Spatiotemporal Analysis of Drought Evolution in France and Attribution to Atmospheric Drivers

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EGU25 – 2 May 2025

Introduction

The 2018-2020 drought in Europe established a new benchmark in drought severity and persistence, highlighting the potential risks associated with the intensification of these events under climate change (Rakovec et al., 2022). This event exemplifies the complex nature of droughts as spatiotemporal phenomena that propagate through the hydrological cycle with cascading ecological and socioeconomic consequences.

By analyzing droughts as contiguous spatiotemporal events (Lloyd-Hughes, 2012) in France, we investigated two questions:

1. How might meteorological and soil drought characteristics evolve across France under future climate scenarios?
2. What is the role of meteorological drivers in soil moisture drought development?

1. Data

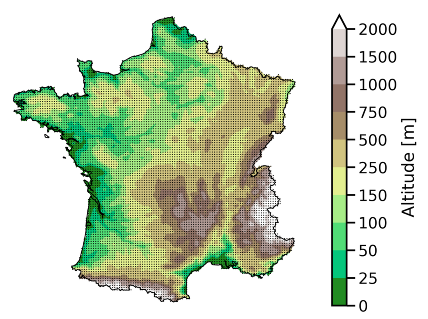

Figure 1 - Spatial distribution of data across France. Black dots represent grid points (n=8806) from the EXPLORE2 grid at 8km x 8km resolution used in this analysis.

This study uses the EXPLORE2 hydroclimatic dataset (French national project), including the SAFRAN reanalysis (1958-2020) (Quintana-Seguí et al., 2008) and 12 hydro-climate simulations (1950-2100). The modeling chain follows the **RCP8.5** emissions scenario, using 6 CMIP5 global climate models dynamically downscaled with 7 regional climate models within the EURO-CORDEX project (Vautard et al., 2021). Notably, these RCMs differ in their treatment of aerosols: some use a constant aerosol climatology while others incorporate evolving aerosol scenarios, significantly affecting the simulated energy budget. Data were bias-corrected using the ADAMONT method (Verfaillie et al., 2017) before driving the ORCHIDEE land surface model (Krinner et al., 2005). All analyses utilize monthly data on an 8km×8km grid covering France.

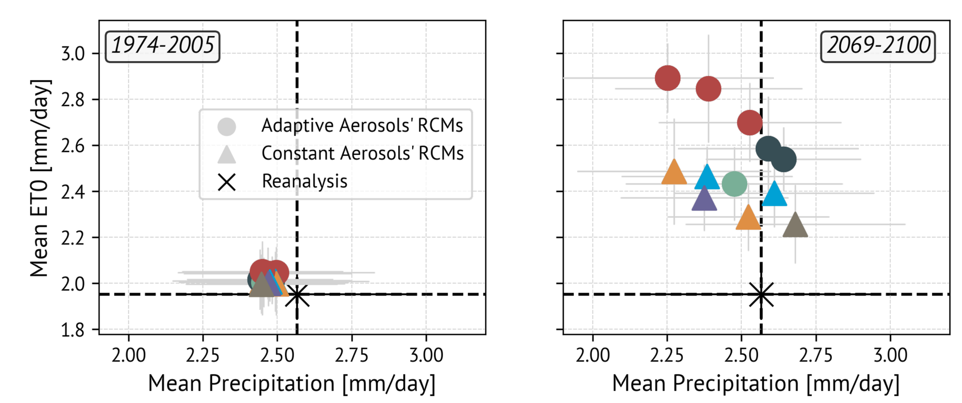

Figure 2 - Mean hydroclimatic conditions for reference period (1974-2005) and projected changes (2069-2100, RCP8.5). Colors correspond to the RCM used for downscaling the simulation. Grey lines correspond to the temporal uncertainties of the spatial averages during the selected period.

» Simulations for the past period (1974-2005) underestimate precipitation and systematically overestimate reference evapotranspiration (ET0) compared to SAFRAN reanalysis.

» Under RCP8.5, all simulations project substantial ET0 increases by 2069-2100, with evolving aerosol scenarios showing stronger increases than constant aerosol climatology. Precipitation projections exhibit divergent trends across simulations.

2. Methods

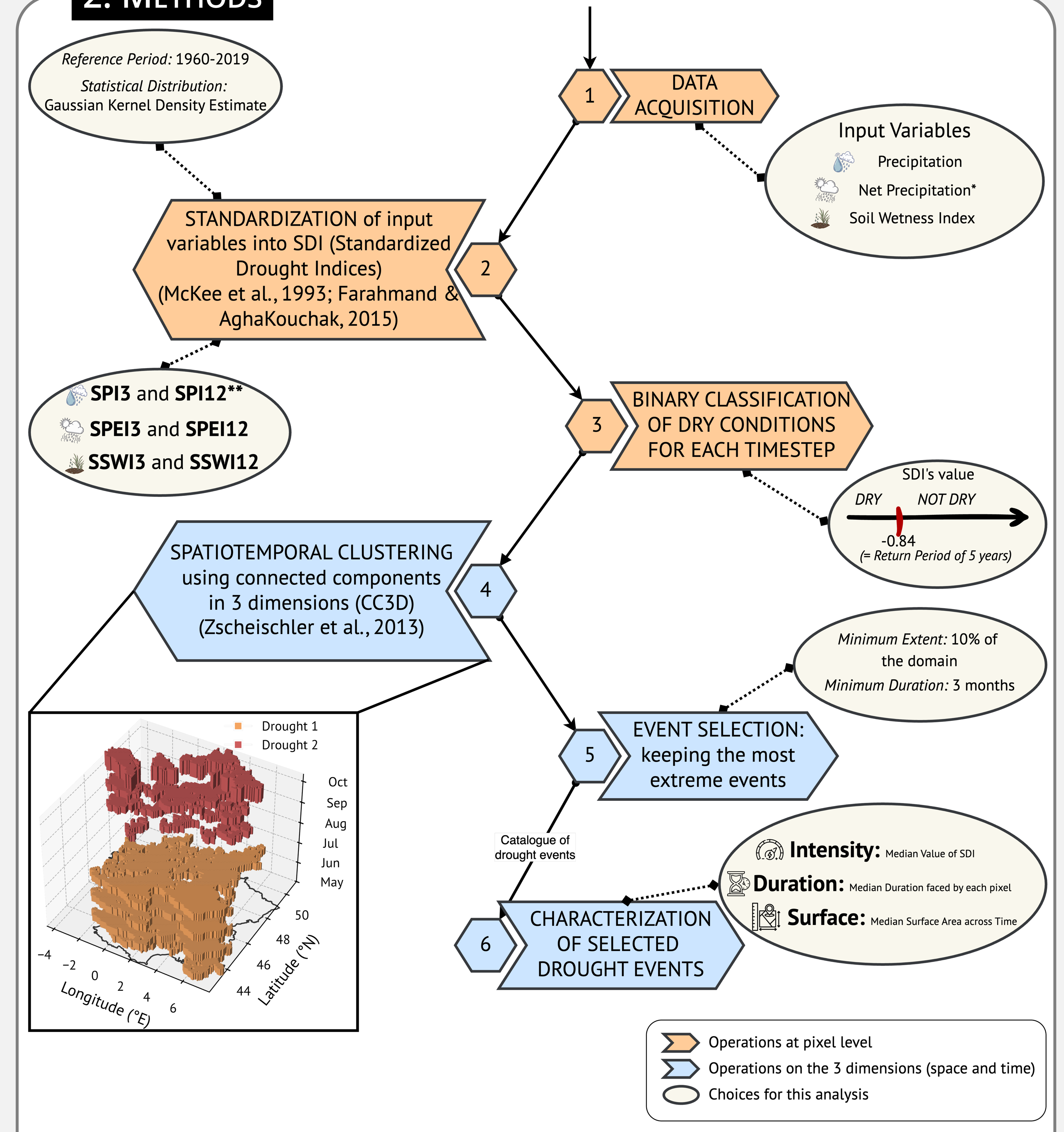

Figure 3 – Methodological framework for identifying and extracting extreme contiguous spatiotemporal drought events.

** Net Precipitation = Precipitation – Reference Evapotranspiration: atmospheric water balance*

***Data standardization enables the assessment of variable deviations from the reference period mean (expressed as standard deviations). Input variables are first smoothed using a moving average, with the window length determining the type of impacts captured (McKee et al., 1993). This study examines two timescales: 3 and 12 months, reflected in the standardized drought index (SDI) naming convention (e.g., SPI12 for the 12-month Standardized Precipitation Index).*

3. Drought Evolution

Drought Evolution on the ensemble

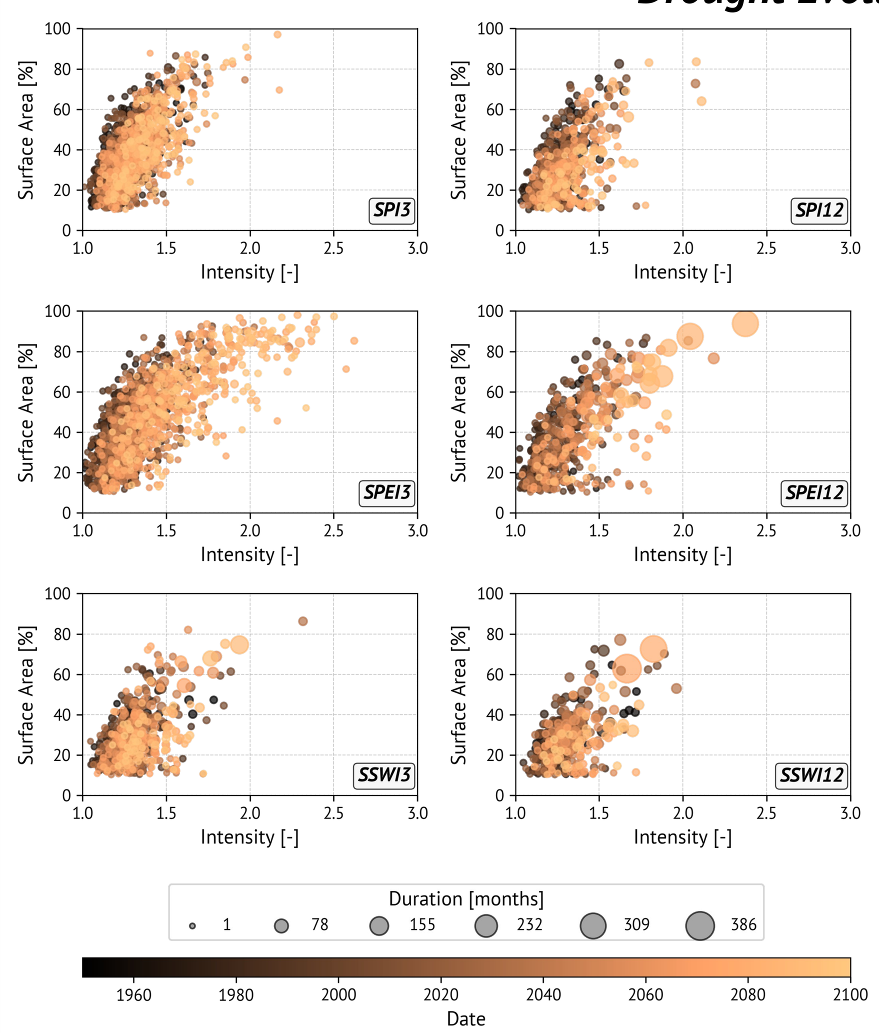

Figure 4 – Temporal evolution of major drought events in France (1950-2100) characterized by their spatiotemporal characteristics. Drought events are represented as bubbles where size indicates duration (months), position shows surface area (% of France affected) and intensity, and color represents the date of peak severity. Multiple drought indices are compared: SPI3/SPI12 and SPEI3/SPEI12 for meteorological droughts and SSWI3/SSWI12 for soil moisture droughts.

	Duration (months)	Surface Area (% of France)	Intensity (-)
SPI3	**+1**	**+10**	**+0.2**
SPI12	**+4**	-0.2	**+0.2**
SPEI3	**+3**	**+24**	**+0.5**
SPEI12	**+36**	**+11**	**+0.3**
SSWI3	**+5**	+2	**+0.1**
SSWI12	**+14**	-2	**+0.1**

Table 1 – Significant drought characteristic changes over 100 years in France. *Values show projected changes between 2000 and 2100 (derived from linear regression) for drought duration, spatial extent, and intensity (probability of occurrence) across different indices. Bold values indicate statistically significant trends (Mann-Kendall test, p < 0.1); other cells indicate non-significance.*

All drought types (SPI, SPEI, SSWI) worsen under RCP8.5, with longer, more intense events, though magnitudes differ.

Aerosols treatment in the RCM and drought evolution

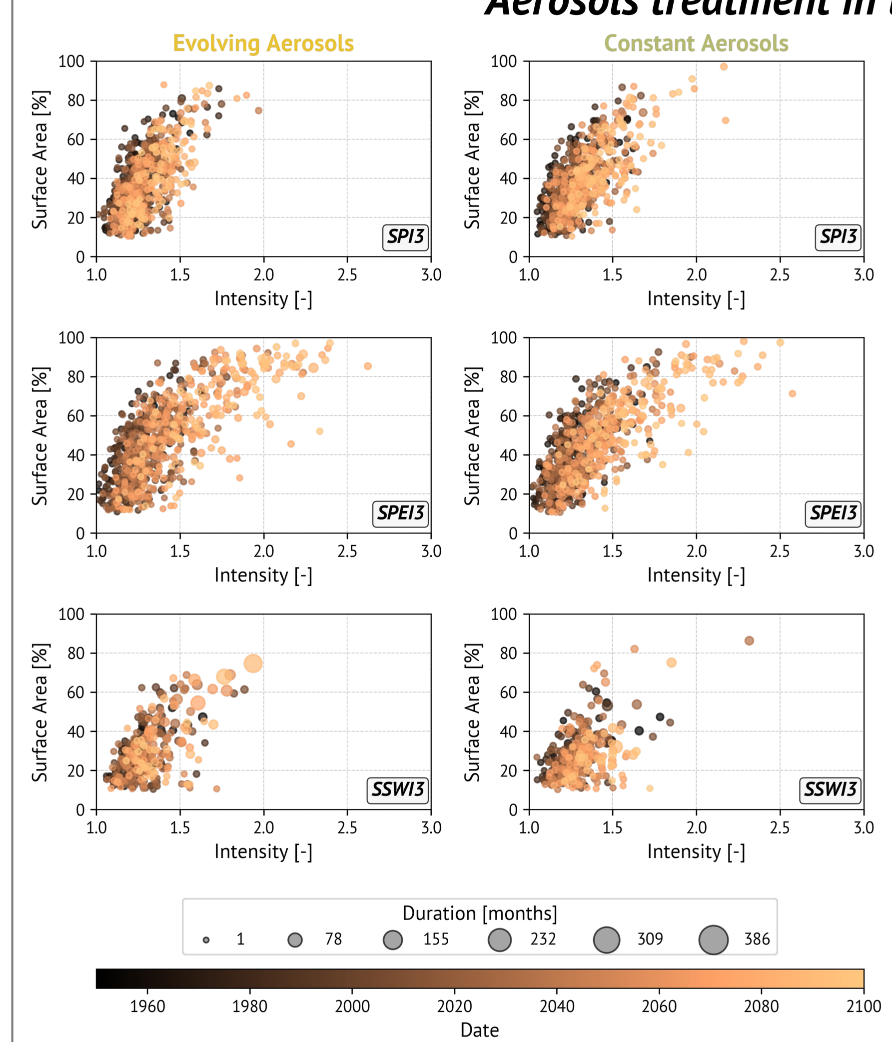

Figure 5 – Temporal evolution of major drought events in France (1950-2100) characterized by their spatiotemporal characteristics as in Figure 4. Comparison of three drought indices (SPI3, SPEI3 for meteorological droughts; SSWI3 for soil moisture droughts) under two aerosol treatments in the regional climate model: constant aerosol climatology (right column) versus evolving aerosol scenarios (left column).

	Duration (months)	Surface Area (% of France)	Intensity (-)
SPI3-EA	**+1**	+7	**+0.1**
SPI3-CA	**+1**	**+12**	**+0.2**
SPEI3-EA	**+4**	**+27**	**+0.6**
SPEI3-CA	**+3**	**+22**	**+0.5**
SSWI3-EA	**+8**	**+5**	**+0.1**
SSWI3-CA	+8	+5	**+0.1**

Table 2 - Significant drought characteristic changes over 100 years under two aerosol treatments in the regional climate model. *Values show differences in projected changes (2000-2100), as in Table 1, between simulations with evolving aerosols (EA) versus constant aerosol climatology (CA) for drought duration, spatial extent, and intensity. Bold values indicate statistically significant trends (Mann-Kendall test, p < 0.1) for each index (SPI3, SPEI3, SSWI3); other cells indicate non-significance.*

Drought evolution is sensitive to aerosol treatment. Constant aerosol climatology amplifies precipitation-only drought changes (SPI), while evolving aerosol intensify soil moisture drought changes (SSWI), particularly affecting spatial extent and duration.

4. Influence of Meteorological Drivers on Soil Moisture Droughts

Focus on a drying simulation

	Trend	Initial Value (1952)
ET0	+0.72 mm/day/century	1.85 mm/day
Precipitation	-0.12 mm/day/century	2.52 mm/day
SWI	-0.36 1/century	2.84

Table 3 – Evolution of the mean hydroclimatic state over France between 1952 and 2100 for the drying simulation under focus.

Drivers Influence on Soil Moisture Drought Intensity

- Net precipitation most strongly correlates with drought intensity ($R^2 = 0.71$)
- ET0 is the dominant driver ($R^2 = 0.5$ V.S $R^2 = 0.27$ for Precipitation alone)
- Meteorological drivers are not sufficient to explain soil moisture drought intensity

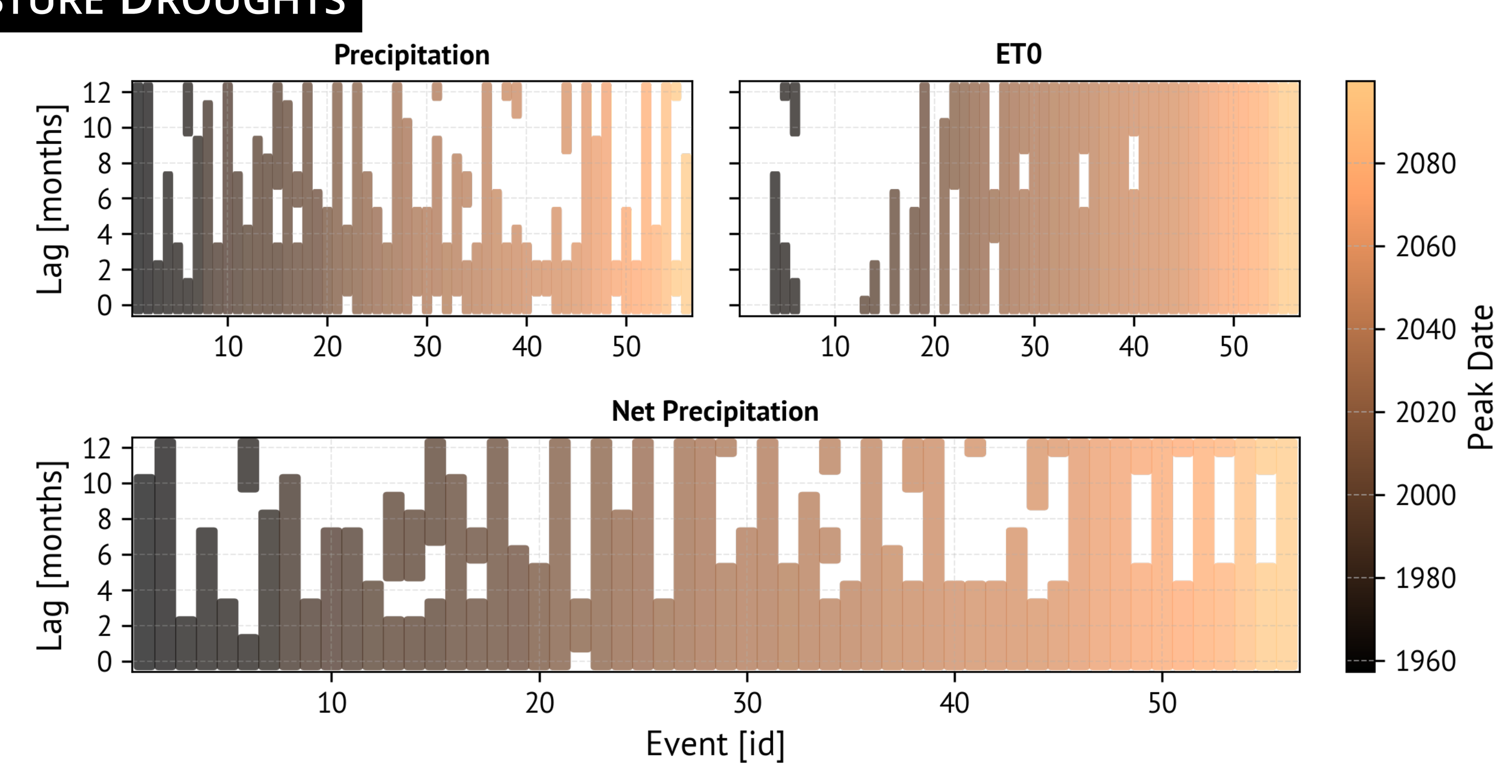

Figure 6 – Significant meteorological anomalies preceding soil moisture drought events in the DRY storyline. Colored area indicate months with significantly low precipitation (top left), high reference evapotranspiration (ET0, top right), or low net precipitation (bottom) before each drought event (x-axis). Colors represent drought peak dates; y-axis shows lag time in months.

Temporal Patterns (Figure 6)

- Precipitation deficits consistently precede drought events but decrease in temporal extent for future events
- ET0 significance shifts from sporadic (historical) to persistent (future)
- Net precipitation (combined effect of Precipitation and ET0) shows consistent patterns, with significant anomalies typically 0-3 months before onset

Conclusions and Outlooks

✓ **All drought types intensify under climate change**
✓ **Drought evolution is sensitive to aerosol treatment in the RCM**
✓ **Soil moisture droughts are triggered by precipitation deficits**

❑ Analyze specific extreme drought events to understand their mechanisms
❑ Investigate seasonal timing of soil moisture droughts
❑ Extend analysis to European scale using complementary databases

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