We thank the referee for investing her/his valuable time to help us improve our work with her/his accurate suggestions. We have revised our manuscript, taking into consideration all the referee's comments. The parts in red have been added to the manuscript to improve our work.

1. In Introduction, the research motivation of the spatial patterns and features of meteorological droughts is not clear enough.

We strongly extended the second to last paragraph in the introduction as follows.

Our main objective here is to uncover spatial features of meteorological droughts in Europe, highlighting underlying mechanisms and patterns which could potentially support drought's forecast in the future. We aim at distinguishing regions in Europe whose main feature lies in drought occurrence and propagation's coherence. Identifying such territories could be of a great importance to further investigate this phenomenon within those areas where its characteristics are homogeneous. Indeed, droughts display a high spatial and temporal variability, and it is thus fundamental to study their evolution accounting for these irregularities to possibly lower uncertainties. Furthermore, with our model we are able to describe the average historical patterns in droughts' evolution which could be a starting point for future climate studies to identify the spatial tracks that are followed by this climate hazard, building a forecasting scheme.

Our study is based on climate complex networks and on the concept of Event Synchronization, a nonlinear statistical similarity method useful to determine the correlations among spatial locations in terms of event co-occurrences. Using these tools we are able to identify drought regions in Europe based on the process itself and not depending on any external classifications, bringing out key aspects concerning drought dynamics at a regional scale for different rainfall accumulation periods from 1981 to 2020, while introducing new methodologies in general climate networks reconstruction from raw data. The understanding and ability of describing droughts as a complex phenomenon is still in a preliminary stage, but climate complex networks prove to be a powerful tool to reveal hidden features of this climatic process.

2. Why is Hamming distance used to calculate the difference between two subnetworks, is there any other distance (measure) can be used.

Several algorithms have been proposed in graph theory to compare the topology of two networks. Graph similarity metrics are often needed in several applications where different topologies have to be compared (see [6, 12, 13]). Graph edit distances are amongst the most used metrics, aiming at finding the cost of transforming a first graph into another with subsequent edit operations (generally nodes and edges insertions, deletions and substitutions) [7]. One of the issue of this procedure is that the cost of each different edit operation has to be set arbitrarily. A special case in GEDs is the Hamming distance, which measures the structural difference between two graphs only in terms of edges' placement. The reason why we have chosen this metric over the others is threefold: the networks we are comparing are undirected, unweighted and have the same link density. The fact that the networks are undirected and unweighted allows us to compute the Hamming distance by simply counting the times in which an edge is present in one of the graph and does not appear in the other, a procedure which is computationally very easy and which gives an enough informative result. Moreover, the compared graphs have the same link density: we do not need to account for the difference in the sparsity of the networks, which could be done with the Jaccard distance, another structural GED metric [4].

We should also mention that instead of looking at local differences through structural distances, it is possible to use spectral methods to capture the changes of a graph as a whole [8], by investigating the spectral properties of the adjacency matrix. However, we are using the Hamming procedure precisely because we want to minimize the differences in edges' placement and we have no reason to value one specific edge presence more than any other (the Hamming distance treats all edges uniformly); for different purposes, the distance measure has to be chosen to address specific aspects of a network's properties, e.g. information flow, geometrical information, nodes' centrality, etc.

The following paragraph has been added to the manuscript.

The Hamming distance is not the only possible choice to compare the topology of two networks [6, 12, 13]. The reason why we have chosen this metric over the others is threefold: the networks we are comparing are undirected, unweighted and have the same link density. For this specific case, this method gives an enough informative result, being also computationally very easy. For more complicated scenarios, one should look into other more refined Graph edit distances [7] or into spectral methods [8] to capture the changes of a graph as a whole.

3. In the study of the spatial pattern and characteristics of meteorological drought, what are the advantages of using method Synchronization analysis compared to other methods.

We choose to use Event Synchronization to assess the pairwise similarities between locations in terms of droughts' occurrences. The event-like nature of the phenomenon under study calls for a statistical measure designed to estimate correlations among time series with events defined on them. Moreover, ES is a nonlinear method, able to treat event series with not equal spacing between successive occurrences without fixing a time lag a priori. For these reasons it has become one of the most used method to study extreme events in the climate network's field [1–3, 5, 9–11]. Ultimately, we would summarize the advantages of this method as follows:

- ES is designed to treat event-like time series;
- by using ES there is no need to set a specific time lag;
- ES has both a symmetric and asymmetric formulation, eventually being able to show driver-response relationships (we have used it in both ways in our study);
- ES has been extensively used as a tool to construct climate extreme events' networks, proving to be enough efficient and informative.

We extended the explanation of ES in the manuscript as follows.

Event synchronization is a powerful nonlinear method to assess the similarity of event series with not equal spacing between successive occurrences and thus it is especially appropriate for studying extreme events [5]. The degree of synchronicity of two event series is measured based on the relative timings of events and it is obtained from the number of quasi-simultaneous occurrences. We summarize the advantages of this method as follows: (i) ES is designed to treat event-like time series; (ii) by using ES there is no need to set a specific time lag; (iii) ES has both a symmetric and asymmetric formulation, eventually being able to show driver-response relationships; (iv) ES has been extensively used as a tool to construct climate extreme events' networks, proving to be enough efficient and informative [1–3, 5, 9–11]. The detailed algorithm is described in [5] and is shortly repeated in the Appendix for the convenience of the reader.

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