Analyzing the dynamics of extreme events with marked point processes

joint work with D. Allard, E. Gabriel and T. Opitz.

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funded by Chaire Geolearning

Natural hazards in 2022 in France

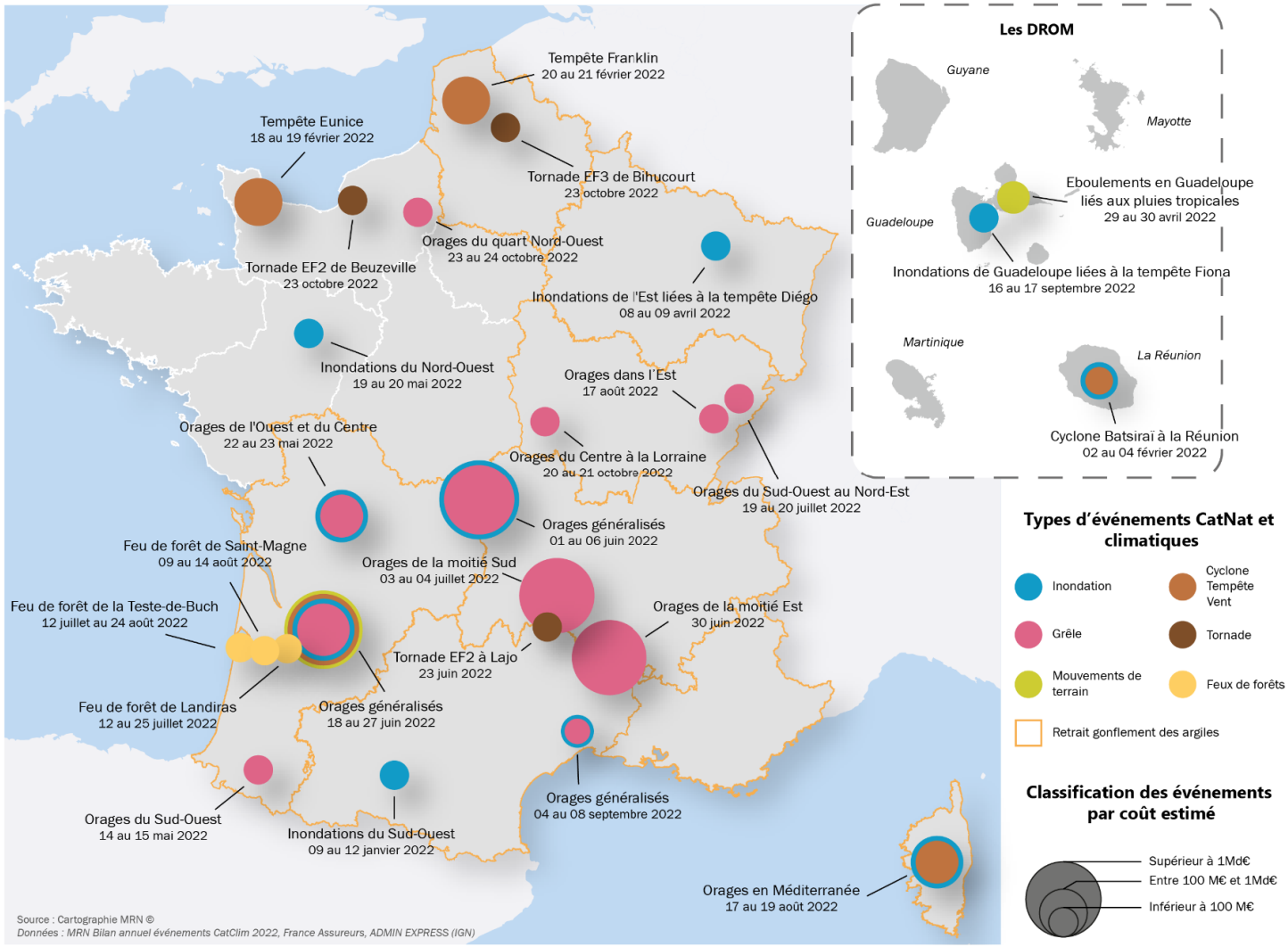

Figure: Source: MRN

Motivation

- **Context:** Transforming climate model "big data" into actionable knowledge on extreme event
- **Challenges:** Use methods from point processes, extreme value theory, and spatial graphs
- **Objectives:** Understand and model the spatial and temporal (co-)occurrence of extreme events focusing on event representation, subdivision of geographic space, and risk analysis

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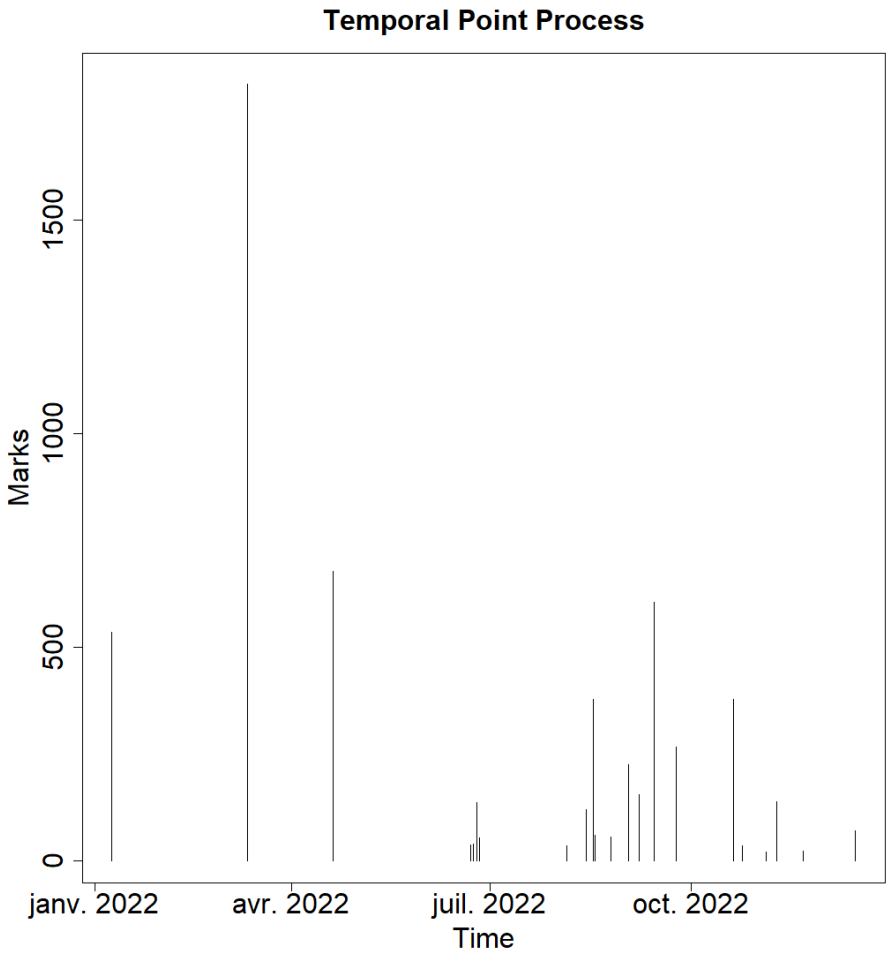
Marked Point Processes

- A collection of discretely observed stochastic events.
- Each event is characterized by:
  - A **point**: a coordinate in time, space, or space-time.
  - A **mark**: one or more numerical variables (e.g., duration, size of the event or numerical value).
- Examples:
  - Spatial processes: clustered distributions (e.g., urban heat islands) or regular patterns (e.g., wind farm layouts).
  - Temporal processes: clustered events (e.g., rainfall bursts during storms), periodic events (e.g., seasonal floods).
  - Spatio-temporal processes: wildfire occurrences over a landscape with marks representing burned area and duration (Koh et al (2022)).

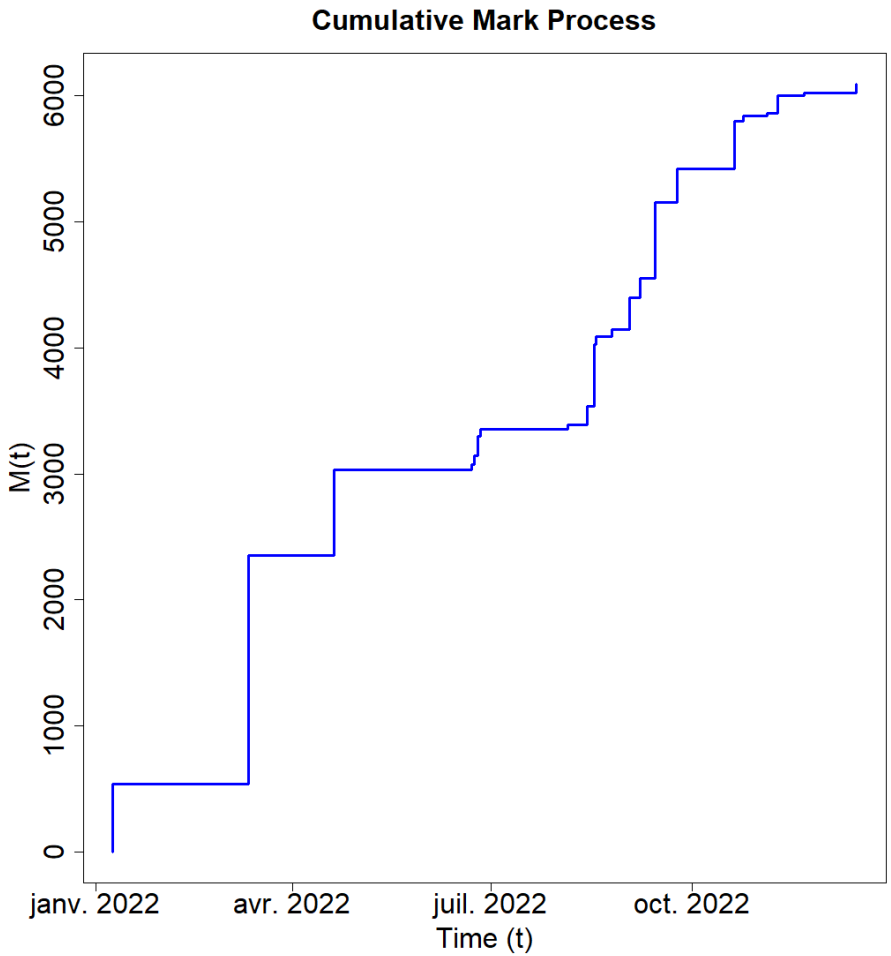
Temporal Point Processes

- Points (times) with (possibly) marks.
- Cumulative representations:
  - **Counting process**:
$$N(t) = \sum_i \mathbb{I}(t_i \leq t).$$
  - **Cumulative mark process**:
$$M(t) = \sum_i m_i \mathbb{I}(t_i \leq t).$$
- Applications:
  - Tracking the number of extreme weather events over time.
  - Monitoring cumulative impacts of storms (e.g., total rainfall or wind speed).

Temporal Point Processes



Severe precipitation in Languedoc-Roussilon in 2022



Cumulative mark, sum of the total precip

Intensity and Correlation Functions (stationary)

- **Intensity Function (λ):**
  - Represents the mean number of events in a time interval:

$$\lambda = \frac{1}{T}\mathbb{E}\left[\#(t_i \in [0, T])\right]$$

  - Calculated as total number of events divided by total observation time
- **Correlation Function (K-Function):**
  - Measures temporal correlation between events:

$$K(r) = \frac{1}{\lambda}\mathbb{E}\left[\#\{t_i \in [t_0 - r, t_0 + r]\} \,|\, \text{event at } t_0\right]$$

  - Quantifies the clustering or dispersion of events around a typical event
  - Can be adapted to:
    - ★ Marked point processes
    - ★ Cross-correlation analysis

Cross K-Function

- To study multiple point processes, consider a cross-K function
- **Cross K-Function estimation from (Cebrián et al. 2020):**

$$\hat{K}_{xy}(r) = \frac{1}{T} \sum_{t_i \in N_x} \sum_{s_j \in N_y} \frac{I(|t_i - s_j| \leq r)}{\lambda_x \lambda_y}$$

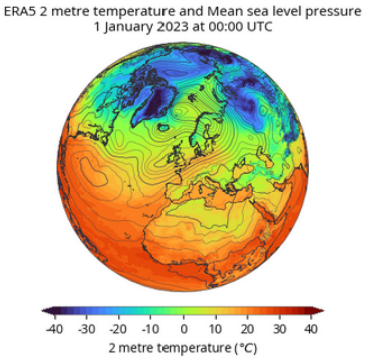
- Where:
  - T: Total observation time
  - N_x, N_y: Point sets of processes x and y
  - λ_x, λ_y: Local intensities
  - $0 \leq r < T$: Time interval
- The package **IndTestPP** implements a test based on this method to measure the independence between processes.

Compound Extreme Events

- Compound events — a combination of multiple drivers and/or hazards that contribute to societal or environmental risk — are responsible for many of the most severe weather- related and climate- related impacts. (Zscheischler et al 2020)
- Types of compound extreme events:
  - **Multivariate**: Multiple drivers/hazards occur together (e.g., thunderstorms with extreme precipitation and wind).
  - **Preconditioned**: One driver/hazard creates conditions for another (e.g., flash floods after extreme dry periods).
  - **Temporally compounding**: Consecutive events (e.g., several heatwaves in France, 2019).
  - **Spatially compounding**: Concomitant events across regions due to large-scale atmospheric conditions.

Data Analysis

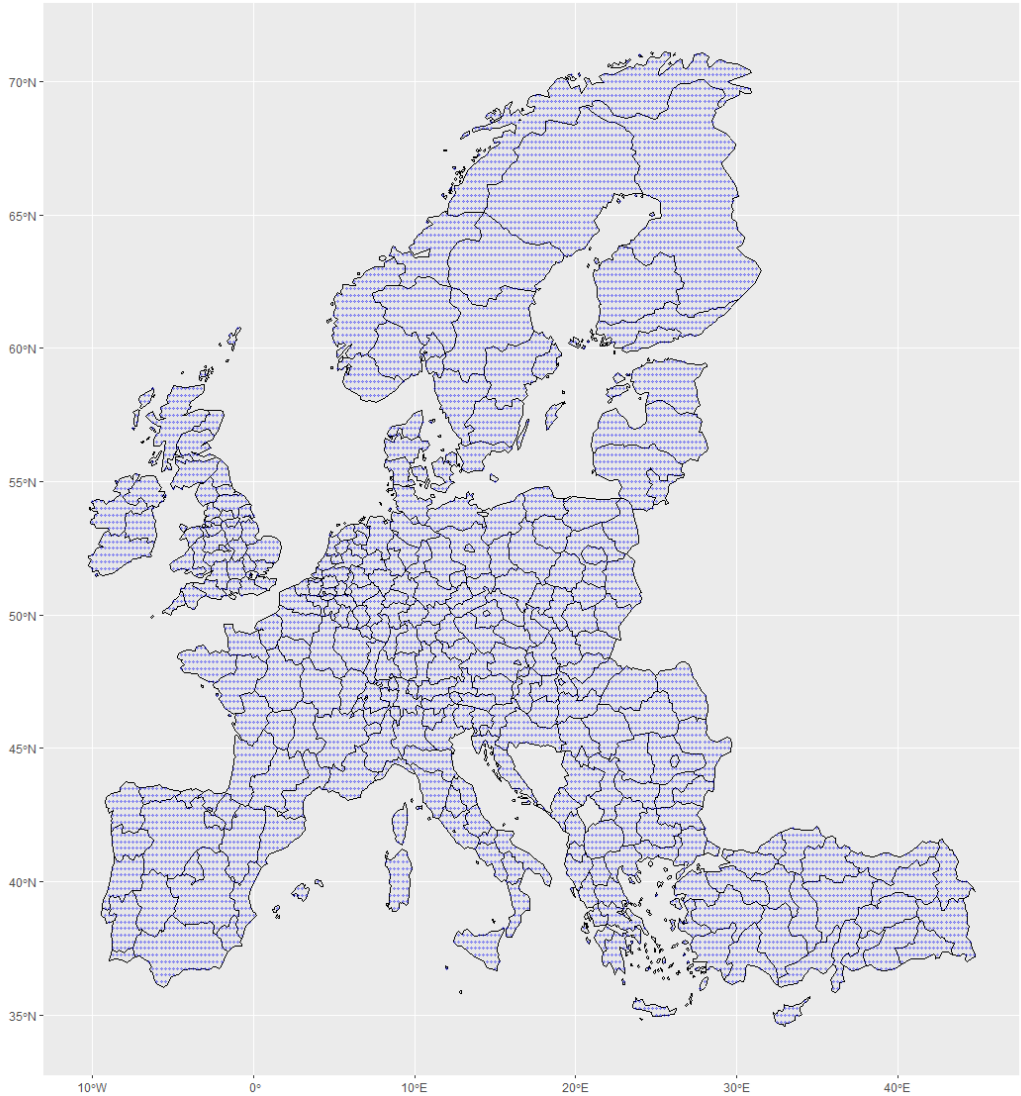
- **Dataset:** ERA5 hourly data on single levels from the Copernicus Data Store.
- **Period:** 2003-01-01 to 2023-12-31.



Variable	**Description**
10m u-component of wind	Eastward wind speed
10m v-component of wind	Northward wind speed
2m temperature	Near-surface air temperature
Mean sea level pressure	Atmospheric pressure at sea level
Sea surface temperature	Ocean surface temperature
Total precipitation	Accumulated rainfall
Evaporation	Water evaporation rate
Total cloud cover	Fractional cloud cover
Convective precipitation	Rainfall from convective systems
Volumetric soil water layer 1	Topsoil moisture
Volumetric soil water layer 4	Deep soil moisture

Regionalisation

- NUTS level 2 : 332 regions, 11,796 data points.



Construction of extreme events

- The variables are transformed into daily measures
- **Precipitation Events:**
  - Presence/absence events (<1mm daily)
  - Moderately events (sum above the 95th percentile with dry<0.2mm)
  - Extreme events (sum above the 99th percentile with dry<0.2mm)
- **Temperature Events:**
  - Seasonal historical mean calculated using ERA5 monthly data from 1940-present
  - Hot events based on **anomalies** (mean daily anomalies above the 95th percentile)
  - Cold events based on **anomalies** (mean daily anomalies below the 5th percentile)
- **Clustering method:** Connected component analysis within each NUTS region.
  - Spatial separation: 50 km.
  - Temporal separation: 3 days (1 day before, 1 day after).

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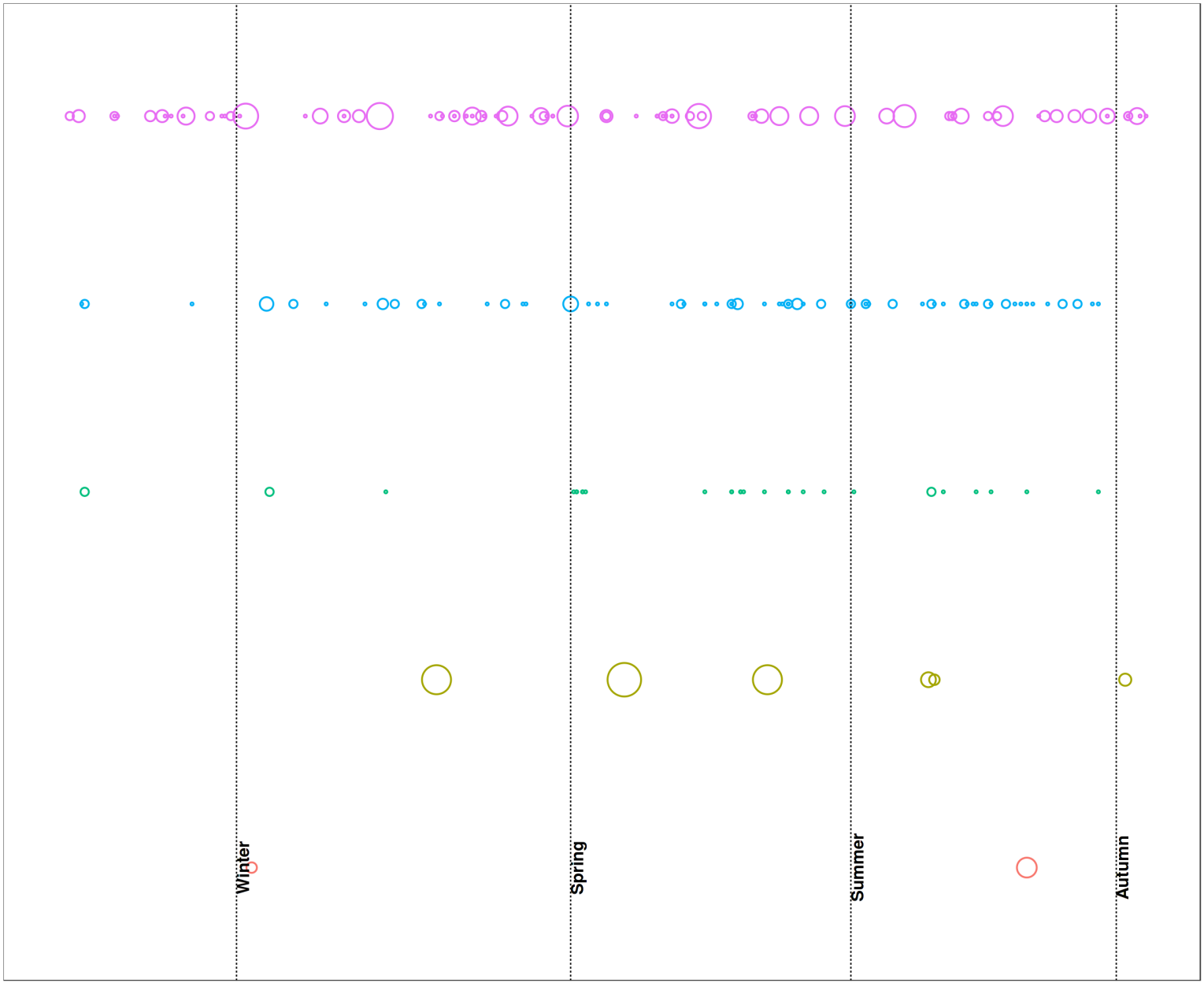
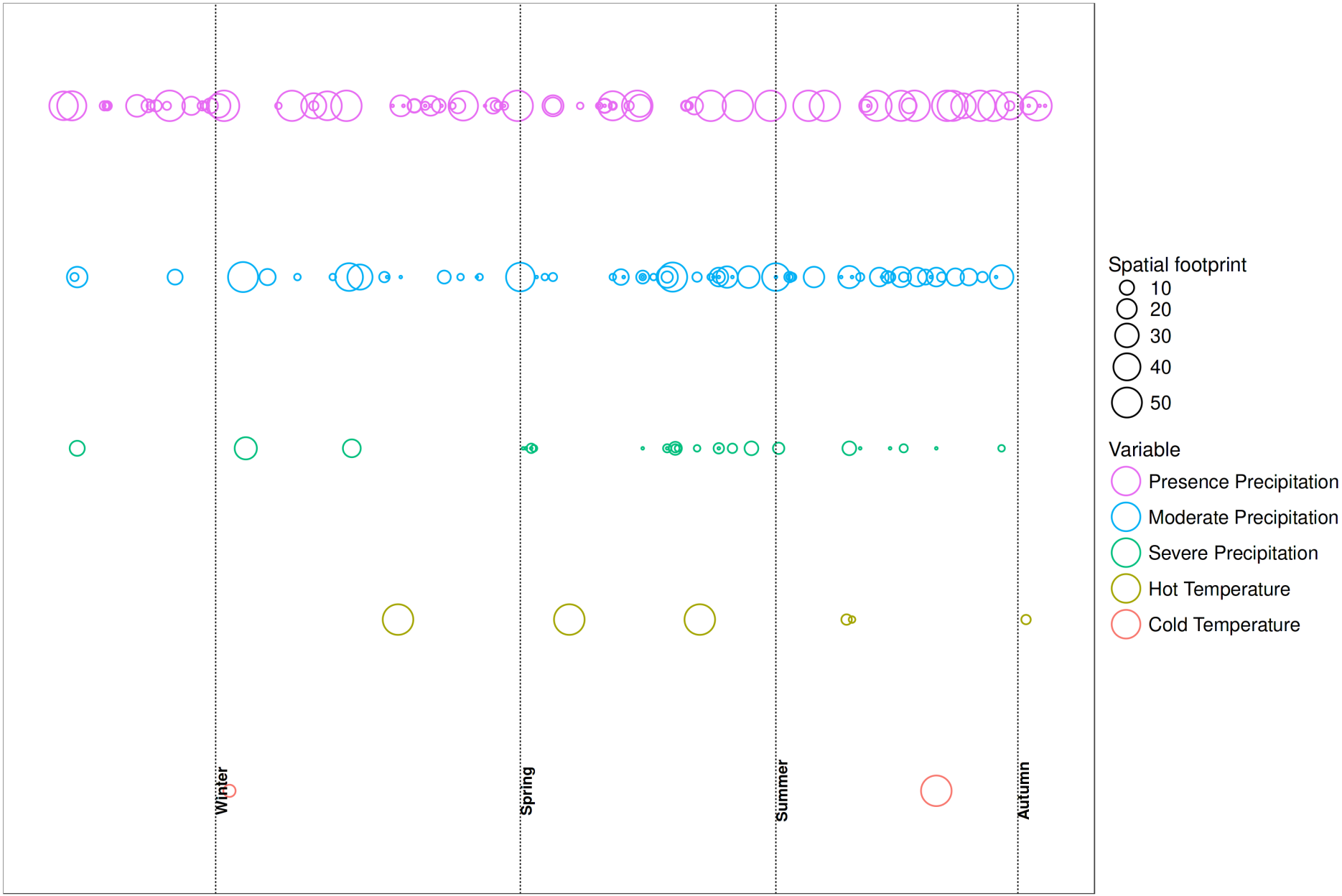
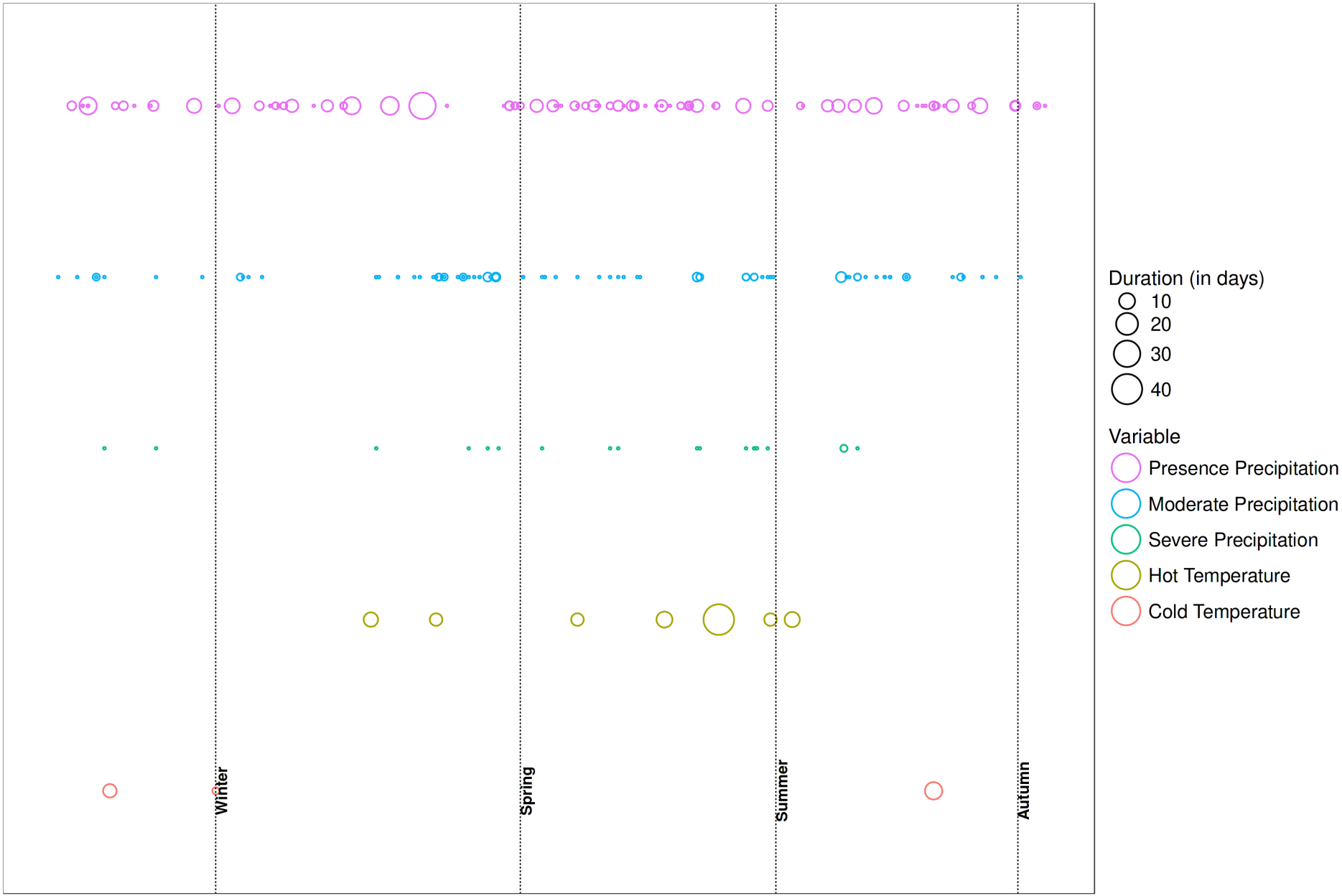
Temporal MPPs for Languedoc-Roussillon in 2022



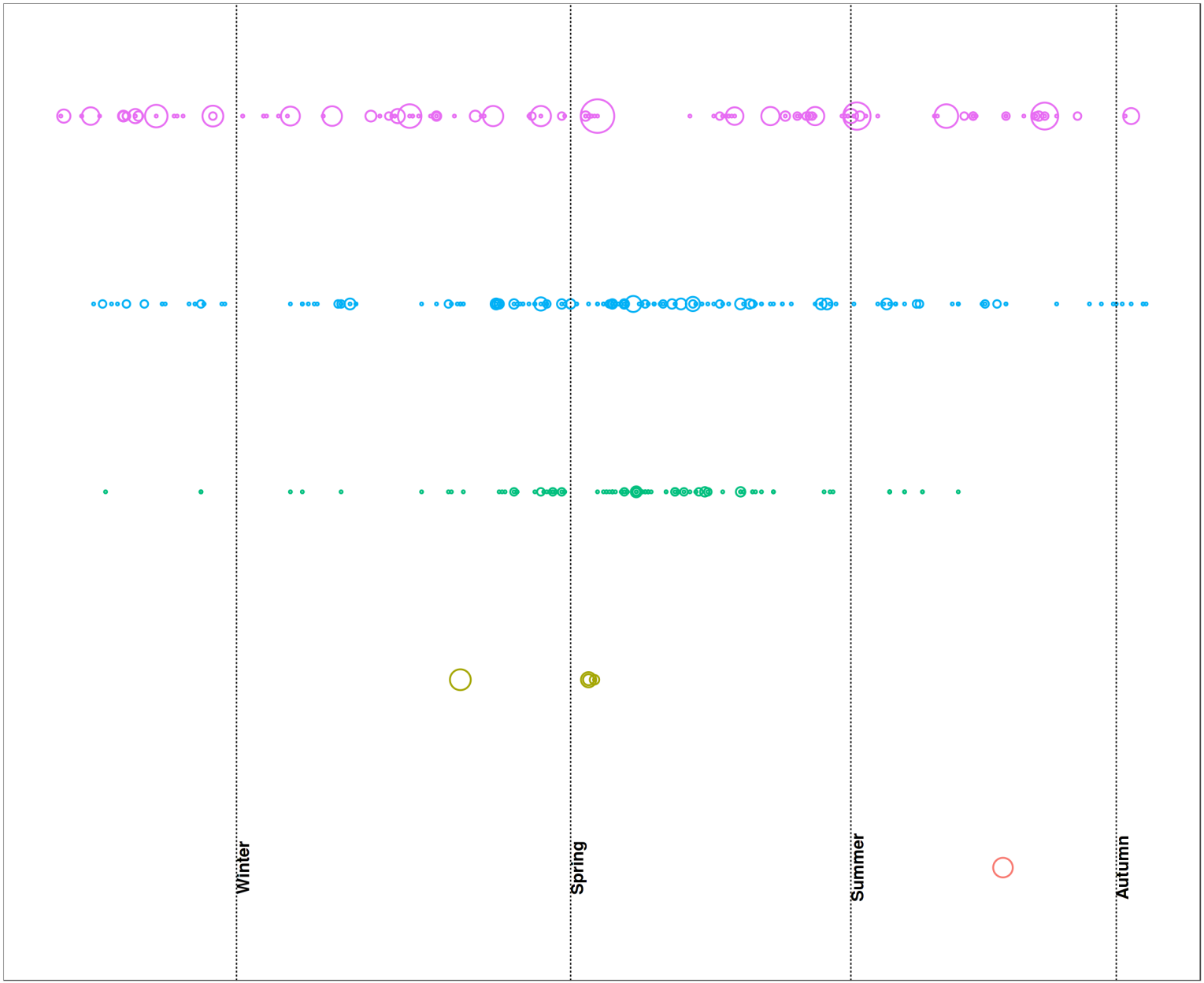
Idem with spatial footprint



Temporal MPPs for Languedoc-Roussillon in 2023



Temporal MPPs for Northern and Eastern Finland in 2022



K cross function for neighboring NUTS

- The bounds show 95% confidence interval, where the correlation is expected if there is no dependency between the processes.
- Positive correlation implies clustering

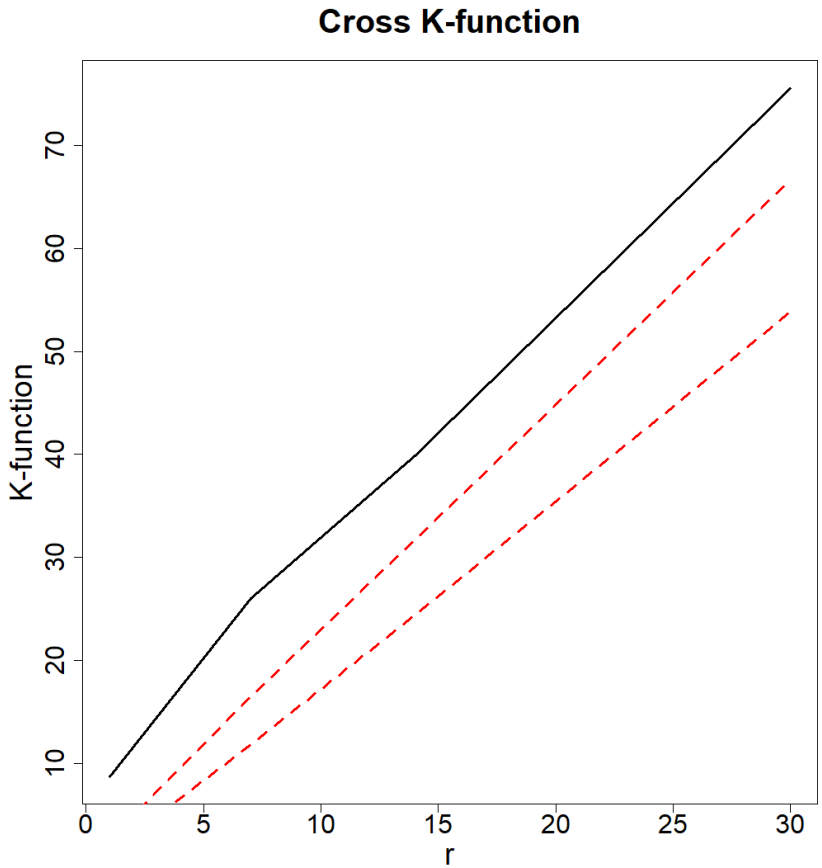


Figure: Severe precipitation Languedoc-Roussillon/Provence-Alpes-Côte d'Azur

K cross function for distant NUTS

- The dependency seems to be lost when we look at distant NUTS.

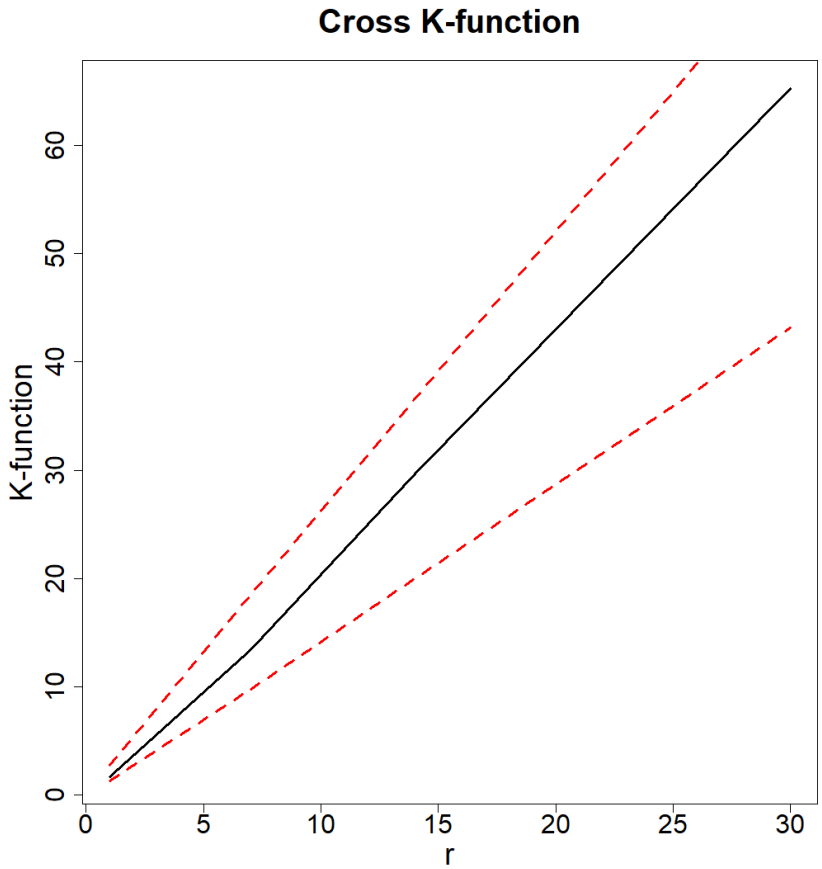


Figure: Severe precipitation Languedoc-Roussillon/-Northern and Eastern Finland

K-cross function for different variables

- No dependency apparent for hot events.

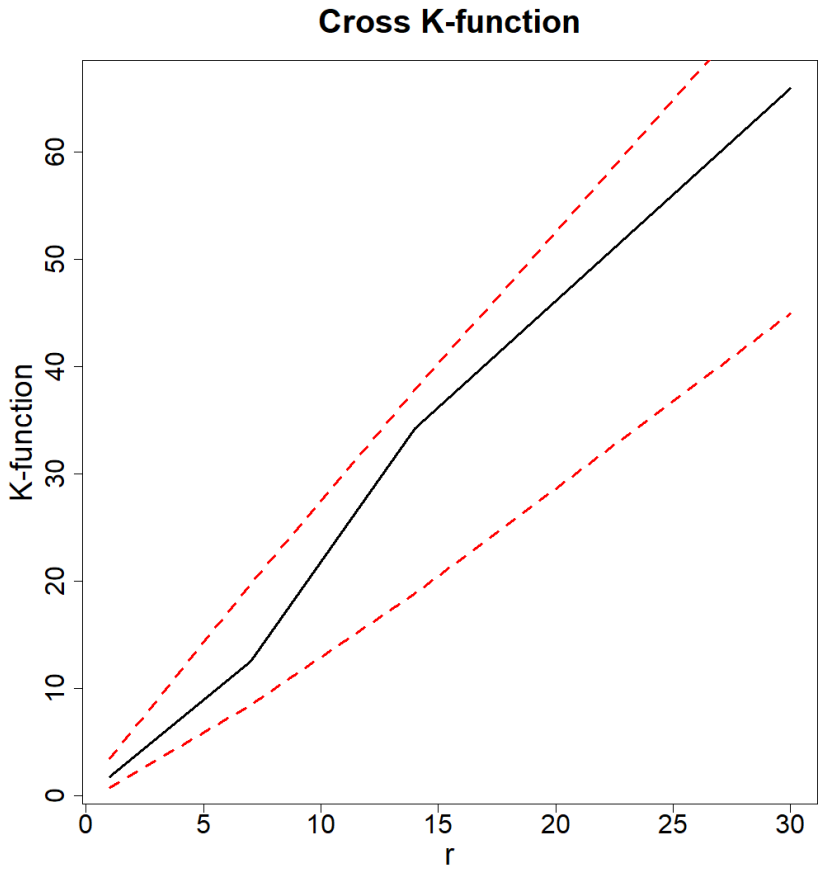


Figure: Languedoc-Roussillon Severe precipitation/Hot events

K-cross function for different variables

- Small dependency at close range for cold events.
- Small clustering, more pronounced at 5 days

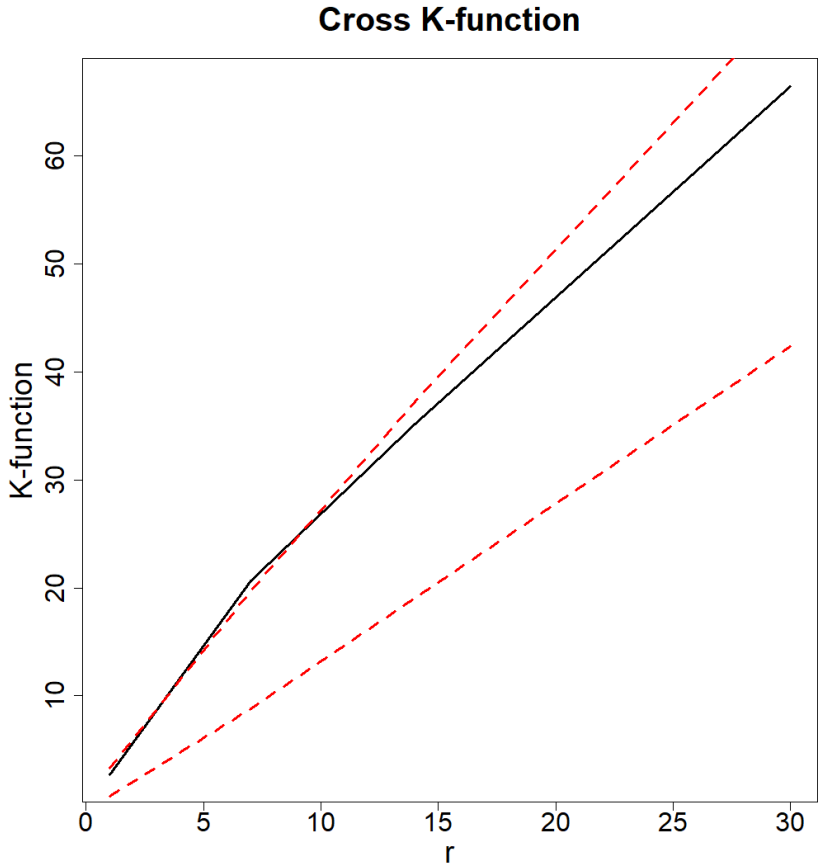


Figure: Languedoc-Roussillon Severe precipitation/Cold events

K cross function for cold and hot events

- Dependency below a month for temperature events in a NUTS region with many points (and thus events)
- Negative dependence suggests a repulsive effect.

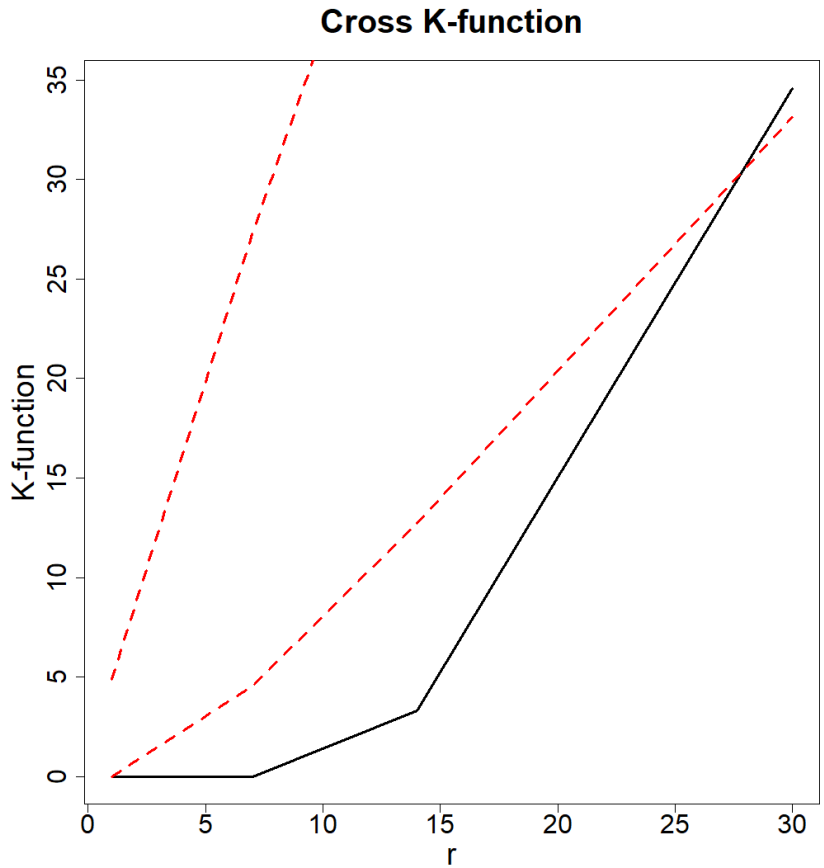


Figure: Northern and Eastern Finland HOT/COLD anomalies events

Future Directions

- **Conditional Extremes Models:**
  - Multivariate marks linked to threshold exceedance
- **Trend Analysis:**
  - Long-term changes in intensity functions
- **Compound Extreme Event Analysis:**
  - Joint occurrence of precipitation and heatwaves
- **Ruin Processes in Ecology:**
  - Impacts of consecutive extremes on ecosystems
- **Global connectivity function:**
  - Characterize extreme temperature events with a global connectivity function

Thank You for Your Attention

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