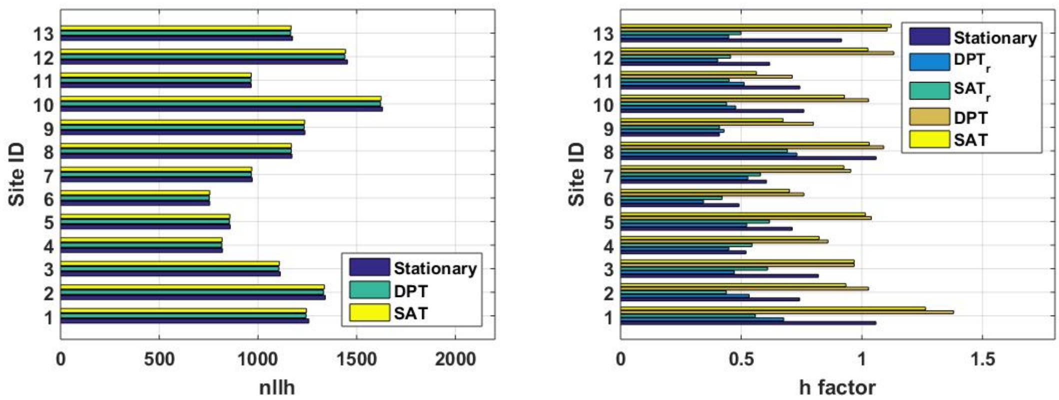
Response to Anonymous Referee #3

The manuscript models the POT based extreme rainfall at Busan and Seoul sites of Korea using the Generalized Pareto distribution fitted under stationary and non-stationary settings. The authors compare the stationary GPD and non-stationary GPD based on the parameter uncertainty estimated using the Metropolis-Hastings (MH) algorithm. The manuscript can be published after addressing the following comments:

Your detailed comments were very helpful in making a better manuscript. The authors would like to express great gratitude for this. The main additions are as follows. First, data from 11 sites, which began to be observed in 1961, were further analyzed. That is, a total of 13 sites were used in this study, including 2 sites that were previously applied. As a covariate, analysis was performed by adding surface air temperature (SAT) in addition to the dew point temperature. The results of applying the added sites and an added covariate were prepared in the form of Supplementary Material and included in the revised manuscript. Also, as a figure showing the final result, Figure 7 of the revised manuscript was newly added. This further analysis may dispel concerns about whether the method proposed in this study applies only to two sites or is not valid only for dew point temperature. In addition, further analysis results will increase the representativeness of the results derived from this study and provide local insights into Korea. More specific details of how and where the manuscript has been revised are described in response to the comments presented below.

Figure 7(a) shows the values of the negative log likelihood function of the stationary model and the non-stationary models at 13 sites. The stationary model, the SAT-based non-stationary model, and the DAT-based non-stationary model were found to have no significant difference in the fit performance with the observed POT excesses. Figure 7(b) shows the h-factor of rainfall quantile corresponding to the return level of 100-year. When all the values of covariate observed on the day of POT excesses are considered ("DPT" and "SAT" in Figure 7(b)), at all sites except Mokpo site, the non-stationary h-factor is greater than the stationary h-factor. However, when the reference covariate is applied, the non-stationary h-factor is smaller than the stationary h-factor. Results from 13 sites and most of the non-stationary models using SAT or DPT as a covariate indicate that how to determine the appropriate value of the covariate corresponding to the rainfall quantile plays an important role in securing the reliability of the non-stationary frequency analysis.



(a) negative log likelihood (b) h factor

Figure 7. Performance of stationary and non-stationary frequency analysis models. At Site ID, 1: Ghangreung, 2: Seoul, 3: Incheon, 4: Chupungryeong, 5: Pohang, 6: Daegu, 7: Jeonju, 8: Ulsan, 9: Ghwangju, 10: Busan, 11: Mokpo, 12: Yeosu and 13: Jeju site.

For constructing non-stationary GPD, the authors use DPT as the covariate. The reason for selecting DPT as a covariate is not clearly mentioned in the manuscript. Further, the authors should include a number of other covariates that affect the rainfall of the study area in the non-stationary setting.

In addition to using DPT as a covariate, SAT was added. Based on a study by Sim et al. (2019), this study selected DPT or SAT as the covariate on the day of POT excesses. However, in the previous study (Lee et al., 2020), DPT or SAT prior to t-day was selected as well as the day when POT excesses occurred. This study aimed to address how to explain the amplification of uncertainty that occurs when covariates are included in non-stationary frequency analysis, rather than the issue of deciding what covariates are suitable for POT excesses in Korea. The reason why we used DPT or SAT as a covariate to construct the non-stationary GPD is described below in the revised manuscript. We also included a description of the physical relationship between DPT or SAT and rainfall extreme to further support this.

In this study, a non-stationary frequency analysis using dew point temperature (DPT) or surface air temperature (SAT) as a covariate is performed. As can be seen from Leopore et al. (2014), there is a strong scaling relationship between rainfall extreme and DPT or rainfall extreme and SAT. In addition, changes in DPT and SAT can directly affect the atmospheric moisture retention governed by the Clausius-Clapeyron equation, and in warmer climates, the moisture content of the atmosphere increases and the intensity of precipitation increases at a similar rate (Trenberth et. al., 2003; Giorgi et al., 2019). That is, according to the Clausius-Clapeyron relationship, the amount of moisture in the atmosphere increases exponentially as the temperature increases, and the amount of moisture in the atmosphere represents an increase rate of 6 - 7 %/K when other atmospheric conditions are kept constant. To obtain a necessary understanding of the relationship between daily rainfall and DPT and daily rainfall and SAT in Korea, two prior studies have been conducted (Sim et al., 2019; Lee et al., 2020). Sim et al. (2019) analyzed the effects of DPT and SAT on daily rainfall extremes. Their results indicated that even if there was some cooling effect in the event of summer rainfall (Ali and Mishra, 2017), daily rainfall extremes in Korea were very sensitive to DPT and SAT. Lee et al. (2020) presented a procedure for performing non-stationary frequency analysis using DPT or SAT as a covariate. They revealed that non-stationary frequency analysis using future DPT or SAT could yield more reasonable and persuasive projections of future rainfall extremes. The purpose of this study is to focus on the uncertainty of covariate-based non-stationary frequency analysis using DPT or SAT.

(Additional references)

Ali, H. and Mishra, V. (2017) Contrasting response of rainfall extremes to increase in surface air and dewpoint temperatures at urban locations in India. Scientific Report, 7, 1228, DOI:10.1038/s41598-017-01306-1.

Giorgi, F., Raffaele, F. and Coppola, E. (2019) The response of precipitation characteristics to global warming from climate projections. Earth System Dynamics, 10, pp. 73-89.

Lepore, C., Veneziano, D. and Molini, A. (2014) Temperature and CAPE dependence of rainfall extremes in the eastern United States, Geophysical Research Letters, 42, pp. 74–83.

Trenberth, K., Dai, A., Rasmussen, R. and Parsons, D. (2003) The changing character of precipitation. Bulletin of the American Meteorological Society, 84, pp. 1205-1218.

The reason estimating the parameters using the probability weighted moments (PWM) over the other state-of-the-art methods such as the maximum likelihood or L-moments should be mentioned in the manuscript.

In this study, we will add the reason for estimating the parameter using PWM to the modified manuscript as follows:

The parameters of the GP distribution were estimated using the method of probability weighted moments (PWM) and MH algorithm, respectively. Although maximum likelihood estimation is an efficient method, it does not clearly show efficiency even in samples larger than 500 (Smith, 1985). The method of moments is generally known to be reliable except when the shape parameter is less than -0.2. When the likelihood that the shape parameter is less than 0 is high, PWM estimation is recommended (Hosking and Wallis, 1987). Figure 3 shows the result of PWM parameter estimation and the posterior distribution of parameters by the MH algorithm at Busan and Seoul sites.

(Additional reference)

Smith, R. (1985) Maximum Likelihood Estimation in a Class of Nonregular Cases, Biometrika, 72, pp. 67-90.

The language of the manuscript is not adequate for an international journal. There are many vague/substandard sentences throughout the manuscript. For example, Line # 44-48, 75-79, etc. Further, the title of the manuscript is not clear and wordy. Include rainfall or precipitation in the title.

We will check for ambiguous or non-standard sentences so that the language of the manuscript is suitable for international journals. First of all, we will modify the abstract and line #75-79 as below. There is an ongoing discussion about what to do with title. The current discussion is below:

(Abstract including Line #44-48)

Several methods have been proposed to analyze the frequency of non-stationary anomalies. The applicability of the non-stationary frequency analysis has been mainly evaluated based on the agreement between the time series data and the applied probability distribution. However, since the uncertainty in the parameter estimate of the probability distribution is the main source of uncertainty in frequency analysis, the uncertainty in the correspondence between samples and probability distribution is inevitably large. In this study, an extreme rainfall frequency analysis is performed that fits the Peak-over-threshold series to the covariate-based non-stationary Generalized Pareto distribution. By quantitatively evaluating the uncertainty of daily rainfall quantile estimates at 13 sites of the Korea Meteorological Administration using the Bayesian approach, we tried to evaluate the applicability of the non-stationary frequency analysis with a focus on uncertainty. The results indicated that the inclusion of dew-point temperature (DPT) or surface air temperature (SAT) generally improved the goodness of fit of the model for the observed samples. The uncertainty of the estimated rainfall quantiles was evaluated by the confidence interval of the ensemble generated by the Markov chain Monte Carlo. The results showed that the width of the confidence interval of quantiles could be greatly amplified due to extreme values of the covariate. In order to compensate for the weakness of the non-stationary model exposed by uncertainty, a method of specifying a reference value of a covariate corresponding to a non-exceedance probability has been proposed. The results of the study revealed that the reference co-variate plays an important role in the reliability of the non-stationary model. In addition, when the reference co-variate was given, it was confirmed that the uncertainty reduction of quantile estimates for the increase in the sample size was more pronounced in the non-stationary model. Finally, it was discussed how information on global temperature rise could be integrated with DPT or SAT-based non-stationary frequency analysis. It has been formulated how to quantify the uncertainty of the rate of change in future quantile due to global warming using rainfall quantile ensembles obtained in the uncertainty analysis process.

(Line #75-79)

Several methods have been proposed to address non-stationarities in the time series (Cunha et al., 2011; Yilmaz et al., 2013; Jang et al., 2015, Moon et al., 2016), and many studies have been conducted to examine changes in design rainfall depth or return levels under non-stationary conditions (Salvadori and DeMichele, 2010; Graler et al., 2013; Hassanzadeh et al., 2013; Salas and Obeysekera, 2013; Shin et al., 2014; Choi et al ., 2019).

(Title)

Uncertainty in non-stationary frequency analysis of Korea's daily rainfall POT excesses associated with covariates

Fig. 2: Add legend or explain different lines in the figure caption.

I will add the following description to the caption in Figure 2.

Figure 2. Mean residual life plot at (a) Busan and (b) Seoul sites. The solid line is the mean of the excesses of the threshold, and the dotted line is approximated 95% confidence intervals.

Fig. 3: Why the PDF of the non-stationary model is shown for the DPT values of 20.2576 (Busan site) and 21.4962 (Seoul site)? Expand S and NS in the legend.

The scale parameter in this study is a function of the covariate. Therefore, the posterior distribution of scale parameters depends on the covariate. The dependence of scale parameters on covariates is the most important part of this study. Since the uncertainty of the non-stationary model is excessively amplified when the dependence of the covariate is reflected in the uncertainty, this study attempted to prevent excessive amplification of the uncertainty of the non-stationary model by introducing the concept of a reference covariate. Through this, it was possible to secure the reliability of the non-stationary model. The 'S' and 'NS' in the legend in Figure 3 will be modified to 'Stationary' and 'Non-stationary', respectively. The revised manuscript is presented below:

(L 327)

The h-factor of rainfall quantile corresponding to the return level of 100-year was calculated in two ways. First, under the condition that the reference DPT is given (i.e., when the reference value of DPT is applied), the h-factor of the non-stationary model is reduced by 37 % (at Busan site) and 28 % (at Seoul site) than that of the stationary model. However, under the condition that all observed DPTs corresponding to POT excesses are applied, the uncertainty from parameter estimation and the effects from extreme values of the covariate overlap, and the h-factor of the non-stationary model exceeds the h-factor of the stationary model. That is, if samples of the scale parameter (i.e., α) is made by combining all samples of the coefficients of the scale parameter (i.e., α_1 and α_2) and samples of all observed DPTs corresponding to each POT excess, the uncertainty of rainfall quantiles in the non-stationary model is greater than the uncertainty of rainfall quantiles in the stationary model. The amplification of the uncertainty in the non-stationary model is because, as can be seen from Eq. (4), samples of some extreme DPTs significantly dissipate the samples of the scale parameter of the non-stationary GP distribution. This can also be confirmed through the lower right figure of Figure 4(a) and (b). The width of the 95PPU of the scale parameter of the non-stationary model corresponding to the value of the individual DPT is not significantly different from the width of the scale parameter of the stationary model. However, when all observed DPTs corresponding to the POT excesses are involved in sampling of the scale parameter, it can be recognized that the range of the 995 PPU of the scale parameter of the non-stationary model is very wide.

(Page 13)

We want to note here the condition in which the value of the covariate is given. In the upper left figure of Figure 4(a) and (b), the stationary quantile has a single value, while the ensemble average of the non-stationary quantile shows various values depending on the value of DPT. In addition, the 95 PPU of the stationary quantile has a constant range regardless of the value of the covariate, whereas the 95 PPU of the non-stationary quantile has a relatively wider range depending on the value of the covariate (see upper right figure in Figure 4(a) and (b)). This is due to the covariate dependence inherent in the scale parameter of the non-stationary GP distribution, as mentioned before. That is, since the range of the ensemble of the non-stationary rainfall quantile is a result of additionally reflecting the extreme values of the covariate in addition to the parameter uncertainty, it is more likely to be formed relatively wider than the range of the ensemble of the stationary rainfall quantile. It should be noted, however, that the width of the non-stationary 95PPU for a particular covariate value is less than the width of the stationary 95PPU.

In fact, since the covariate corresponding to each POT excess is a known value, the h-factor of the rainfall quantile corresponding to each POT excess can be obtained (see lower left figure in Figure 4(a) and (b)). Given the value of covariate, it can be recognized that the non-stationary h-factor is smaller than the stationary h-factor. That is, if the value of the covariate of the non-stationary model can be determined, there is a room to say that the non-stationary frequency analysis is better in terms of reliability than the stationary frequency analysis.

(The first half of Section 4.1)

As described above, when performing the uncertainty analysis of the non-stationary frequency analysis, an undesired disturbance in which the ensemble of rainfall quantile is excessively dispersed due to some extreme covariate values appears. Since the value of the covariate is the data observed on the day that the POT excess occurred (i.e., a deterministic variable), analyzing the uncertainty in rainfall quantile by randomly sampling the value of DPT or SAT from a predefined probability distribution of covariate is likely to result in overestimating uncertainty. We thought that the uncertainty analysis of randomly sampling the values of covariate from a predefined distribution of covariate was not feasible. The method of randomly sampling the value of the covariate in this study is implemented under the condition that all observed covariate samples corresponding to POT excesses are applied. Therefore, this study investigated the relationship between the value of covariate and rainfall quantile.

From Eq. (10), the DPT value (i.e., reference DPT) of the non-stationary GP distribution that returns the rainfall quantile equal to the stationary GP distribution can be calculated (reference SAT can be calculated in the same way). Figure 6 shows an example of determining a reference DPT. The results of calculating the reference DPT at Busan and Seoul sites indicate that the reference DPT increases as the return level increases. The right figure in Figure 6(a) and (b) shows the histogram of DPT corresponding to POT excesses. The distribution of DPT is slightly distorted to the left. It can be found that the reference DPT corresponding to various return levels at Busan and Seoul sites is similar to the location of the mode of the DPT distribution. This fact reveals that covariate values that deviate significantly from the reference covariate (i.e., some extreme values of the covariate) amplify the uncertainty of rainfall quantile from the non-stationary frequency analysis. From the results of regression analysis of rainfall quantile for various return levels and the corresponding reference DPT, the relationship of DPT = 18.8589RL^0.01555 (where RL is the return level in year and the unit of DPT is °C) was obtained at Busan site. At Seoul site, a relationship of DPT = 19.8540RL^0.01728 was obtained. The coefficient of determination of the regression analysis was 0.99 or higher at Busan and Seoul sites. From these results, the reference DPT corresponding to the return level of 100-year at Busan site could be applied to 20.2567 °C and Seoul site to 21.4958 °C. As shown in Figure 6 and Figures S3 and S4 of supplementary material, the value of the reference covariate is almost completely dependent on the return level. It should be noted that the return level and the reference covariate are proportional to each other at some sites, and are inversely proportional to other sites. This means that it is not easy to identify a single covariate value corresponding to a rainfall quantile. In this study, we tried to overcome the problem of random sampling of covariates by introducing the concept of reference covariate when estimating rainfall quantile estimation and its uncertainty from non-stationary frequency analysis based on covariate. From a practical point of view, how to set the value of the reference covariate may be an important research topic in the covariate-based non-stationary frequency analysis.

Most of the Figures & Tables: Use sentence case for figure title, legend and axis title.

We will use the sentence case to modify the picture and table.