

## General comments

The manuscript introduces the Angles method (based on Euclidean geometry of the so-called “subject space”) for visualizing the dependence structure of compound flooding drivers. Then it is evaluated the utility of the methodology for risk communication through a survey with diverse group of end-users, including academic and non-academic respondents.

**Answer:** We sincerely appreciate your time and constructive feedback on our manuscript. We have carefully addressed your comments and made the necessary updates to the manuscript. We hope the revisions align with your suggestions and strengthen the clarity and impact of our work. Thank you for your valuable input.

**C#1)** The Authors use a geometrical interpretation of Pearson’s correlation coefficient (Eq.s 4-9). This issue is interesting and promising.

However, the Pearson’s correlation coefficient has some weaknesses: 1) problems of existence [see e.g., Salvadori et al. 2007 and De Michele et al. 2005]; 2) represent the linear association between the variables (as highlighted also by the Authors); 3) It is not invariant under monotonous transformation (only linear ones), issue of great importance for the application of Sklar’s theorem and thus copulas applications (see Salvadori et al. 2007). In this respect, why not using the Spearman correlation coefficient? According to the connection between the Pearson’s correlation coefficient and the Spearman’s one, you can write easily Eq.s 3-9 in terms of the pseudo-observations / transformed variables  $F(Q)$  and  $F(S)$ . I suggest to develop this case in substitution (better) or alternative.

**Answer:** Thank you for this insightful comment about the limitations of Pearson's correlation and the suggestion to use Spearman's correlation coefficient. We agree that Pearson's correlation has several important limitations as you've noted, particularly regarding problems of existence, and its restriction to linear associations and lack of invariance under monotonic transformations. To address these limitations, we have made two major updates to the manuscript:

1) At the end of Section 2, we now include a paragraph acknowledging these limitations and pointing readers to an alternative geometric interpretation using Spearman's rank correlation, which addresses many of these concerns:

*“While we present the geometric interpretation using Pearson's correlation coefficient in this section, it is important to acknowledge its limitations, including problems of existence in certain cases, restriction to linear associations between variables, and lack of invariance under monotonic transformations (Salvadori et al., 2007; De Michele et al., 2005; Serinaldi et al., 2022). To address these limitations, this approach can be extended to Spearman's rank correlation coefficient, which offers advantages in handling non-linear relationships, maintains invariance under monotonic transformations, and provides more robust estimations when dealing with outliers or non-normal distributions. The complete derivation of the geometric interpretation using Spearman's correlation is presented in Appendix A.”*

2) We have added Appendix A, which provides a complete derivation of the geometric interpretation using Spearman's rank correlation coefficient.

### ***“Appendix A: Geometric Interpretation Using Spearman's Rank Correlation***

*The geometric interpretation presented in Section 2 can be extended to Spearman's rank correlation coefficient ( $\rho$ ), which offers several advantages over Pearson's correlation ( $r$ ), including better handling of non-linear relationships and invariance under monotonic transformations. Here we present the complete derivation:*

*Instead of working with the original variables directly, we first transform the data into ranks and then into pseudo-observations:*

$$q^S = F_Q(Q) = \frac{\text{rank}(Q)}{N+1}, s^S = F_S(S) = \frac{\text{rank}(S)}{N+1} \quad (A1)$$

*where  $q^S$  and  $s^S$  are the pseudo-observations representing the probabilistic ranks of discharge and surge respectively,  $F_Q$  and  $F_S$  are the empirical cumulative distribution functions,  $\text{rank}(Q)$  and  $\text{rank}(S)$  are the ranks of observations, and  $N$  is the sample size.*

*Similar to the Pearson-based approach, we can represent these transformed variables as vectors in the subject space. The length of these vectors can be calculated as:*

$$|\overline{q^S}| = \sqrt{(q_1^S)^2 + (q_2^S)^2 + (q_3^S)^2 + \dots + (q_N^S)^2} \quad (A2)$$

*with the squared length being:*

$$|\overline{q^S}|^2 = \sum_{i=1}^N (q_i^S)^2 \quad (A3)$$

*The standard deviation of the transformed variables is given by:*

$$\sigma_{q^S} = \frac{|\overline{q^S}|}{\sqrt{N-1}}, \sigma_{s^S} = \frac{|\overline{s^S}|}{\sqrt{N-1}} \quad (A4)$$

*The Spearman correlation coefficient ( $\rho$ ) can then be expressed geometrically as the cosine of the angle between the transformed vectors:*

$$\rho = \cos(\theta^S) = \frac{\sum_{i=1}^N q_i^S s_i^S}{\sqrt{\sum_{i=1}^N (q_i^S)^2 \sum_{i=1}^N (s_i^S)^2}} \quad (A5)$$

*This formulation maintains all the geometric properties discussed in Section 2, including the relationship between the angle  $\theta$  and the correlation coefficient, but offers additional robustness to non-linear relationships between the original variables  $Q$  and  $S$ . Like the Pearson-based approach, uncorrelated variables are represented by perpendicular*

vectors ( $\theta = 90^\circ$ ), while perfectly correlated variables have parallel vectors ( $\theta = 0^\circ$  or  $180^\circ$ ).

*The key advantage of this Spearman-based geometric interpretation is that it captures monotonic relationships between the variables, not just linear ones, making it particularly suitable for analyzing compound flooding drivers that may exhibit complex, non-linear dependencies. Additionally, the rank transformation makes the approach less sensitive to outliers and more appropriate for non-normally distributed data, which is often encountered in environmental extremes.”*

## **References:**

De Michele, C., Salvadori, G., Canossi, M., Petaccia, A., and Rosso, R.: Bivariate statistical approach to check adequacy of dam spillway, *Journal of Hydrologic Engineering*, 10, 50-57, 2005.

Salvadori, G., De Michele, C., Kottegoda, N. T., and Rosso, R.: *Extremes in nature: an approach using copulas*, Springer Science & Business Media 2007.

Serinaldi, F., Lombardo, F., and Kilsby, C. G.: Testing tests before testing data: an untold tale of compound events and binary dependence, *Stochastic Environmental Research and Risk Assessment*, 36, 1373-1395, 2022.

**C#2)** In the manuscript you have considered/referred to two variables (Q and S). If you have more than two variables, it could be interesting to say how to proceed, through a pairwise analysis?

**Answer:** Thank you for this important question about handling more than two variables. We have updated the text to address your comment and clearly mention that for more than two variables, the analysis proceeds through pairwise comparisons, with each pair being visualized in the subject space:

*“The subject space provides an effective approach when dealing with more than two variables, e.g., multi-driver compound flooding from discharge, surge, precipitation, and wind waves. It is inherently difficult to illustrate 4-dimensional scatterplots, and the interactions of multiple flooding drivers cannot be visually captured by such a plot. In such cases, Euclidean geometry offers a systematic solution through pairwise analysis. Each pair of flood drivers can be represented as vectors in a 2-D plane, with their angular separation revealing their dependence structure. This pairwise projection approach allows for clear visualization and interpretation of relationships between multiple flood drivers, overcoming the limitations of multi-dimensional scatterplots while maintaining geometric intuition.”*

Specific issues

**C#3)** Lines 84-87: I suggest to report also the p-value of the correlation coefficients to show the statistical significance.

**Answer:** In the revised version, we have added p-values in parenthesis:

*“... the linear Pearson’s  $r$  correlation coefficient is found to be 0.96 ( $p$ -value=0.000), while the non-linear Spearman’s  $\rho$  correlation coefficient is 0.84 ( $p$ -value=0.000).”* and

*“... with Pearson’s  $r$  and Spearman’s  $\rho$  being 0.41 ( $p$ -value=0.005) and 0.52 ( $p$ -value=0.000), ...”*

**C#4)** In eq.(9) it is missing a parenthesis “(”

**Answer:** Resolved!

**C#5)** Line 121 clarify the acronym “CCF”.

**Answer:** It refers to Coastal Compound Flooding. Title 3.1 has now been updated to “Application of the Angles method for visualizing Coastal Compound Flooding (CCF) dependencies.”

**C#6)** Lines 153-154 “From Figure 4, it is clear that the correlation coefficient of the period 1997-2022 is greater than that of 1972-1996 since  $\theta$  is smaller (thus, the cosine is greater).” I suggest also here to calculate the statistical significance of the estimates of the coefficient, also in light of the non-stationarities claim made by the authors (lines 163-164).

**Answer:** Thank you for this important point about statistical significance. We have calculated the correlation coefficients and their corresponding p-values for both periods:

- 1972-1996: Pearson's  $r = 0.21$  ( $p$ -value = 0.393)
- 1997-2022: Pearson's  $r = 0.42$  ( $p$ -value = 0.035)

These results align with our visual interpretation from Figure 4, showing a higher correlation coefficient in the more recent period (1997-2022). While the correlation in the earlier period (1972-1996) is statistically insignificant ( $p$ -value>0.05) that indicates the absence of sufficient evidence to reject the null hypothesis of "no correlation", the more recent period shows a statistically significant correlation. We have updated the manuscript text to include these statistical details:

*"From Figure 4, we observe that the correlation coefficient of the period 1997-2022 ( $r = 0.42$ ,  $p$ -value = 0.035) is higher than that of 1972-1996 ( $r = 0.21$ ,  $p$ -value = 0.393),*

