

Dear Reviewer#1,

Thank you for your detailed comments about our manuscript. All your suggestions have been considered, and we propose the following changes to address the questions you raised in your review.

In the following point-by-point responses your comments are in normal font and our responses are in *italic*.

Hoping that the proposed improvements will fulfill your expectations,
Best regards,

Lionel Benoit, on behalf of the authors.

Major comments:

I/- There are other ways to introduce non-stationarity in a Gaussian process. It would be nice to have some brief insight into different ways to introduce non-stationarity and provide some argument why your choice of using this parametrised covariance better suits your target.

In general, non-stationary Gaussian processes are Gaussian processes that do not verify the stationarity assumptions, namely a constant mean and a covariance function that depends only on the spatial lag. In this work, the latent Gaussian random field we consider has by construction a constant mean (equal to 0) and a constant variance (equal to 1), and the non-stationarity of rainfall intensity is therefore modeled by another part of the model: the transform function. When we refer to the non-stationarity of the covariance function of the latent field we thus only consider non-stationarity of a correlation function (i.e., with zero mean and unit variance), and we see three main ways to model it: the convolution approach (Paciorek and Schervish, 2006; Fouedjio et al., 2016), the space deformation approach (Sampson and Guttorp, 1992; Fouedjio et al., 2015) and the locally varying diffusion operator in SPDE approach (Fuglstad et al., 2015; Pereira et al., 2022). In this study we adopted the convolution approach because it provides a direct extension of the Matérn covariance function to the non-stationary case, and because the use of locally stationary covariance kernels simplifies the calibration of the model based on sparse rain gauge observations.

We will add a paragraph including these references to the section “Making the trans-Gaussian model non-stationary” in order to mention the other ways to introduce non-stationarity and justify our choice of the convolution approach.

Associated references:

Fouedjio, F., Desassis, N., and Romary, T. (2015). Estimation of space deformation model for non-stationary random functions. Spatial Statistics, 13, 45-61.

Fouedjio, F., Desassis, N., and Rivoirard, J. (2016). A generalized convolution model and estimation for non-stationary random functions. Spatial Statistics, 16, 35-52.

Pereira, M., Desassis, N., and Allard, D. (2022). Geostatistics for Large Datasets on Riemannian Manifolds: A Matrix-Free Approach. Journal of Data Science, 20(4).

Sampson, P. D., and Guttorp, P. (1992). Nonparametric estimation of nonstationary spatial covariance structure. Journal of the American Statistical Association, 87(417), 108-119.

II/- To make the paper easier to read, it would be better to introduce the data, the climatic regions and the rain clusters before describing the components of the models. Indeed, there are instances where rain climatology, climatic regions and clusters are mentioned before being introduced and understanding that there is one model per cluster/region earlier would be nice.

This is a good idea. We will create a new section entitled “2. Example dataset: orographic precipitation on the Island of Hawai‘i” just after the introduction. This new section will introduce the climate of Hawai‘i, the dataset

we use and the climate divisions early in the paper. This section will include the material of the former section “3.1 Orographic precipitation on the Island of Hawai‘i” as well as the following new figure (and associated description in the main text) illustrating the rainfall climate of each climate division, with focus on seasonality and inter-annual variability.

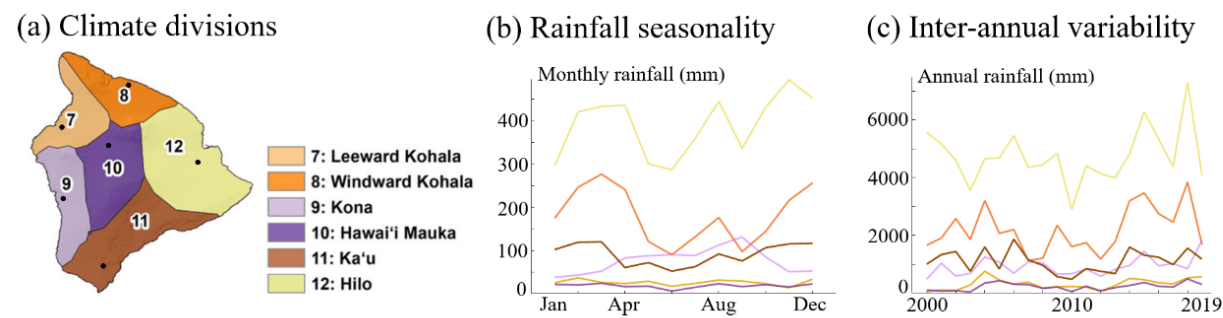


Figure 2. Climate divisions of the Island of Hawai‘i. (a) Footprint of the climate zones (adapted from Luo et al. (2024); the numbering over the Island of Hawai‘i starts at 7 because the original zonation covers the whole State of Hawaii). (b) Rainfall seasonality and (c) rainfall inter-annual variability for 6 rain gauges spread in the different climate divisions (gauge locations are denoted by black dots in (a)).

III/- What are the modelling differences between the model developed in this paper and the benchmark model? It can be presented as a table in the paper (Appendix).

This is a good idea. We will add the following table in appendix to summarize the differences between the benchmark model and the model developed in the paper (NB: the table outlines rainfall modeling conditionally to a pre-defined rain type).

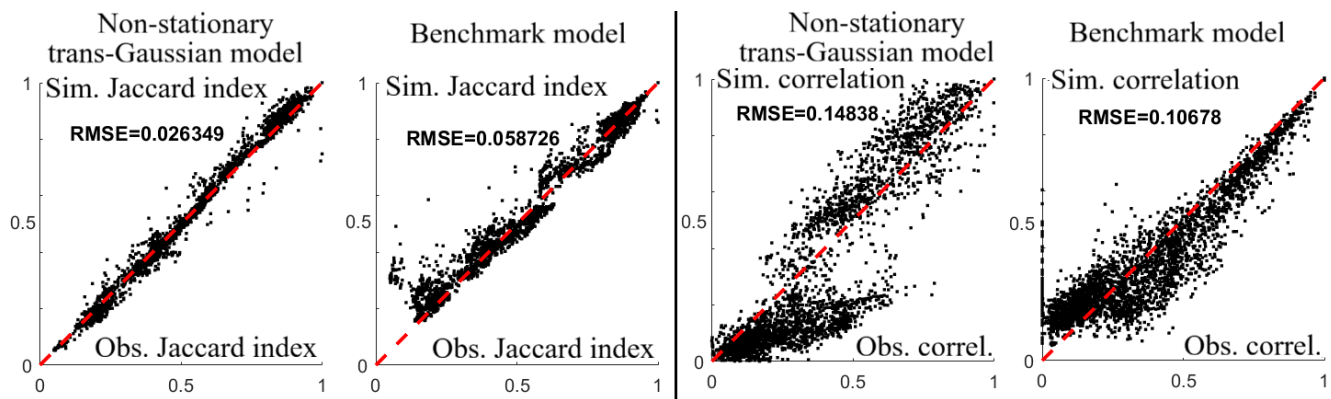
	Benchmark model	This study
Simulation locations	Observation sites only	Any location
Marginal distribution	Single Gamma across the island	Gamma at each location (non-stationary)
Spatial dependencies	Empirical copulas	Non-stationary Matérn covariance

IV/- Before assessing the spatial pattern, is it possible to look at the seasonal and inter-annual variability for a sub-sample of stations (section 3.3)?

Yes, this will be added in the new figure of the new section “2. Example dataset: orographic precipitation on the Island of Hawai‘i” (cf our answer to major comment II/).

V/- Can we see some evaluation of correlation /auto-correlation for all pairs of stations in addition to the correlation spatial pattern, conditionally to one location given in Figure 4.

This is a good idea. We will add a line to the current figure 4 to display the following scatter-plots of observed vs simulated Jaccard index and correlation for all pairs of stations (and for both the non-stationary trans-Gaussian model and the benchmark model).



VI/- It seems that there are non-negligible correlations (>0.5) in the observation between different climatic regions for the three examples given in Figure 4(c) between regions 12/11 (top), 9/11 (middle) and 8/12 (bottom). Limiting the covariance estimation to climatic regions seems to cause this. Why not estimate one non-stationary covariance function for the whole island (at least to compare)?

Actually we are estimating one non-stationary covariance function for the whole island. Indeed, although stationary covariance models are first estimated for each climate division, the associated parameters are subsequently interpolated and finally used in the model of Paciorek and Schervish (2006) to design a single non-stationary covariance function for the whole island. This is thanks to this unique non-stationary covariance function for the whole island that we are able to draw island-scale simulations without discontinuities, and to obtain correlation patterns with more diverse isolines than “simple ellipses” (which would occur if an anisotropic but locally stationary model was used for each climate division).

We acknowledge the underestimation of some inter-divisions correlations as pointed out by the reviewer, but we would like to make the observation that imperfections in inter-divisions correlation simulation are (by far) not systematic, and we therefore believe that the problem does not come from the convolution approach we selected here. As discussed in the section “3.3 Stochastic generation of orographic rainfall” we originally thought that the under-estimation of long-range correlations can “be explained by the fact that the trans-Gaussian model relies on a covariance function that is strictly decreasing with separation distance (cf. Eq. 2), and therefore cannot plateau as would be necessary in some areas to properly match the observations”. Nevertheless, the reviewer’s comment made us realize that the problem could also come from the use of relatively large climate divisions for the estimation of the locally stationary covariances, which is necessary to have enough observations to estimate all parameters of an anisotropic Matérn covariance function. The use of a coarse zoning makes the interpolated covariance parameters smooth, which in some cases misrepresent the actual values in areas with strong covariance parameter gradient located far from the center of the climate divisions.

We will re-write the description of Figure 4 in section 3.3 to fully acknowledge the underestimation of inter-division correlations pointed out by the reviewer, and discuss in details the possible causes for this problem following the lines elaborated above.

VII/- I also suspect the results would be very similar with an anisotropic stationary covariance function estimated for each climatic region. I would like to see the result with the stationary version of your covariance.

We agree that within each climate division the results would be relatively similar with an anisotropic but stationary covariance function estimated for the climatic region at hand. However, as mentioned above, the non-stationary covariance model leads to correlation patterns with more diverse isolines than the “simple ellipses” that would occur if anisotropic but locally stationary models were used.

In addition, the use of anisotropic stationary covariance functions estimated for each climatic region would hinder the simulation of rainfall fields covering the whole island, which is the main goal of the paper. The result would be spatially disconnected maps for each climate division, and not rainfall maps (or synthetic rainfall fields) covering the whole island. Since such discontinuities would create unrealistic rainfall maps we decided to not further explore this option.

VIII/- What is the purpose of performing conditional simulations? Are the unconditional simulations not enough? How would it be necessary for hydrological simulations?

The purpose of performing conditional simulation is the estimation of the uncertainty of spatial rainfall estimates derived from sparse rain gauge observations. The resulting datasets can be used to assess input errors in distributed hydrological models, in particular during the calibration of the hydrological model (Vischel et al., 2009; Caseri et al., 2016; Renard et al., 2011). In contrast, unconditional simulations are more useful to assess the impact of the natural variability of rainfall on hydrological simulations, and to conduct sensitivity analysis of spatially explicit hydro-meteorological modeling chains (Moraga et al., 2022; Liu et al., 2024). The introduction will be re-written to better highlight this point, and include the above references.

Associated references:

Caseri, A., Javelle, P., Ramos, M. H., and Leblois, E. (2016). Generating precipitation ensembles for flood alert and risk management. Journal of Flood Risk Management, 9(4), 402-415.

Liu, Y., Wright, D. B., and Lorenz, D. J. (2024). A nonstationary stochastic rainfall generator conditioned on global climate models for design flood analyses in the Mississippi and other large river basins. Water Resources Research, 60(5), e2023WR036826.

Moraga, J. S., Peleg, N., Molnar, P., Fatichi, S., and Burlando, P. (2022). Uncertainty in high-resolution hydrological projections: Partitioning the influence of climate models and natural climate variability. Hydrological Processes, 36(10), e14695.

Renard, B., Kavetski, D., Leblois, E., Thyer, M., Kuczera, G., and Franks, S. W. (2011). Toward a reliable decomposition of predictive uncertainty in hydrological modeling: Characterizing rainfall errors using conditional simulation. Water Resources Research, 47(11).

Vischel, T., Lebel, T., Massuel, S., and Cappelaere, B. (2009). Conditional simulation schemes of rain fields and their application to rainfall-runoff modeling studies in the Sahel. Journal of Hydrology, 375(1-2), 273-286.

Minor comments:

- In the introduction, it is not fully clear that the paper only tackles spatial non-stationarity; please clarify this.

The introduction will be largely re-written and will be more clear on the fact that the proposed model only tackles spatial non-stationarity.

- I do not see the contrast between paragraph lines 45 and 50. Indeed, the authors mention in lines 47-49: “non-stationary geostatistical models tend to have a large number of parameters [...] focus on one aspect of non-stationarity, the choice of which is driven by the problem at hand.”. How are you handling the high number of parameters in your “fully non-stationary trans-Gaussian geostatistical model?”

We agree that this part of the introduction was confusing, and it will be re-written. What we meant is that our fully non-stationary model has many parameters and therefore need a good quality and extensive dataset for calibration. We handle the high number of parameters by using an extensive dataset for calibration, and by combining the estimation of locally stationary parameters with parameter interpolation and the construction of a non-stationary model from these interpolated parameters (hence, e.g., the use of climate divisions discussed above). All this will be detailed in the new introduction.

- line 145: spectral simulation? Is that what the authors do?

Both the Cholesky decomposition and the spectral simulation approaches have been tested and give similar results. In the current version of the Matlab code attached to the paper only the Cholesky decomposition method is available, but we will add the spectral simulation code when revising the manuscript.

- Can you give the total surface of Hawai‘i in section 3.1

The area of the Island of Hawai‘i is 10432 km². This information will be added in the new section “2. Example dataset: orographic precipitation on the Island of Hawai‘i”.

- Appendix A: Since α iteratively determined for each dry station, how big N_{iter} needs to be?

Usually few thousand iterations are enough to ensure convergence. This information will be added in the description of the inputs of the algorithm.

- Appendix B: Can you precise how $Y_{f,sim}$ is obtained, in particular how is it initialized?

$Y_{f,sim}$ is initialized with the latent field corresponding to the daily rainfall maps without conditioning to monthly amounts (i.e., conditional simulations described in section 2.5). The description of this step (1503 in the early version of the manuscript) will be improved to avoid ambiguity.

- In Figure 4: Are the simulations with the non-stationary model unconditional? Can you clarify this?

Yes, the simulations with the non-stationary model in figure 4 are unconditional simulations. This will be clarified in the caption of the figure as well as in the figure description in the main text.

- line 502 & 511: Appendix A (not 1).

Thank you for the comment. This mistake will be corrected in the next version of the manuscript.