

# On the use of at-site estimated quantiles in regional frequency analysis

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## Introduction

**Regression-based models** are the most widely used tools for estimation purposes in regional frequency analysis (RFA). These latter are built using the **estimated at-site quantiles**.

**Problems of classical RFA** are mainly related to the use of the at-site estimated quantiles since the quality of these latter is related to the:

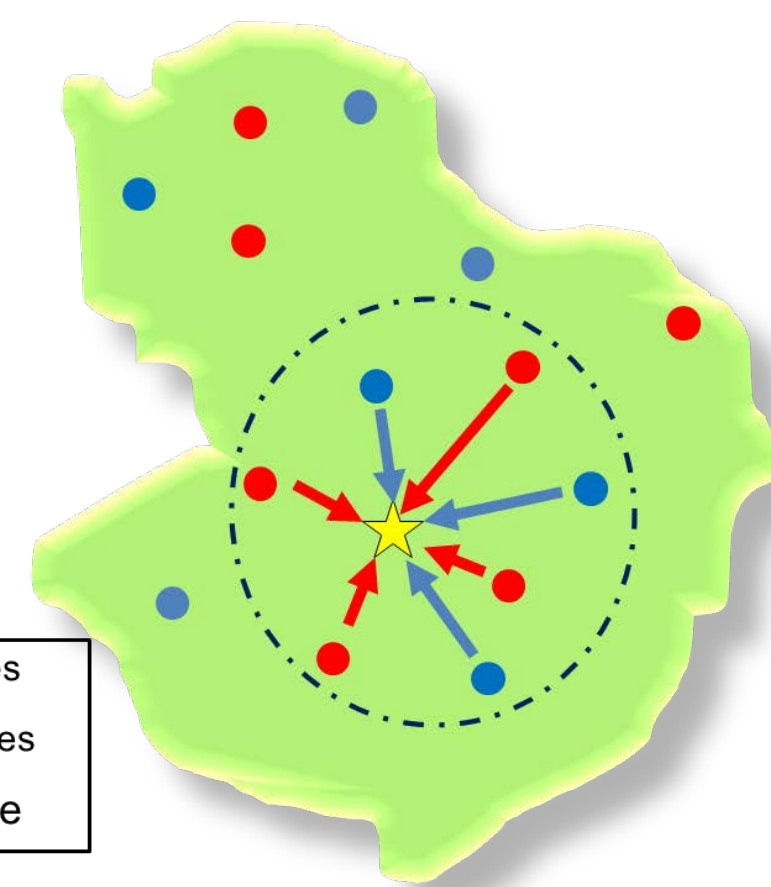
- **data series record length**, which lead to ignore a number of gauged sites with short records,
- model selection,
- parameter estimation...

### How to address this issue?

Use a regression model based on **the observed data** instead of the estimated one and allowing accounting for **the whole hydrological information** in the region.

### Objective:

Propose a new RFA framework based on **quantile regression (QR)** model that gives directly the conditional quantile and avoids performing an at-site FA at each gauged site.

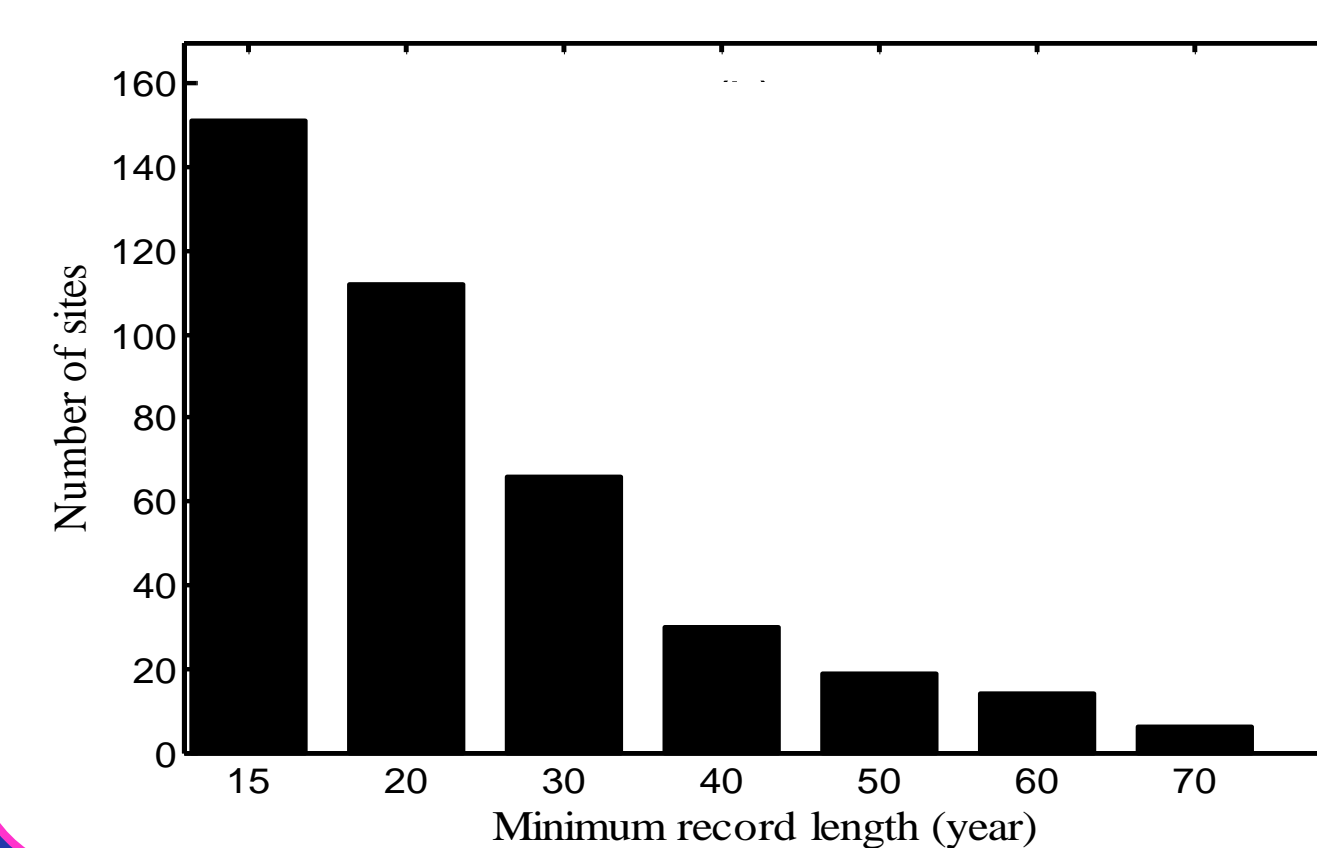


• Long data series  
• Short data series  
• Ungauged site

## Data and models

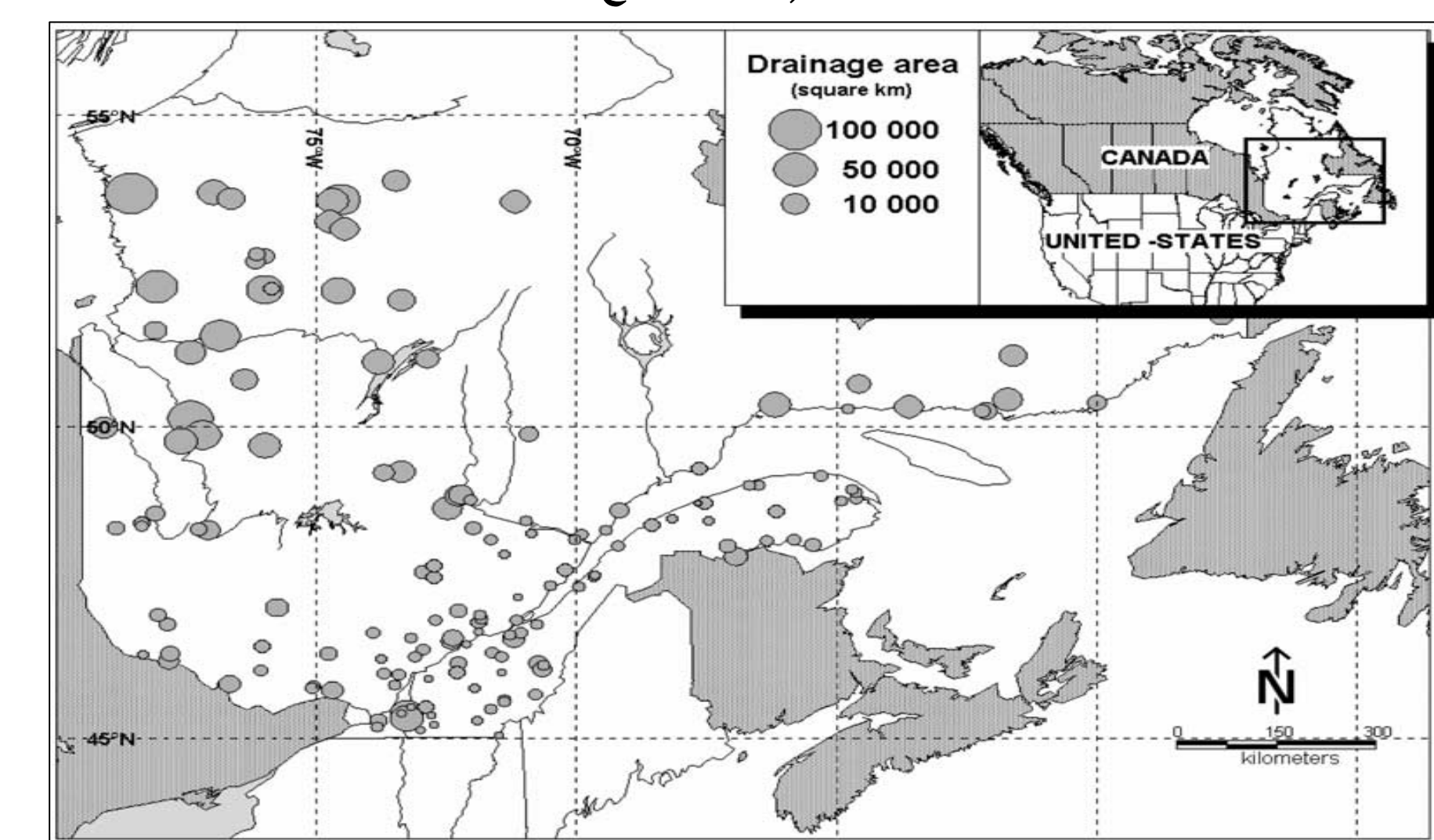
### Case study

151 hydrometric stations in Quebec, CA;  
5 physio-meteorological variables;  
3 hydrological variables:  $Q_{S10}$ ,  $Q_{S50}$  and  $Q_{S100}$ ;  
Historical record of annual maximum flow between 1900 and 2002.



Bar plot of number of stations. Classes are defined to indicate the number of stations with records length exceeding a given minimum.

Geographical location of hydrometric stations, Quebec, Canada



## Data and models

### Classical RFA approach

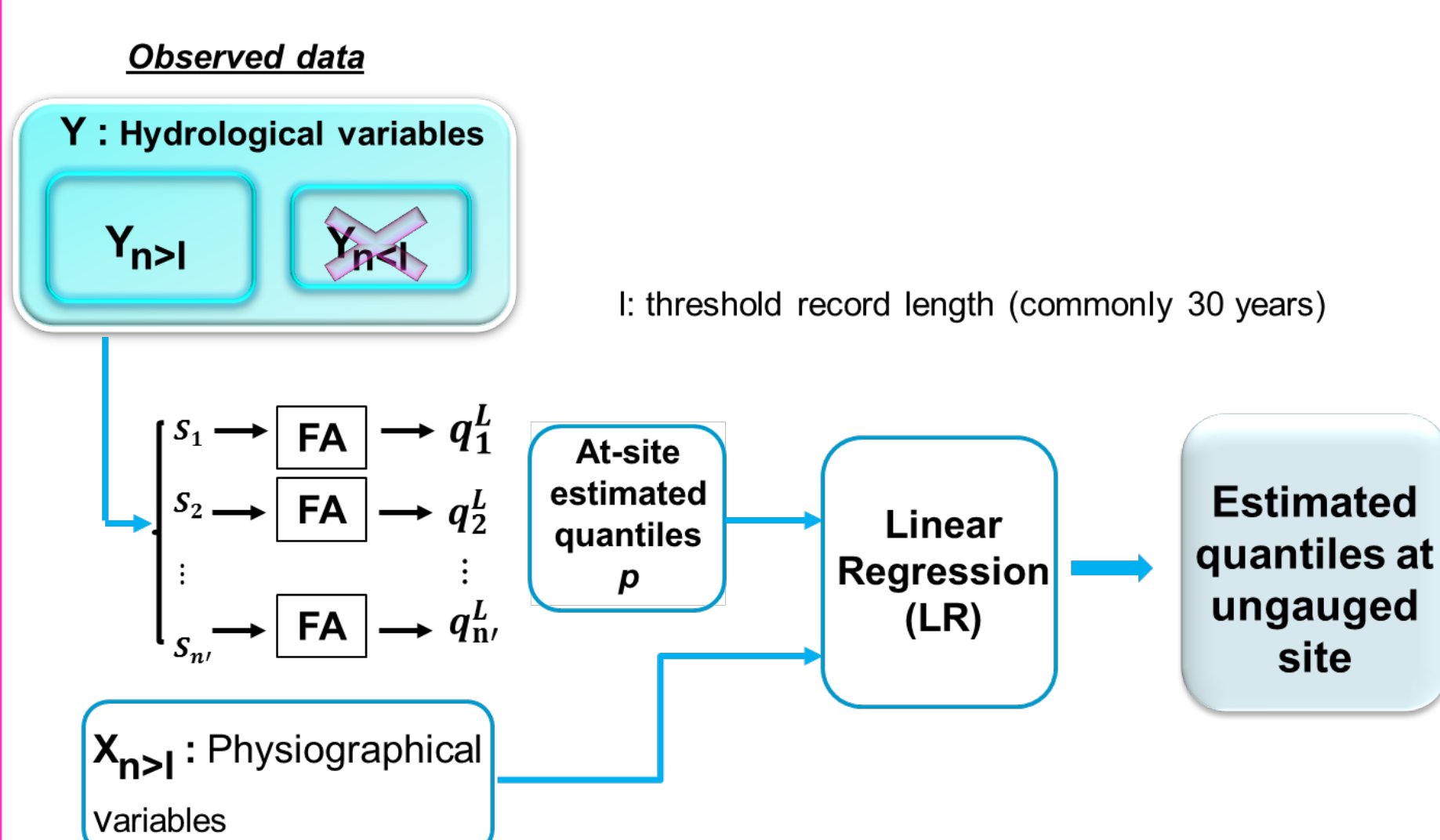
#### Ordinary Linear Regression:

Estimating the conditional mean of the response:  $Y = AX + B + \varepsilon$

$\varepsilon$  is the model error

Minimizing:  $\min \sum \varepsilon_i^2$

#### General procedure



### Proposed QR-based approach

#### Quantile regression

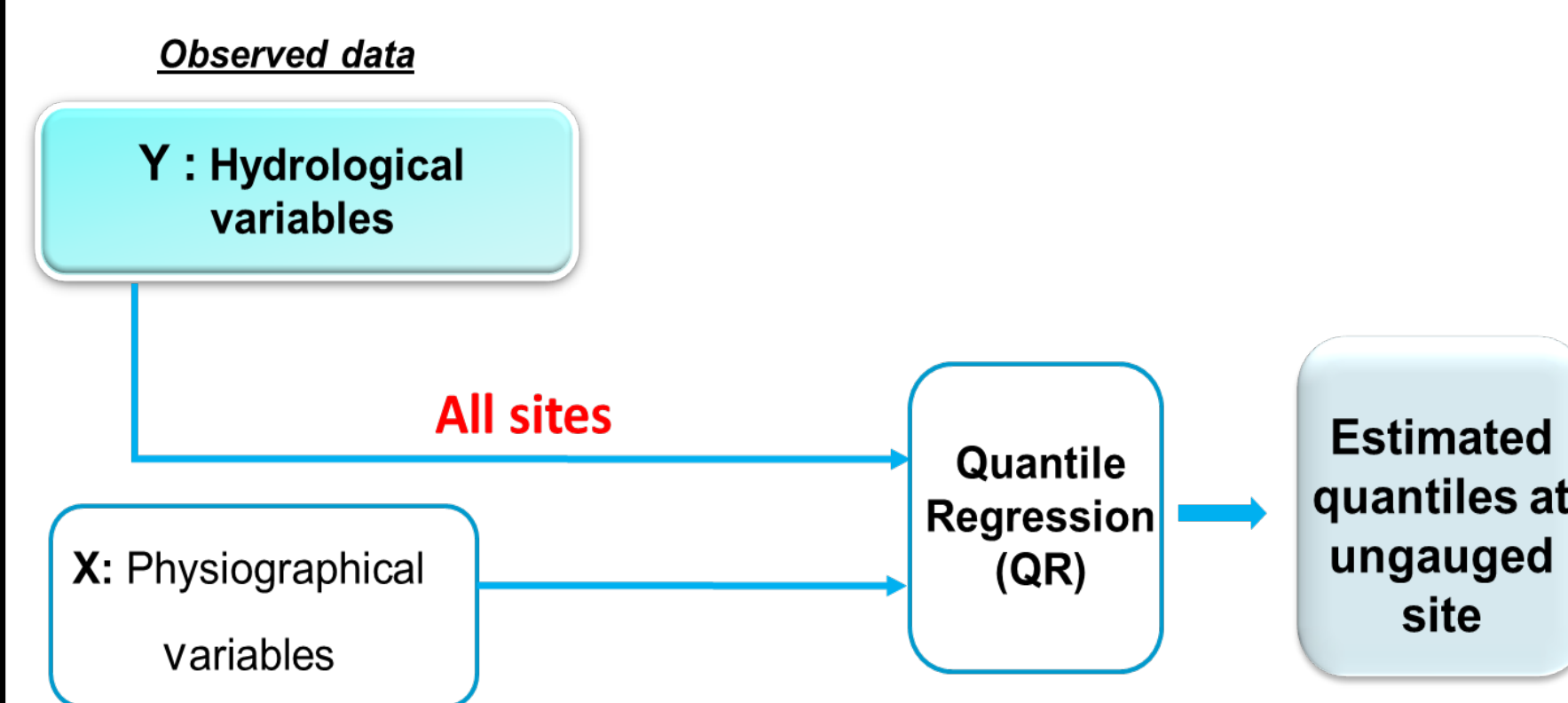
Estimating the conditional quantile of the response:  $Q_p(y | \mathbf{x}) = \mathbf{x}^T \mathbf{b}_p$

Minimizing:  $\min_{\beta} \sum_{i=1}^n \rho_p(y_i - \mathbf{x}_i^T \beta)$

$\rho$  is the check function defined as:

$$\rho_p(\alpha) = \begin{cases} \alpha(p-1) & \text{if } \alpha < 0 \\ \alpha p & \text{if } \alpha \geq 0 \end{cases}$$

#### General procedure



#### Quality assessment

A natural analog of the RMSE in a cross-validation procedure is:

$$MPLF(p) = \frac{10^3}{n} \sum_{i=1}^n \sum_{j=1}^{n_i} \rho_p(y_{ij} - \hat{q}_{ip}^R); \quad p \in (0,1)$$

**MPLF: Mean Pewise Loss Function**

#### Quality assessment

Use of the RMSE in a cross-validation procedure:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (q_L - \hat{q}_i^R)^2}$$

#### Study design

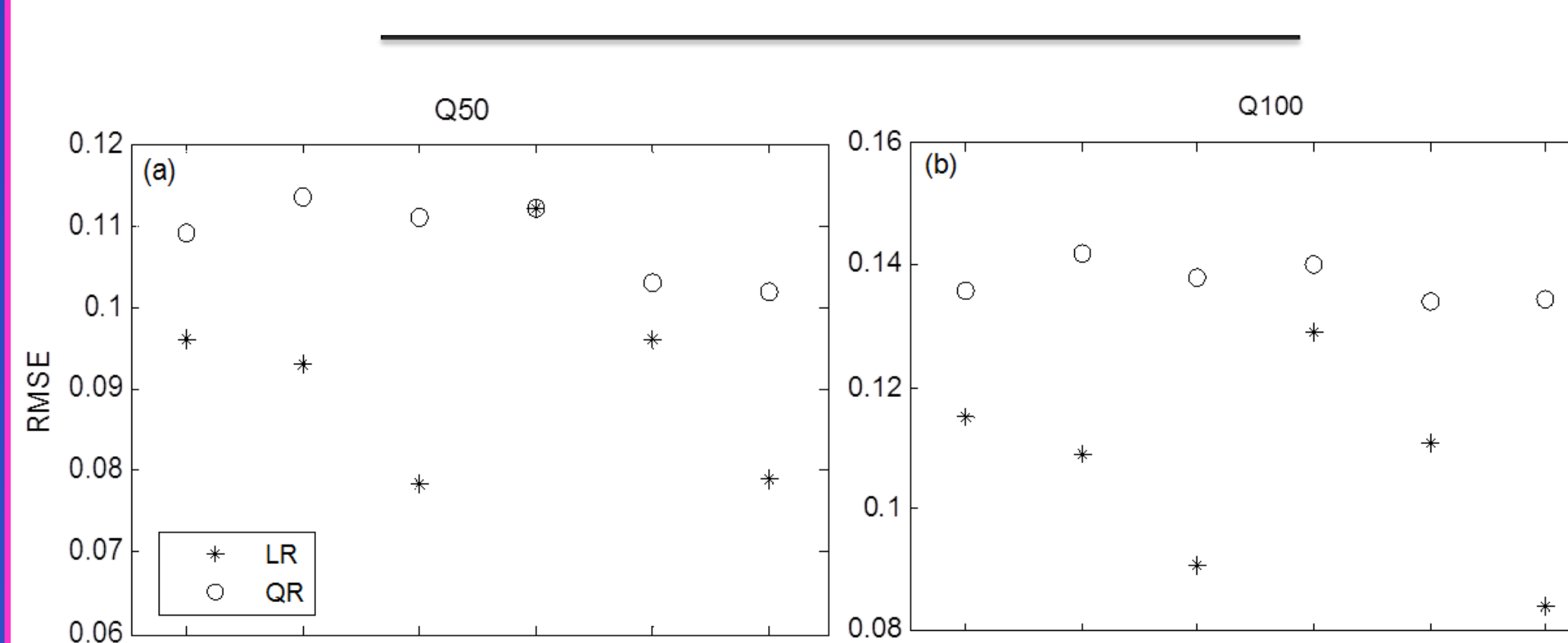
The application of both classical and proposed approaches is performed in several ways:

- Apply and compare the considered models (QR and LR) using different criteria; the calibration and the application of both models are performed using the entire data.
- Take into account the at-site quantile estimation quality; modify the data used for the calibration step.
- Consider a more suitable case for which the LR performs well and the QR advantages are accounted for; the QR model built and assessed using the entire data / the LR model built using only sites with record length exceeding 30 years and evaluated using the entire data.
- Compare both models using the MPLF criterion; the concept of this criterion permits the model assessment using the entire data set.

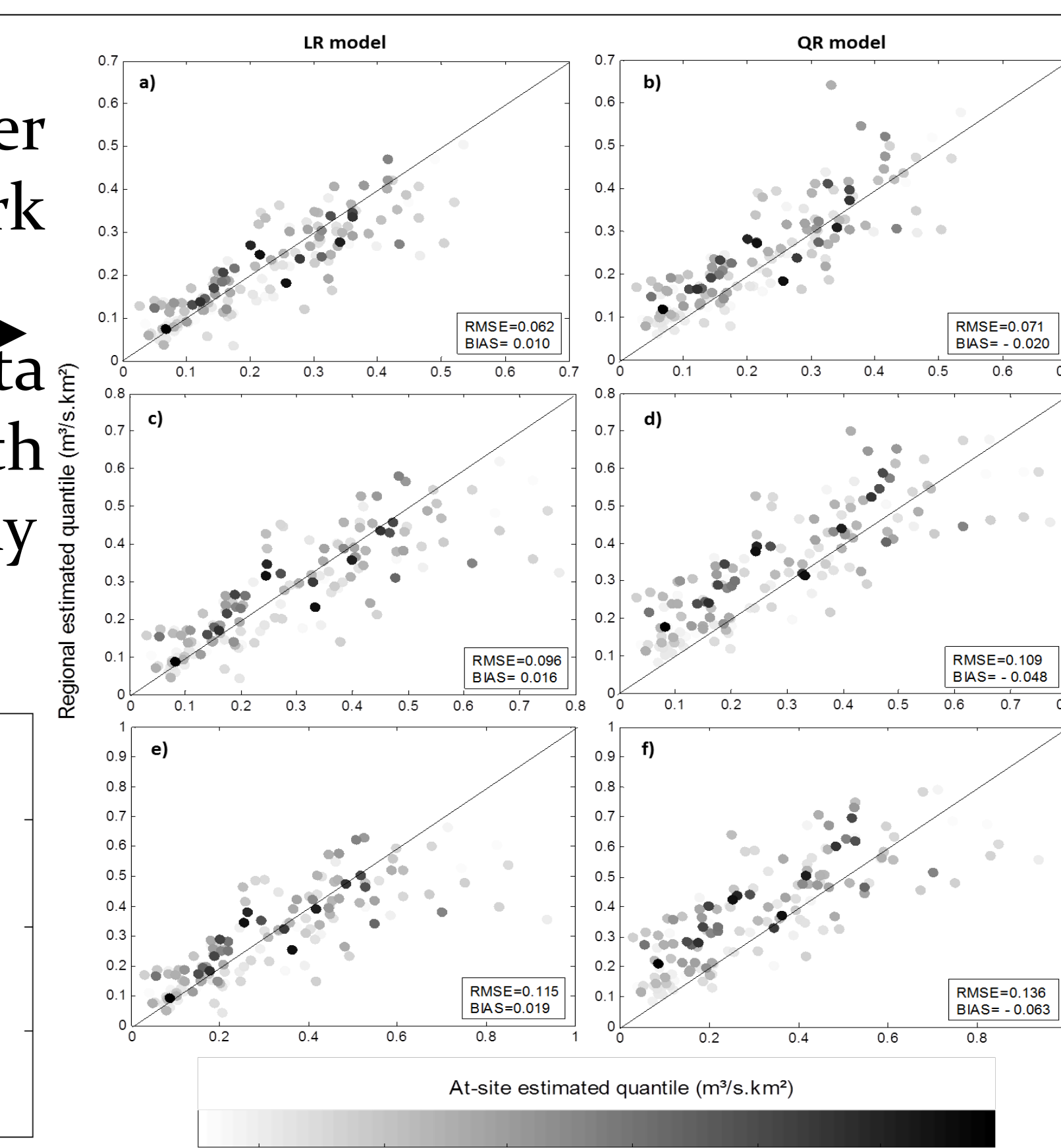
## Results

### Modelling results of LR and QR approaches in terms of BIAS and RMSE

- Both models are calibrated and evaluated over the entire data set. Points plotted in deep dark designate sites with long records.
- The RMSE and BIAS are insensitive to the data series record lengths at each site, i.e. both short and long records are weighted identically

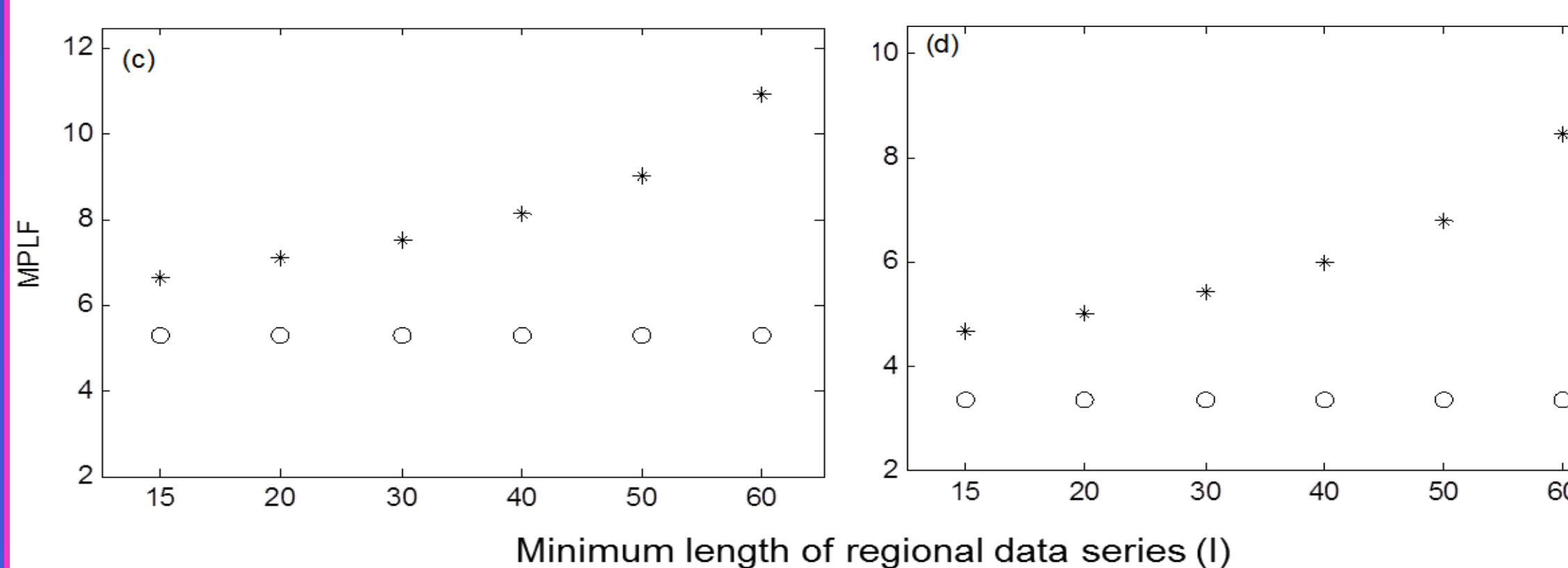


RMSE of the regional estimators of  $Q_{S50}$  (a) and  $Q_{S100}$  (b) according to the length of regional data series. Both models are calibrated using sites with record length exceeding  $l$  years. Validation is done using the whole data set.



Scatter plots of at-site and regional estimated quantiles using the LR model (first column) and the QR model (the second column) for quantiles  $Q_{S10}$ ,  $Q_{S50}$  and  $Q_{S100}$

### Modelling results of LR and QR approaches in terms of BIAS and RMSE



MPLF of the regional estimators of  $Q_{S50}$  (c) and  $Q_{S100}$  (d) according to the length of regional data series. QR was calibrated using the whole data set; Validation of both models is done using the whole data set.

- The QR model shows a better performance than the classical model
- For higher record lengths (i.e. fewer sites for the calibration step) the LR performance decreases.

MPLF values associated to QR and LR approaches

	$Q_{S10}$		$Q_{S50}$		$Q_{S100}$	
	LR	QR	LR	QR	LR	QR
MPLF (m <sup>3</sup> /s.km <sup>2</sup> )	16.07	15.43	6.62	5.30	4.65	3.43

## Conclusions

Consider observed data directly in the RFA instead of estimated at-site quantiles using the QR model  
Evaluate the estimation performance of the two regional models (LR and QR) through an objective criterion.  
The proposed approach is a promising method for the estimation and evaluation of flood quantiles at-sites with short to medium length records