal 15-day

EA+,SCA-,NAO+

→ **Spatial-group 15**: High chance of storm occurrence, when 15-day index EA+,SCA+,NAO+

→ **Spatial-group 20**: High chance of storm occurrence when 15-day index EA+,SCA-,NAO+



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Conclusions and future work

Conclusions:

- The **Spatial clustering method** developed by Leckebusch et al. (2008b) **successfully identified 5 primary storm clusters** from events with similar spatial development (spatial-group: 1, 5, 9, 15, 20)
- For specific locations where we see an increase in temporal clustering, **certain spatial-groups contribute more than others**, depending on the time within the season
- Certain configuration of large-scale modes on 15-day timescales has a higher occurrence of windstorms
- The **peaks and dips** in clustering can be **explained by large-scale patterns** and the **temporal distance** between storm arrivals

Future work:

- Further investigate the intra-seasonal variability of the spatial-groups
    - ➔ Those spatial-group that do not contain storms – a source of regularity in storm counts
- Why certain spatial storm clusters occur more often at certain times within the winter season
- Investigate how anthropogenic climate change will impact this behaviour

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Many thanks! Any suggestions welcome!

Temporal intra-seasonal clustering preprint:
doi.org/10.22541/essoar.176840797.70711745/v1

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Probability of windstorm footprint occurrences per spatial-group

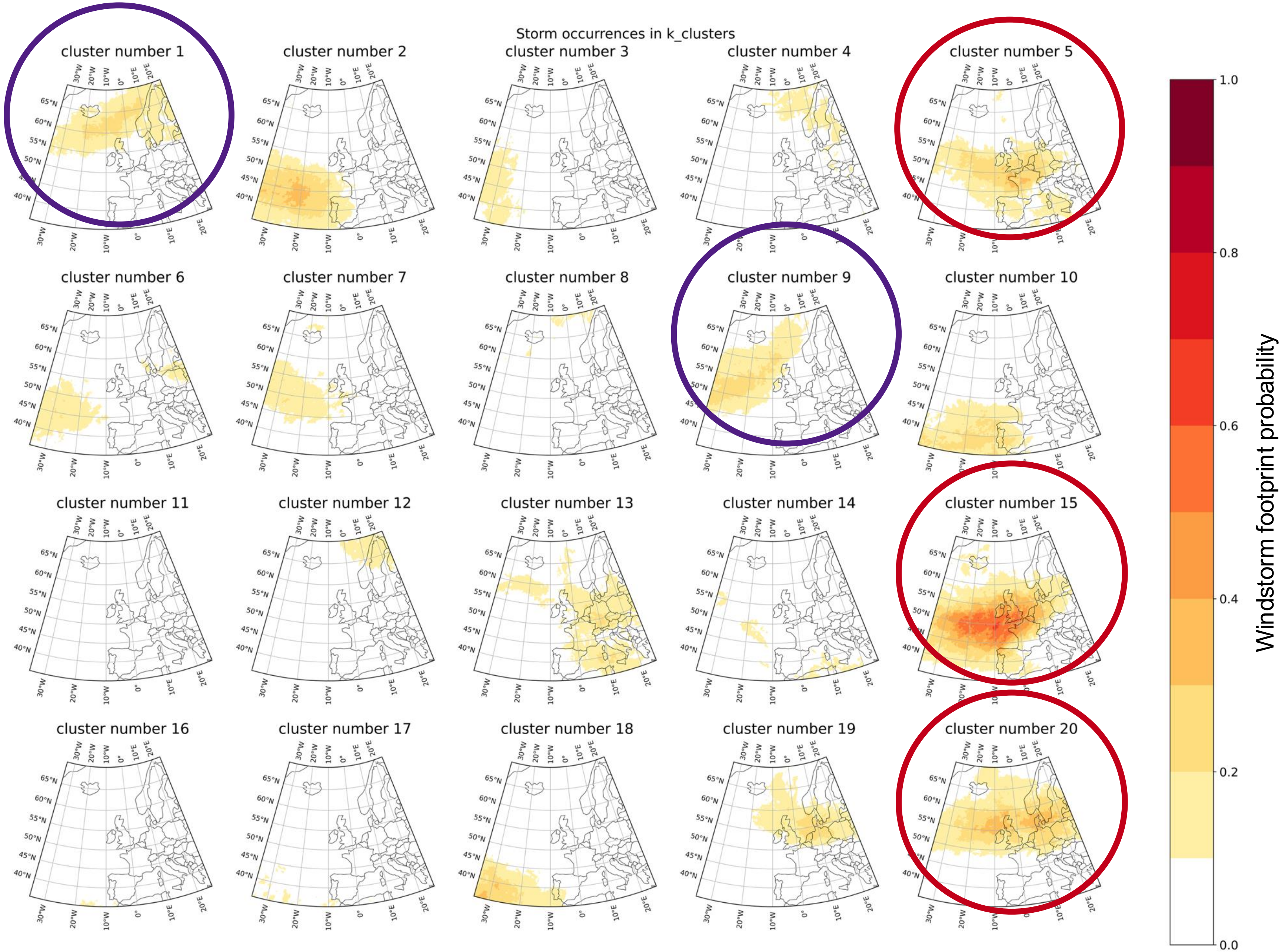

Figure 5. Probability of windstorm footprint occurrences per spatial-group. (Probability of the number of times a k-cluster has occurred when there have been at least 1 or more windstorm footprints in the 3-day period)

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