Dear Reviewer#2,

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.

Main comments :
The article is well written and very clear. The topic is clearly worth for HESS journal. However,

- Although the results are clearly convincing on the ability of the model to reproduce strong spatial variability, it's not completely clear to me what part of the model makes it suitable for modeling such orographic gradients : is it the use of a non stationary covariance function (however is it new in the context of SWG?) ? And/or the use of climate zones ? By the way, I think the climate zones should be introduced before, and their use should be motivated. Here they appear for the first time l. 100 and we don't really understand what they are, and why.

The good performance of the model to reproduce the strong spatial variability of orographic rainfall comes from both the non-stationary transform function AND the non-stationary covariance function. This is the combination of these two components coupled with a robust strategy for model calibration that makes the novelty of the proposed approach. In more details, we think that the non-stationary covariance mostly improves the spatial patterns simulated in case of unconditional simulations (i.e., when the purpose is stochastic rainfall generation) as shown in Figure 4. In contrast the non-stationary transform function is mostly responsible for the good results in rainfall mapping (i.e., conditional simulation) because in that setting the non-stationary covariance only affects the weight of neighboring observations and in turn the rank of the sample drawn from the local marginal distribution, while the non-stationary transform function influences the marginal distribution of rainfall intensity itself which has more impact on the estimated rainfall.
The introduction will be re-written to better explain what is the novelty of the model, and how this model compares with existing models (in particular trans-Gaussian models).
Regarding the resort to climate divisions, their use is directly linked to the estimation of the parameters of the non-stationary covariance function, and therefore they can not be separated from this non-stationary covariance. We would say that the climate divisions are absolutely necessary to estimate the parameters of the non-stationary covariance from sparse rain gauge observations. They could be left out if reliable gridded rainfall observations where available over the whole target area, in which case the parameters of the covariance could be estimated using a sliding window strategy. But since our framework uses rain gauge observations, the climate divisions are necessary to estimate the parameters of the non-stationary covariance function.
Finally we agree that the description of the climate divisions must appear earlier in the manuscript. To this end 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. 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.

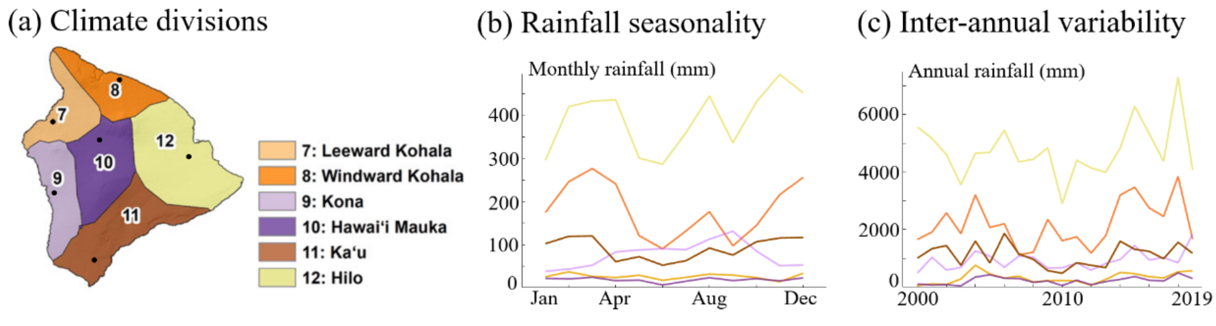

Figure 2. Climate divisions of the Island of Hawaiʻi. (a) Footprint of the climate zones (adapted from Luo et al. (2024); the numbering over the Island of Hawaiʻi starts at 7 because the original zonation covers the whole State of Hawaii). (b) Rainfall seasonality and (c) rainfall inter-annual variability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

- I got pretty much confused with the covariance function. Reading Sections 2.2 and 2.3, I understood that the covariance function was non stationary within the climate zone (given by eq 2), then its location-dependent parameters were interpolated in space to produce maps. But then it is written in the conclusion that the covariance function is first assumed to be stationary within the climate zones and then a non-stationary covariance function is subsequently obtained by convolution (??) of these stationary covariance. So I probably strongly misunderstood this part of modeling. Please consider clarifying.

The covariance function is first considered stationary within each climate division at the beginning of the calibration step, and then the estimated parameters are interpolated at each target location, which makes them non-stationary (even within a climate division). Finally a non-stationary covariance is obtained using these interpolated parameters combined with the model of Paciorek and Schervish (2006) (Equation 2), which lead to a single non-stationary covariance function for the whole island. This is currently explained in section "2.2 Making the trans-Gaussian model non-stationary", but we will re-emphasize on it in section "2.3 Model calibration" in the revised manuscript.
We think that the mention to "the convolution of these locally stationary covariance kernels (l 437)" in the conclusion was misleading, and this sentence will therefore be reformulated in the revised version of the paper.

- I found Section 2.6 difficult to understand because all the steps of the procedure are actually described later in Section 3. More importantly, I haven't understood what monthly total you use to condition at the virtual stations since there is no data there ? Is is with HCDP ? In which case, I find the comparison in Fig 6 unfair because of course we expect at the end to retrieve the right monthly totals since we used them to condition.

We agree that the presentation of the different processing steps was poorly positioned in "section 2.6 Conditioning daily rainfall maps to monthly totals". It will therefore be moved at the beginning of section "3 Model assessment and application" so that section 2.6 can fully focus on the conditioning to monthly totals. In addition a schematic describing the Metropolis within Gibbs algorithm will be added to improve the description of the conditioning to monthly totals.
Regarding the monthly total used to condition at the virtual stations we do use the HCDP dataset. However we don't think Figure 6 is unfair. Indeed, Figure 6 was not made to compare the conditioned monthly total with the HCDP, but rather to (1) show the need for conditioning to monthly totals (i.e., show that the rain gauge only monthly total has significant differences with HCDP) and (2) show that the conditioning algorithm based on Gibbs within Metropolis is effective. We will reformulate the description of figure 6 to avoid misunderstanding and make it clear that the fact that monthly totals conditioned to the virtual stations match the HCDP monthly map is not an external validation but just a check that the proposed algorithm performs properly.

• The temporal dependence seems not to be modeled at all. Are daily rainfall fields in this region almost independent ? Please justify this assumption.

This is true that this paper focuses on the spatial modeling of rainfall, and that only the spatial dependencies are explicitly modeled. However, the temporal variability of rainfall is not overlooked since it is accounted for by the rain types. Daily rainfall fields are therefore not fully independent, but are independent conditionally to the rain types, which explains why a purely spatial model (i.e., without temporal dependence) is calibrated for each rain type. This hypothesis of independence of daily rainfall fields conditionally to rain types that encode the temporal variability has been tested for different tropical islands (incl. Hawai'i) in Benoit et al. (2022) and has shown good skill in capturing the temporal variability of daily rainfall in all islands and locations tested in that paper. This is what we tried to explain l 65-69 of the original manuscript, but this paragraph will be re-written to be more clear and include the above explanation.

Associated reference:
Benoit, L., Sichoix, L., Nugent, A. D., Lucas, M. P., and Giambelluca, T. W. (2022). Stochastic daily rainfall generation on tropical islands with complex topography, Hydrology and Earth System Sciences, 26(8): 2113-2129.

Minor comments :
- eq 2 : can the parameters (gamma, nu, rho) take any value ?

The parameters nu and rho must be positive. This is mentioned after eq1 but we will recall it when introducing Eq2. The gamma parameters can take any value. We will add this information in the revised manuscript.

- eq 4 : shouldn't the parameters be \nu_i, \nu_j, \gamma_{1,i}, \gamma_{2,i}, \gamma_{1,i}, \gamma_{2,i}, \rho_{2,i}, \rho_{2,j} as in eq. 1 ? I guess your notations are that \nu=(\nu_i,\nu_j) but that's not clear.

For model calibration the parameters of the model are first estimated assuming local stationarity as mentioned l 98-99. For the parameters of the covariance function the domain used to define local stationarity is a climate division. The assumption of local stationarity explains why nu, gamma1, gamma2, and rho2 are constant (during model calibration) within a climate division and why the indices i and j do not appear in Eq 4. We will add a short paragraph after Eq4 to make it clear.

- in the interpolation process, how do you constrain the positive parameters (e.g. k, theta) to be >0 ?

We constrain these parameters to be >0 by assigning a small value (0.01) to the locations with a negative Kriging estimate. In practice this case is very rare.

- Section 2.6 : In step 4, «assess the uncertainty of rainfall interpolation (described in Section 3.4) » : I don't see any uncertainty in Section 3.4.

This is true that although the conditional simulation allows for uncertainty quantification this was not shown in Section 3.4. A figure will be added in this section to illustrate rainfall mapping and the assessment of the associated uncertainty.

- In step 5 « Identify areas where rainfall maps are highly uncertain» : actually in Section 3.5, the virtual stations cover all the island, not only the most uncertain parts.

This is correct, in the present setting the virtual stations have been placed homogeneously in the ungauged areas. We will reformulate this sentence.

- Fig 2 : the number on the color scales are to small

We agree. These numbers will be enlarged.

- l 265 : please specify what are the main differences with the benchmark BSNLG2022 ? Is it only the covariance non stationarity ?

The main difference is that BSNLG2022 is a multi-site model while the present model is spatially explicit and can therefore model rainfall at any location on the island. As proposed by another reviewer the differences between the two models will be presented in the following table placed in appendix, with a brief overview in the main text (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

- Section 3.4 : I guess that BSNLG2022 could not be used as benchmark because it's multisite and not spatial ?

Yes this is correct. We will add a sentence in Section 3.4 to make it clear.

- Fig 5 : it's confusing that the same color scale is used for positive and negative criteria (MB ; best color=green) and positive criteria (MAE, best color=blue).

This is a good point. The color scale of the mean bias will be changed to avoid this problem.

- Fig. 6 : please consider adding the raingauge locations in the middle row

We agree and will add the raingauge locations in the middle row.