Non-stationary flood frequency analysis in continental Spanish rivers using climate and reservoir indexes as external covariates

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INTRODUCTION

Traditionally, **stationary** has been the cornerstone of the ***"flood frequency analysis" (FFA)***. Recently, the hypothesis of stationarity in the hydrological variables is being questioned (e.g. Milly et al., 2008).

Two factors impact in the violations of the stationarity in the flood regime:

- ❑ **Climatic** (climate variability)
- ❑ **Anthropogenic** (changes in land use/land cover and river regulation by dams)

Problems in the classical *FFA*: Not represent the dynamic of nature.

Stationary world? Incorrect assumption → Non-stationary world? It is necessary and appropriate

How to address this problem?

Use **new statistical models and procedures** that capture the evolution of pdf's over time.

Which external forcing can be used as covariates in the modelling annual floods?

- ❑ Climate indexes (large scale atmospheric circulation patterns)
- ❑ Reservoir index

Objective: Develop a framework of ***FFA* under non-stationary conditions** based on the GAMLSS models and use climate and reservoir indexes as external drivers in a covariate analysis to describe the variability of annual floods in Spanish rivers.

GAMLSS

GAMLSS models were proposed by Rigby and Stasinopoulos [2005] and provide a flexible modelling frame work for annual flood peaks. In a GAMLSS model the observations y_i (for i=1, ..., n) are assumed to be independent with a distribution function $F_Y(y_i \mid \theta_i)$, where $\theta_i=(\theta_{1i}, ..., \theta_{mi})$ represents a vector of m distribution parameters accounting for location, scale, and shape.

GAMLSS involve several important sub-models, relating the distribution parameters with explanatory variables through an additive model (Eq. 2) or semi-parametric additive model (Eq.3).

$$g_k(\theta_k) = \eta_k = X_k\beta_k + \sum_{j=1}^{J_k} Z_{jk}\gamma_{jk} \quad (2) \qquad g_k(\theta_k) = \eta_k = X_k\beta_k + \sum_{j=1}^{J_k} h_{jk}(x_{jk}) \quad (3)$$

Probability Density Functions (PDF`s)

We selected 5 distributions usually used in floods frequency analysis: *Gumbel (GU), Lognormal 2p (LNO), Weibull (WEI), Gamma 2p (GA) y Generalized Gamma (GG)*.

Model Fitting Criteria

To avoid model over-fitting and in agreement with the parsimony principle, stepwise methods were used with respect to both **Akaike Information Criterion** (AIC) and **Schwarz Bayesian Criterion** (SBC), equations 4 and 5 respectively. The use of these criteria represents a tradeoff between model complexity and precision.

$$AIC = -2ln(ML)+2k \quad (4) \qquad SBC = -2ln(ML)+kln(n) \quad (5)$$

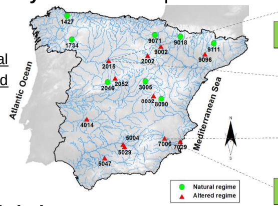
The goodness of fit of the selected models was verified in accordance with the recommendations of Rigby and Stasinopoulos [2005], checking the normality and independence of the residuals.

DATA & MODELS

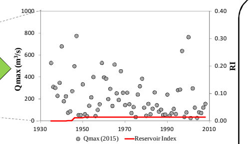
Case – study: Continental Spain

Basins:

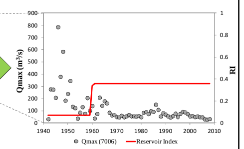
- ❑ 8 natural
- ❑ 12 altered



Low Altered regime



High Altered regime



Reservoir index:

We evaluate the hydrologic effect of dams by means of a dimensionless reservoir index (*RI*) defined as:

$$RI = \sum_{i=1}^{N}\left(\frac{A_i}{A_T}\right)\cdot\left(\frac{C_i}{C_T}\right) \quad (1)$$

N number of upstream dams
A_i drainage area of each dam
A_T is the drainage area of flow gauge station
C_i reservoir capacity
C_T mean annual runoff at the flow gauge station

Reservoir index values

6 flow gauge station exhibit a higher dam impact ($RI > 0.25$).

Flow Gauge Station	RI_{MAX}	Flow Gauge Station	RI_{MAX}
2002	0.276	5047	0.991
2015	0.014	7006	0.360
2052	0.058	7029	0.465
4014	0.517	8032	0.013
5004	0.329	9002	0.009
5029	0.019	9096	0.129

Models Covariates:

First approach: using only the time (t) as covariate

Modelling annual floods without external forcing

Second approach: Using climate and reservoir indexes as covariates

Modelling annual floods with external drivers

- **Model 1** – Monthly climate indexes and reservoir indexes
- **Model 2** – Winter climate indexes and reservoir indexes
- **Model 3** – Principal components taken from the EFO´s analysis of the winter climate indexes and reservoir indexes

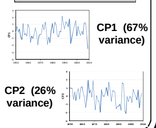
Climate indexes:

- ❑ North Atlantic Oscillation
- ❑ Arctic Oscillation
- ❑ Mediterranean Oscillation
- ❑ Western Mediterranean Oscillation

Monthly indexes (AOi, MOi, NAOi and WeMOi): Monthly climate index corresponding to month annual flood occurrence and considering 2 lag months

Winter indexes (AOw, MOw, NAOw and WeMOw): Average winter climate indexes from the period December to February

Principal Components



RESULTS

Modelling annual floods using the time as covariate

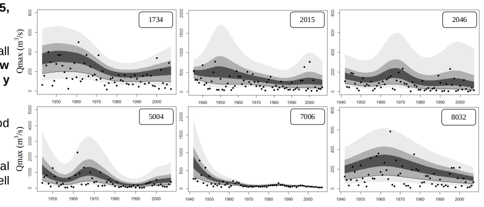
The results are shown by six different quantiles (**0.25, 0.50, 0.75, 0.90, 0.95 and 0.99**).

The plots shown can be considered as a general representation of all results, we show 2 cases in **natural regime (1734 y 2046)**, 2 in **low altered regime (2015 y 8032)** and 2 in **high altered regime (5004 y 7006)**.

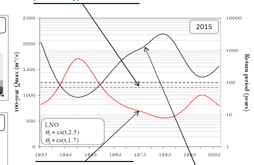
It is clearly the presence of **non-stationarities** in the interannual flood regime in Spanish rivers.

Decreasing trends are observed in most flood records in natural regime and low altered since the early 1960`s to late 1990`s, as well as an increasing trends is also evident in the period after 1990's.

Some results:



Annual flood with 0.01 exceedance probability (stationary): 1151.5 m³/s



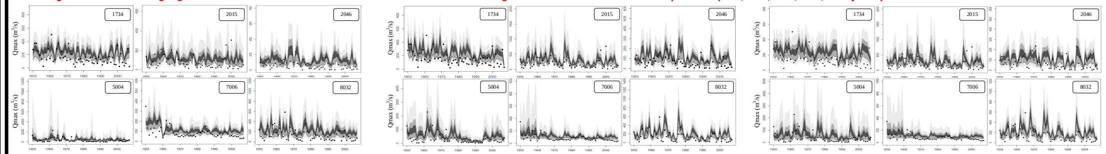
Time trends in the annual flood with 0.01 exceedance probability (non-stationary)

Estimated Tr for the 1151.5 m³/s annual flood, under non-stationary conditions

Modelling annual floods with external drivers: climate and reservoir indexes as covariate

***Model 1:* Monthly climate indexes and RI** — ***Model 2:* Winter climate indexes and RI** — ***Model 3:* PC`s of winter climate indexes and RI**

Modelling results in six flow gauge station for the 3 models addressed. The results exhibit the regions between the 0.25 and 0.99 quantiles (0.25, 0.50, 0.75, 0.90, 0.95 y 0.99)



Stationary and non-stationary models: The results are based on the fitted GAMLLS models for the 2015 flow gauge station.

Model 1 vs Stationary model

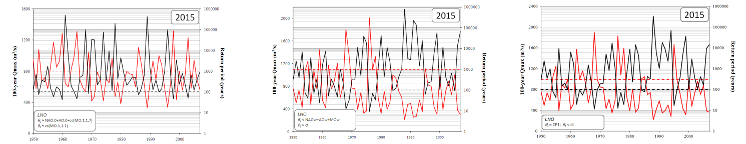
- ❑ Most complex models.
- ❑ Climate indexes are significant covariates in θ_1 and θ_2.
- ❑ *RI* is significant covariate in 6 models (particularly in southern basins).
- ❑ Dependence between distribution parameters and external covariates are modeled by mean of non-parametrics formulations.
- ❑ The results seem to adequately reproduce the behavior exhibited by the floods.

Model 2 vs Stationary model

- ❑ Climate indexes are significant covariates in $\theta_1$and θ_2 exhibits be independent of external forcings.
- ❑ The results for Model 2 are less noisy than for the Model 1, and seem to better reproduce the behavior exhibited by the floods.
- ❑ In 1970-1990 the annual floods experiment a lesser frequency and magnitude.
- ❑ In 1955-1970 and 1995-2005 the annual floods experiment a higher frequency and magnitude.

Model 3 vs Stationary model

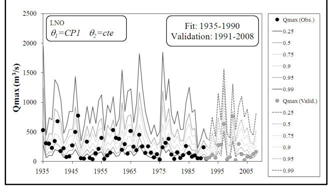
- ❑ Using the PC`s from the FOES analysis we obtain the most parsimonious models.
- ❑ The models reproduce better the non-stationarities in the annual flood regime.
- ❑ Gamma 2p, Generalized Gamma and Lognormal 2p result the best distribution to fit the annual flood data.
- ❑ The models exhibit significant differences with respect to stationary model.



Annual floods with 0.01 annual exceedance probability under non-stationary conditions (red line) and stationary conditions (dotted red line). The estimated return period with 0.01 annual exceedance probability (black line) derived from the period 1950-2007.

GAMLSS models as predictive tool?

Modeling results of annual floods for the 2015 flow gauge station in the period 1935-1990 using the Model 3. The modeling results are represented by solid lines. The model is then used as a predictive tool (dotted line) and the observation not included in the fitting of the model are represented by gray circles



CONCLUSIONS

1. The presence of **increasing and decreasing trends** in the temporal evolution of the flood regime, **can be associated to changes in the climate indexes**, particularly in the observed in the winter indexes and the CP`s.
2. GAMLSS provide a useful modelling framework for representing **non-stationarities exhibited in annual flood records**.
3. Results show climate indices **can be incorporate as external covariates in the non-stationary models**.
4. As expected, **AO and NAO** tend to be a **significant predictors** for the majority of the cases in continental Spanish rivers.
5. **RI** results seem to adequately **reproduce sudden changes caused by dam construction**.
6. A proper estimation based on the non-stationary flood frequency model shows that any flood quantile **varied dramatically during the flood record**.

Acknowledgements

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