Better Exploration of Drought Risks Under Climate Uncertainties Using Locally Relevant Climatic Drivers

WAGENINGEN UNIVERSITY & RESEARCH

Deltares

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1. Background:

- Drought is generally defined as an **unusual and prolonged** period of **precipitation deficit** that cascades through soil, aquifers, and surface water. It is the **costliest** natural hazard **globally**, responsible for **22% of disaster-related** damage and affecting **one-third of all people affected** by disasters.
- In the **EU**, nearly every country has experienced significant drought in recent decades. For example, the **2018 European drought** caused widespread **agricultural losses** and severe impacts across several countries.
- Within the EU, the **Mediterranean basins** stand out as particularly vulnerable drought hotspots and are most affected by prolonged droughts. **Spain** is especially exposed, with about **$7.7 billion in damages since 1990**. It is also a major **olive oil producer**, so drought impacts can affect the **EU food supply.**
- According to the **IPCC**, **drought impacts** are **expected to increase** and become more frequent due to **climate change**. Higher temperatures raise **evaporative demand**, while **precipitation becomes more uncertain**. This leads to **more frequent, longer**, and more **severe droughts.**

2. Problem statement:

- Projecting future drought impacts depends on **Global Climate Models (GCMs),** which simulate the climate under different emission scenarios. However, these **projections** include large **uncertainties** from **model structure, internal variability**, and **emission scenarios**, leading to different signals in both direction and magnitude.
- The common approach groups models by **Shared Socioeconomic Pathways (SSPs)** and uses the **multi-model ensemble mean (MME)**. While this reduces bias, it often **averages out extremes**, especially for **precipitation**, where model disagreement is high, and scenario influence is weak **(see Figure 1)**.
- This is a key problem: **extreme but plausible drought events are smoothed out**, even though they are most important for **risk planning**.
- An alternative is the **Climatic Impact Drivers (CIDs) framework** (Buskop et al., 2024), which groups models based on **relevant climate drivers** such as **precipitation** and **evaporative demand**, instead of emission scenarios. This **bottom-up approach** focuses on **physically consistent extremes**, rather than average conditions **(see conceptual Figure 2)**.
- This method has been shown to work for **flood risk**, but it has **not yet been tested for drought,** which is more complex due to **seasonal drivers, multi-year memory**, and the interaction between **water supply and demand**.

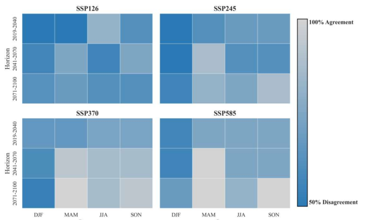


Figure 1: Model Agreement on Precipitation Change direction (ΔP) in Study Area

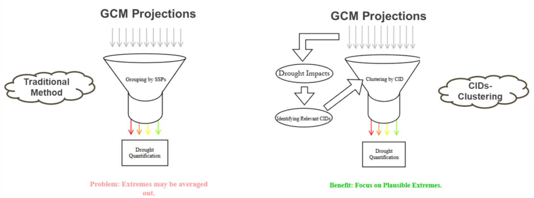


Figure 2: Traditional vs CID-based approach: Grouping models by SSP averages signals and can hide extremes, while clustering by CIDs preserves physically plausible drought extremes.

3. Research Objective:

Objective

To improve the exploration of **plausible future drought risks** by defining a **problem-specific uncertainty envelope** using Global Climate Models clusters based on **Climatic Impact Drivers** (CIDs).
The **Guadalquivir River Basin (GRB)** in Spain is used as a **case study** due to its high **drought vulnerability** and **agricultural importance**.

Research Questions:

1. Which **climate impact drivers (CIDs)** control drought impacts?
2. How do **GCM clusters based on CIDs** define the **uncertainty envelope**?
3. How does CID-based clustering **expand the drought range** compared to Shared Socioeconomic Pathways?
4. What are the **future drought impacts** for the GRB?

4. Study Area and Methods:

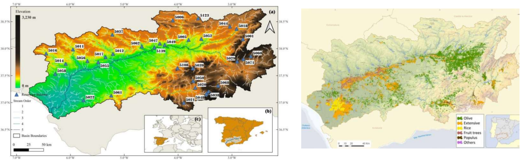
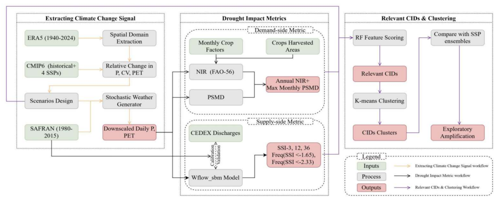


Figure 3: Study Area: Guadalquivir River Basin (GRB), Spain

The Guadalquivir River Basin (**GRB**) is located in southern Spain and covers about 57,500 km², with more than 4.2 million inhabitants. It is one of the most important agricultural regions in the country.
The basin has around **800,000 hectares of irrigated land**, accounting for about 87% of total water use. It represents nearly **25% of Spain's** irrigated area and is the main **olive-producing** region in the country.
The GRB is also highly regulated, with more than **60 reservoirs**, making water management strongly controlled.
Despite this, the basin is highly vulnerable to drought. **Multi-year droughts** occur every **decade**, leading to significant economic and agricultural losses.

Methods:



5. Results:

Sensitivity of drought Impact to CID (Figure 4):

- Winter precipitation is the dominant driver of streamflow drought change.
- Spring and summer PET dominate the agricultural drought change.
- Winter PET emerges as a secondary amplifier of extreme and multi-year streamflow drought, enhancing storage depletion one drought is established.

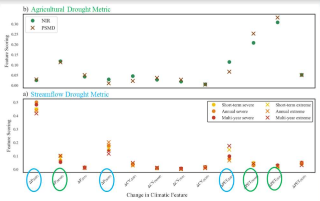


Figure 4: CIDs' Importance for each drought metric.

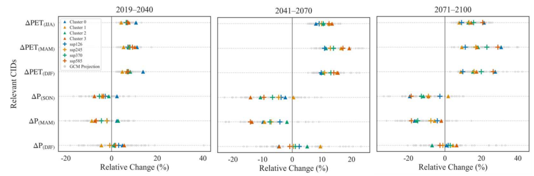


Figure 5: Projected relative changes in the six most relevant CIDs across three future horizons, comparing CID-based cluster means (triangles) against SSP ensemble means (crosses) and individual GCM projections (grey dots).

Relevant CIDs Clustering vs SSP grouping (Figure 5):

- CID clustering expands the range of projected climate change signals relative to SSP grouping, most pronounced for winter precipitation.
- PET changes expanded range by CID clustering were relatively limited, especially for the far-end horizon, following the warming signal.

Exploratory Amplification (Figure 6):

- CID clustering has an average median above or close to 1 for both drought impact metrics.
- Streamflow drought: only significant for med-term, with some reservoirs having below 1 EA.
- Agricultural drought: consistently above 1 EA; however, the extreme values remained below 2%.
- EA approach 1 for the far-end horizon, limited by warming-driven PET signal.

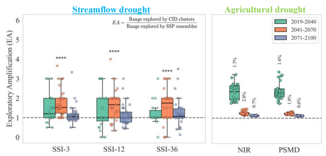
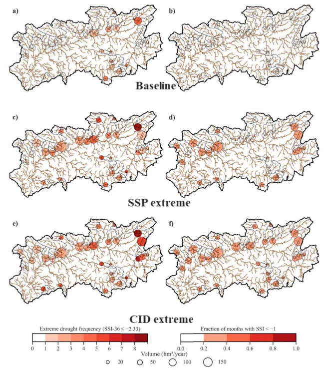


Figure 6: Exploratory Amplification between CID and SSP for each drought impact metric.



Plausible extreme futures (Figures 7 & 8):

- CID extreme storyline (Cluster 3, mid-term) -simultaneous precipitation decrease and PET increase- drives basin-wide **intensification** of drought compared to SSP ensemble ranges.
- Nearly all reservoirs are projected to experience at least one **SSI-36 < −2.33 event,** with **20–40%** of months under drought conditions across the basin.
- **Eastern and northern** catchments show the strongest increases in **extreme drought frequency**; SSI-36 time series breaches the extreme threshold (−2.33) in CID scenarios not reached by any SSP. These reservoirs are located where most **of tree olives** are planted.
- The increased explored range was consistent **over time** when looking into one reservoir project SSI timeseries.

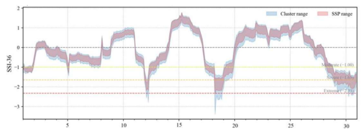


Figure 8: Historical and scenario-based SSI-36 variability for reservoir 5001.

6. Discussion:

- CID-based clustering **expands** the explored drought range, but this effect is **not consistent** across all time periods.
- Streamflow drought is mainly driven **by precipitation deficits** (winter and autumn), which control drought onset, while **PET** acts as an **amplifier** during long and extreme droughts.
- The **largest added** value of CID clustering occurs in the mid-term (2041–2070), when **precipitation uncertainty** is **highest,** and models show diverging responses.
- In the near-term, the benefit is masked by **internal variability**, and in the far-term, it decreases due to **scenario-driven convergence** (Hawkins & Sutton, 2010).
- **Agricultural** drought shows **limited** sensitivity to **CID** clustering, as PET increase is **consistent** across **models**, leading to similar outcomes.
- A key **limitation** is the absence of **reservoir operations** and **irrigation** management, which may **overestimate** the role of PET.
- **Implication**: CID clustering helps reveal **plausible extreme droughts** that are hidden in **traditional averaging**, making it more useful for **risk-informed water management**.
- **Key insight**: The **mid-term** is the **critical** window for **adaptation**, where uncertainty is highest and different drought pathways become visible.

7. Conclusion:

- Key drivers: **precipitation** controls change **streamflow** drought, **PET** controls change **agricultural** drought.
- **CID clustering** reveals much stronger mid-term extremes (≈2× increase in extreme streamflow drought vs. SSP).
- A **critical worst-case** scenario (low P + high PET) emerges with mid-term CID, causing widespread **multi-year droughts (higher frequency and longer duration)**.
- **Agricultural impacts** remain limited (<2% increase), constrained by consistent **PET** response to **warming**.
- Despite a simplified drought impact metric, CID clustering adds clear value for near- to mid-term drought risk assessment, especially under high **precipitation uncertainty**.

References:

Buskop, F. E., Weiland, F. S., & Van Den Hurk, B. (2024). Amplifying exploration of regional climate risks: clustering future projections on regionally relevant impact drivers instead of emission scenarios. Environmental Research Climate, 3(4), 045030. https://doi.org/10.1088/2752-5295/ad9f8f

Hawkins, E., & Sutton, R. (2010). The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dynamics*, *37*(1–2), 407–418. https://doi.org/10.1007/s00382-010-0810-6

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Abstract