

Catchment Characterization based on Runoff Copulas

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Outline

1. Introduction
2. Overview of the method
3. Application
4. Conclusions and outlook

1. Introduction

Main objective:

Estimate time series characteristics using a set of catchment descriptors, **specially** where there is no discharge data (PUB)

Methods: Unsupervised/supervised clustering

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- ANN, k-NN, fuzzy-rules, spectral signatures...
- Generalized k-Nearest Neighbors + copulas

2. Traditional Catchment Characterization Procedure

- **Data:**

$$\mathcal{D} = \{(\mathbf{x}_i, y_i) \mid i = 1, \dots, n\}$$

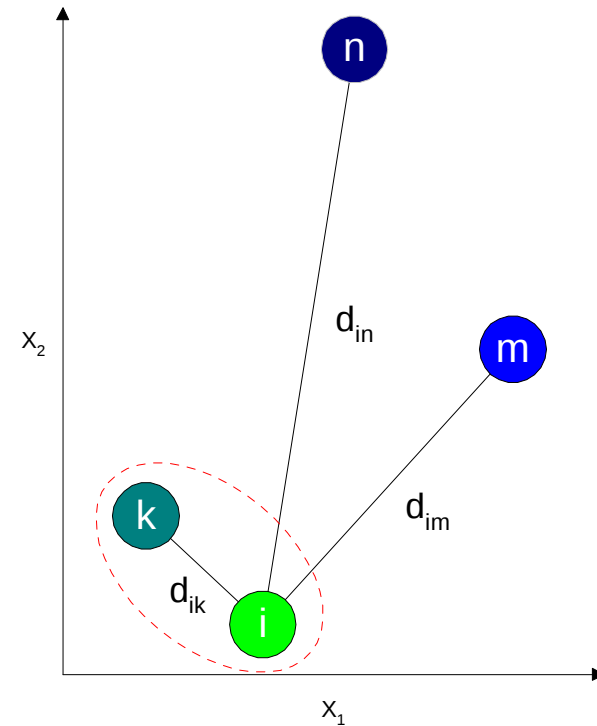
- Outputs: $y \rightarrow$ Highly dynamic
- Inputs: $\mathbf{x} \rightarrow$ Static or slightly dynamic

- **Similarity $\Leftrightarrow$ Metric:**

Selected *a priori*, e.g. Euclidian distance

- **Results:**

- Unsupervised approaches highly uncertain
- Characterization is not unique
~ runoff characteristic(s) y e.g. $\bar{q}$, q_5
~ metric



What is a Copula?

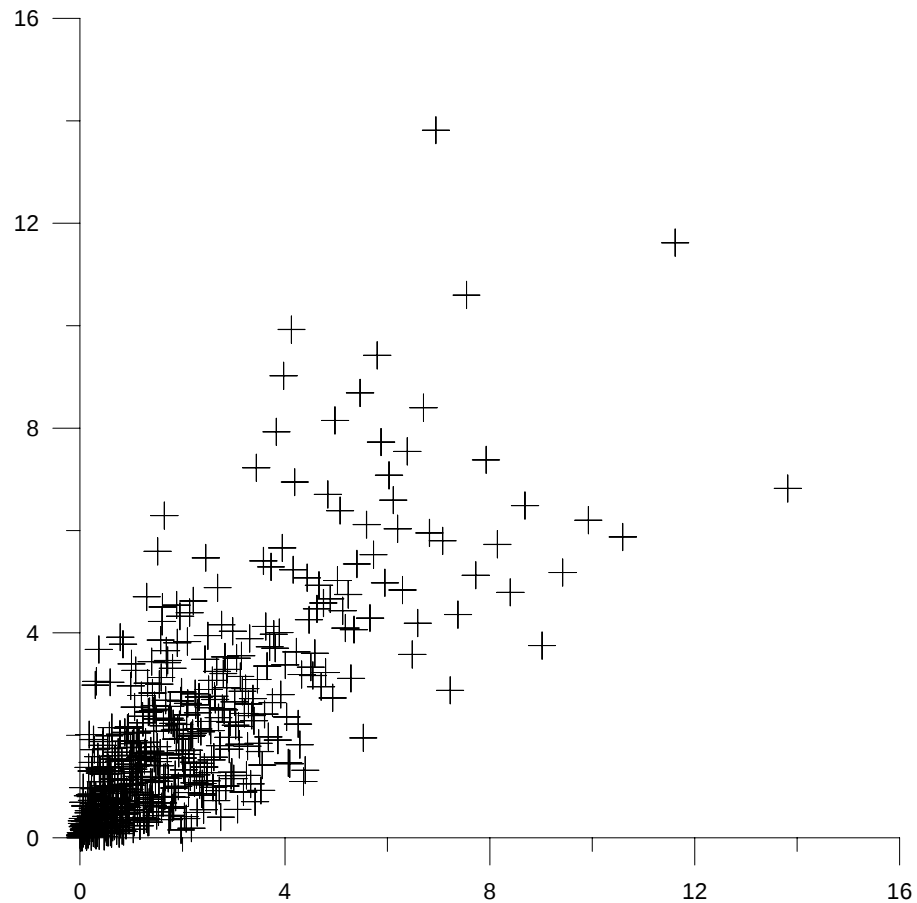
“In statistics, a **copula** is a multivariate distribution function on the unit hypercube with **uniform** marginals.”

Bárdossy, 2006, WRR

⇒ “Describes the dependence structure between random variables without information on the marginals.”

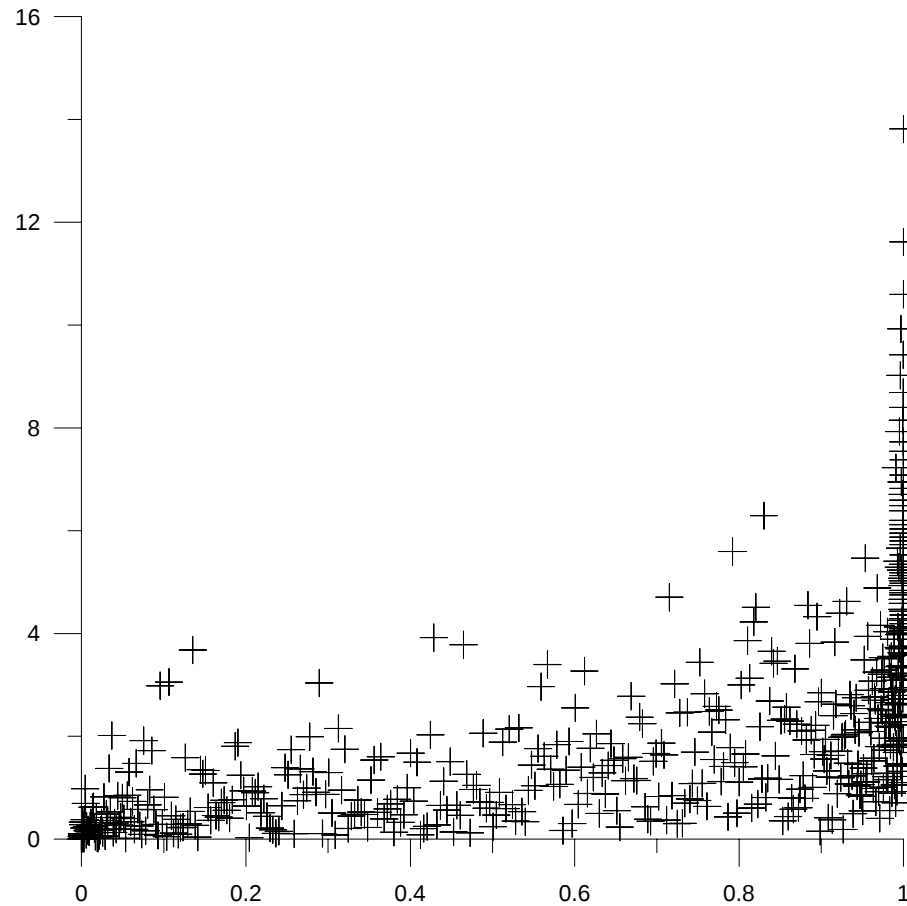
$$F(x_1, \dots, x_n) = C[F_1(x_1), \dots, F_n(x_n)]$$

Effect of the Marginal Distributions



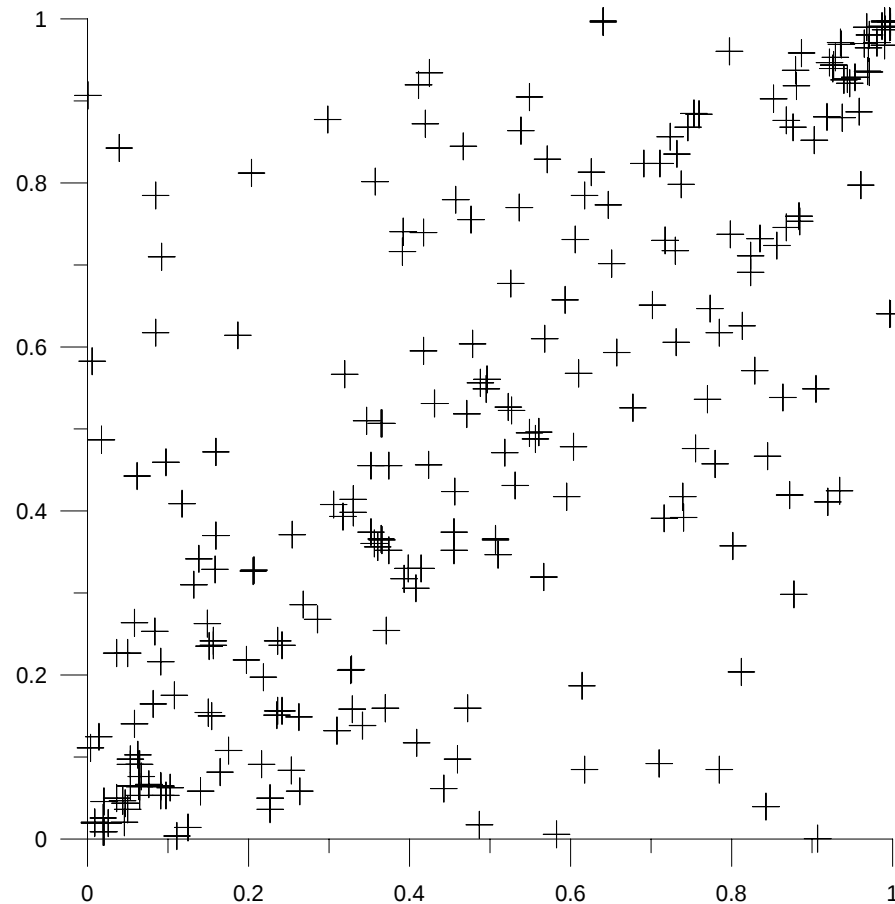
x_1 vs. x_2 , marginals: F, G

Effect of the Marginal Distributions



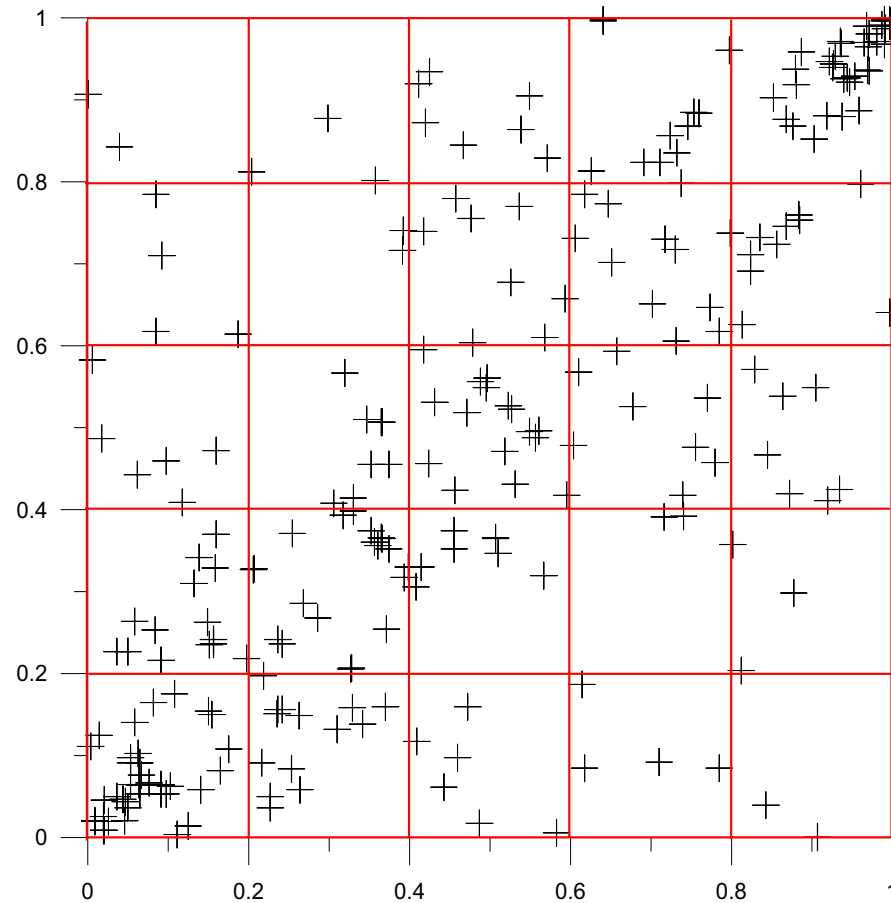
x_1 vs. x_2 , marginals: H, G

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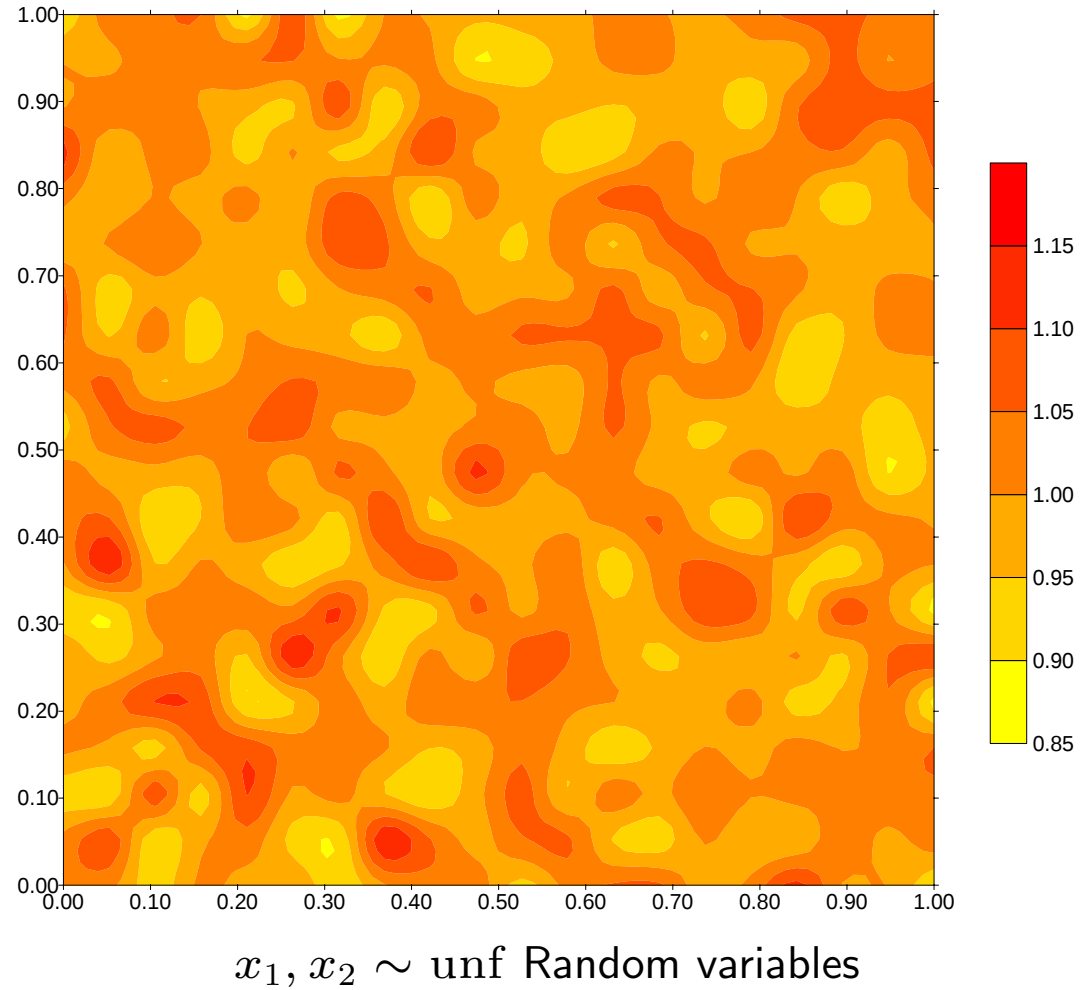
Empirical copula of x_1 vs. x_2

Effect of the Marginal Distributions

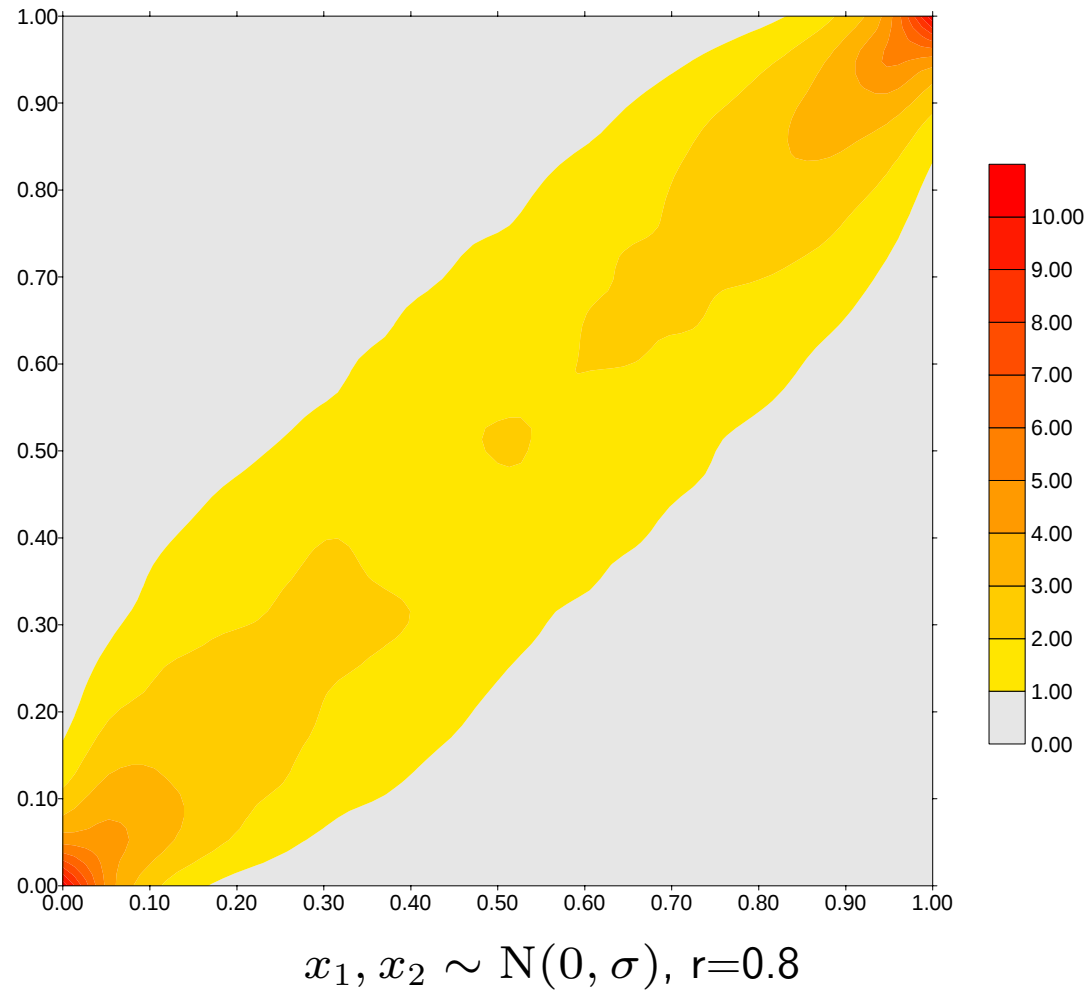


Empirical copula of x_1 vs. x_2

Examples of Copula Density



Examples of Copula Density



Empirical Runoff Copula

Given: $q_i^t, q_j^t \equiv$ daily time series (1908-2000)

$$\begin{aligned} C(v_i, v_j) &= P\left[F_i(q_i) < v_i; F_j(q_j) < v_j\right] \\ &= C\left(F_i(q_i), F_j(q_j)\right) \end{aligned}$$

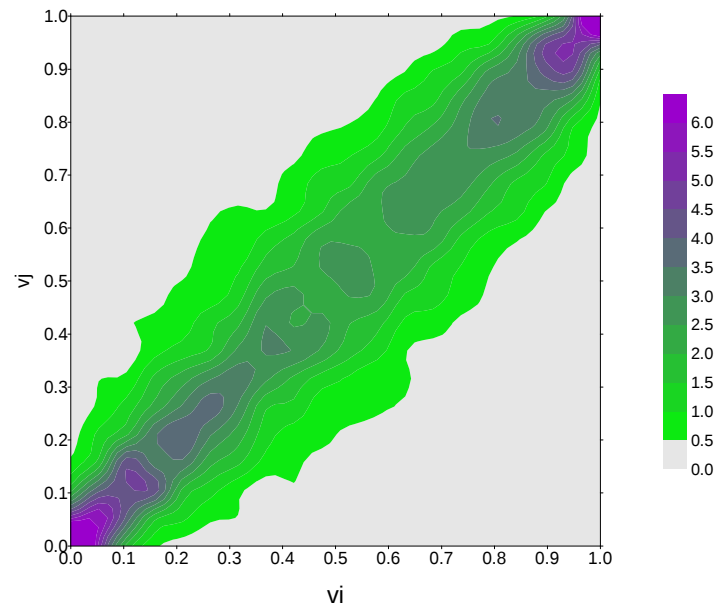
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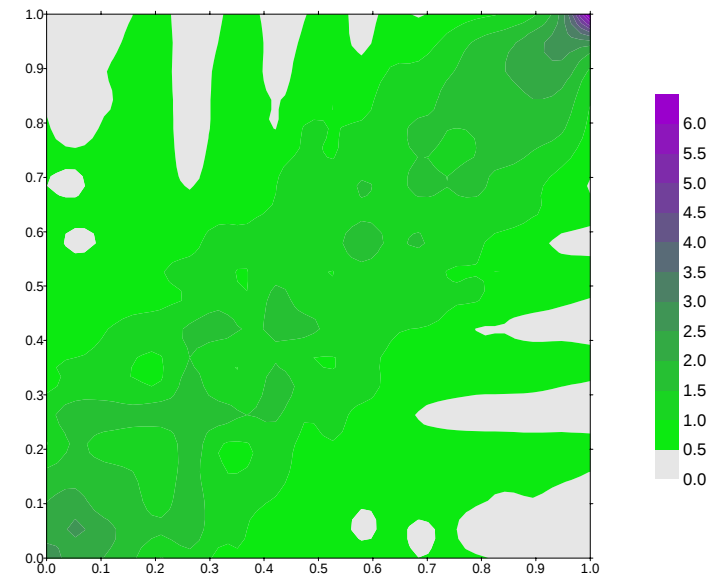
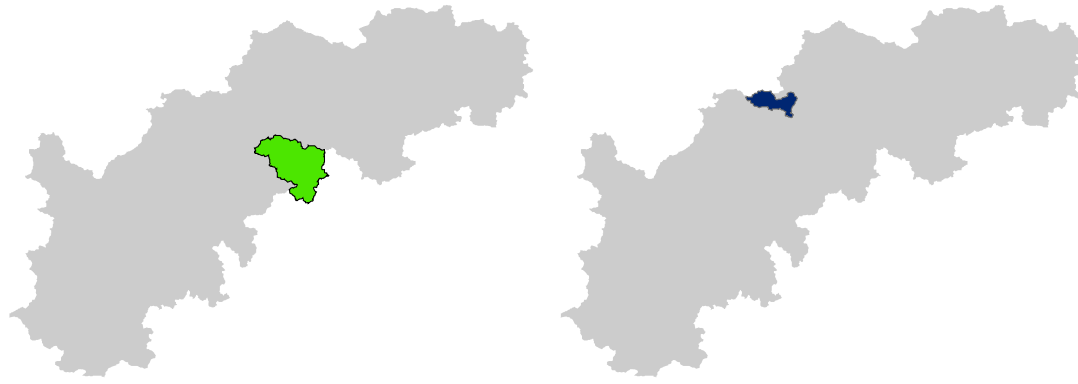
$$C(v_i, v_j) = P[F_i(q_i) < v_i; F_j(q_j) < v_j]$$

$$= C(F_i(q_i), F_j(q_j))$$

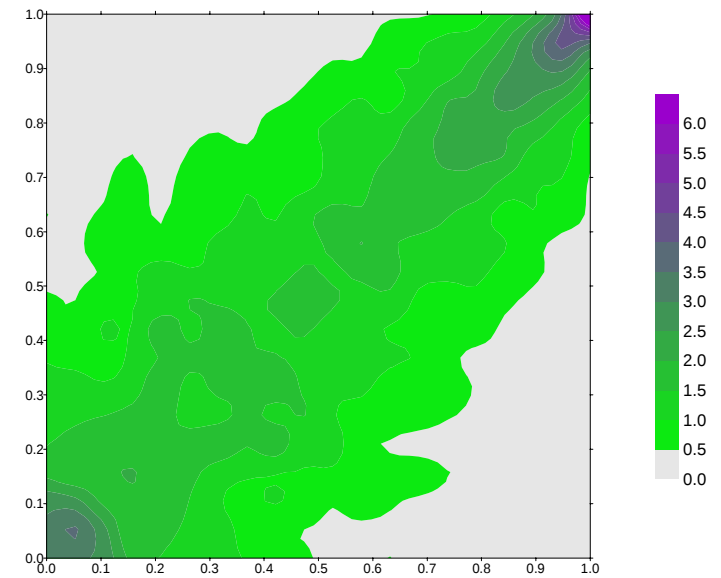
$$c(v_i, v_j) = \frac{\partial^2 C(v_i, v_j)}{\partial v_i \partial v_j}$$



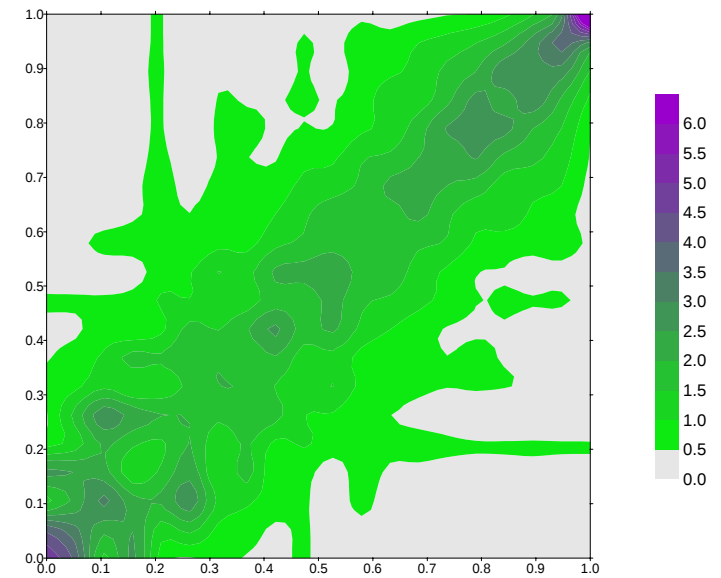
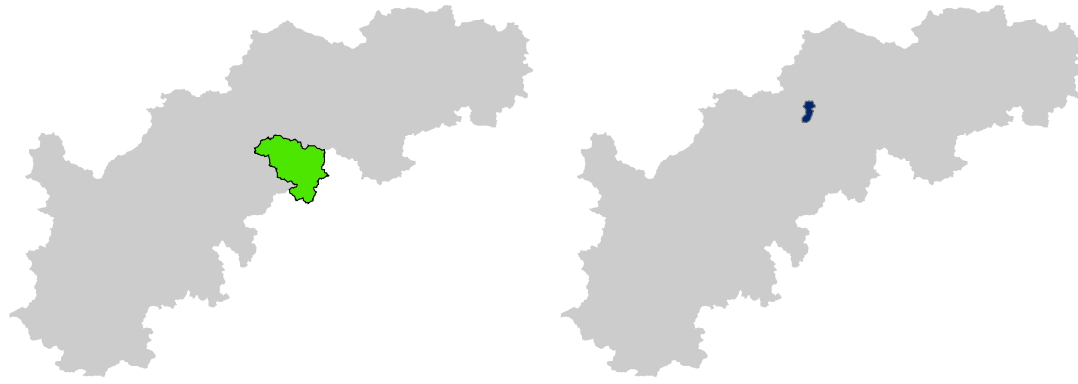
Distance Based on Runoff Copulas



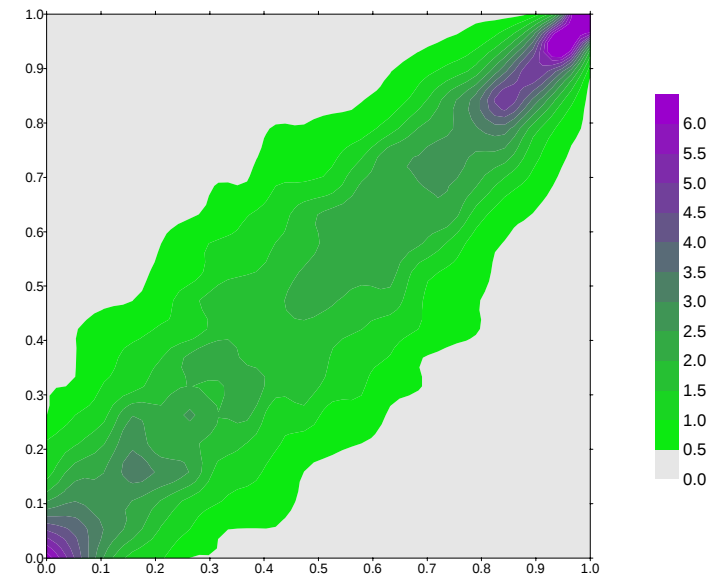
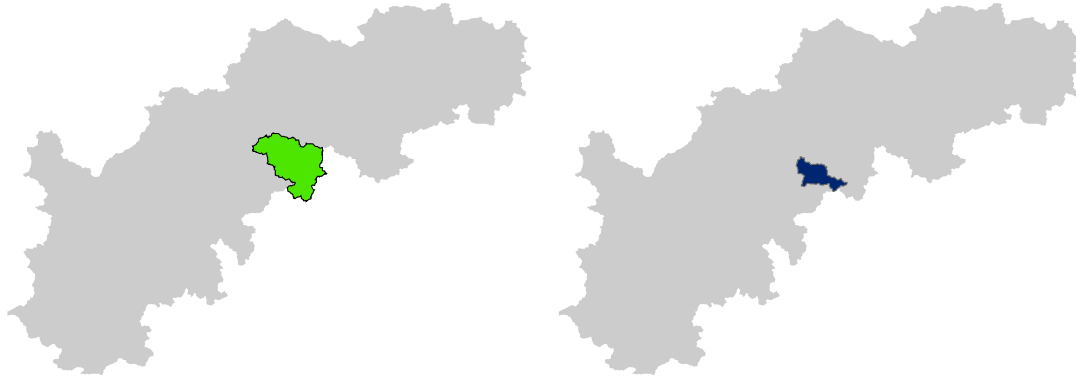
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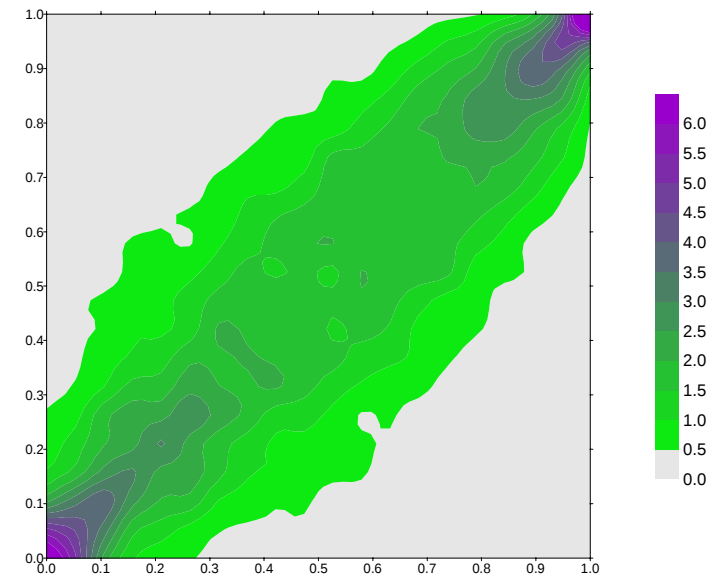
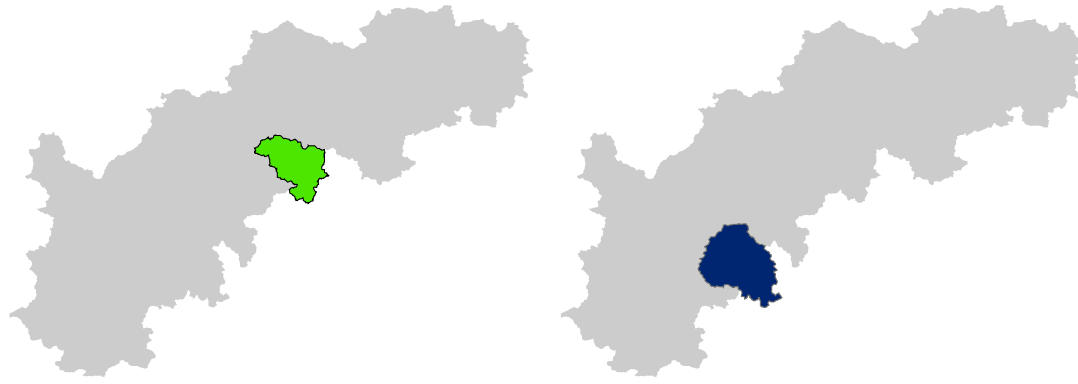
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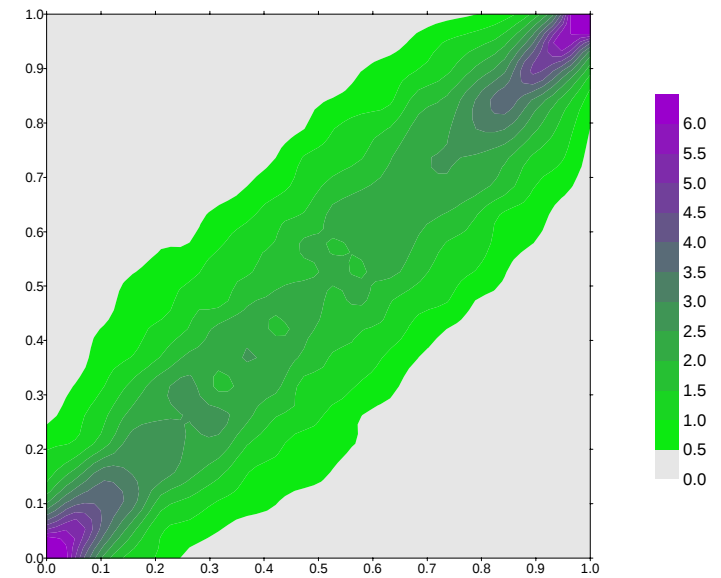
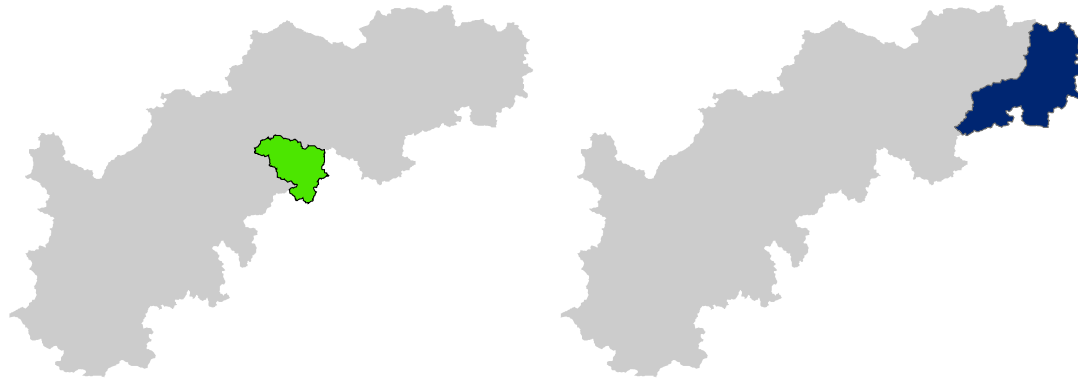
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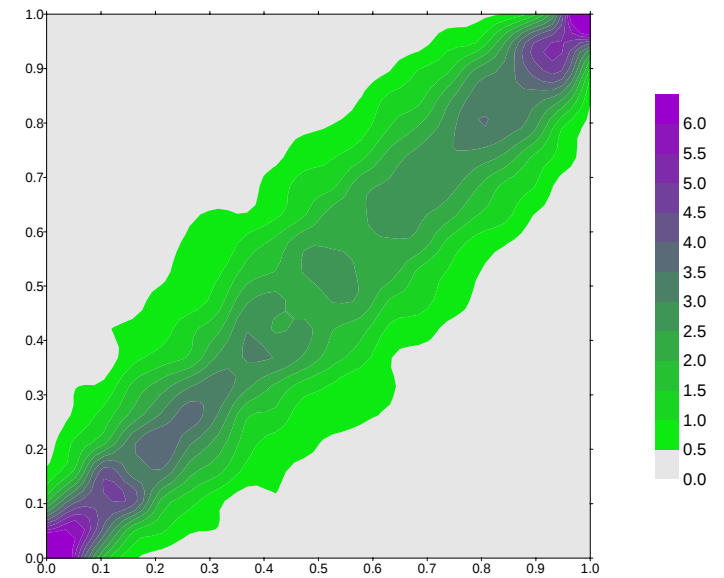
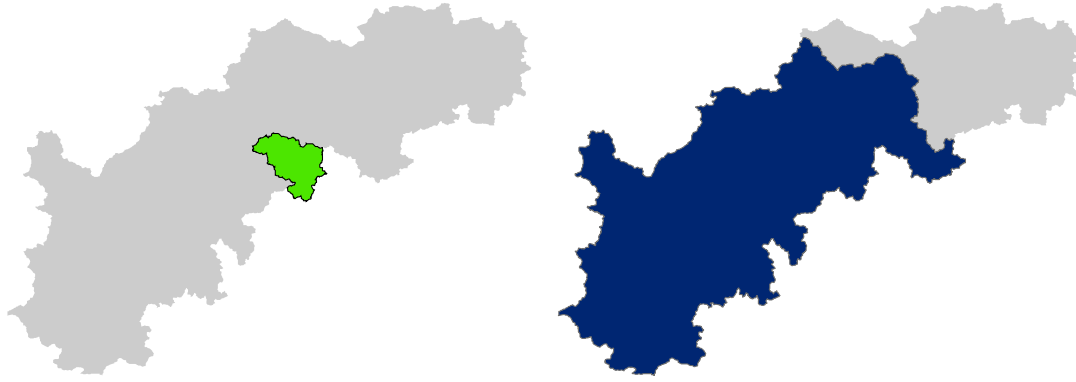
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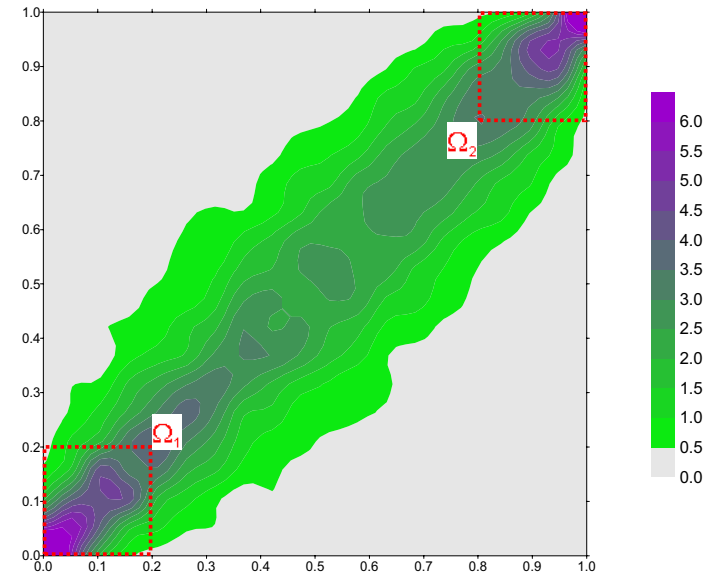
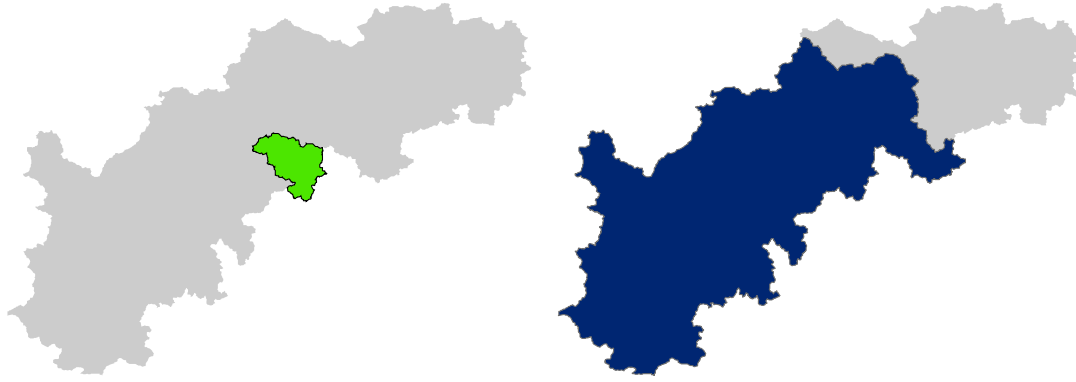
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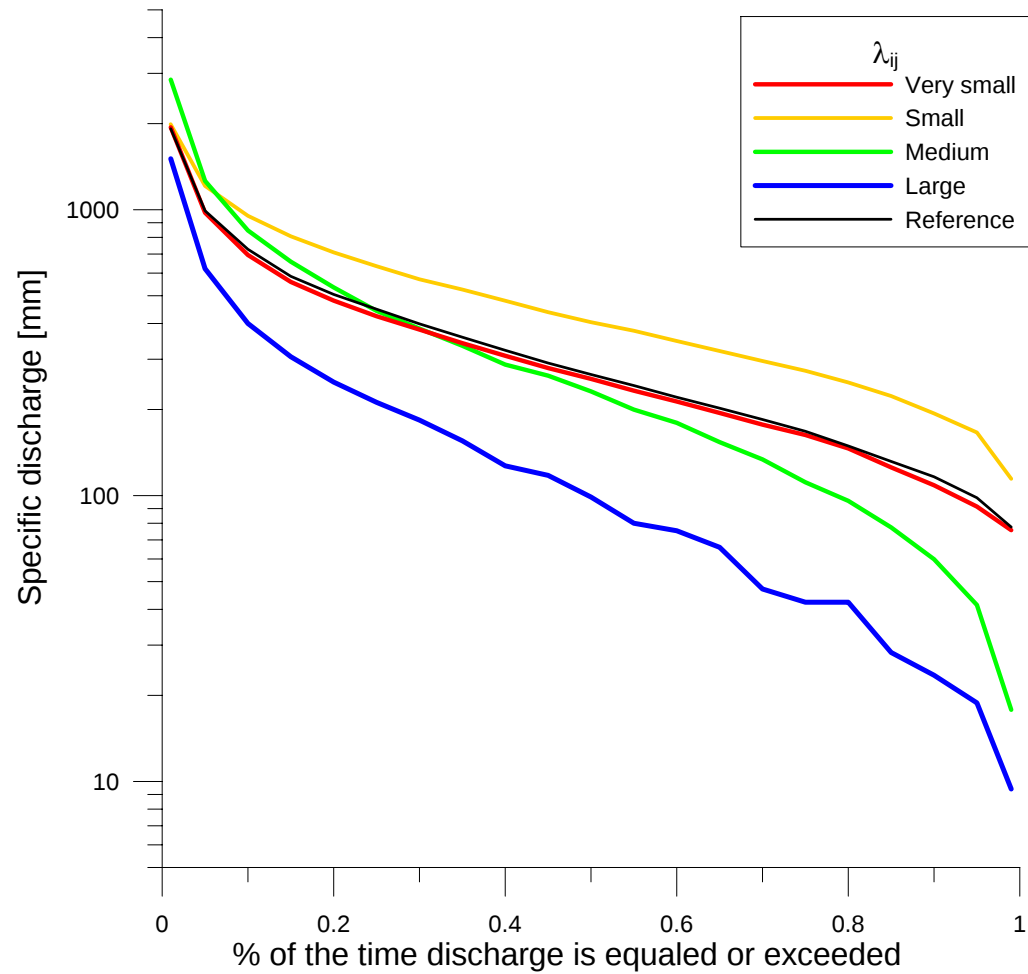


$$L_{ij} = \int \int_{\Omega_1} c(v_i, v_j) d\Omega$$

$$U_{ij} = \int \int_{\Omega_2} c(v_i, v_j) d\Omega$$

$$\lambda_{ij} = \frac{|U_{ij} - L_{ij}|}{U_{ij} + L_{ij}} + (p - L_{ij})$$

Distance λ and the FD Curves



Proposed Characterization Method

Training $\longrightarrow$ $\mathcal{T} = \{\mathbf{x}_i, [\lambda_{ij}], y_i \quad \forall i, j \in n\}$

Embedding $\longrightarrow$ $\mathbf{u} = B[\mathbf{x}]$

Condition $\longrightarrow$ Small $d(\mathbf{u}_i, \mathbf{u}_j) \rightarrow$ Small λ_{ij}

$$d_{ij}^2 = (\mathbf{u}_i - \mathbf{u}_j) \mathbf{g} (\mathbf{u}_i - \mathbf{u}_j)^T$$

Validation $\longrightarrow$ $\mathcal{V} = \{(\mathbf{x}, y)\}$

Prediction $\longrightarrow$
$$y = \frac{1}{N} \sum_{d_B(\mathbf{u}, \mathbf{u}_i) < D(N)} y_i$$

Defining the Metric in the Predictor's Space

**Euclidean Metric
(Mahalanobis)**

$$\mathbf{g} = \mathbf{I}_k = \text{diag}(1, 1, \dots, 1)$$

Riemannian Metric

$$\mathbf{g} = [g_{ij}]$$

e.g.

$[g_{ij}]$ is positive definite

$$g_{ij} = 1 + \alpha_{i,j} u_i u_j \quad \forall i = j$$

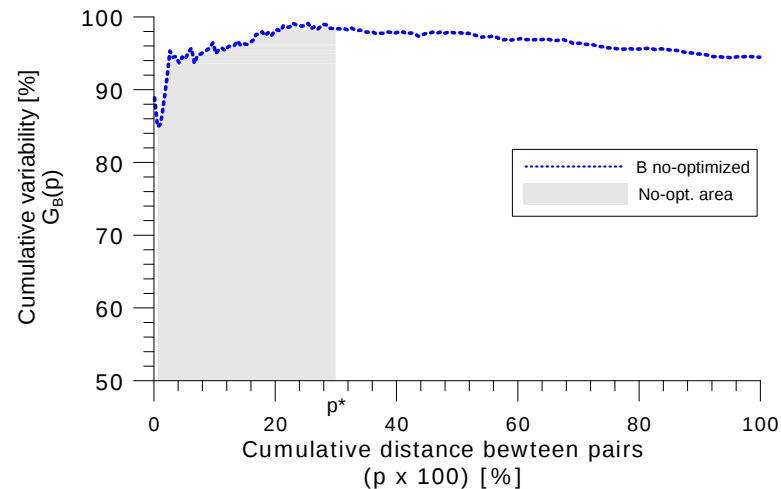
$$g_{ij} = \alpha_{i,j} u_i u_j \quad \forall i \neq j$$

Finding an Appropriate Embedding Space

Define a variance function:

Bárdossy, Pegram & Samaniego, 2005, WRR.

$$G_B(p) = \frac{1}{\mathcal{N}(D_B(p))} \sum_{d_B(i,j) < D_B(p)} (\lambda_{ij})^2$$

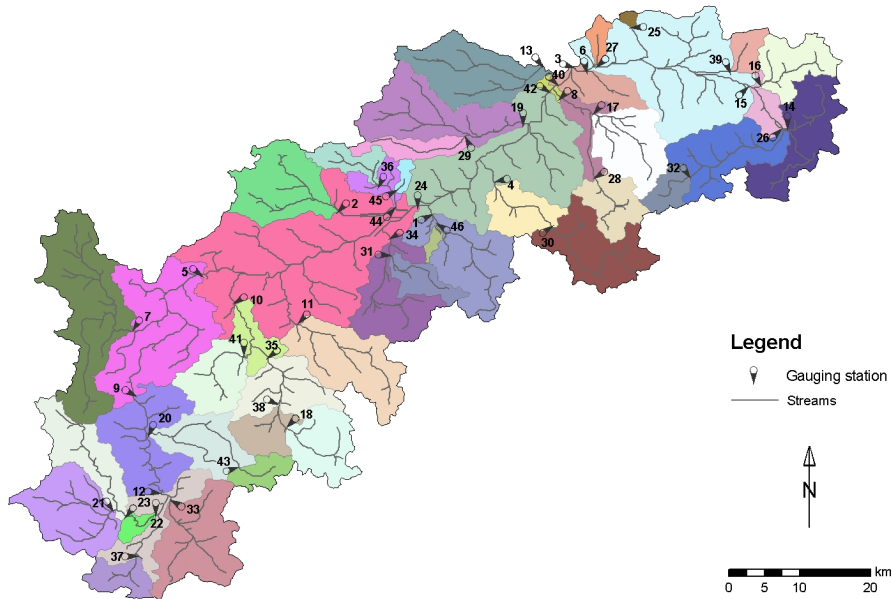


Find a transformation $B[\cdot]$ (e.g. $\mathbf{u} = \mathbf{B}\mathbf{x}$) and a metric g so that

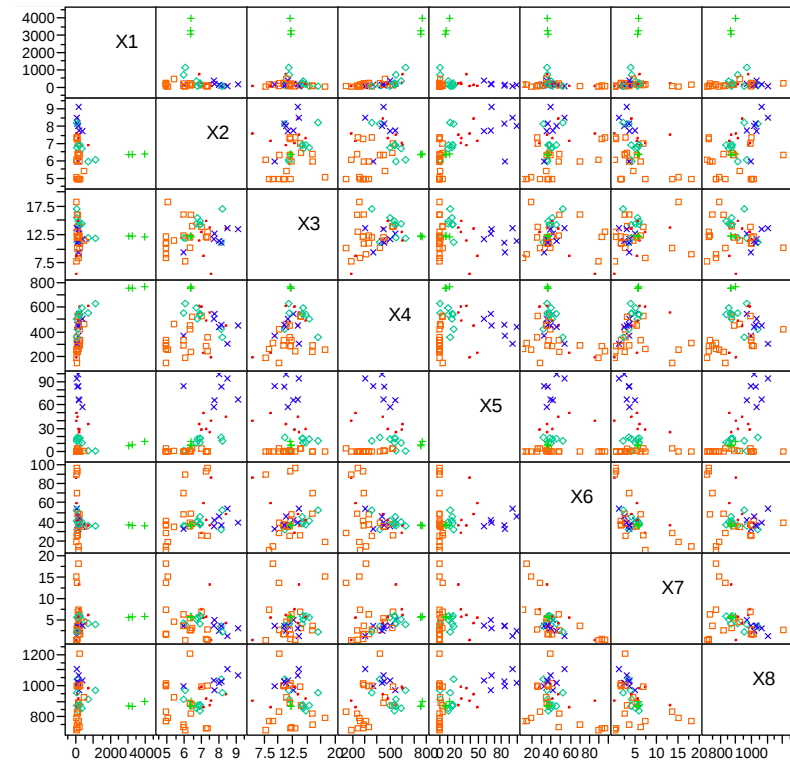
$$\int_0^{p^*} G_B(p) dp \rightarrow \min$$

3. Application

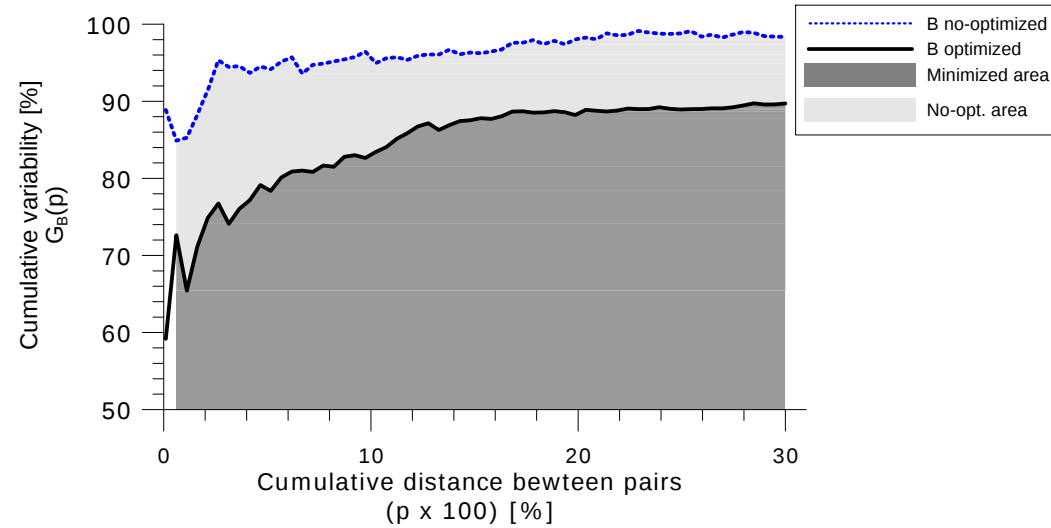
Study Area



- x_1 area
- x_2 trimmed mean slope $P_{15} - P_{85}$
- x_3 north facing slopes
- x_4 $h_{max} - h_{min}$ (elevation)
- x_5 percentage of karstic formation
- x_6 mean share of forest
- x_7 mean share of impervious areas
- x_8 30y-mean annual precipitation

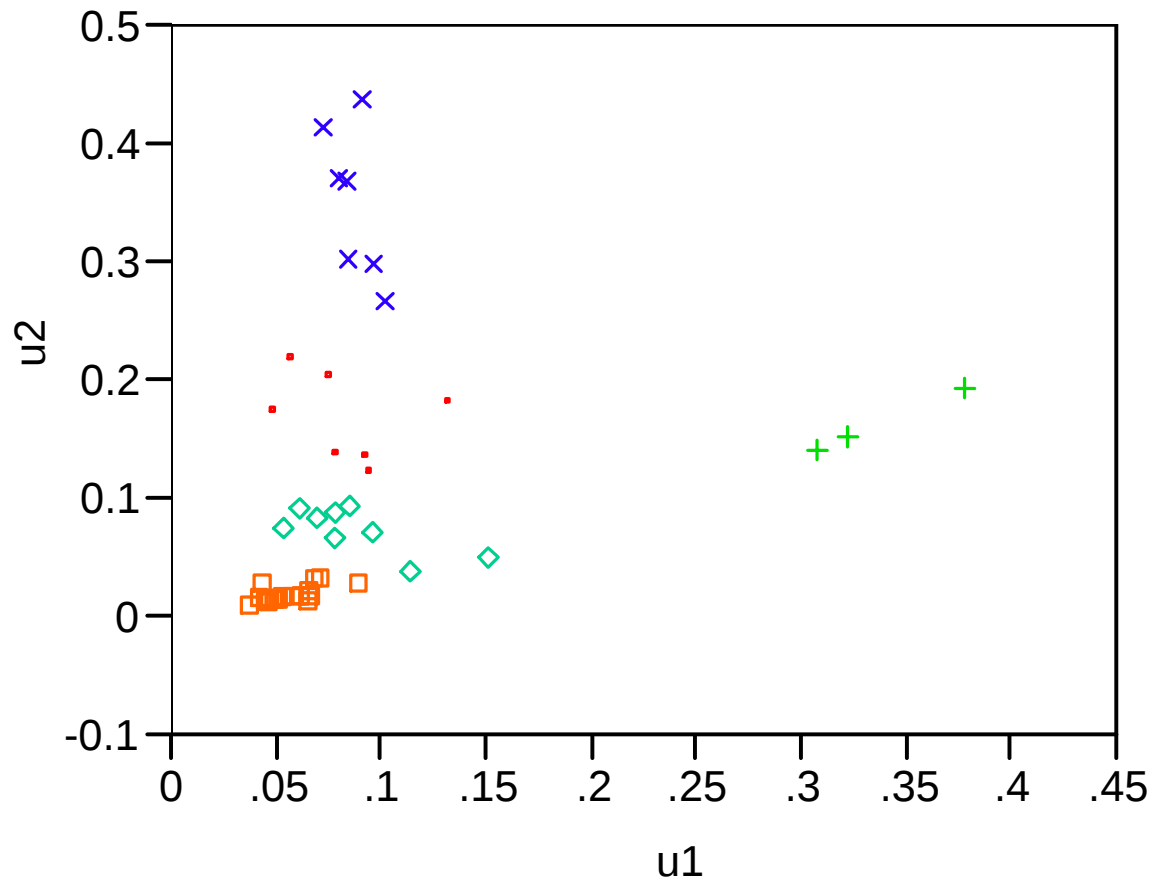


Results



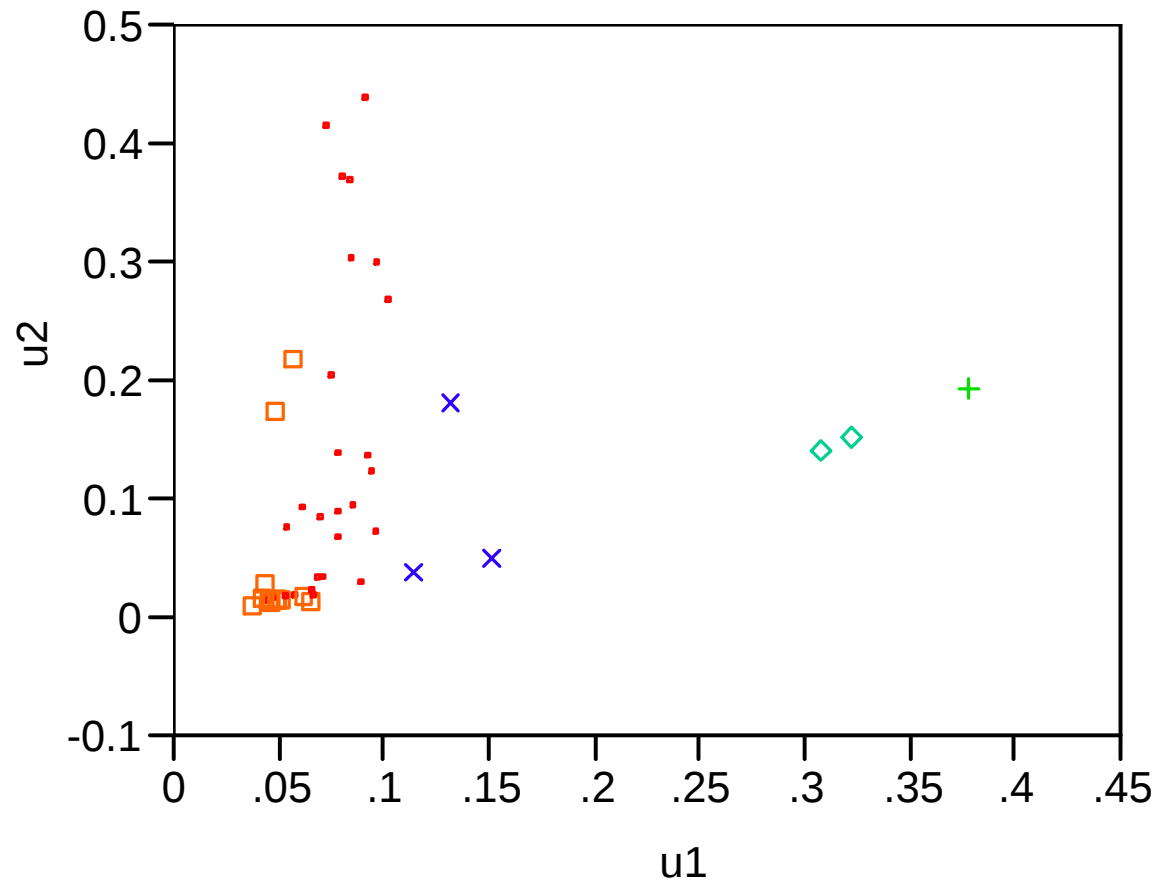
$$\begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = \begin{pmatrix} 0.29 & 0.00 & 0.00 & 0.07 & 0.03 & 0.02 & 0.03 & 0.01 \\ 0.13 & 0.01 & 0.01 & 0.00 & 0.42 & 0.00 & 0.00 & 0.00 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{pmatrix}$$

Basin Characterization



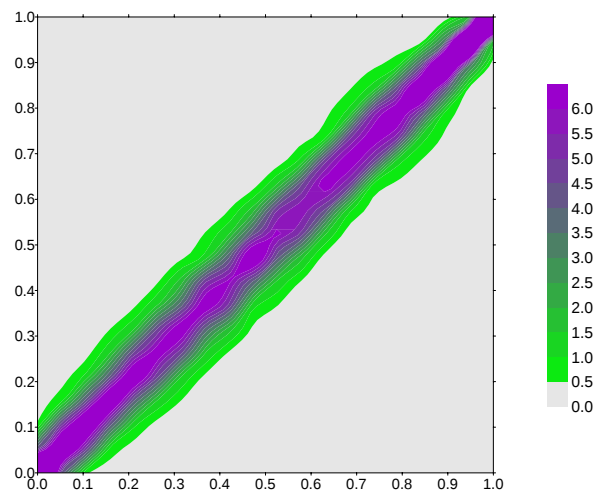
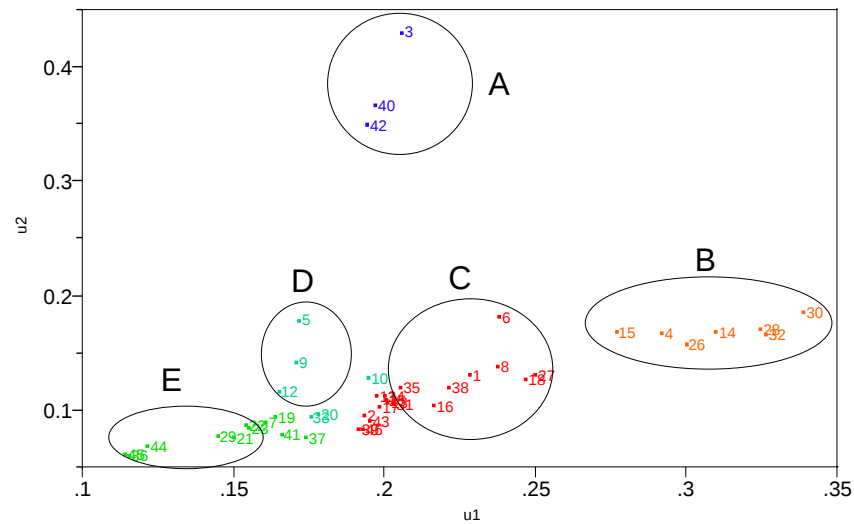
Based on distances in the embedded space $\mathbf{u}$

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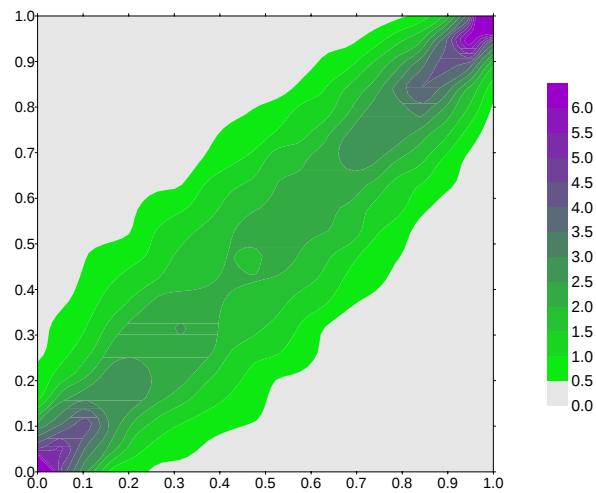
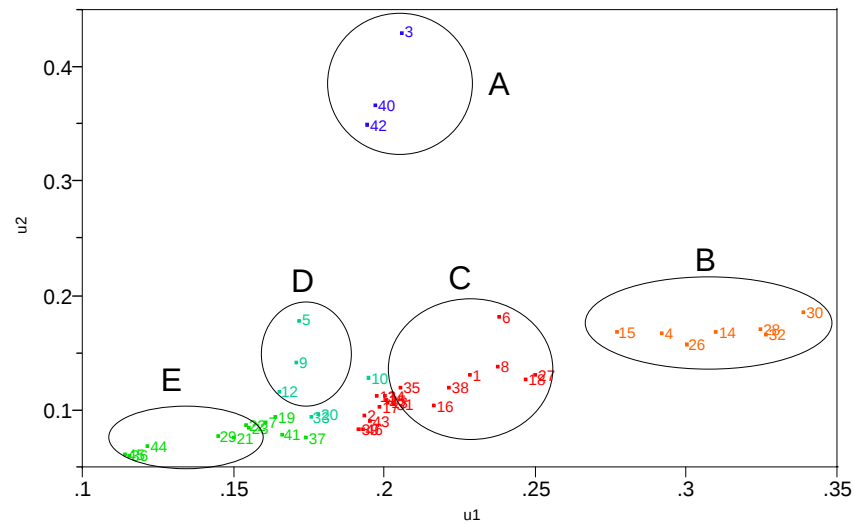
Based on distances in the input space x

Typical Copulas within the Clusters



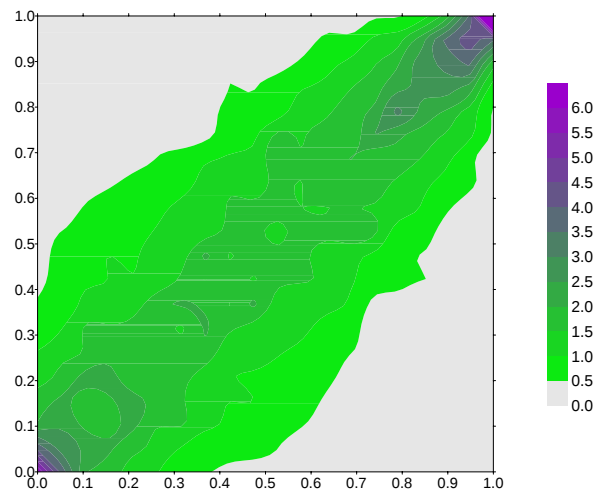
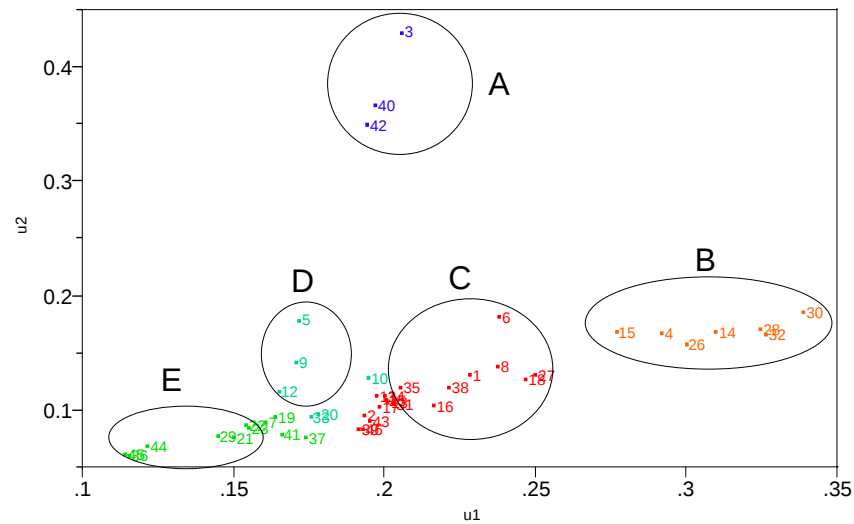
Cluster A

Typical Copulas within the Clusters



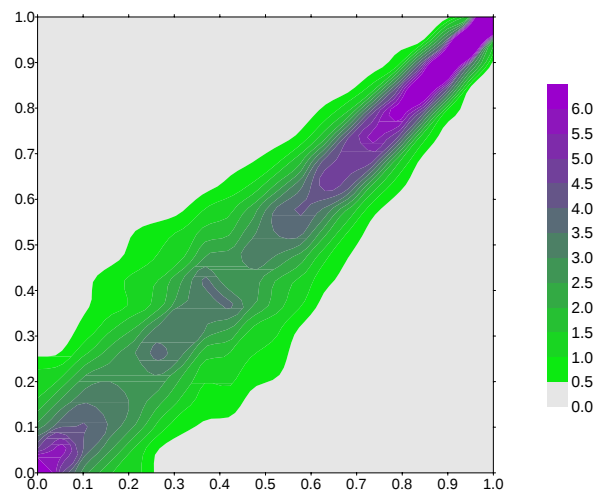
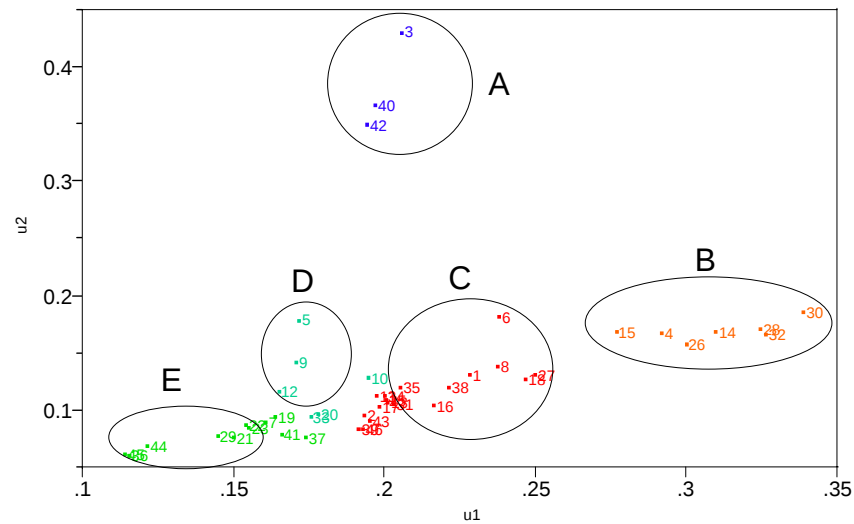
Cluster B

Typical Copulas within the Clusters



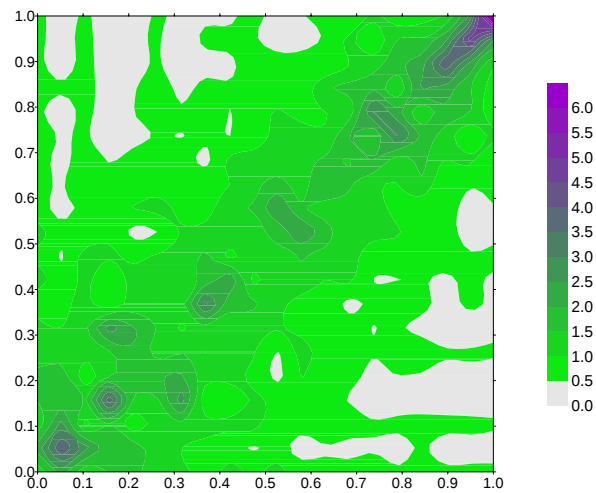
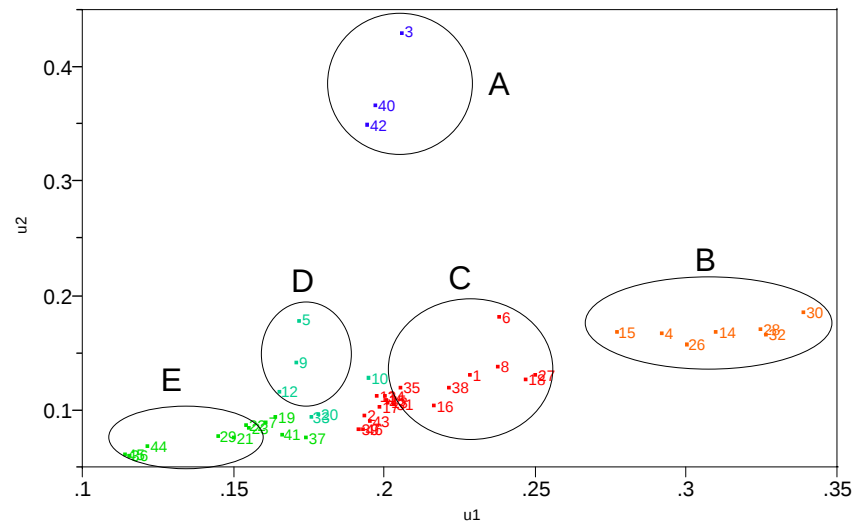
Cluster C

Typical Copulas within the Clusters



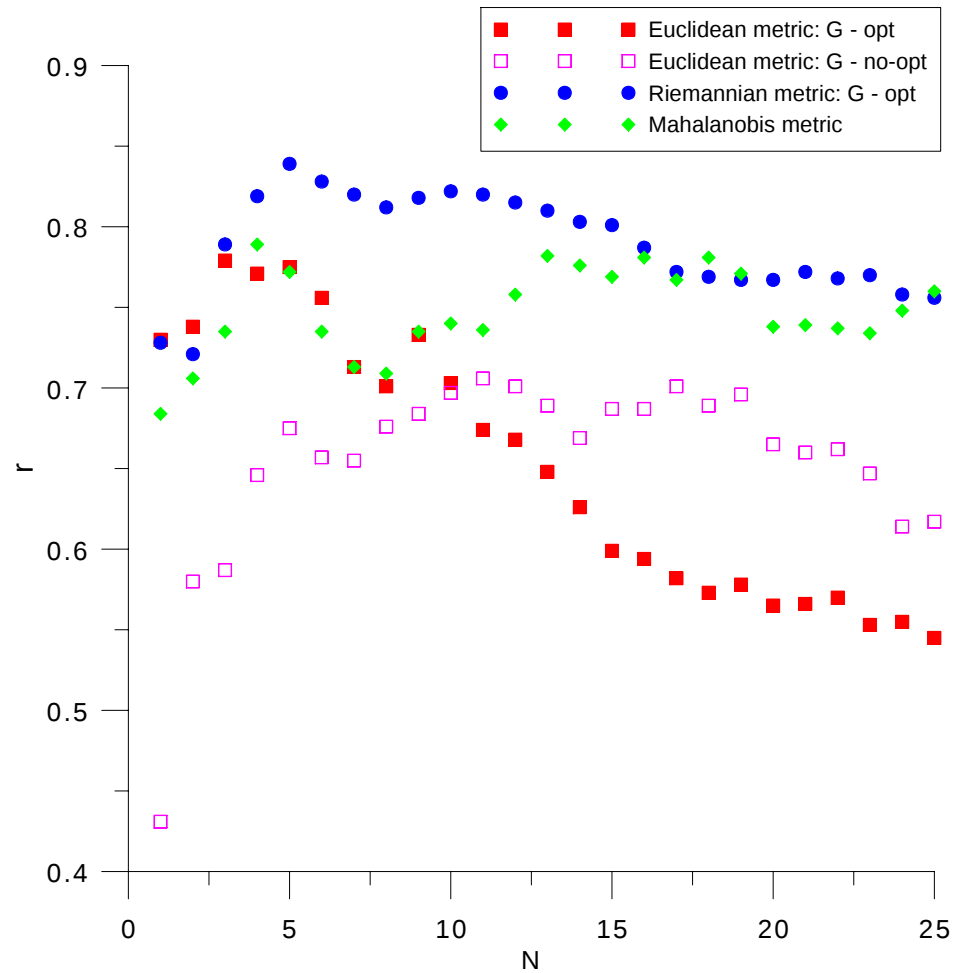
Cluster D

Typical Copulas within the Clusters



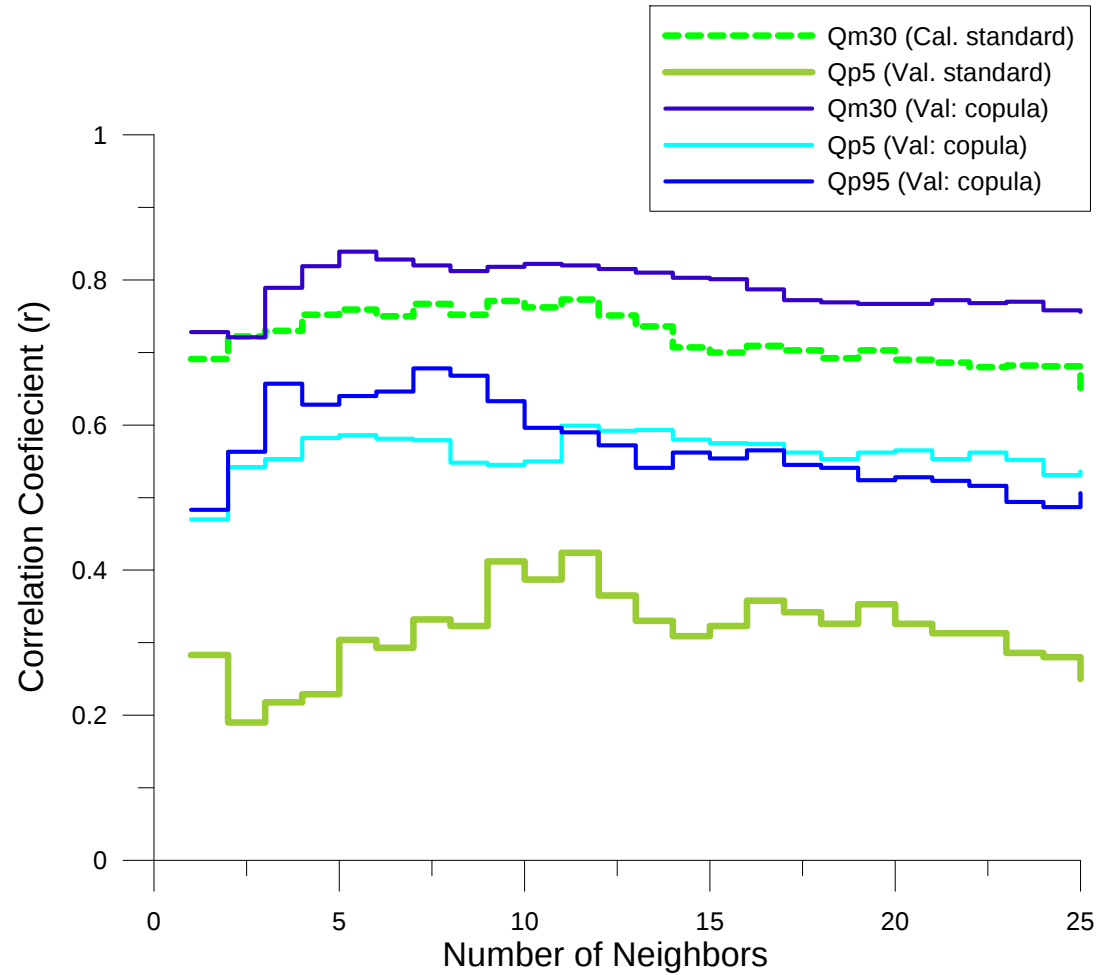
Cluster E

Validation



Performance of different metrics

Validation



Standard vs. copula based

4. Conclusions and Outlook

- The embedding space and the adaptive metric performed better than *a priori* selected standard metrics.

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- The distance based on density copulas lead to robust characterizations.
- Validation with several runoff characteristics (y) gives $r > 0.65$.
- Additional similarity (or dissimilarity) measures are still to be investigated.
- Expand the data set to include a number of basins with different hydrological regimes.

Thank you

Appendix