Dear Editor and Reviewers,

Thank you for your detailed comments and suggestions about our manuscript entitled "Dealing with non-stationarity in sub-daily stochastic rainfall models".

To capitalize on your propositions of improvement, we suggest to thicken the validation and discussion parts of our manuscript. To this end, we consider to modify the plan of the paper as detailed hereafter. The content of the new sections is introduced together with our point-by-point responses to the comments of the reviewers.

Hoping that our responses answer your concerns, and that our propositions of improvements will fulfil your expectations,

Best regards,

Lionel Benoit, Mathieu Vrac and Gregoire Mariethoz.

General overview of the proposed changes:

Considering the comments and recommendations of the reviewers, we plan to add some material to the validation and discussion parts of our paper. The guidelines of the paper will be amended as follow:

1. Introduction
2. Overview of rainfall space-time patterns observed in radar images
3. Assessing rain statistics stationarity from radar images
    3.1. Extracting space-time information from radar images
    3.2. Classification of radar images based on rainfall space-time statistics
4. Validation and application
    4.1. Stochastic rainfall model
    4.2. Detection of rainfall non-stationarity in a controlled setting
    4.3. Impact of rainfall non-stationarity on stochastic modelling of an actual dataset
    4.4. Seasonality of rain type occurrence [new material]
    4.5. Sensitivity of the rain typing approach to the size of the calibration dataset [new material]
5. Discussion [now separated from the conclusion]
    5.1. Model dependence of rain typing [new material]
    5.2. Consequences of non-stationarity on sub-daily stochastic rainfall modelling [new material + part of the current conclusion section]
6. Conclusion

The new sections will be written and the others amended to answer the concerns of the referees as detailed hereafter. In the following RC denotes a reviewer comment and AR denotes our response to the comment.

Responses to the comments of Reviewer #2:

RC: The authors suggests that a rainfall type can alter from convective to frontal, or the other way around. I suspect whether this assumption can be verified (did you find any supporting literature?). I do not think that the similar conclusion would have been drawn if the authors adopted a Lagrangian approach instead of the Eulerian approach of fixing spatial window.

AR: You are pointing out the critical choice of the reference that is used to perform the rain typing.
As you mention, in our approach, we adopt an Eulerian reference, i.e. a reference that is fixed with regard to the Earth surface. We think that it is coherent with the target of assessing the temporal stationarity of rainfall statistics at a given location (or over a restricted area) for the purpose of stochastic rainfall modelling.
Because of the choice of this Eulerian reference, the rain type that is 'flying over' the area of interest can change along time due to the travel of distinct storms over the area. This is this succession of rain types that we are trying to identify. This is in line with a large literature about rainfall typing (e.g. Biggerstaff and Listemaa, 2000; Llasat, 2001), with the difference that the number of rain types considered is usually lower, and that the rain types are usually defined from physical properties (e.g. convective vs stratiform rains) while in this study we characterize rain types from their statistical properties.
Therefore our conclusion of sharp transitions between rain types (in an Eulerian reference) does not implies that the nature of a given 'piece of clouds' defined in a Lagrangian reference (i.e. moving with the rain storm) will change along time, but only that distinct 'sub-storms' with distinct features follow each other over the area of interest under the influence of storm advection.
We acknowledge that the question of changing rain types in a Lagrangian reference frame is an interesting and open question, but it is thought to be out of the scope of the present paper. Moreover we do not know any supporting literature about this point, and we do not aim to show that this phenomenon actually occurs. This would require homogenized radar data over large areas (in any case larger than Switzerland) in order to follow rain storms to track potential changes of their statistics, and for now we do not have access to such data.
In order to dispel any doubts about the aim of our work, we will improve the sections "1. Introduction" and "2. Overview of rainfall space-time patterns observed in radar images" by introducing the notions of Eulerian and Lagrangian references and by clearly specifying that an Eulerian approach has been followed. In addition we will better contextualize our study in comparison with former works about rain typing, including the references proposed by Reviewer #1.

RC: Are the 10 rainfall characteristics used to parameterize each rainfall imagery independent?

AR: No, we do not assume that the 10 indices used to characterize the rain fields are independent. That is why we use a full covariance model (i.e., accounting for correlations) for the covariance matrices implied in the GMM model, following the guidelines formulated in the review paper by Fraley and Raftery (2002) about GMM clustering.

RC: I suspect validity of the 10-dimensional Gaussian mixture model because most Copula tend to show awkward behavior as its dimension exceeds 2. Would you show a way to validate the GMM model you developed?

AR: GMM clustering has already been successfully applied to relatively high dimensional problems (more than 10 components). For instance Vrac & Yiou (2010), Rust et al. (2010) or Pernin et al. (2016) applied GMM clustering to problems of dimension 10 to 20.
Regarding the implementation of the GMM clustering, we used the build-in Matlab functions fitgmdist and cluster. We forgot to mention it in the first version of the manuscript, but we will add this information in the next version.

RC: I do not believe that the distribution of all 10 variables used for GMM classification has a normal distribution, which is a fundamental model assumption. For example, most rainfall intensity in a time series (in your case, it corresponds to the II-2) has a skewed distribution. You may want to use a type of transfer function to convert the original variables to be normally distributed, and then run the GMM classification algorithm.

AR: The GMM classification does not require normal distributions. Indeed, the idea behind GMM classification is that any multivariate distribution can be approximated by a mixture of multivariate Gaussian distributions if enough components are added. For more insights about GMM classification we refer to the review paper by Fraley and Raftery (2002).
We believe that this misunderstanding originates from our too brief description of the GMM classifier. Therefore, in the next version of our manuscript, we will expend the description of this method.

RC: If you cannot validate the previous two points, I suggest you perform the principal component analysis to extract the principle variables, and then apply a simpler clustering algorithms based on the Euclidean distance (e.g. K-means clustering, Hierarchical clustering).

AR: We hope that our responses to the two previous points convinced you that GMM is a rational choice to carry the classification in the specific context of our study. In addition, we would like to mention (cf response to Reviewer #1 comments) that we preferred GMM to other classification methods because this framework allows for a consistent automatic selection of the number of clusters through a model selection approach based on the BIC criterion.

RC: I believe that the result will be much more stronger if the analysis is performed on the years of the radar rainfall data at multiple locations. I agree with the view of the authors that the absolute validation of the result is not possible because we cannot see the nature thoroughly. However, it cannot be an excuse of not validating your model for a variety of situations.

AR: We agree that for a more exhaustive assessment, our framework should be applied to a wider variety of situations. However, since our method focuses on <u>temporal</u> non-stationarities, we prefer to focus on different seasons rather than on different locations. We therefore plan to develop an assessment of our method on a variety of situations in the new section “4.4 Seasonality of rain type occurrence”. In this section we will apply our rain typing approach to an entire year of data (2017) in order to qualitatively assess the seasonality of rain type occurrence inferred by our classification method. Therefore, multiple meteorological situations will be investigated including e.g. stratiform rain events, convective thunderstorms, spring showers, etc.

RC: In this view, running a sensitivity analysis will be more helpful. For example, you can change the size of the spatial window, or run the model at different locations with different meteorology, and see how your model behaves.

AR: We agree with the need of a sensitivity analysis to further validate our method, but here again we prefer to focus on the time axis. We therefore plan to investigate the sensitivity of our method to the length of the calibration dataset in a new section: “4.5 Sensitivity of the rain typing approach to the size of the calibration dataset”. In this section, we will split the rainy periods of the summer of 2017 into stationary rain events based on two calibrations of the GMM classifier: using the data of the summer of 2017 only, and using the data of the whole year 2017. The two classifications will be compared and we will discuss the robustness of the proposed approach to the choice of the modelling domain (in time).

References:

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