UNIVERSITAT POLITÈCNICA DE VALÈNCIA

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Non-stationary analysis of extreme precipitation

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Bridging the gap between water science and solutions – A joint conference
9th IWRM 14th STAHY 1st EBHE

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Introduction

The Guardian

Afghanistan flash floods kill more than 300 as torrents of water and mud crash through villages

Survivors pick through debris-littered streets and damaged buildings as rescue workers dispatched amid warning some areas cut off by flooding

Europe hit by severe floods in the north and heatwaves in the south

Research question and objective

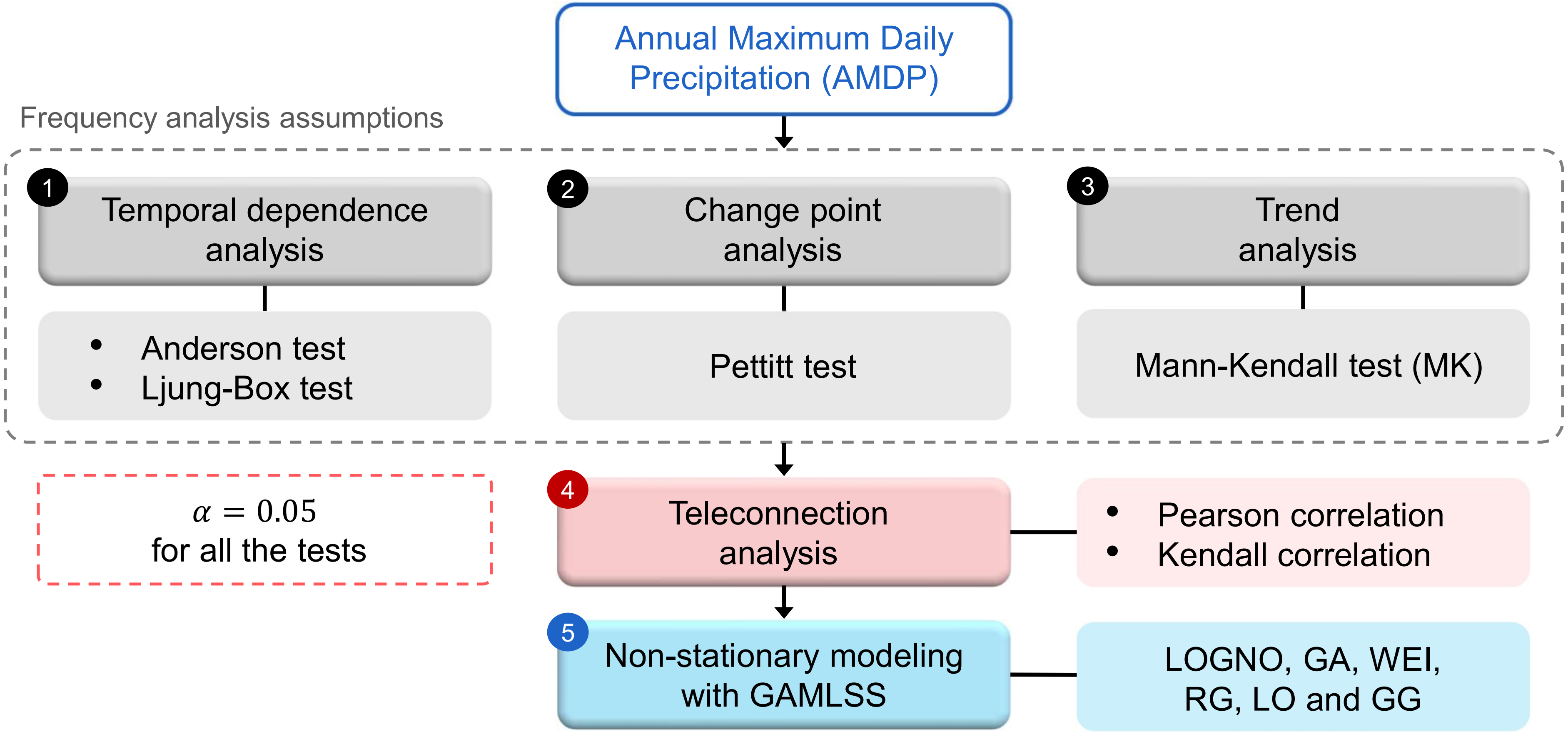
- Research question:

  Are extreme precipitations in Spain experiencing any deviation from the stationary assumption that makes it necessary to consider a non-stationary frequency analysis?

- Objective:

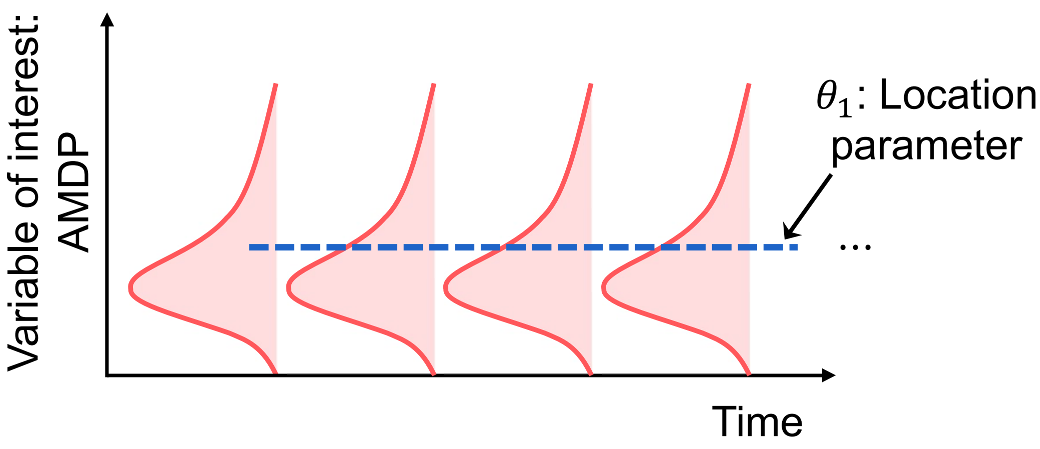
  Analyze the frequencies of Annual Maximum Daily Precipitation (AMDP) over Spain through a non-stationary approach and make predictions under climate change scenarios

Methodology: workflow

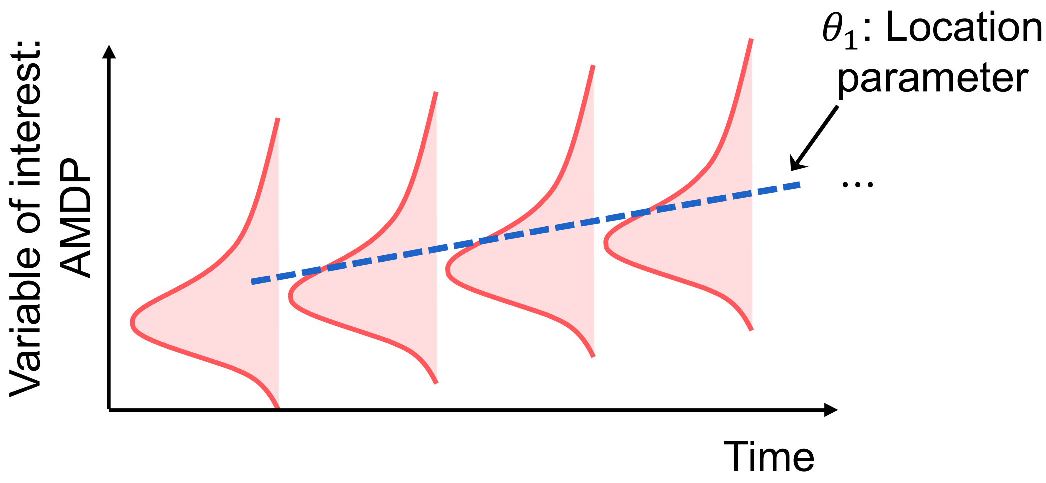


Methodology: non-stationary approach

Conventional frequency analysis (stationary)



Non-stationary frequency analysis



Methodology: GAMLSS framework

Generalized Additive Models for Location, Scale and Shape (Rigby & Stasinopoulos, 2005)

Semi-parametric additive model:

$$g_k(\theta_k) = X_k\beta_k + \sum_{j=1}^{m_j} h_{jk}(x_{jk})$$

Probability distribution with three parameters:

$$g_1(\theta_1) = X_1\beta_1 + \sum_{j=1}^{m_1} h_{j1}(x_{j1})$$

$$g_2(\theta_2) = X_2\beta_2 + \sum_{j=1}^{m_2} h_{j2}(x_{j2})$$

$$g_3(\theta_3) = X_3\beta_3 + \sum_{j=1}^{m_3} h_{j3}(x_{j3})$$

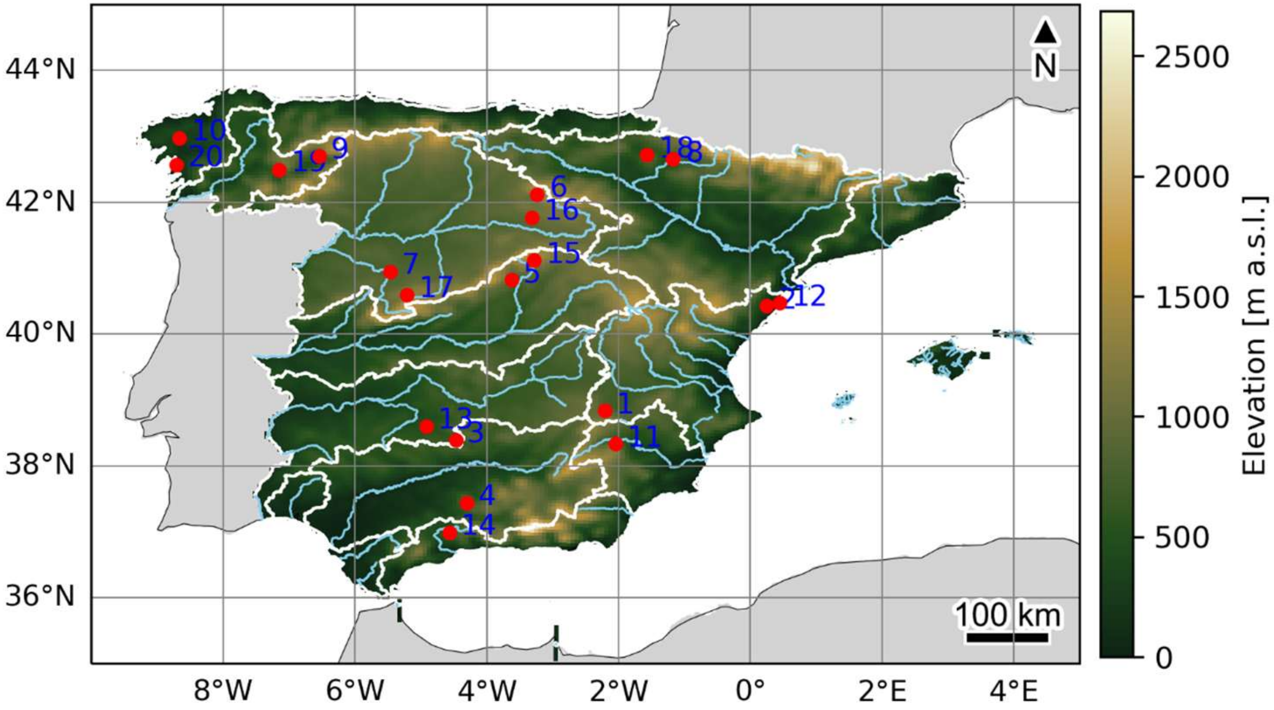
$g_k(\cdot)$ is the link function (e.g., identity, logarithmic)

$X_k\beta_k$ is the parametric linear component

$h_{jk}(\cdot)$ represents the functional dependence of the distribution parameters on covariates x_{jk}; it can be linear or non-linear through smoothing terms (cubic splines were used in this study)

Study region

Peninsular Spain and Balearic islands



Precipitation data

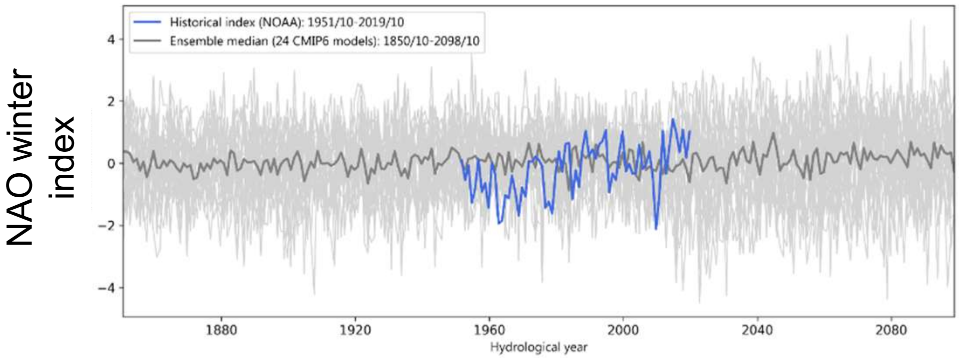
- Gridded dataset by AEMET
- Spatial resolution: $0.05° \times 0.05°$ ($\sim 5\ km \times 5\ km$; 16 156 grid points)
- Temporal resolution: daily
- Temporal coverage: 1/1/1951-31/12/2020 (70 calendar years)

Winter climate indices data

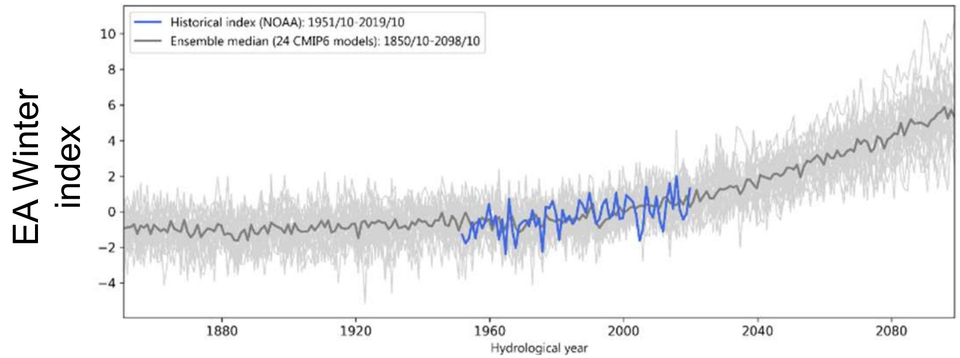
- Historical: CPC-NOAA (USA)
- Future: Cusinato et al. (2021) 24 climate models (CMIP6) / ssp585

Historical and projected winter climate indices

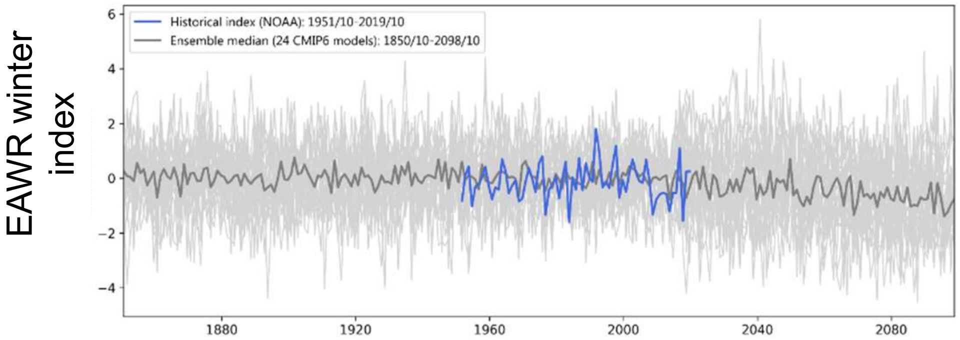
North Atlantic Oscillation (NAO) index



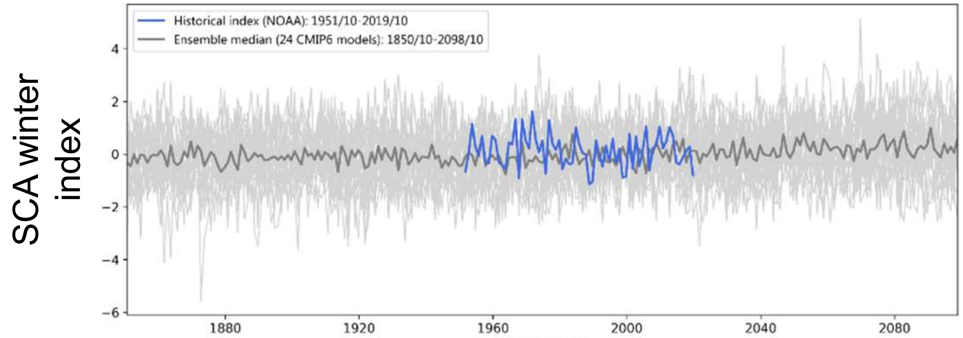
East Atlantic (EA) index



East Atlantic-Western Russia (EAWR) index

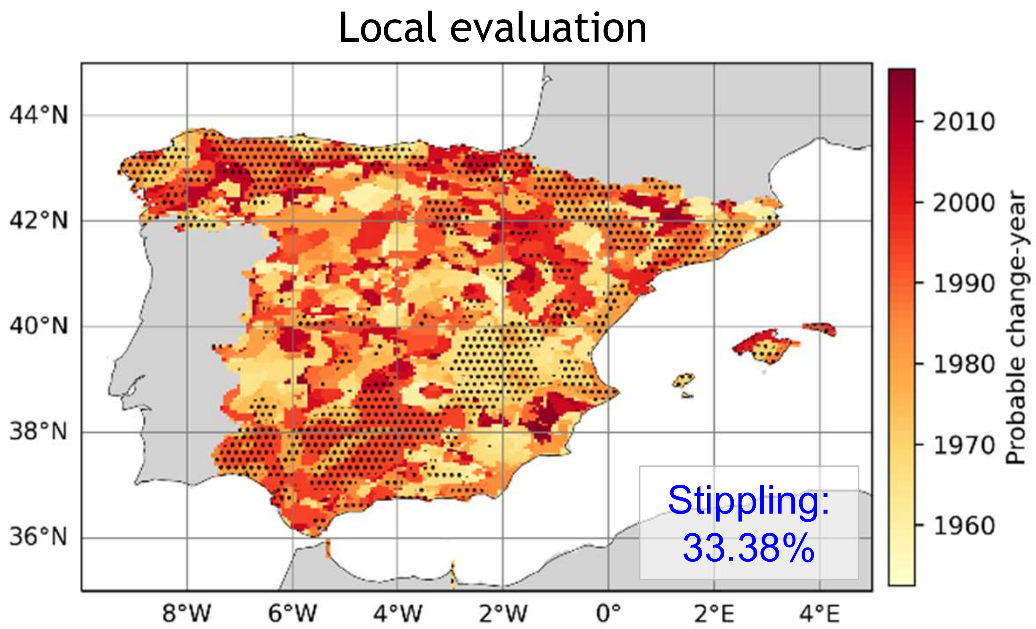


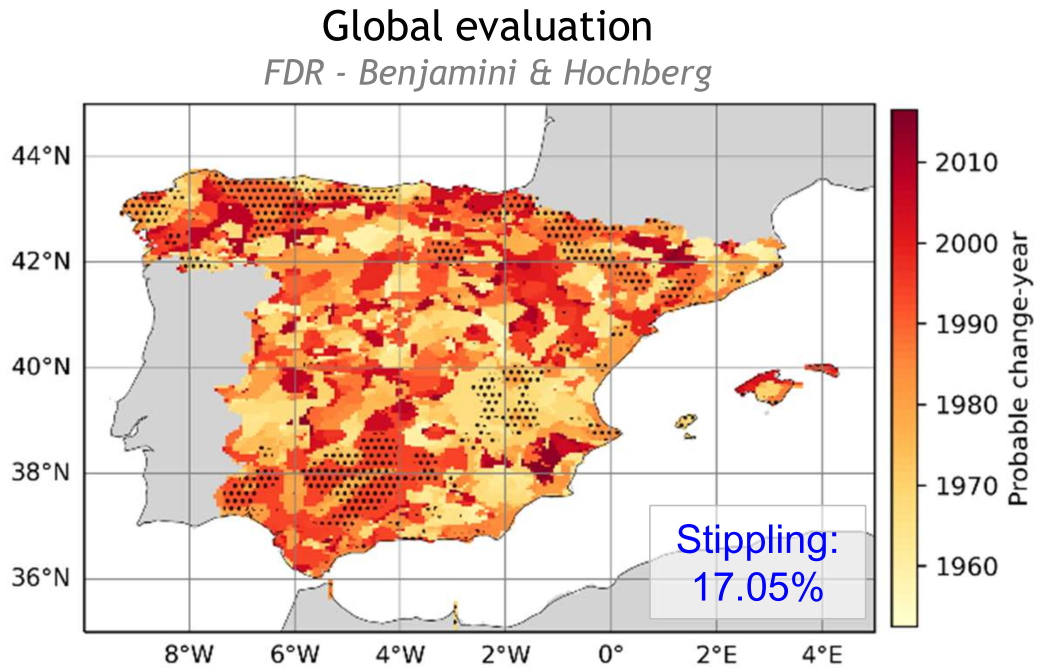
Scandinavian (SCA) index



Results: change points

Pettitt test



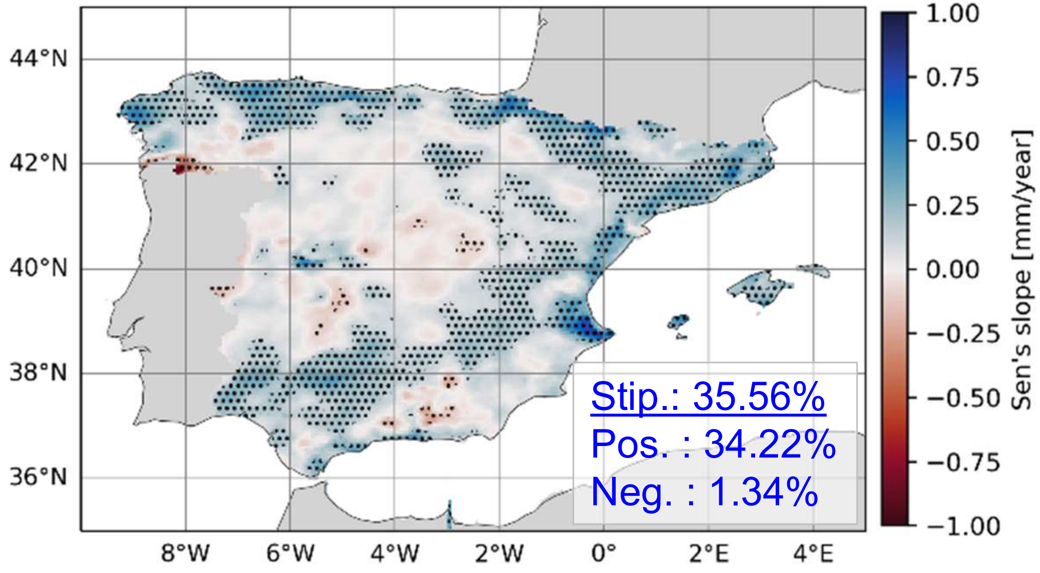


Effect of test multiplicity ➡ Reduction of significant results

Results: monotonic trends

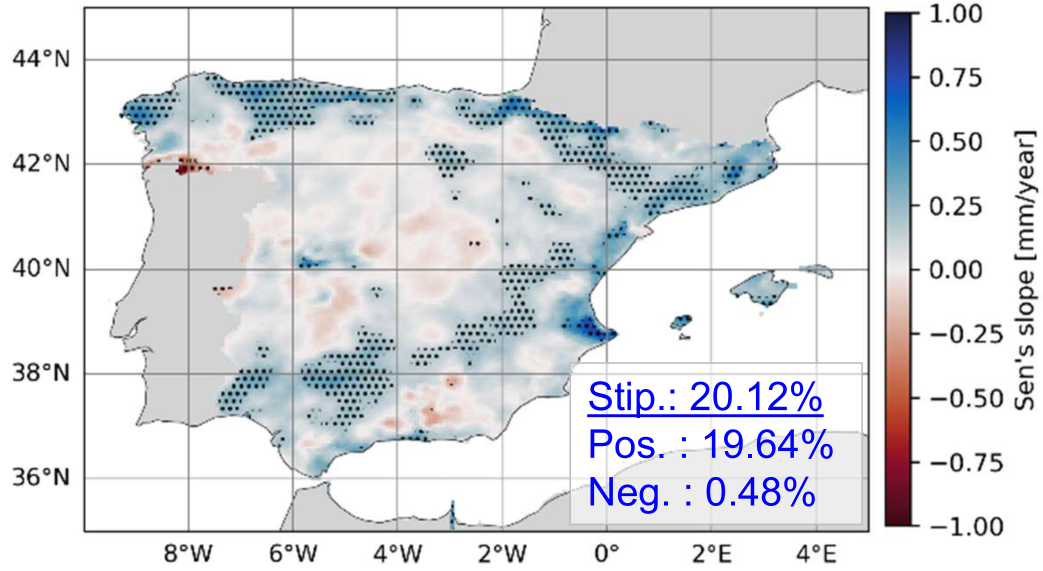
Mann-Kendall test

Local evaluation



Global evaluation

FDR - Benjamini & Hochberg

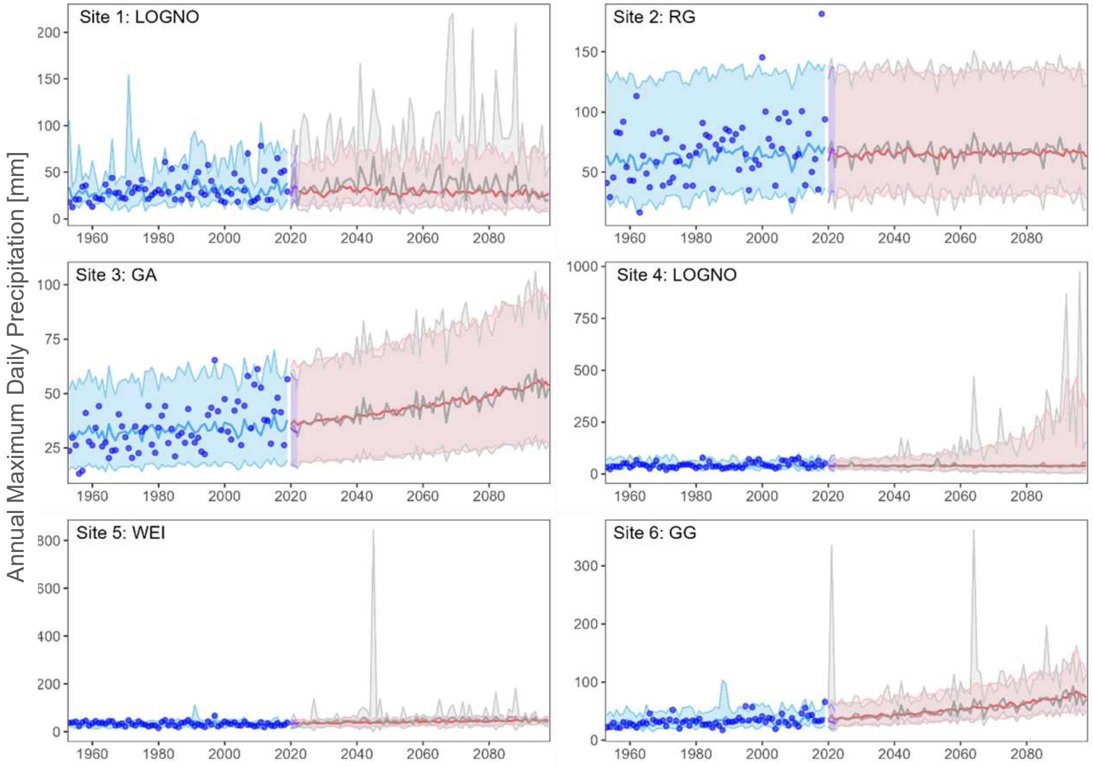


Effect of test multiplicity ➡ Reduction of significant results

Results: non-stationary modeling, non-lagged covar.

Series of 20 sites were modeled

Site	PDF	AIC-S	AIC-NS	DF	Par.	Model structure
1	LOGNO	528.421	511.639	6	θ_1	$3.434 + 0.155 \cdot NAOw + 0.222 \cdot EAWRw$
					θ_2	$-1.089 + 0.498 \cdot SCAw + 0.308 \cdot NAOw$
2	RG	626.705	623.282	3	θ_1	$56.896 + 6.606 \cdot NAOw$
					θ_2	3.027
3	GA	509.627	507.384	3	θ_1	$3.553 + 0.086 \cdot EAw$
					θ_2	-1.180
4	LOGNO	539.202	522.229	10	θ_1	$3.703 + cs(NAOw, 2)$
					θ_2	$-1.327 + cs(EAw, 3) + 0.277 \cdot NAOw$
5	WEI	494.420	472.068	11	θ_1	$3.607 + cs(EAw, 3) + 0.193 \cdot EAWRw$
					θ_2	$1.623 + cs(EAWRw, 3)$
6	GG	483.709	467.206	7	θ_1	$3.443 + 0.155 \cdot EAw$
					θ_2	$-1.518 + cs(SCAw, 2)$
					θ_3	-1.962



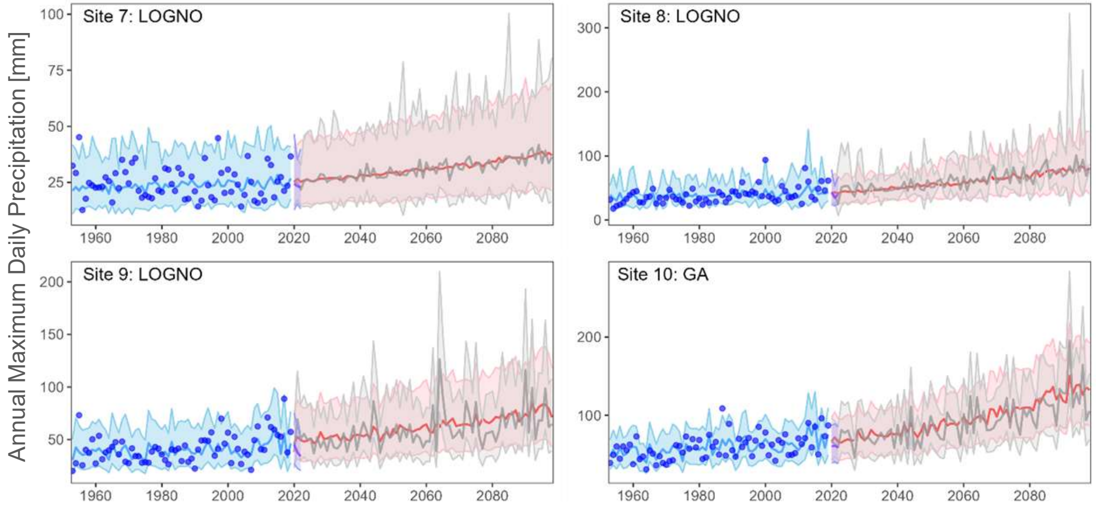
Legend

- 2.5%-97.5% quantiles-ACCESS_CM2 (prediction)
- 2.5%-97.5% quantiles-ensemble (prediction)
- 2.5%-97.5% quantiles (fit)
- 2.5%-97.5% quantiles (prediction*)
- 50% quantile-ACCESS_CM2 (prediction)
- 50% quantile-ensemble (prediction)
- 50% quantile (fit)
- 50% quantile (prediction*)
- Observations

Sudden increases and decreases in variance

Results: non-stationary modeling, non-lagged covar.

Site	PDF	AIC-S	AIC-NS	DF	Par.	Model structure
7	LOGNO	449.596	447.669	4	θ_1	$3.180 + 0.081 \cdot EAw$
					θ_2	$-1.339 + 0.239 \cdot SCAw$
8	LOGNO	520.824	500.781	10	θ_1	$3.665 + 0.113 \cdot EAw + 0.163 \cdot SCAw + 0.091 \cdot NAOw$
					θ_2	$-1.490 - 0.391 \cdot EAWRw + cs(SCAw, 3)$
9	LOGNO	531.261	522.387	10	θ_1	$3.688 + cs(NAOw, 3) + cs(EAWRw, 2) + 0.078 \cdot EAw$
					θ_2	-1.353
10	GA	557.921	530.475	5	θ_1	$4.111 + 0.122 \cdot EAw + 0.093 \cdot NAOw - 0.114 \cdot EAWRw$
					θ_2	-1.600



Legend

- 2.5%-97.5% quantiles-ACCESS_CM2 (prediction)
- 2.5%-97.5% quantiles-ensemble (prediction)
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- 2.5%-97.5% quantiles (prediction*)
- 50% quantile-ACCESS_CM2 (prediction)
- 50% quantile-ensemble (prediction)
- 50% quantile (fit)
- 50% quantile (prediction*)
- Observations

The scale parameter covariates took values at the limits and outside their historical range

Combined effects

Maximization/minimization of the variance

Origin?

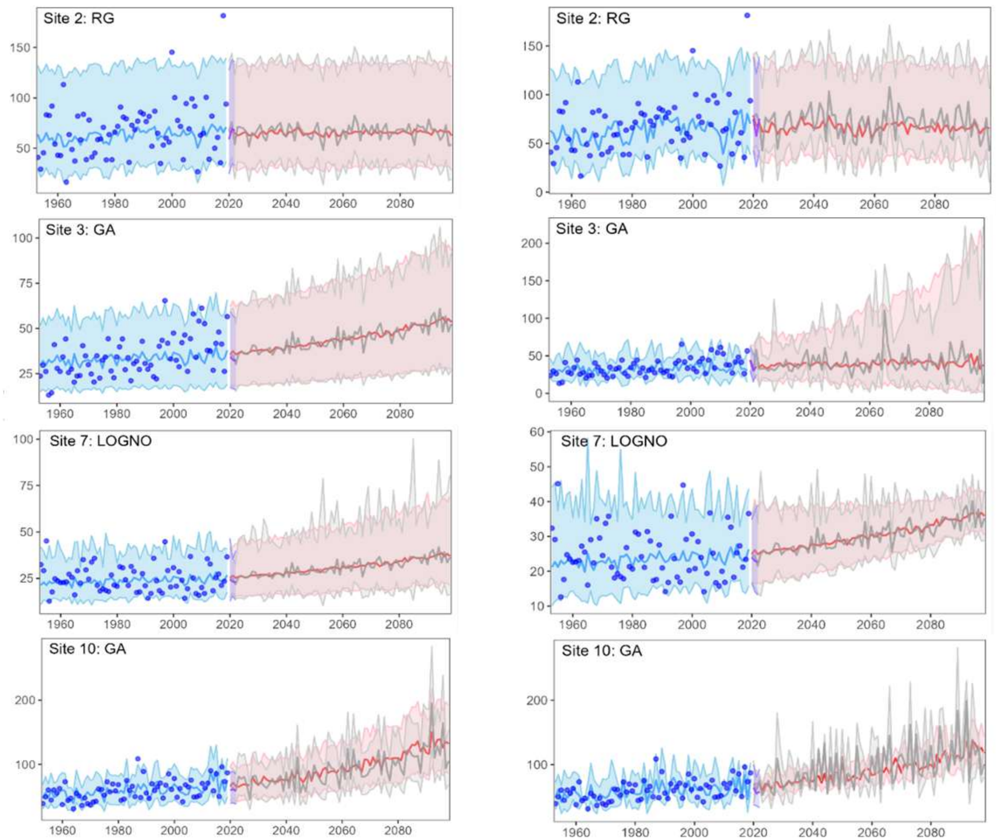
<u>Extrapolation</u>

Results: non-stationary modeling, lagged covar.

Site	PDF	AIC-S	AIC-NS	DF	Par.	Model structure
2	RG	626.705	615.604	4	θ_1	$59.761 + 11.321 \cdot NAOw_1 + 5.937 \cdot EAWRw$
					θ_2	2.956
3	GA	509.627	500.219	10	θ_1	$3.550 + 0.096 \cdot EAw_1 - 0.176 \cdot SCAw_1 + cs(NAOw_1, 3)$
					θ_2	$-1.367 - 0.355 \cdot NAOw_1 + 0.242 \cdot EAw$
7	LOGNO	449.596	445.722	4	θ_1	$3.170 + 0.077 \cdot EAw$
					θ_2	$-1.378 - 0.223 \cdot EAw_1$
10	GA	557.921	516.951	14	θ_1	$4.118 + 0.129 \cdot EAw + 0.056 \cdot NAOw - 0.094 \cdot EAWRw + 0.154 \cdot EAWRw_1$
					θ_2	$-1.900 + cs(EAWRw, 3) + cs(NAOw, 3)$

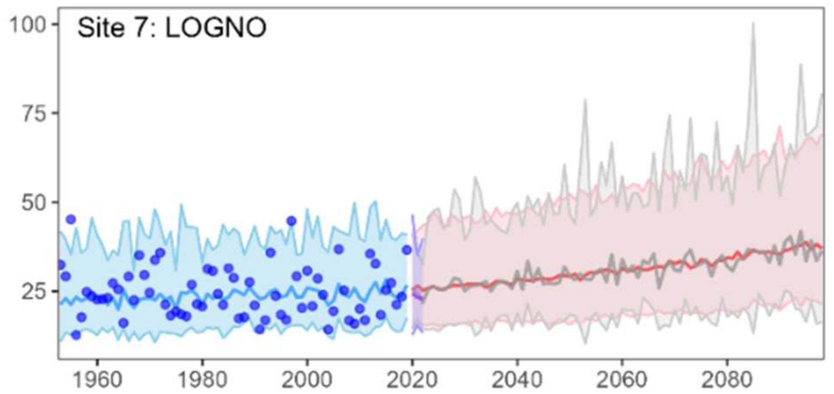
- Models with lagged covariates have higher performance than models with non-lagged covariates, but their complexity also increases
- High sensitivity of models in the predictive phase

Non-lagged covariates **Lagged-1 covariates**

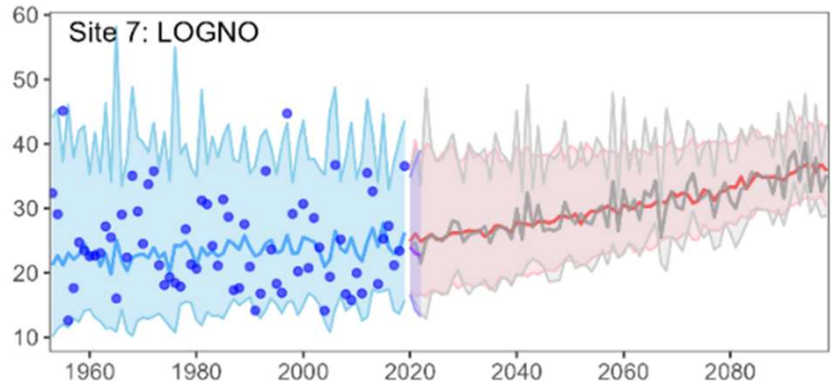


Results: equifinality

Non-lagged covariates



Lagged-1 covariates



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7	LOGNO	449.596	445.722	4	θ_1	$3.170 + 0.077 \cdot EAw$
					θ_2	$-1.378 - 0.223 \cdot EAw_1$

- Different model structures (see θ_2)
- Similar AIC
- Opposite behavior in projected variance (?)

Which model do I select? ➡ Equifinality

Conclusions

- AMDP over several Spanish regions are experiencing some deviation from the stationary assumption (change points and trends)
- Non-stationary modeling revealed serious problems that led to doubts about the reliability of the adopted models
  - Equifinality makes it difficult to select a representative non-stationary model
  - There is uncertainty associated with extrapolating the relationships between distribution parameters and covariates into the future, as these relationships may change as the sample data increase
- There are no projections for all climate indices
- We need to find a physical mechanism to explain non-stationarities

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Thank you for your attention!

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