Author response to the reviews of the paper “Discrete k-nearest neighbor resampling for simulating multisite precipitation occurrence and adaption to climate change”

(Manuscript # gmd-2018-181-RC1,)

Interactive comment on “Discrete k-nearest neighbor resampling for simulating multisite precipitation occurrence and adaption to climate change” by Taesam Lee and Vijay P. Singh

1. The manuscript presents discrete k-nearest neighbor resampling for simulating multisite precipitation occurrence and adaption to climate change, which is interesting. The subject addressed is within the scope of the journal.

Reply: The authors appreciate this reviewer’s comment.

2. However, the manuscript, in its present form, contains several weaknesses. Appropriate revisions to the following points should be undertaken in order to justify recommendation for publication.

Reply: The authors appreciate the reviewer’s comments. the authors improved the quality of the current study according to the given comments. Hope this reviewer is satisfactory to this modification.

3. For readers to quickly catch your contribution, it would be better to highlight major difficulties and challenges, and your original achievements to overcome them, in a clearer way in abstract and introduction.

Reply: The authors appreciate the reviewer’s comment. Accordingly, the introduction and abstract were improved as follows. Hope the modification is satisfactory.

Abstract:
Stochastic weather simulation models are commonly employed in water resources management agricultural applications, forest management, transportation management, and recreational activities. The data simulated by these models, such as precipitation, temperature, and wind, are used as input for hydrological and agricultural models. Stochastic simulation of multisite precipitation occurrence is a challenge because of its intermittent characteristics as well as spatial and temporal cross-correlation. The multisite occurrence model with standard normal variate (MONR) has been used for preserving key statistics and contemporaneous correlation, but it cannot reproduce lagged crosscorrelation between stations and long stochastic simulation is therefore required to estimate its parameters. Employing a nonparametric technique, k-nearest neighbor resampling (KNNR), and coupling it with Genetic Algorithm (GA), this study proposes a novel simulation method for multisite precipitation occurrence, overcoming the shortcomings of the existing MONR model. The proposed discrete version of KNNR (DKNNR) model is compared with an existing parametric model, called multisite occurrence model with standard normal variate (MONR).

The datasets simulated from both the DKNNR model and the MONR model are tested using a number of statistics, such as occurrence and transition probabilities as well as temporal and spatial cross-correlations. Results show that the proposed DKNNR model can be a good alternative for simulating multisite precipitation occurrence, while preserving the lagged crosscorrelation between sites and simulating multisite occurrence from a simple and direct procedure without no parameterization. We also tested the model capability to adapt climate change. It is shown that the model is capable but further improvement is required to have specific variations of the occurrence probability due to climate change. Combining with the generated occurrence, the multisite precipitation amount can then be simulated by any multisite amount model.

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Introduction:

Wilks (1998) presented a multisite simulation model for the occurrence process (i.e. X) using the standard normal variable that is spatially dependent, representing the relation between the occurrence variable and the standard normal variable with simulation data. Originally, the occurrence of precipitation had been simulated with discrete Markov Chain (MC) model (Katz, 1977). Compared to the MC model requiring a significant number of parameters to generate multisite occurrence, the multisite occurrence model proposed by Wilks (1998) transforms the standard normal variate and simulates the sequence with multivariate normal distribution, and then back-transforms the multivariate normal sequence to the original domain. The model is able to reproduce the contemporaneous multisite dependence structure and lagged dependence only for the same site while requiring a complex simulation process to estimate parameter for each site and being unable to preserve lagged dependence between sites.

Meanwhile, Lee et al. (2010a) proposed a nonparametric-based stochastic simulation model for hydrometeorological variables. They overcame the shortcoming of a previous nonparametric simulation model (Lall and Sharma, 1996), called k-nearest neighbor resampling (KNNR) such that the simulated data cannot produce patterns different from those of the observed data (Brandsma and Buishand, 1998; Mehrotra et al., 2006; St-Hilaire et al., 2012). In addition to this KNNR, Lee et al. (2010a) used a meta-heuristic algorithm Genetic Algorithm (GA) that led to the reproduction of similar populations by mixing the simulated dataset. While the KNNR is employed to find similar historical analogues of multisite occurrence to the current status of a simulation series, GA is applied to use its skill to generate a new descendant from the historical parent chosen with the KNNR. In this procedure, the multisite occurrence of the precipitation variable can be simulated while preserving spatial and temporal correlations. Note that meta-heuristic techniques to GA have been popularly employed in a number of hydrometeorological applications (Chau, 2017; Fotovatikhah et al., 2018; Taormina et al., 2015; Wang et al., 2013). A number of variants of KNNR-GA have since been applied (Lee et al., 2012; Lee and Park, 2017). None of these models can adopt the multisite occurrence in precipitation whose characteristics are binary and temporally and spatially related.

Therefore, in the current study we propose a novel stochastic simulation method for multisite occurrence of the precipitation variable with the KNNR-GA based nonparametric approach that (1) simulates multisite occurrence with a simple and direct procedure without parameterization of all the required occurrence probabilities; and (2) reproduces the complex temporal and spatial correlation between stations as well as the basic occurrence probabilities. Note that the proposed nonparametric model is compared with the most

popularly employed model proposed by Wilks (1998). Even though the multisite occurrence data from this model (Wilks, 1998) preserves various statistical characteristics of the observed data well, significant underestimation of lagged cross-correlation still exists. Furthermore, the relation between standard normal variable and occurrence variable relies on long stochastic simulation.
The paper is organized as follows. The next section presents a mathematical background of existing multisite occurrence modeling. The modeling procedure is discussed in section 3. The study area and data are reported in section 4. The model is applied in section 5. Results of the proposed model are discussed in section 6, and summary and conclusions are presented in section 7."

4. It is shown in the reference list that the authors have several publications in this field. This raises some concerns regarding the potential overlap with their previous works. The authors should explicitly state the novel contribution of this work, the similarities and the differences of this work with their previous publications.

Reply: The authors appreciate th reviewer's thoughtful comment. We have explicitly described the detailed difference and stated the novel contribution of this study as follows

"Meanwhile, Lee et al. (2010a) proposed a nonparametric-based stochastic simulation model for hydrometeorological variables. They overcame the shortcoming of a previous nonparametric simulation model (Lall and Sharma, 1996), called k-nearest neighbor resampling (KNNR) such that the simulated data cannot produce patterns different from those of the observed data (Brandsma and Buishand, 1998; Mehrotra et al., 2006; St-Hilaire et al., 2012). In addition to this KNNR, Lee et al. (2010a) used a meta-heuristic algorithm Genetic Algorithm (GA) that led to the reproduction of similar populations by mixing the simulated dataset. While the KNNR is employed to find similar historical analogues of multisite occurrence to the current status of a simulation series, GA is applied to use its skill to generate a new descendant from the historical parent chosen with the KNNR. In this procedure, the multisite occurrence of the precipitation variable can be simulated while preserving spatial and temporal correlations. Note that meta-heuristic techniques to GA have been popularly employed in a number of hydrometeorological applications (Chau, 2017; Fotovatikhah et al., 2018; Taormina et al., 2015; Wang et al., 2013). A number of variants of KNNR-GA have since been applied (Lee et al., 2012; Lee and Park, 2017). None of these models can adopt the multisite occurrence in precipitation whose characteristics are binary and temporally and spatially related."

5. It is mentioned in p.2 that k-nearest neighbor resampling coupling with genetic algorithm is adopted to simulate multisite precipitation occurrence. What are other feasible alternatives? What are the advantages of adopting this particular soft computing technique over others in this case? How will this affect the results? The authors should provide more details on this.

Reply: The authors appreciate the reviewer's comment. While the KNNR is employed to find similar historical analogues of multisite occurrence to the current status of a simulation series, GA is applied to use its skill to generate a new descendant from the historical parent chosen with the KNNR. In this procedure, the multisite occurrence of the precipitation variable can be simulated with preserving spatial and temporal correlations.

We added the following in the manuscript accordingly. Note that the location of the page has been changed especially in the introduction section for replying the comment 3 of this reviewer.

"While the KNNR is employed to find similar historical analogues of multisite occurrence to the current status of a simulation series, GA is applied to use its skill to generate a new descendant from the historical parent chosen with the KNNR. In this procedure, the multisite occurrence of the precipitation variable can be simulated while preserving spatial and temporal correlations. Note that meta-heuristic techniques to GA have been popularly employed in a number of hydrometeorological applications (Chau, 2017; Fotovatikhah et al., 2018; Taormina et al., 2015; Wang et al., 2013). A number of variants of KNNR-GA have since been applied (Lee et al., 2012; Lee and Park, 2017). None of these models can adopt the multisite occurrence in precipitation whose characteristics are binary and temporally and spatially related."

6. It is mentioned in p.2 that multisite occurrence model with standard normal variate is adopted as benchmark for comparison. What are the other feasible alternatives? What are the advantages of adopting this particular model over others in this case? How will this affect the results? More details should be furnished.

Reply: The authors thanks to this reviewer's comment. Another alternative is to use a multisite version of Markov Chain (M-MC) model by estimating the transition matrix of multisite occurrence. However, this M-MC model requires a number of parameters even difficult to handle and very often no data exist to estimate some of parameters. If this model is applied for comparison, the proposed model shows much better performance than the MONR model. The following is added in the manuscript accordingly.

"Wilks (1998) presented a multisite simulation model for the occurrence process (i.e. X) using the standard normal variable that is spatially dependent, representing the relation between the occurrence variable and the standard normal variable with simulation data. Originally, the occurrence of precipitation had been simulated with discrete Markov Chain (MC) model (Katz, 1977). Compared to the MC model requiring a significant number of parameters to generate multisite occurrence, the multisite occurrence model proposed by Wilks (1998) transforms the standard normal variate and simulates the sequence with multivariate normal distribution, and then back-transforms the multivariate normal sequence to the original domain. The model is able to reproduce the contemporaneous multisite dependence structure and lagged dependence only for the same site while requiring a complex simulation process to estimate parameter for each site and being unable to preserve lagged dependence between sites"

7. It is mentioned in p.8 that a random selection procedure is adopted to take into account the cases with the same quantity. What are other feasible alternatives? What are the advantages of adopting this particular procedure over others in this case? How will this affect the results? The authors should provide more details on this.

Reply: The authors appreciate this reviewer's comment. Other than the random selection, one can use always the first one. In such a case, only one historical combination of occurrence will be selected among the combinations with the same distance. The following is added in the manuscript. Hope this modification is satisfactory to this reviewer.

"For example, if $S=2$ and $X_c^1=0$ and $X_c^2=1$, the two sequences has the same $D=1$ as [$x_i^1=0$ and $x_i^2=0$] and [$x_i^1=1$ and $x_i^2=1$]. In this case, a random selection procedure is required to take into account the cases with the same quantity. One particular time index is randomly selected with the equal probabilities among the time indices of the same distances. Note that instead of the random selection, one can choose always the first one. In such a case, only one historical combination of multisite occurrences will be selected."

8. It is mentioned in p.9 that the reproduction procedure in (6-1) is adopted in this study. What are other feasible alternatives? What are the advantages of adopting this particular approach over others in this case? How will this affect the results? The authors should provide more details on this.

Reply: The authors appreciate this reviewer's comment. This reproduction process is a mating process by finding another individual that has similar characteristics with the current one $\mathbf{x}_{p+1}$. With this procedure, a similar vector to the current vector will be mated and produce a new descendant. Alternatively, this procedure can be skipped. Then all the elements of the generated vector will be the same as the historical. The following is added accordingly in the manuscript.

"This reproduction process is a mating process by finding another individual that has similar characteristics to the current one $\mathbf{x}_{p+1}$. With this procedure, a similar vector to the current vector will be mated and produce a new descendant."

9. It is mentioned in p.9 that Eq.(13) is adopted for crossover. What are other feasible alternatives? What are the advantages of adopting this particular crossover type over others in this case? How will this affect the results? The authors should provide more details on this.

Reply: The same answer as in the comment 8 can be made to this comment for the feasible alternative. The advantage of this crossover is that a new occurrence vector whose elements are similar to the historical is generated. The following is added in the manuscript accordingly.

"From this crossover, a new occurrence vector whose elements are similar to the historical is generated."

10. It is mentioned in p.9 that Eq.(14) is adopted for mutation. What are other feasible alternatives? what are the advantages of adopting this particular mutation type over others in this case? How will this affect the results? The authors should provide more details on this.

Reply: Another alternative can be skipped this procedure. Then always similar multisite occurrence to historical combinations would be generated, which is not feasible for a simulation purpose. The advantage of this mutation is to allow a totally new combination of multisite occurrence to be simulated with this mutation process compared to historical *records. The following is added in the manuscript accordingly.*

"This mutation procedure allows to generate a multisite occurrence combination that is totally different from the historical records. Without this procedure, always similar multisite occurrences to historical combinations are generated, which is not feasible for a simulation purpose."

11. It is mentioned in p.9 that a simple selection method is adopted for the selection of the number of nearest neighbors. What are other feasible alternatives? What are the advantages of adopting this particular method over others in this case? How will this affect the results? The authors should provide more details on this.

Reply: The authors appreciate this reviewer's critical comment. Another alternative is to use generalized cross-validation (GCV) as shown in Sharma and Lall1996 and Lee and Ouarda 2011 by treating this simulation as a prediction problem. However, the current multisite occurrence simulation does not necessarily require accurate value prediction and not much difference on simulation using the simple heuristic approach is reported. Also, this heuristic approach of k *selection has been popularly employed for hydrometeorological stochastic simulations (Lall and Sharma, 1996; Lee and Ouarda, 2012; Lee et al., 2010b; Prairie et al., 2006; Rajagopalan and Lall, 1999). The following is added in the manuscript accordingly.*

"One can use generalized cross-validation (GCV) as shown in Sharma and Lall1996 and Lee and Ouarda 2011 by treating this simulation as a prediction problem. However, the current multisite occurrence simulation does not necessarily require accurate value prediction and not much difference on simulation using the simple heuristic approach is reported. Also, this heuristic approach of k *selection has been popularly employed for hydrometeorological stochastic simulations (Lall and Sharma, 1996; Lee and Ouarda, 2012; Lee et al., 2010b; Prairie et al., 2006; Rajagopalan and Lall, 1999)."*

12. It is mentioned in p.11 that 12 weather stations were selected from Yeongnam province are adopted as the case study. What are other feasible alternatives? What are the ad- vantages of adopting this particular case study over others in this case? How will this affect the results? The authors should provide more details on this.

Reply: The authors appreciate this reviewer's comment. The object of the current study is to build a simulation model for multisite precipitation occurrence. To validate the proposed model appropriately, tested sites must be highly correlated with each other as well as significant temporal relation. The employed stations inside the Gyeongnam area cover one of the most important watersheds, the Nakdong River basin, where the Nakdong river pass through the entire basin and its hydrological assessments for agriculture and climate change has particular values in water resources management such as floods and droughts. The following has been added accordingly.

"To validate the proposed model appropriately, tested sites must be highly correlated with each other as well as significant temporal relation. The employed stations inside the Yeongnam area cover one of the most important watersheds, the Nakdong River basin, where the Nakdong river pass through the entire basin and its hydrological assessments for agriculture and climate change has particular values in water resources management such as

floods and droughts."

13. It is mentioned in p.11 that historical records of 1976 to 2008 are taken. Why are more recent data not included in the study? Is there any difficulty in obtaining more recent data? Are there any changes to situation in recent years? What are its effects on the result?

Reply: The authors appreciate this reviewer's comment. This dataset was employed to illustrate the performance of the proposed model especially for the base period. This dataset has been well evaluated from a number of the previous studies (Lee, 2017). According to this comment, more recent data up to the year2015 whose quality has been checked was added and all the results were modified accordingly. Not much significant difference was found from the results of the previous dataset.

14. It is mentioned in p.12 that the root mean square error is adopted to evaluate statistics from 100 generated series. What are the other feasible alternatives? What are the advantages of adopting this particular evaluation metric over others in this case? How will this affect the results? More details should be furnished.

Reply: Another alternative would be MAE and Bias. The estimates showed that MAE has no difference from RMSE and Bias of the lag-1 correlation presents significant negative values implying the underestimation of the lag-1 correlation. The following is added in the manuscript including Table 9 and Table 10.

"We further tested the performance measurements of MAE and Bias. The estimates showed that MAE has no difference from RMSE. In addition, Bias of the lag-1 correlation presents significant negative values implying its underestimation for the simulated data of the MONR model shown in Table 9 while Table 10 of the DKNNR model shows much smaller bias."

Table 9. Bias of lag-1 cross-correlation of the generated data from the Wilks model. Note that a positive value indicates the overestimation of lag-1 cross-correlation, while a negative value shows underestimation.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.000	-0.058	-0.078	-0.059	-0.040	-0.092	-0.073	-0.057	-0.061	-0.046	-0.056	-0.043
S2	-0.076	0.000	-0.073	-0.060	-0.037	-0.095	-0.078	-0.068	-0.065	-0.040	-0.068	-0.051
S3	-0.082	-0.066	0.000	-0.049	-0.034	-0.104	-0.097	-0.074	-0.077	-0.046	-0.055	-0.039
S4	-0.106	-0.090	-0.082	-0.002	-0.036	-0.128	-0.107	-0.099	-0.100	-0.059	-0.074	-0.037
S5	-0.141	-0.114	-0.121	-0.092	0.000	-0.146	-0.136	-0.116	-0.130	-0.084	-0.113	-0.048
S6	-0.062	-0.054	-0.075	-0.062	-0.038	0.001	-0.063	-0.054	-0.069	-0.041	-0.059	-0.043
S7	-0.059	-0.050	-0.072	-0.055	-0.041	-0.078	0.000	-0.036	-0.052	-0.037	-0.055	-0.049
S8	-0.085	-0.073	-0.081	-0.076	-0.047	-0.106	-0.068	0.000	-0.082	-0.050	-0.078	-0.060
S9	-0.065	-0.044	-0.075	-0.061	-0.039	-0.093	-0.063	-0.062	0.000	-0.049	-0.068	-0.046
S10	-0.118	-0.104	-0.111	-0.095	-0.068	-0.134	-0.121	-0.107	-0.117	-0.001	-0.086	-0.080
S11	-0.086	-0.079	-0.079	-0.063	-0.037	-0.113	-0.098	-0.087	-0.089	-0.036	-0.001	-0.045
S12	-0.127	-0.111	-0.111	-0.077	-0.025	-0.141	-0.126	-0.113	-0.118	-0.083	-0.099	-0.001

Table 10. Bias of lag-1 cross-correlation of the generated data from the DKNNR model. Note that a positive value indicates the overestimation of lag-1 cross-correlation, while a negative value shows underestimation.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.005	0.005	0.006	0.006	0.005	0.003	0.007	0.007	0.005	0.005	0.006	0.005
S2	0.007	0.006	0.009	0.009	0.006	0.007	0.007	0.008	0.005	0.005	0.006	0.007
S3	0.009	0.008	0.006	0.006	0.005	0.007	0.007	0.007	0.007	0.005	0.005	0.007
S4	0.005	0.005	0.007	0.006	0.005	0.002	0.003	0.005	0.005	0.005	0.007	0.006
S5	0.000	0.000	0.001	0.001	-0.001	0.002	-0.002	0.002	0.000	0.001	-0.002	0.000
S6	0.003	0.001	0.004	0.003	0.000	0.001	0.001	0.002	0.002	0.000	0.000	0.001
S7	0.004	0.004	0.005	0.005	0.003	0.002	0.002	0.005	0.005	0.003	0.005	0.004
S8	-0.002	-0.003	0.001	0.000	-0.001	-0.005	-0.001	-0.001	-0.003	-0.002	-0.001	0.000
S9	0.007	0.007	0.007	0.007	0.007	0.006	0.008	0.006	0.008	0.003	0.006	0.006
S10	-0.001	-0.005	-0.002	-0.001	-0.003	0.000	-0.004	-0.003	-0.002	-0.008	-0.004	-0.002
S11	0.007	0.006	0.007	0.008	0.008	0.008	0.007	0.007	0.007	0.007	0.007	0.008
S12	0.002	0.003	0.003	0.003	0.002	0.002	0.002	0.003	0.002	0.000	0.002	0.002

15. It is mentioned in p.16 that “: : :Special remedy should be applied, such as decreasing cross-correlation by force, but further remedy was not applied in the current study since: : :” More justification should be furnished on this issue.

Reply: The authors appreciate this reviewer’s comment. We tried to discuss about the possible improvement of the existing MONR model not the proposed model in the current study. The improvement of the existing model is not within the scope of the current study. Following study can be doable for this issue. The authors consider that no further justification was necessary in the current study since the MONR model has not been proposed in the current study. Hope this reviewer understand this. We improved the sentence as the following to avoid the confusion of the model we discuss.

“Special remedy for the existing MONR model should be applied, such as decreasing cross-correlation by force, but further remedy was not applied in the current study since it was not within the current scope and focus.”

16. It is mentioned in p.17 that “: : :However, the probability P01 fluctuated along with the increase of Pcr. Elaborate work to adjust all the probabilities is however required: : :” More justification should be furnished on this issue.

Reply: The authors appreciate this reviewer’s insightful comment. We agree that more justification and application might be needed to show the capability of the proposed model. However, the current study is focused on proposing a novel approach that simulates multisite occurrence process. Further development for adopting climate change and its application will be presented as a separate work as explained in the conclusion in the following. Hope this reviewer understand the intention of the authors.

“We tested further enhancement of the proposed model for adapting climate change through

modifying the mutation and crossover probability P_m and P_{cr} with the current and previous states. The results show that the current model has the capability to adapt to the climate change scenarios, but elaborate work is required however. Further study on improving the model adaptability to climate change will be followed in near future."

17. Some key parameters are not mentioned. The rationale on the choice of the particular set of parameters should be explained with more details. Have the authors experimented with other sets of values? What are the sensitivities of these parameters on the results?

Reply: The authors appreciate this reviewer's critical comment. The authors totally agree with this comment. Accordingly, we tested the key parameters for the proposed DKNNR method found that the parameter set of P_{cr} and P_m as 0.02 and 0.003 shows the best from the result of RMSE estimated with the transition and limiting probabilities of the tested stations. Hope this result is satisfactory to this reviewer. The following is added in the manuscript:

"The roles of crossover probability P_{cr} (Eq. 13) and mutation probability P_m (Eq.14) were studied by Lee et al. [2010a]. In the current study, we further tested to select appropriate parameter set of these two parameters with the simulated data from the DKNNR model and the record length of 100,000. RMSE (Eq. 18) of the transition and limiting probabilities (P_{11}, P_{01}, and P_1) between the simulated data and the observed was used since those probabilities are key statistics that the simulated data must be met with the observed and no parameterization on these probabilities has been made for the current DKNNR model. The results are shown in Figure 2 and Figure 3 for P_{cr} and P_m, respectively. For P_{cr} in Figure 2, the probability of 0.02 shows the smallest RMSE in all transition and limiting probabilities. The RMSE of P_m in Figure 3 shows slight fluctuation along with P_m. However, all three probabilities have relatively small RMSEs in P_m =0.003. Therefore, the parameter set 0.02 and 0.003 is chosen for P_{cr} and P_m, respectively and employed in the current study."

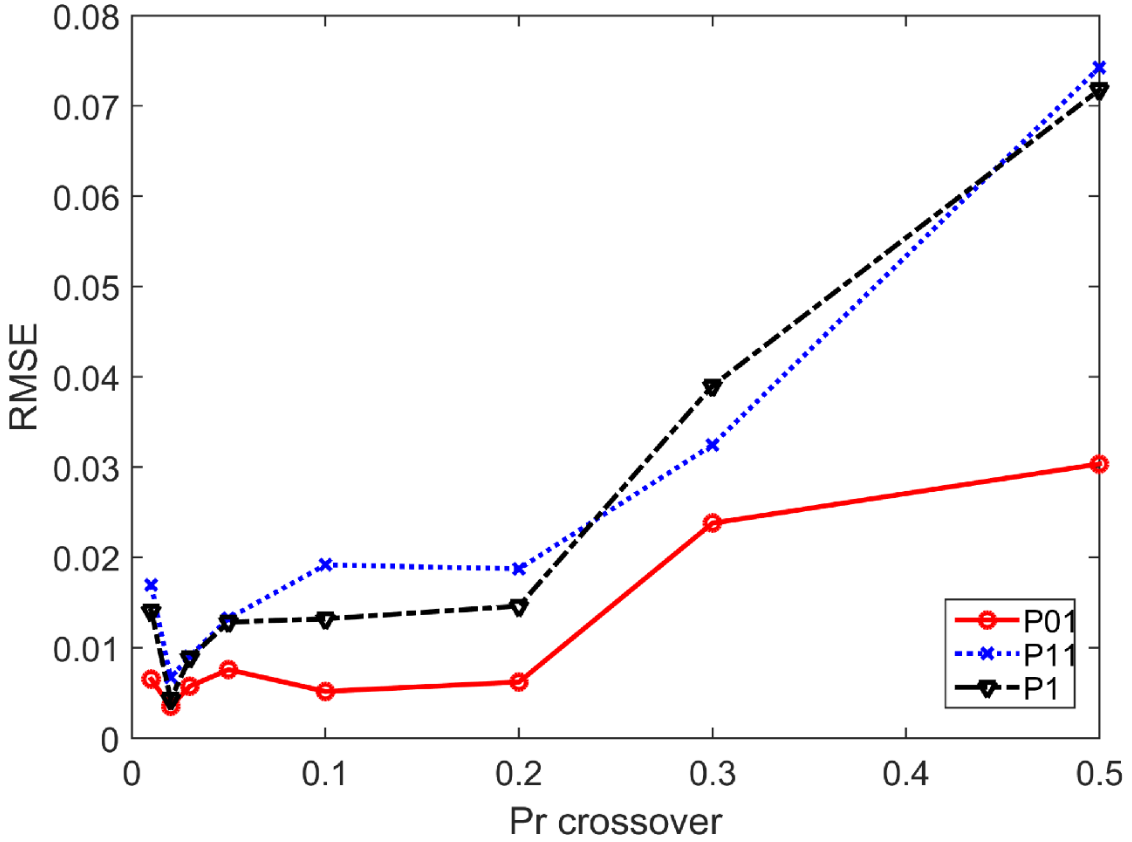

Figure 2. Testing for different probabilities of crossover Pcr. RMSE is estimated for all the tested 12 stations for each transition probability.

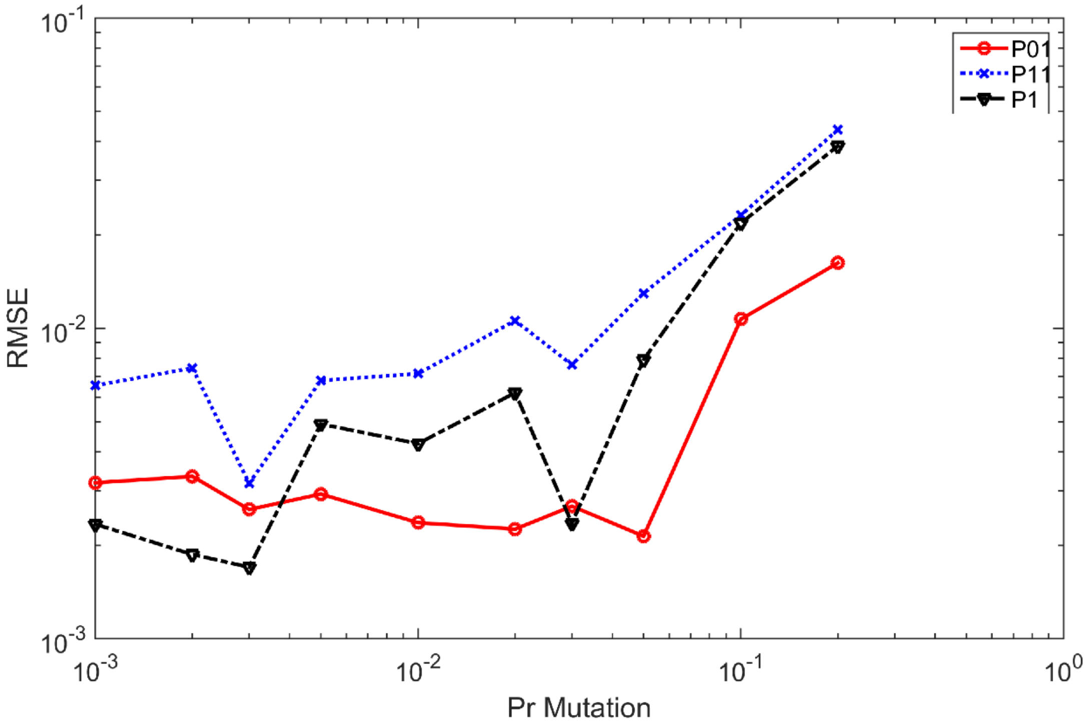

Figure 3. Testing for different probabilities of mutation Pm. RMSE is estimated for all the tested 12 stations for each transition probability.

18. Some assumptions are stated in various sections. Justifications should be provided on these assumptions. Evaluation on how they will affect the results should be made.

Reply: The authors appreciate this reviewer's comment. Following the comments from the above, we tried our best to show how the assumption may affect the results. Hope the modification following the previous comment meet this reviewer's expectation.

19. The discussion section in the present form is relatively weak and should be strengthened with more details and justifications.

Reply: The authors appreciate this reviewer's critical comment. The discussion has been intensified at the conclusion section. Hope this modification is satisfactory to this reviewer. Note that there is no separate discussion section in the current manuscript. If this reviewer implies other specific section, please let us know.

20. Moreover, the manuscript could be substantially improved by relying and citing more on recent literatures about contemporary real-life case studies of soft computing techniques in hydrological forecasting such as the followings:

ïA¸nˇ Fotovatikhah, F., et al., "Survey of Computational Intelligence as Basis to Big Flood Management: Challenges, research directions and Future Work," Engineering Applications of Computational Fluid Mechanics 12 (1): 411-437 2018. (Fotovatikhah et al., 2018) ïA˛nˇ Wu, C.L., et al., “Rainfall-Runoff Modeling Using Artificial Neural Network Coupled with Singular Spectrum Analysis”, Journal of Hydrology 399 (3-4): 394-409 2011. (Wu and Chau, 2011)

ïA˛nˇ Taormina, R., et al., “Neural network river forecasting through optimization”, Journal of Hydrology 529 (3): 1788-1797 2015. (Taormina et al., 2015)

ïA˛nˇ Wang, W.C., et al., “Improved annual rainfall-runoff forecasting using PSO-SVM model based on EEMD,” Journal of Hydroinformatics 15 (4): 1377-1390 2013. (Wang et al., 2013)

ïA˛nˇ Cheng, C.T., et al., “Flood control management system for reservoirs,” Environmental Modeling & Software 19 (12): 1141-1150 2004.(Cheng and Chau, 2004)

ïA˛nˇ Chau, K.W.,et al., “Use of Meta-Heuristic Techniques in Rainfall-Runoff Modelling” Water 9(3): article no. 186, 6p 2017. 21. (Chau, 2017)

Reply: The authors appreciate relevant works. Almost all the suggested papers that are relevant with this study were included in the current study as the following:

“In this procedure, the multisite occurrence of the precipitation variable can be simulated with preserving spatial and temporal correlations. Note that meta-heuristic techniques to GA have been popularly employed in a number of hydrometeorological applications (Chau, 2017; Fotovatikhah et al., 2018; Taormina et al., 2015; Wang et al., 2013).”

Some inconsistencies and minor errors that needed attention are: ïA˛nˇ Replace “: : :had a slight better: : :” with “: : :had a slightly better: : :” in line 250 of p.13 22. In the conclusion section, the limitations of this study and suggested improvements of this work should be highlighted.

Reply: The authors appreciate this reviewer’s detailed comment. The suggested minor error was corrected accordingly, and the conclusion was modified accordingly as the following.

“In the current study, a nonparametric simulation model, based on discrete KNNR and DKNNR, is proposed to overcome the shortcomings of the existing MONR model such as long stochastic simulation for the parameter estimation and underestimation of the lagged crosscorrelation between sites. Occurrence and transition probabilities and cross-correlation as well as lag-1 cross-correlation are estimated for both models. Better preservation of cross-correlation and lag-1 cross-correlation with the DKNNR model than the MONR model is observed. For some cases (i.e., the whole year data and other seasons than the summer season), the estimated cross-correlation matrix is not a positive semi-definite matrix so the multivariate normal simulation is not applicable for the MONR model, because the tested sites are close to each other with high cross-correlation.
Results of this study indicate that the proposed DKNNR model reproduces the occurrence and transition probabilities fairly well and preserves the cross-correlations better than the existing MONR model. Furthermore, not much effort is required to estimate the parameters in the DKNNR model, while the MONR model requires a long stochastic simulation just to estimate each parameter. Thus, the proposed DKNNR model can be a good alternative for simulating multisite precipitation occurrence.”

Response to Reviews of the paper “Discrete k-nearest neighbor resampling for simulating multisite precipitation occurrence and adaption to climate change”

(Manuscript # gmd-2018-181-RC1,)

Interactive comment on “Discrete k-nearest neighbor resampling for simulating multisite precipitation occurrence and adaption to climate change” by Taesam Lee and Vijay P. Singh

Anonymous Referee #2 Received and published: 31 December 2018

Reply: The authors appreciate this reviewer’s comments. The authors have improved the quality of the current study according to the comments of the reviewer. Hope this reviewer is satisfied with this modification.

Present study attempts to develop a novel simulation method for multi-site precipitation occurrence, combining the k-nearest neighbor sampling technique and genetic algorithm. The coupled model has been applied in precipitation occurrence simulation in single sites. The (only) novelty probably lies in the application of this coupled technique in generating the multi-site precipitation occurrence. Authors may clarify these and may specify whether the novelty lies in the method deployed or in the application (See line 35 in the abstract and further such claims in the manuscript body).

Reply: The authors appreciate this reviewer’s insightful comment. The novelty of the current study is to propose the discrete version of KNNR-GA model in simulating multisite occurrence. The KNNR-GA model has been developed for multisite simulation of streamflow for continuous variables. The novelty of the current study is how to handle the multisite discrete binary process which is the main difference between the continuous version and the discrete version of the current study. The authors have improved the abstract and manuscript to emphasize this point. Hope this modification is satisfactory.

While, stochastic weather models (like the one deployed in this study) are commonly deployed in various applications, it would be preferable to give some physical justification to the application and comprehend the results obtained. This would bring more confidence into the purely statistical methods which otherwise may not have captured any physical relationships/behavior of the system been dealt. This is particularly significant in the present study, since multi-site occurrences might be directed by many climatic feedbacks and also controlled by many local factors also. Absence of any such physical explanation may leave the methods sound robotic and put doubt s in its generic applicability.

Reply: The authors have tried to provide the physical connection to the current results. For example, the following statement for the GA mixing process has been connected with the physical process of the proposed model.

"This can be problematic for the simulation purpose in that one of the major simulation purposes is to simulate sequences that might possibly happen in future. The wet (1) or dry (0) for multisite precipitation occurrence is decided by the spatial distribution of a precipitation

weather system. A humid air mass can be distributed randomly relying on wind velocity and direction as well as surrounding air pressure. In general, any combinations of wet and dry stations can be possible, especially when the simulation continues infinitely. Therefore, the patterns of simulated data must be allowed to have any possible combinations, here 4096 even if it has not been observed from the historical records. Also, its probability to have this new pattern must not be high since it has not been observed in the historical records and this can be taken into account by low probability of the crossover and mutation. "

"Daily precipitation occurrence, in general, shows the strongest serial correlation at lag-1 and its correlation decays as the lag gets longer. This is because a precipitation weather system moves according to the surrounding pressure and wind direction that dynamically change within a day or week. Therefore, we analyzed the lag-1 cross-correlation in the current study as the representative lagged correlation structure."

"In the DKNNR modeling procedure, the simple distance measurement in Eq. (11) allows to preserve transition probabilities in that the following multisite occurrence is resampled from the historical data whose previous states of multisite occurrence (x_i^s) are similar to the current simulation multisite occurrence (X_c^s). This summarized distance (D_i) is an essential tool in the proposed DKNNR modeling. The condition of the current weather system is memorized and the system is conditioned on simulating the following multisite occurrence with the distance measurement like a precipitation weather system dynamically changes but often it impacts the system of the following day."

In addition, the present method is compared with a method (MONR) which is developed almost two decades back. Is MONR a frequently used method for multi-site precipitation occurrence simulation? It would be convincing to compare the present technique with more recent methods deployed for multi-site precipitation occurrence simulation. More specific comments are provided below for the kind consideration of the authors.

Reply: The authors appreciate the reviewer's insightful comment. Even if MNOR model is rather old-fashioned, this model has been popularly employed in this field and its performance is more comparable to the Markov Chain model especially in multisite occurrence cases of precipitation dataset.

1. Line 68 – 74: Wilks (1998) model assumes standard normal variate and underestimates the lagged cross correlation. As mentioned before, is it really worth to compare the present method to this model, which works on an entirely different hypothesis? As mentioned by the authors in the next paragraph (lines 75-81), KNNR and KNNR-GA are proved to be efficient. Won't it be better to compare the present model (DKNNR) to compare with the above model, to highlight its applicability in multi-site precipitation occurrence, given that the novelty of the study is claimed to be in this application.

Reply: The authors appreciate the reviewer's insightful comment. The MONR model is the model of Wilks (1998) and it has been popularly employed in the literature. The present study compared the discrete version of KNNR-GA with the model of Wilks (1998), named as MONR here. See the first line of the section 2.2 as the following:
"Wilks (1998) suggested a multisite occurrence model using a standard normal random number (here, denoted as MONR) that is spatially dependent but serially independent."

2. Line 78-81: It is mentioned that KNNR model cannot produce different patterns and coupling with GA solves this drawback. Please provide more details on how GA could possibly solve this. And how the application of GA could ensure generation of similar populations. It would be interesting if some physical sense can also be provided here – how possibly GA could simulate those system behavior?

Reply: The authors appreciate the reviewer's detailed comment. Further explanation is added in the manuscript to improve the clarity in the result section.

"We further tested and discuss why the GA mixing is necessary in the proposed DKNNR model as follows. For example, assume that three weather stations are considered and observed data only has the occurrence cases of 000, 001,011,010, 011,100,111 among 2^3=8 possible cases. In other words, no patterns for 110 and 101 is found in the observed data. Note that 0 is dry day and 1 is rainy (or wet) day. The KNNR is a resampling process in that the simulation data is resampled from the observation. Therefore, no new patterns such as 110 and 101 can be found in the simulated data.

This can be problematic for the simulation purpose in that one of the major simulation purposes is to simulate sequences that might possibly happen in future. The wet (1) or dry (0) for multisite precipitation occurrence is decided by the spatial distribution of a precipitation weather system. A humid air mass can be distributed randomly relying on wind velocity and direction as well as surrounding air pressure. In general, any combinations of wet and dry stations can be possible, especially when the simulation continues infinitely. Therefore, the patterns of simulated data must be allowed to have any possible combinations, here 4096 even if it has not been observed from the historical records. Also, its probability to have this new pattern must not be high since it has not been observed in the historical records and this can be taken into account by low probability of the crossover and mutation.

This drawback of the KNNR model frequently happens in multisite occurrence as the number of stations increases. Note that the number of patterns increases as 2^n where n is the number of stations. If n=12, then 4096 cases must be observed. However, among 4096 cases, observed cases are limited, since the number of data is limited. The GA process can mix two candidate patterns to produce new patterns. For example, in the three station case, a new pattern 101 can be produced from two observed occurrence candidates of 001 and 100 by the crossover of the first value of 001 to the first value of 100 (i.e. 001 →101), which is not in the observed data.

Note that the data employed in the case study are 40 years and 122 days (summer months) in each year. The total number of the observed data is 4880 and the number of possible cases is 4096. We checked how many of possible cases are not found in the observed data. The result shows that 3379 cases are not observed at all for the entire cases as shown in Figure 4.

We further investigated how many new patterns are generated with the probabilities P_{cr}=0.02, P_m=0.001 by the proposed GA mixing. The generated data for 100 sequences from DKNNR with the GA mixing shows that the number 3379 was reduced to 1200, which is not in the dataset among the 4096 possible patterns. Therefore, more than 2000 new patterns were simulated with the GA mixing process. The KNNR model without the GA mixing does not produce any new patterns in the 100 sequences with the same length of the historical data."

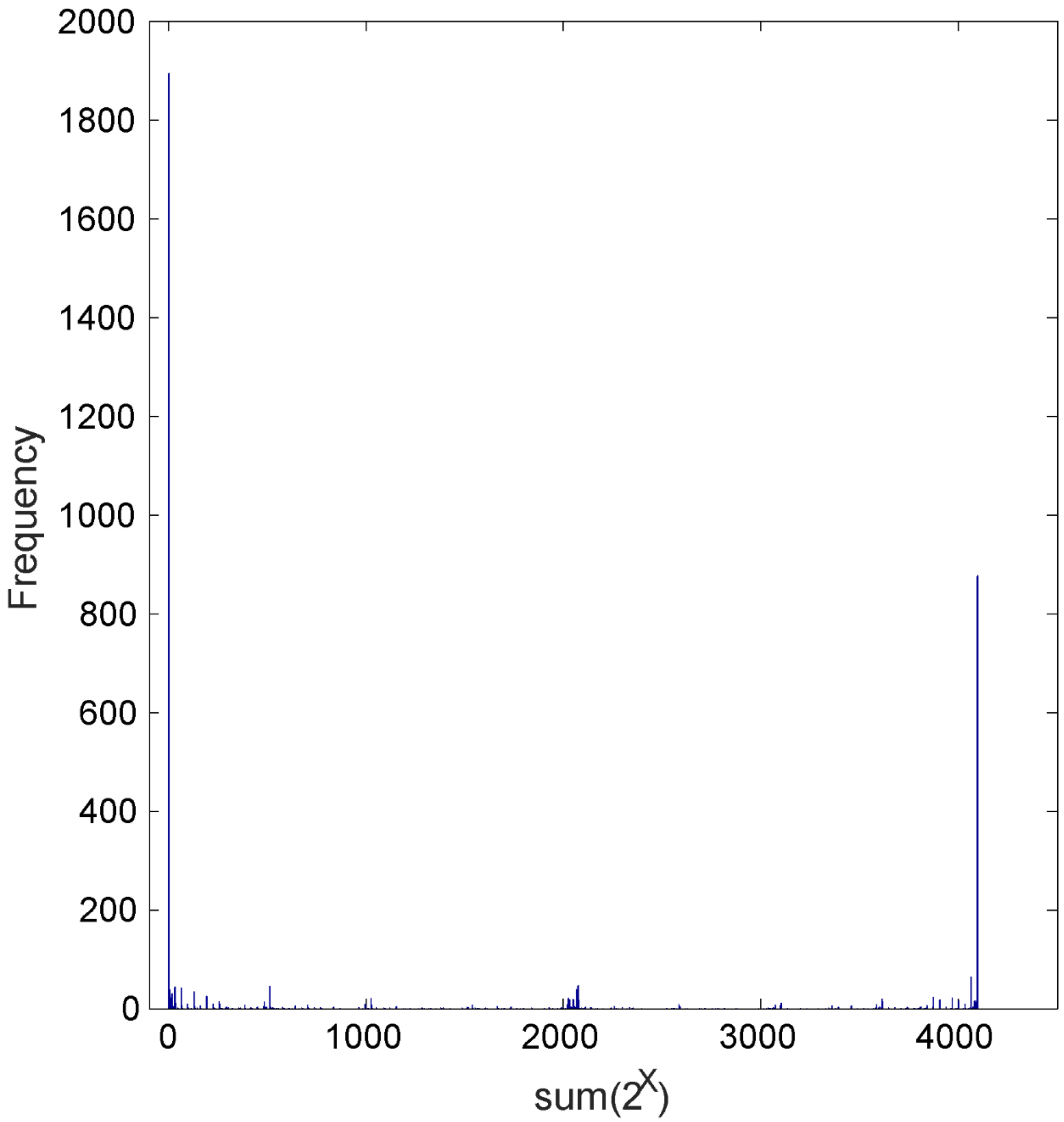

Figure S 1. Frequency of the observed patterns among all the possible cases (4096). The X coordinate indicates each pattern. All zero (0) and all one (4095) has the largest and second largest number of frequency (i.e. 1894 and 877, respectively) as expected meaning all dry and all wet stations. Note that the bars are very sporadic indicating a number of occurrence patterns are not observed.

3. Line 142: “multisite occurrence X and the observed multisite occurrence x”. Aren’t both these variables multi-dimensional and of same size? It would be ideal to denote both in capitals then.

Reply: The authors appreciate the reviewer’s detailed comment. We denote the observed occurrence with a lower case and the simulate variable with an upper case. For representing a multisite variable, we use the bold character. This separation is inevitable to express the simulation procedure from the observed dataset (especially in KNNR model). In Eq.11, X_c^s

and x_i^s represent only the simulation variable and observed data of the s^{th} station. Hope this is reasonable to this reviewer. To avoid confusion, we modify the sentence as follows:

"Estimate the distance between the current (i.e. time index: c) multisite occurrence X_c^s and the observed multisite occurrence x_i^s for the s^{th} station s=1,…,S. Here, the distance is measured for i=1,…, n-1 as

$$D_i = \sum_{s=1}^{S} \left| X_c^s - x_i^s \right| \qquad (1)$$

"

4. Line 158: When the algorithm will select the GA mixing? What is the criterion for GA mixing in the procedure?

Reply: The authors appreciate the reviewer's insightful comment. It is subjective. If one wants to simulate the dataset as the same observed pattern, this procedure can be skipped. Otherwise, the GA procedure gives the benefit of generating new patterns that we already discussed under comment 2. The sentence is modified accordingly.
"Execute the following steps for GA mixing if GA mixing is subjectively selected. Otherwise, skip this step."

5. Line 178-179: It is mentioned later in the manuscript that the changes in the mutation and cross-over probabilities may be carried out to adapt to the changes in the transition and marginal probability distributions (See lines 187-188). Considering that, would it be ideal to fix these as 0.01, following Lee et al (2010b). Shouldn't this be case specific? If not then, the later statement (lines 187-188) are questionable.

Reply: From the comment of the Reviewer 1, the estimation of parameter set was reinvestigated thoroughly. We concluded that the parameter set of P_{cr} and P_m as 0.02 and 0.003 showed the best from the result of RMSE estimated with the transition and limiting probabilities of the tested stations. The detailed results are as follows. Hope this investigation is satisfactory.

"The roles of crossover probability P_{cr} (Eq. (13)) and mutation probability P_m (Eq.(14)) were studied by Lee et al. (2010b). In the current study, we further tested by selecting an appropriate parameter set of these two parameters with the simulated data from the DKNNR model and the record length of 100,000. RMSE (Eq. (18)) of the three transition and limiting probabilities (P_{11}, P_{01}, and P_1) between the simulated data and the observed was used, since those probabilities are key statistics that the simulated data must match with the observed data and no parameterization of these probabilities was made for the current DKNNR model. Results are shown in Figure 2 and Figure 3 for P_{cr} and P_m, respectively. For P_{cr} in Figure 2, the probability of 0.02 shows the smallest RMSE in all transition and limiting probabilities. The RMSE of P_m in Figure 3 shows a slight fluctuation along with P_m. However, all three probabilities (P_{11}, P_{01}, and P_1) have relatively small RMSEs in P_m =0.003. Therefore, the parameter set 0.02 and 0.003 was chosen for P_{cr} and P_m, respectively, and employed in the current study."

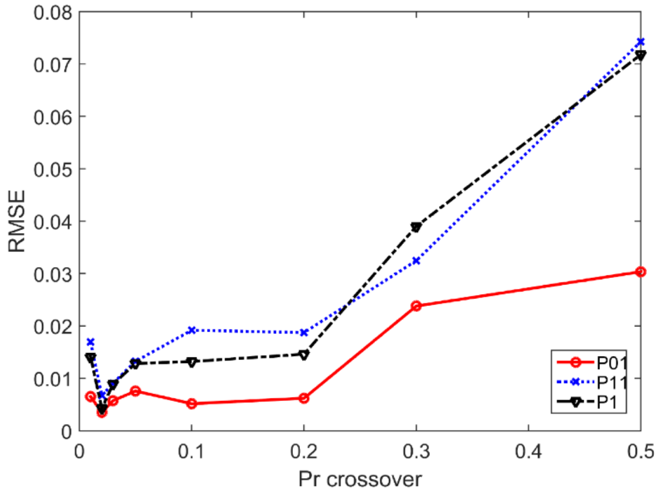

Figure 2. Testing for different probabilities of crossover Pcr. RMSE is estimated for all the tested 12 stations for each transition probability.

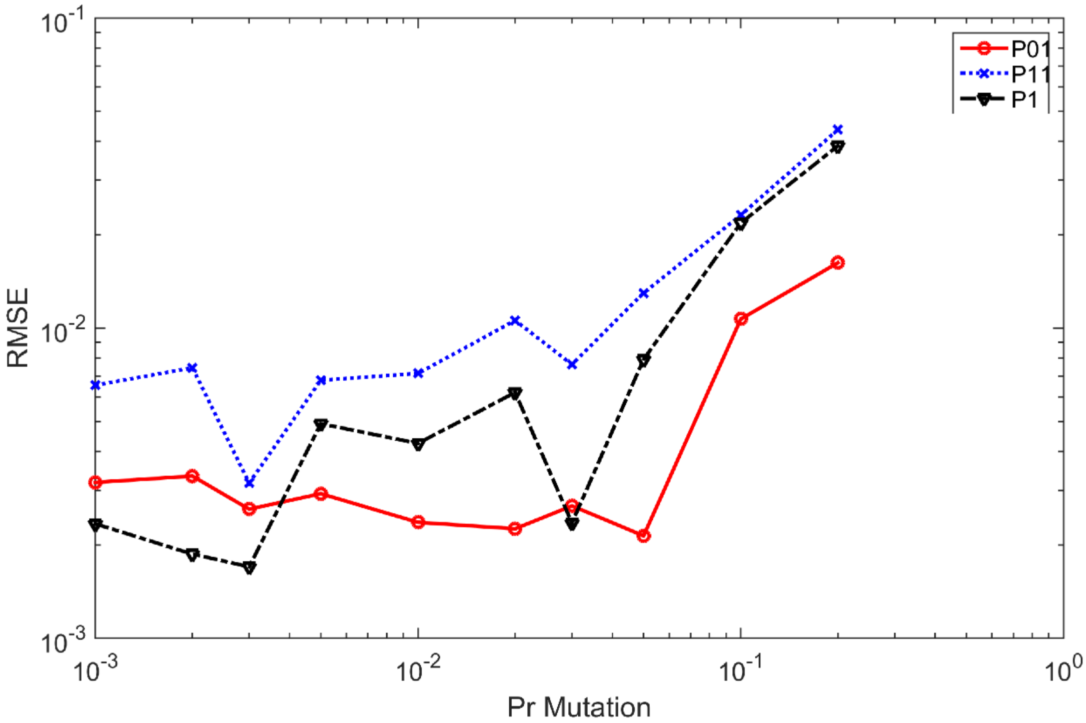

Figure 3. Testing for different probabilities of mutation Pm. RMSE is estimated for all the tested 12 stations for each transition probability.

6. Section 3.2: Authors must be pointing towards "Dealing with Non-stationarity" than "Adaptation to climate change". It is clear that only changes in marginal and transition probabilities are been considered, by tuning the crossover and mutation probabilities? "Climate change" may refer to a larger phenomenon, which might not be addressed directly in the present study. Please explain.

Reply: The authors totally agree with the concern of the reviewer. Tuning the crossover and mutation probabilities only affected the marginal and transition probabilities. This limitation must be addressed as this reviewer commented. We added the following to address the

concern from this reviewer at the end of section 6. The authors hope that this statement is satisfactory.
"Climate change, however, may refer to a larger phenomenon, which cannot be addressed directly through modifying only the marginal and transition probabilities as in the current study. Further modeling development on systematically varying temporal and spatial cross-correlations is required to properly address the climate change of the regional precipitation system."

7. How tuning of crossover and mutation probabilities could handle the non-stationarity in the time series of multiple stations? Can the model change these parameters in between the time frame of the simulation, so as to incorporate the parameter change(s) in the probability distributions?

Reply: The authors totally agree with the concern of the reviewer as with the previous comment that tuning the crossover and mutation probabilities only effected the marginal and transition probabilities. The authors consider that it is possible that the model can change the parameter to adapt to the climate change between the time frame of the simulation to incorporate the parameter change automatically. But this capability has not been fully investigated. In addition, the focus of the current study is to propose a novel approach that simulates multisite occurrence process through the nonparametric approaches. Further development for adopting to climate change and its application is presented as a possible improvement of the proposed model in the near future and will be presented as a separate work as explained in the conclusion section as the following.

"We tested further the enhancement of the proposed model for adapting to climate change by modifying the mutation and crossover probabilities P_m and P_{cr}. The results showed that the proposed DKNNR model has the capability to adapt to the climate change scenarios, but further elaborate work is required to find the best probability estimation for climate change. Also, only the marginal and transition probabilities cannot address the climate change of regional precipitation. The variation of temporal and spatial cross-correlation structure must be considered to properly address the climate change of the regional precipitation system. Further study on improving the model adaptability to climate change will be followed in the near future.Also, the simulated multisite occurrence can be coupled with a multisite amount model to produce precipitation events, including zero values. Further development can be made for multisite amount models with a nonparametric technique, such as KNNR and bootstrapping."

8. Section 4: Please provide more details about the precipitation data used, its seasonality, rainy day characteristics etc. Are the stations selected meteorologically homogenous?

Reply: The authors appreciate the reviewer's detailed comment. The following is added to address this comment. Hope this statement is satisfactory.

"The employed precipitation dataset presents strong seasonality, since this area is dry from late fall to early autumn and humid and rainy during the remaining seasons, especially in summer. The employed stations are not far from each other, at most 100 km apart, and not much high mountains are located in the current study area. Therefore, this region can be considered as a homogeneous region (Lee et al., 2007)."

“To validate the proposed model appropriately, test sites must be highly correlated with each other as well as have significant temporal relation. The stations inside the Yeongnam area cover one of the most important watersheds, the Nakdong River basin, where the Nakdong River passes through the entire basin and its hydrological assessments for agriculture and climate change have a particular value in flood control and water resources management such as floods and droughts.”

9. Section 5: This may go into the results section, if it sounds fine.

Reply: The authors appreciate the reviewer’s comment. The authors separate this section to explain how the developed model is applied to the datasets and what measurements were used to show its performance. The authors consider that the separation of this application part is reasonable because there are no specific results in this section. The results of the GA mixing and its probability section in the result section are also added for the comments of the reviewer.

10. Line 222: “ . . ..., since a synoptic scale weather system could result in lagged cross-correlation” – Can this statement be generalized for all locations?

Reply: The authors appreciate the reviewer’s specific comment and understand his concern. The statement might not be always true. Therefore, the sentence was modified accordingly as follows:

“In the current study, this statistic was analyzed, since a synoptic scale weather system often results in lagged cross-correlation for daily precipitation data (Wilks, 1998).”

11. Figure 2-4: Ensemble means from MONR are close to the observed mean, than those of DKNNR model. Is MONR better in that sense? Please clarify.

Reply: The authors agree with the reviewer’s comment and it is already mentioned in the manuscript as the following (see the L250-251). We also modified the sentence to include the same implication to P01 and P1 as well as P11.
“It seems that the MONR model had a slightly better performance since this statistic is parameterized in the model as shown in section 2.2 and that is the same for P01 *and* P1 *as shown in Figure 5 and Figure 6.”*

12. Line 254-255: “Even though the transition probabilities were not employed in simulating rainfall occurrence, the DKNNR model preserved this statistic fairly well” – Is it merely by chance? Please provide justification to build confidence. Do you expect the results to vary, when deployed in different regions?

Reply: The authors appreciate the reviewer’s crucial comment. The KNN resampling with the distance in Eq. (11) between the current simulation multisite occurrence (X_c^s) and the historical multisite occurrence states (x_i^s) allows to preserve the transition probabilities. The following statement is added accordingly.

“In the DKNNR modeling procedure, the simple distance measurement in Eq. (1) allows to preserve transition probabilities in that the following multisite occurrence is resampled from the historical data whose previous states of multisite occurrence (x_i^s) are similar to the

current simulation multisite occurrence (X_c^s). This summarized distance (D_i) is an essential tool in the proposed DKNNR modeling. The condition of the current weather system is memorized and the system is conditioned on simulating the following multisite occurrence with the distance measurement like a precipitation weather system dynamically changes but often it impacts the system of the following day."

13. Line 273-274: "Precipitation is not significantly correlated with more than one day" – Please provide reference. The statement may not hold well globally, as Box-Jenkins models of higher order are often applied for simulating precipitation events.

Reply: The authors totally agree with the reviewer's comment. The sentence was modified accordingly. Hope this modification is satisfactory.

"Daily precipitation occurrence, in general, shows the strongest serial correlation at lag-1 and its correlation decays as the lag gets longer. This is because a precipitation weather system moves according to the surrounding pressure and wind direction that dynamically change within a day or week. Therefore, we analyzed the lag-1 cross-correlation in the current study as the representative lagged correlation structure."

14. It would be better to number the stations considering its proximity. It will help in analyzing the results.

Reply: The authors appreciate the reviewer's comment. The author tried to change the numbers but consider that this may not be meaningful much since the order from west to east or north to south can be different with its numbering. Readers might be confused from this numbering. For example, the current 8,7,6, 10,2,9,1 stations can be changed to 1,2,3,4,5,6,7. The stations 3 and 4 seem close to each other due to renumbering, which is not correct. We also tested with 1,2,3,7,6,5,4. However, 1 and 7 must be far away from each other according to its numbering but they are very close to each other. We tried different numbering to consider the proximity but did not find any logical ordering. Therefore, we prefer staying as it is. Hope this can be understandable to the reviewer.

15. It would be interesting to see the results generated by the simple KNNR model in this application. Also, it would be helpful, if you may please explain how the incorporation of GA possibly helped in modeling the physical laws of the precipitation system.

Reply: The authors appreciate the reviewer's insightful comment. We produced the results without the GA process as presented in the following (See Figure S2-Figure S6). The presented results show that no significant difference from the one with the GA mixing can be found. The following is discussed in the manuscript right before the results of the probability selection (section 6.1).

"We also tested the simulation without the GA mixing procedure (results not shown). The results showed that no better result could be found from the simulation without GA mixing. The necessity of the GA mixing is further discussed in the following."

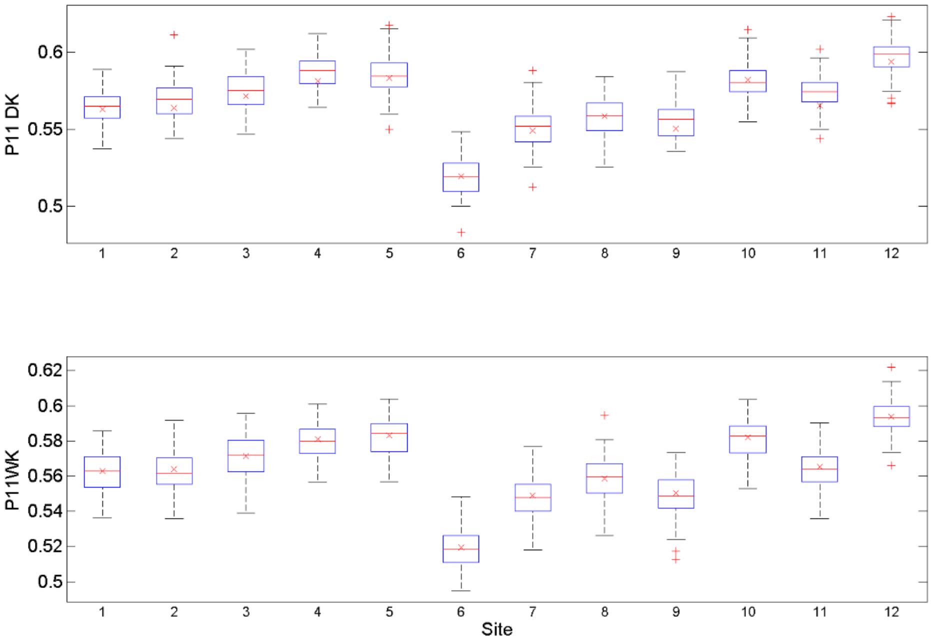

Figure S 2. Boxplots of the P11 probability for the data simulated from the DKNNR model without the GA mixing (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

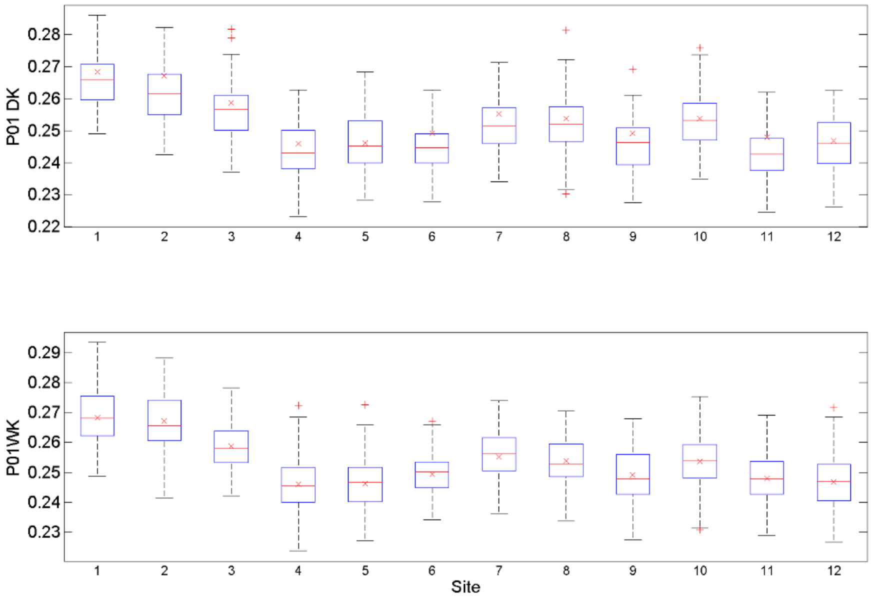

Figure S 3. Boxplots of the P01 probability for the data simulated from the DKNNR model without the GA mixing (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

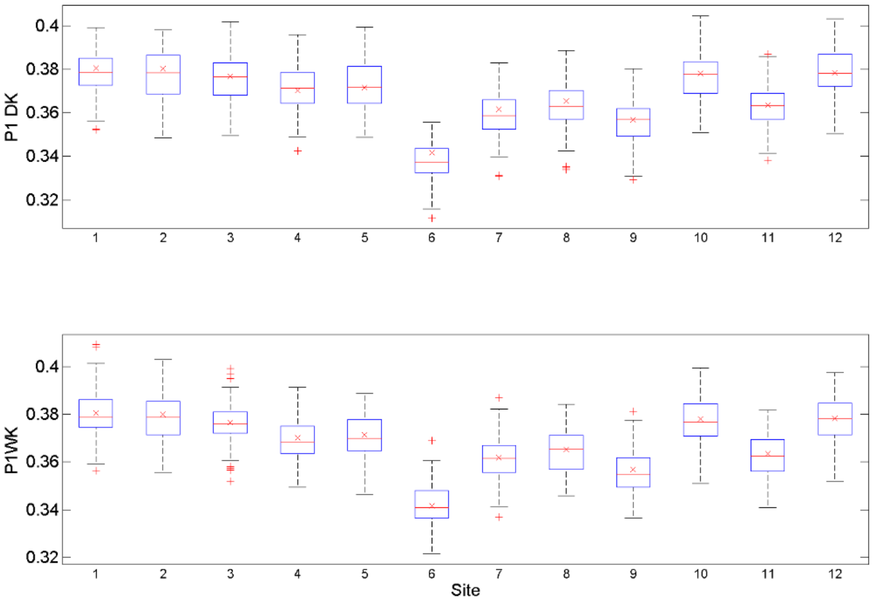

Figure S 4. Boxplots of the P1 probability for the data simulated from the DKNNR model without the GA mixing (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

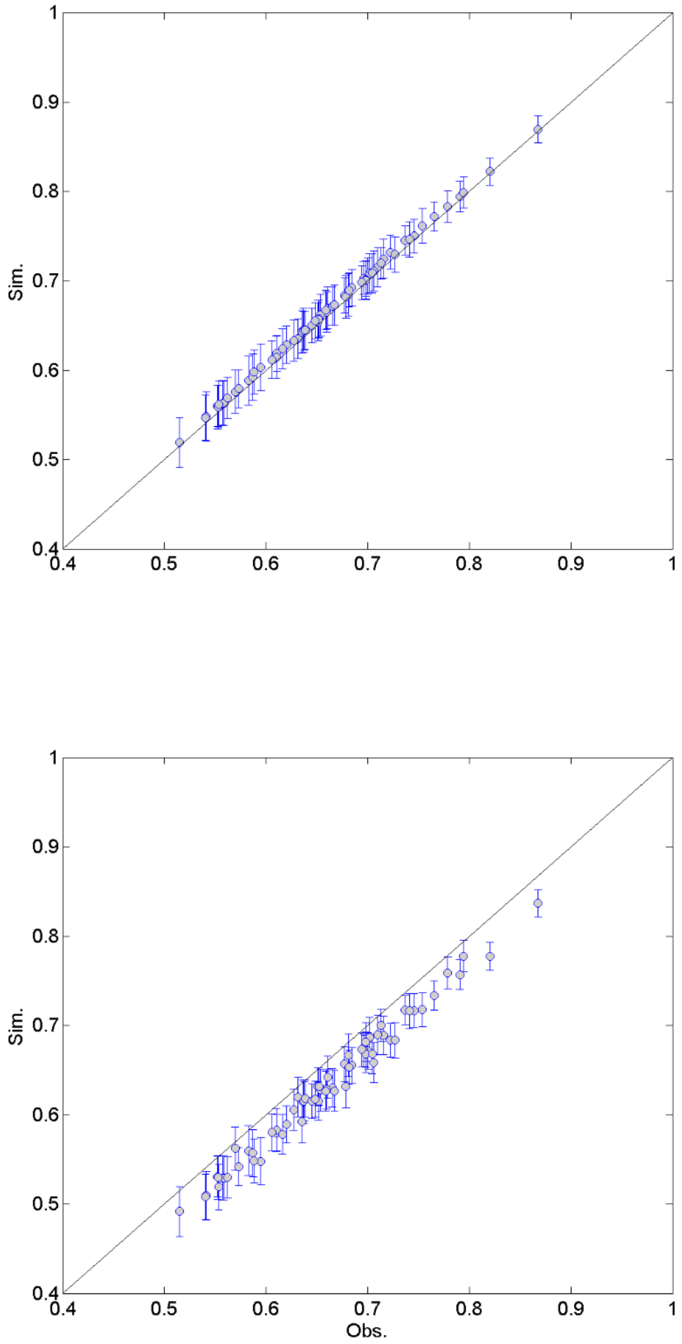

Figure S 5. Scatterplot of cross-correlations between 12 weather stations for the observed data (X coordinate) and the generated data (Y coordinate) generated from the DKNNR model without the GA mixing (top panel) and the MONR model (bottom panel). The cross-correlations from 100 generated series are averaged for the filled circle and the errorbars upper and lower extended lines indicate the range of 1.95×standard deviation.

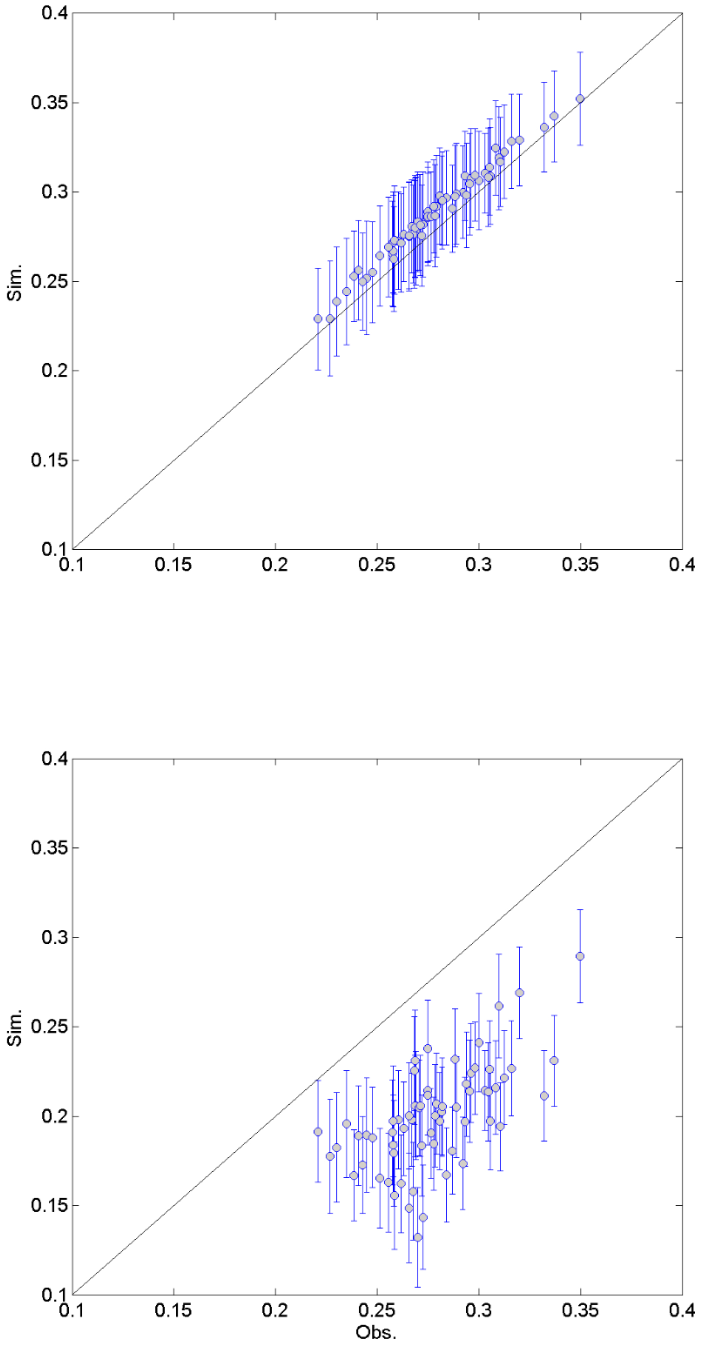

Figure S 6. Scatterplot of lag-1 cross-correlations between 12 weather stations for the observed data (X coordinate) and the generated data (Y coordinate) generated from the DKNNR model without the GA mixing (top panel) and the MONR model (bottom panel). The cross-correlations from 100 generated series are averaged for the filled circle and the errorbars upper and lower extended lines indicate the range of 1.95×standard deviation

16. Disadvantage of the simple KNNR model is the inability to simulate different patterns from the observed series. Do the stations selected exhibit significant nonstationarity? If not, will the KNNR model also serve the purpose?

Reply: The authors appreciate the reviewer's comment. The GA mixing was not applied for nonstationarity. The GA mixing is applied to overcome the disadvantage of the KNNR model that only observed pattern is repeated in the simulated data. This case is not sound for the simulation study purpose. As mentioned under comment 2, more than half of the possible patterns are not observed in the historical data. This has been covered multiple times already under previous comments. Hope this explanation can be acceptable to the reviewer.

17. Section 6.3: I am a little confused here. How can the parameters be changed in the future, for the model to adapt to the future changes, given that we may not clear information about these changes?

Reply: The authors appreciate the reviewer's comment. The authors did not fully investigate the specific changes required to be made for specific climate change assessment at this stage. As mentioned under comment 7, the focus of the current study is to propose a novel approach that simulates multisite occurrence process through nonparametric approaches. Further development for adopting to climate change and its application are partially presented as a possible improvement of the proposed model in the near future and will be presented as a separate work as explained in the conclusion. This limitation and possible development are discussed in the last section.

Discrete k-nearest neighbor resampling for simulating multisite precipitation occurrence and adaption to climate change

: Discrete KNNR for Multisite Occurrence (DKMO version1.0) - model development

Keywords: daily precipitation, discrete, k-nearest neighbor, Markov chain, multisite, occurrence

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Abstract

Stochastic weather simulation models are commonly employed in water resources management and agricultural applications. The data simulated by these models, such as precipitation, temperature, and wind, are used as input for hydrological and agricultural models. Stochastic simulation of multisite precipitation occurrence is a challenge because of its intermittent characteristics as well as spatial and temporal cross-correlation. Multisite occurrence model with standard normal variate (MONR) has been used preserving key statistics and contemporaneous correlation in literature, but it cannot reproduce lagged crosscorrelation between stations and long stochastic simulation is required to estimate its parameters. Employing a nonparametric technique, k-nearest neighbor resampling (KNNR), and coupling it with Genetic Algorithm (GA), this study proposes a novel simulation method for multisite precipitation occurrence overcoming the shortcomings of the existing MONR model. The proposed discrete version of KNNR (DKNNR) model is compared with an existing parametric model, called multisite occurrence model with standard normal variate (MONR). The datasets simulated from both the DKNNR model and the MONR model are tested using a number of statistics, such as occurrence and transition probabilities as well as temporal and spatial cross-correlations. Results show that the proposed DKNNR model can be a good alternative for simulating multisite precipitation occurrence with preserving the lagged crosscorrelation between sites and simulating multisite occurrence from a simple and direct procedure without no parameterization. We also tested the model capability to adapt climate change. It is shown that the model is capable but further improvement is required to have specific variations of the occurrence probability due to climate change. Combining with

the generated occurrence, the multisite precipitation amount can then be simulated by any multisite amount model.

1. Introduction

Stochastic simulation of weather variables has been employed for water resources management, hydrological design, agricultural applications, filling in missing historical data, extending observed records, simulating data, and simulating different weather conditions. Stochastic simulation models play a key role in producing weather sequences, while preserving the statistical characteristics of observed data. A number of stochastic weather simulation models have been developed using parametric and nonparametric approaches (Lee, 2017; Lee et al., 2012; Wilby et al., 2003; Wilks, 1999; Wilks and Wilby, 1999).

Parametric approaches summarize the statistical characteristics of observed weather data with a parameter set (Jeong et al., 2012; Lee, 2016; Zheng and Katz, 2008). The parameters fitted with observed weather data are employed in simulation. In nonparametric approaches, historical analogs with current conditions are searched following the weather simulation data (Buishand and Brandsma, 2001; Lee et al., 2012). Furthermore, combinations of parametric and nonparametric models have also been proposed (Apipattanavis et al., 2007; Frost et al., 2011).

Among weather variables, the precipitation variable possesses intermittency and zero values between precipitation events, and to properly reproduce them is difficult and remains a challenge (Beersma and Buishand, 2003; Hughes et al., 1999; Katz and Zheng, 1999). Due to this difficulty, precipitation is simulated separately from other variables. The main method for reproducing intermittency has been the multiplication of precipitation occurrence and an amount as $Z=X\cdot Y$, where X is the occurrence (binary as either 0 or 1) and Y is the amount (Jeong et al., 2013; Lee and Park, 2017; Todorovic and Woolhiser, 1975). The spatial and temporal dependence in the occurrence and amount of precipitation introduces further complexity multisite simulation.

Wilks (1998) presented a multisite simulation model for the occurrence process (i.e. *X*) using the standard normal variable that is spatially dependent, representing the relation between the occurrence variable and the standard normal variable with simulation data. Originally, the occurrence of precipitation had been simulated with discrete Markov Chain (MC) model (Katz, 1977). Compared to the MC model requiring a significant number of parameters to generate multisite occurrence, the multisite occurrence model proposed by Wilks (1998) transforms the standard normal variate and simulate the sequence with multivariate normal distribution, and then back-transforms the multivariate normal sequence to the original domain. The model is able to reproduce the contemporaneous multisite dependence structure and lagged dependence only for the same site while require a complex simulation process to estimate parameter for each site and unable to preserve lagged dependence between sites.

Meanwhile, Lee et al. (2010a) proposed a nonparametric-based stochastic simulation model for hydrometeorological variables. They overcame the shortcoming of a previous nonparametric simulation model (Lall and Sharma, 1996), called k-nearest neighbor resampling (KNNR) such that the simulated data cannot produce patterns different from those of the observed data (Brandsma and Buishand, 1998; Mehrotra et al., 2006; St-Hilaire et al., 2012). In addition to this KNNR, Lee et al. (2010a) used a meta-heuristic algorithm Genetic Algorithm (GA) that led to the reproduction of similar populations by mixing the simulated dataset. While the KNNR is employed to find similar historical analogues of multisite occurrence to the current status of a simulation series, GA is applied to use its skill to generate a new descendant from the historical parent chosen with the KNNR. In this procedure, the multisite occurrence of the precipitation variable can be simulated with preserving spatial and temporal correlations. Note that meta-heuristic techniques to GA have been popularly employed in a number of hydrometeorological applications (Chau, 2017; Fotovatikhah et al., 2018; Taormina et al., 2015; Wang et al., 2013). A number of variants of KNNR-GA have since been applied (Lee et al., 2012; Lee and Park, 2017). None of these models can adopt the multisite occurrence in precipitation whose characteristics are binary and temporally and spatially related.

Therefore, in the current study we propose a novel stochastic simulation method for multisite occurrence of the precipitation variable with the KNNR-GA based nonparametric approach that (1) simulate multisite occurrence with a simple and direct procedure without the parameterization of all the required occurrence probabilities; and (2) reproduce the complex temporal and spatial correlation between stations as well as the basic occurrence probabilities. Note that the proposed nonparametric model is compared with the most popularly employed model proposed by Wilks (1998). Even though the multisite occurrence data from this model (Wilks, 1998) preserves various statistical characteristics of the observed data well, significant underestimation of lagged cross-correlation still exists. Furthermore, the relation between standard normal variable and occurrence variable relies on long stochastic simulation_ENREF_32.

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~~Lall and Sharma (1996) proposed a nonparametric simulation model, called k-nearest neighbor resampling (KNNR). The model has been updated to simulate multivariate hydro-~~

~~meteorological variables (Brandsma and Buishand, 1998; Mehrotra et al., 2006; St-Hilaire et al., 2012). One of the major drawbacks of this multivariate KNNR model is that the simulated data cannot produce patterns different from those of the observed data. Lee et al. (2010a) overcame this shortcoming by mixing the simulated dataset with Genetic Algorithm (GA) that led to the reproduction of similar populations(Chau, 2017; Fotovatikhah et al., 2018; Taormina et al., 2015; Wang et al., 2013). A number of variants of KNNR-GA have since been applied (Lee et al., 2012; Lee and Park, 2017). For example, Lee et al. (2012) proposed a weather generation model that produces weather variables but only for a single station with further following a further development by Lee and Park (2017). None of these models can adopt the multisite occurrence in precipitation whose characteristics are binary and temporally and spatially related.~~

~~Therefore, in the current study we propose a novel simulation method for multisite occurrence of the precipitation variable with a the KNNR-GA based nonparametric approach. While the KNNR is employed to find a similar historical analogues of multisite occurrence to the current status of a simulation series, GA is applied to use its skill to generate a new descendant from the historical parent chosen with the KNNR. In this procedure, the multisite occurrence of the precipitation variable can be simulated with preserving spatial and temporal correlations.~~

~~The proposed nonparametric model is compared with the existing multisite modelEven though the multisite occurrence data simulated by this model preserves various statistical characteristics of the observed data well, some drawbacks still exist, such as underestimation of lagged cross-correlation. Furthermore, the relation between standard normal variable and occurrence variable relies on long stochastic simulation. Wilks (1998). Originally, the occurrence of precipitation had been simulated with discrete Markov Chain model (Katz, 1977). Compared to the MC model requires a significant amount of parameters to generate multisite occurrence, the~~

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~~multisite occurrence model proposed by (Wilks, 1998) transforms the standard normal variate and simulate the sequence with multivariate normal distribution then back-transforms the multivariate sequence. The model is able to reproduce the contemporaneous multisite dependence structure and lagged dependence only for the same site while require a complex simulation process to estimate parameter for each site and unable to preserve lagged dependence between sites.~~

The paper is organized as follows. The next section presents a mathematical background of existing multisite occurrence modeling. The modeling procedure is discussed in section 3. The study area and data are reported in section 4. The model is applied in section 5. Results of the proposed model are discussed in section 6, and summary and conclusions are presented in section 7.

2. Background

2.1. Single site occurrence modeling

Let X_t^s represent the occurrence of daily precipitation for a location *s* (*s*=1,…, *S*) on day *t* (*t*=1,…, *n*; *n* is the number observed days) and let X_t^s be either zero for dry day or one for wet day. The first order Markov chain model for X_t^s is defined with the assumption that the occurrence probability of a wet day is fully defined by the previous day as

$$\Pr\left\{X_t^s = 1 \mid X_{t-1}^s = 0\right\} = p_{01}^s \qquad (1)$$

$$\Pr\left\{X_t^s = 1 \mid X_{t-1}^s = 1\right\} = p_{11}^s \qquad (2)$$

Also $p_{00}^s = 1 - p_{01}^s$ and $p_{10}^s = 1 - p_{11}^s$, since the summation of zero and one should be unity with the same previous condition. This consists of a transition probability matrix (TPM) as

$$TPM^{s} = \begin{bmatrix} p_{00}^{s} & p_{01}^{s} \\ p_{10}^{s} & p_{11}^{s} \end{bmatrix} = \begin{bmatrix} 1-p_{01}^{s} & p_{01}^{s} \\ 1-p_{11}^{s} & p_{11}^{s} \end{bmatrix} \tag{3}$$

The marginal distributions of TPM (i.e. p_0 and p_1) can be expressed with TPM and its condition of $p_0 + p_1 = 1$ as:

$$p_0^s = \frac{p_{01}^s}{1 + p_{01}^s - p_{11}^s} \tag{4}$$

$$p_1^s = \frac{1 - p_{11}^s}{1 + p_{01}^s - p_{11}^s} \tag{5}$$

Note that p_1 represents the probability of precipitation occurrence for a day, while p_0 does non-occurrence. The lag-1 autocorrelation of precipitation occurrence is the combination of transition probabilities as:

$$\rho_1(s,s) = p_{11}^s - p_{01}^s \tag{6}$$

The simulation can be done by comparing TPM with a uniform random number (u_t^s) as

$$X_t^s = \begin{cases} 1 & \text{if } u_t^s \le p_{i1}^s \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where p_{i1}^s is the selected probability from TPM regarding the previous condition i (i.e. either 0 or 1). Wilks (1998) suggested a different method using a standard normal random number w_t^s ~N[0,1] as

$$X_t^s = \begin{cases} 1 & \text{if } w_t^s \le \Phi^{-1}(p_{i1}^s) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where Φ^{-1} indicates the inverse of the standard normal cumulative function Φ.

2.2. Multisite occurrence modeling

Wilks (1998) suggested a multisite occurrence model using a standard normal random number (here, denoted as MONR) that is spatially dependent but serially independent. The correlation of the standard normal variate for a site pair of *q* and *s* can be expressed as:

$$\tau(q,s) = corr[w_t^q, w_t^s] \qquad (9)$$

Also, the correlation of the original occurrence variate is

$$\rho(q,s) = corr[X_t^q, X_t^s] \qquad (10)$$

Once the correlation of the standard normal variate is known, the simulation of multisite precipitation occurrence is straightforward. Multivariate standard normal distribution is used with the parameter set of [**0**, **T**] where **0** is the zero vector (*S*x1) and **T** is the correlation matrix with the elements of $\tau(q,s)$ for $q \in \{1,...,S\}$ and $s \in \{1,...,S\}$.

Since direct estimation of $\tau(q,s)$ is not applicable, a simulation technique is used to estimate $\tau(q,s)$ from $\rho(q,s)$. A long sequence of the occurrence process is simulated with different values of $\tau(q,s)$ and its corresponding correlation of the original domain $\rho(q,s)$ is estimated with the simulated long sequence by the inverse standard normal cumulative function (i.e. $\mathbf{\Phi}^{-1}$). A curve between $\tau(q,s)$ and $\rho(q,s)$ is derived from this long simulation with the MONR model and is employed for the parameter estimation for real application.

3. DKNNR

3.1. DKNNR modeling procedure

In the current study, a novel multisite simulation model for sdiscrete occurrence of precipitation variable with k-nearest neighbor resampling (KNNR) technique (Lall and Sharma, 1996; Lee and Ouarda, 2011; Lee et al., 2017) for discrete case (denoted as Discrete KNNR; DKNNR) is proposed by combining a mixture mechanism with Genetic Algorithm (GA).

Provided the number of nearest neighbors, *k*, is known, the discrete k-nearest neighbor resampling with genetic algorithm is done as follows:

(1) Estimate the distance between the current (i.e. time index: c) multisite occurrence X_c^s and the observed multisite occurrence x_i^s. Here, the distance is measured for *i*=1,…,*n*-1 as

$$D_i = \sum_{s=1}^{S} \left| X_c^s - x_i^s \right| \tag{11}$$

(2) Arrange the estimated distances from step (1) in ascending order, select the first *k* distances (i.e., the smallest *k* values), and reserve the time indices of the smallest *k* distances.

(3) Randomly select one of the stored *k* time indices with the weighting probability given by

$$w_m = \frac{1/m}{\sum_{j=1}^{k} 1/j}\ , \qquad m = 1,...,k \tag{12}$$

(4) Assume the selected time index from step (3) as *p*. Note that there are a number of values that have the same distance as the selected D_p, since D_p is a natural number between 0 and *S*. For example, if S=2 and X_c^1=0 and X_c^2=1, the two sequences has the same *D*=1 as [x_i^1=0 and x_i^2=0] and [x_i^1=1 and x_i^2=1]. In this case, ~~A~~ a random selection procedure is required to take into account the cases with the same quantity. One particular time index is randomly selected with the equal probabilities among the time indices of the same distances. Note that instead of the random selection, one can use always the first one. In such a case, only one historical combination of multisite occurrences will be selected.

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(5) Assign the binary vector of the proceeding index of the selected time as $\mathbf{x}_{p+1} = [x^s_{p+1}]_{s\in\{1,S\}}$. Here, *p* is the finally selected time index from step (4).

(6) Execute the following steps for GA mixing if GA mixing is selected. Otherwise, skip this step.

(6-1) Reproduction: Select one additional time index using steps (1) through (4) and denote this index as *p**. Obtain the corresponding precipitation occurrence values, $\mathbf{x}_{p^*+1} = [x^s_{p^*+1}]_{s\in\{1,\dots,S\}}$. The subsequent two GA operators employ the two selected vectors, $\mathbf{x}_{p+1}$ and $\mathbf{x}_{p^*+1}$. This reproduction process is a mating process by finding another individual that has similar characteristics to the current one $\mathbf{x}_{p+1}$. With this procedure, a similar vector to the current vector will be mated and produce a new descendant.

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(6-2) Crossover: Replace each element x^s_{p+1} with $x^s_{p^*+1}$ at probability P_{cr}, i.e.,

$$X_{c+1}^{s}=\begin{cases} x_{p^*+1}^{s} & \text{if } \ \varepsilon < P_{cr} \\ x_{p+1}^{s} & \text{otherwise} \end{cases} \tag{13}$$

where ε is a uniform random number between 0 and 1. From this crossover, a new occurrence vector whose elements are similar to the historical is generated.

(6-3) Mutation: Replace each element (i.e., each station, s=1,…, S) with one selected from all the observations of this element for i=1,…,n with probability P_m, i.e.,

$$X_{c+1}^{s}=\begin{cases} x_{\xi+1}^{s} & \text{if } \ \varepsilon < P_{m} \\ x_{p+1}^{s} & \text{otherwise} \end{cases} \tag{14}$$

where $x_{\xi+1}^{s}$ is selected from $[x_i^s]_{i\in\{1,\ldots,n\}}$ with equal probability for i=1,…,n and ε is a uniform random number between 0 and 1. This mutation procedure allows to generate a multisite occurrence combination that is totally different from the historical records. Without this procedure, always similar multisite occurrences to historical combinations are generated, which is not feasible for a simulation purpose. ~~the~~

(7) Repeat steps (1)-(6) until the required data are generated.

The selection of the number of nearest neighbors (k) has been investigated by Lall and Sharma (1996) and Lee and Ouarda (2011). A simple selection method was applied in the current study as $k=\sqrt{n}$. For hydrometeorological stochastic simulations, this heuristic approach of k selection has been employed (Lall and Sharma, 1996; Lee and Ouarda, 2012; Lee et al., 2010b; Prairie et al., 2006; Rajagopalan and Lall, 1999). One can use generalized cross-validation (GCV) as shown in Sharma and Lall1996 and Lee and Ouarda 2011 by treating this simulation as a prediction problem. However, the current multisite occurrence simulation does not necessarily require accurate value prediction and not much difference on simulation using the simple heuristic approach is reported. Also, this heuristic approach of *k* selection has been popularly employed for hydrometeorological stochastic simulations (Lall and Sharma, 1996; Lee and Ouarda, 2012; Lee et al., 2010b; Prairie et al., 2006; Rajagopalan and Lall, 1999).

~~The roles of crossover probability~~ P_{cr} ~~and mutation probability~~ P_m ~~were studied by Lee et al. (2010b). Lee et al. (2010b) showed that~~ ~~P_{cr} =0.1 and P_m=0.01 can be a reasonable parameter set which does not critically affect the performance. Therefore, this parameter set was applied in the current study.~~ In Appendix A, an example of the DKNNR simulation procedure is explained in detail.

3.2. Adaptation to climate change

The capability of model to take climate change into account is critical. For example, the marginal distributions and transition probabilities in Eqs. (5)~~(5)~~ and (3)~~(3)~~ can change in future climate scenarios. It is known that nonparametric simulation models have a difficulty to adapt to climate change, since the models employ in general the current observation sequences. However, the proposed model in the current study possesses the capability to adapt to the variations of probabilities by tuning the crossover and mutation probabilities in P_{cr} (13)~~(13)~~ and P_m (14)~~(14)~~ , adding the condition when applied.

For example, the probability of P_{11} can be increased with the cross-over probability P_{cr} by adding the condition to increase the probability of P_{11} as:

$$X_{c+1}^{s} = \begin{cases} x_{p*+1}^{s} & \text{if } \varepsilon < P_{cr} \ \& \ x_{p*+1}^{s} = 1 \ \& \ X_{c}^{s} = 1 \\ x_{p+1}^{s} & \text{otherwise} \end{cases} \qquad (15)$$

It is obviously possible to increase the probability of P_1 by removing the condition of $X_c^s = 1$.

In addition, further adjustment can be made with the mutation process in Eq. (14)~~(14)~~ as

$$X_{c+1}^{s} = \begin{cases} x_{\xi+1}^{s} & \text{if } \varepsilon < P_{m} \text{ and } x_{\xi+1}^{s} = 1 \\ x_{p+1}^{s} & \text{otherwise} \end{cases} \qquad (16)$$

This adjustment of adding the condition $x_{\xi+1}^{s} = 1$ can increase the marginal distribution as much as $P_m \times P_1$. This has been tested in the case study.

4. Study area and data description

For testing the occurrence model, 12 weather stations were selected from Yeongnam province which is located in the southeastern part of South Korea, as shown in Figure 1~~Figure 1~~. Information on longitude and latitude (fourth and fifth columns) as well as order index and the identification number (first and second columns) of these stations operated by Korea Meteorological Administration with the area name (third column) is shown at Table 1~~Table 1~~.

Figure 1~~Figure 1~~ illustrates the locations of the selected weather stations. All the stations are inside Yeongnam province which consists of two different regions as north and south Gyeongsang as well as the self-governing cities of Busan, Deagu, and Ulsan. Most of the Yeongnam region is drained to Nakdong River. To validate the proposed model appropriately, tested sites must be highly correlated with each other as well as significant temporal relation. The employed stations inside the Yeongnam area cover one of the most important watersheds, the Nakdong River basin, where the Nakdong river pass through the entire basin and its hydrological assessments for agriculture and climate change has particular values in water resources management such as floods and droughts.

It is important to analyze the impact of weather conditions for planning agricultural operations and water resources management especially during the summer season, because around 50-60 percent of the annual precipitation occurs during the summer season from June to September. The length of daily precipitation data record ranges from 1976 to ~~2008~~ 2015 and the summer season record was employed since a large number of rainy days occurs during summer and it is important to preserve these characteristics. Also, the whole year dataset was tested and other seasons were further applied but the correlation coefficient was relatively high and its correlation matrix estimated was not a positive semi-definite matrix for the MONR model.

5. Application

To analyze the performance of the proposed DKNNR model, the occurrence of precipitation was simulated. The DKNNR simulation was compared with that of the MONR model. For each model, 100 series of daily occurrence with the same record length were simulated. The key statistics of observed data and each generated series, such as transition probabilities (P_{11}, P_{01} , and P_1) and cross-correlation (see Eq.(10)~~(10)~~), were determined. The MONR model underestimated the lag-1 cross-correlation, as indicated by Wilks (1998). In the current study, this statistic was analyzed, since a synoptic scale weather system could result in lagged cross-correlation (Wilks, 1998). It was formulated as

$$\rho_1(q,s) = corr[X_{t-1}^{q}, X_{t}^{s}] \qquad (17)$$

Statistics from 100 generated series were evaluated by the root mean square error (RMSE) expressed as below:

$$RMSE = \left(\frac{1}{N} \sum_{m=1}^{N} (\Gamma_m^G - \Gamma^h)^2 \right)^{1/2} \qquad (18)$$

where N is the number of series (here 100), Γ_m^G is the statistic estimated from the m^{th} generated series, while Γ^h is the statistic for the observed data. Note that lower RMSE indicates better performance representing the summarized error of a given statistic of generated series from the statistic of the observed data.

The 100 simulated statistic values were illustrated with boxplots to show their variability as shown in Figure 4~~Figure 4~~ - Figure 6~~Figure 6~~. The box of boxplot represents the interquartile range (IQR) ranging 25 percentile to 75 percentile. The whiskers extend to up and down 1.5×IQR. Data beyond the whiskers (1.5×IQR) are indicated by a plus sign (+). The horizontal line inside the box represents the median of the data. The statistics of the observed data are denoted by a cross (x). The closer a cross is to the horizontal line inside the box, the better the simulated data from a model reproduces the statistical characteristics of the observed data.

The roles of crossover probability P_{cr} (Eq. (13)) and mutation probability P_m (Eq.(14)) were studied by Lee et al. (2010b). In the current study, we further tested to select appropriate parameter set of these two parameters with the simulated data from the DKNNR model and the record length of 100,000. RMSE (Eq. (18)) of the three transition and limiting probabilities (P_{11}, P_{01}, and P_1) between the simulated data and the observed was used since those probabilities are key statistics that the simulated data must be met with the observed and no parameterization on these

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probabilities has been made for the current DKNNR model. The results are shown in Figure 2 and Figure 3 for P_{cr} and P_m, respectively. For P_{cr} in Figure 2, the probability of 0.02 shows the smallest RMSE in all transition and limiting probabilities. The RMSE of P_m in Figure 3 shows slight fluctuation along with P_m. However, all three probabilities (P_{11}, P_{01}, and P_1) have relatively small RMSEs in P_m =0.003. Therefore, the parameter set 0.02 and 0.003 is chosen for P_{cr} and P_m, respectively and employed in the current study.

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6. Results

6.1. Occurrence and transition probabilities

The data simulated from the proposed DKNNR model and the existing MONR model were analyzed. The estimated transition probabilities (P_{11} and P_{01} in Eq. (3)~~(3)~~) as well as the occurrence probability (P_1 in Eq. (5)~~(5)~~) are shown in Table 2~~Table 2~~ and Figure 4~~Figure 4~~ - Figure 6~~Figure 6~~ for the observed data and the data generated from the DKNNR and MONR models. In Table 2~~Table 2~~, the observed statistic shows that P_{11} is always higher than P_{01} and P_1 is between P_{11} and P_{01}. Site 6 shows the lowest P_{11} and P_1 and site 12 shows the highest P_{11}.

As shown in Figure 4~~Figure 4~~, the probability P_{11} of the observed data shows that sites 6, 7, 8, and 9 located in the northern part of the region exhibited lower consistency (i.e. consecutive rainy days) than did the other sites, while sites 5 and 12 had higher probability of P_{11} than did other sites. Both models preserved well the observed P_{11} statistic. It seems that the MONR model had a slightly better performance since this statistic is parameterized in the model as shown in the section 2.2. Note that the MONR model employed the transition probabilities in simulating rainfall occurrence, while DKNNR model did not. The occurrence probability P_1 can be described with the combination of transition probabilities as in Eq. (5)~~(5)~~. Even though the transition probabilities were not employed in simulating rainfall occurrence, the DKNNR model preserved this statistic fairly well.

As shown in Figure 5~~Figure 5~~, the P_{01} probability showed a slightly different behavior such that sites 1, 2, and 3 located in the middle part of the Yeongnam province showed a higher probability than did other sites. A slight underestimation was seen for sites 2 and 11 but it was not critical, since its observed value with a cross mark was close to the upper IQR representing 75 percentile.

The behavior of P_1 was found to be same as that of the P_{11} probability. It can be seen in Figure 6~~Figure 6~~ that no significant underestimation is seen for the DKNNR model (top panel). The P_1 statistic was fairly preserved by both DKNNR and MONR models. Note that the MONR model parameterized the P_1 statistic through the transition probabilities as in Eq. (5)~~(5)~~, while DKNNR model did not. Although the DKNNR model did not use ~~any~~ almost no parameters for simulation, the P_1 statistic was preserved fairly well.

6.2. Cross-correlation

Cross-correlation is a measure of relationship between sites. Preservation of cross-correlation is important for the simulation of precipitation occurrence and is required in the regional analysis for water resources management or agricultural applications. Furthermore, lagged cross-correlation is also essential as much as is cross-correlation (i.e. contemporaneous correlation). For example, the amount of streamflow for a watershed from a certain precipitation event is highly related with lagged cross-correlation. It is accepted that precipitation event is not significantly correlated with more than one day. Therefore, only lag-1 cross-correlation was analyzed in the current study.

The cross-correlation of observed data is shown in Table 3~~Table 3~~. High cross-correlation among grouped sites, such as sites 6, 7, and 8 (northern part) and sites 3, 4, and 5 as well as 12 (southeast coastal area, 0.68-0.87), was found. As expected, sites 5 and 12 had the highest cross-correlation (0.87) due to the proximity. The northern sites and coastal sites showed low cross-correlation. This observed cross-correlation was well preserved in the data generated from both DKNNR and MONR models, as shown in Figure 7~~Figure 7~~ as well as Table 4~~Table 4~~ and Table 5~~Table 5~~. However, consistently slight but significant underestimation of cross-correlation was seen for the data generated by the MONR model (see the bottom panel of Figure 7~~Figure 7~~). Note that the errobars are extended to upper and lower lines of the circles to 1.95×standard deviation. The difference of RMSE in Table 6~~Table 6~~ showed this characteristic, as most of the values were positive, to be indicating that the proposed DKNNR model performed better for cross-correlation.

The lag-1 cross-correlation of observed data, as shown in Table 7~~Table 7~~, ranged from 0.22-0.35. The lag-1 cross-correlation for the same site (i.e. $\rho_1(q,s)$, q=s) was autocorrelation and was highly related with P_{01} and P_{11} as in Eq. (6)~~(6)~~. All the lag-1 cross-correlations exhibited similar magnitudes even for autocorrelation. This implies that the lag-1 cross-correlation among the selected sites was as strong as the autocorrelation and as much as the transition probabilities P_{01} and P_{11}, thereof. ~~Relatively low lag-1 cross-correlation was observed between northern sites (6, 7, and 8) and coastal sites (3, 4, and 5), as shown in Table 7.~~

The observed lag-1 cross-correlations ~~was~~ were well preserved in the data generated by the DKNNR model, as shown in the top panel of Figure 8~~Figure 8~~, while the MONR model showed significant underestimation, as seen in the bottom panel of Figure 8~~Figure 8~~. The difference of RMSE shown in Table 8~~Table 8~~ reflects this behavior. In the bottom panel of Figure 8~~Figure 8~~, some of the lag-1 cross-correlations were well preserved, that was aligned with the base line. From Table 8~~Table 8~~, the MONR model reproduced the autocorrelations well with the shaded values. It is because the lag-1 autocorrelation was indirectly parameterized with the transition probabilities of P_{11} and P_{01} as in Eq. (6)~~(6)~~. Other than this autocorrelation, the lag-1 cross-correlation was not reproduced well with the MONR model. This shortcoming was mentioned by Wilks (1998). Meanwhile, the proposed DKNNR model preserved this statistic without any parameterization.

We further tested the performance measurements of MAE and Bias. The estimates showed that MAE has no difference from RMSE. In addition, Bias of the lag-1 correlation presents significant negative values implying its underestimation for the simulated data of the MONR model as shown in Table 9~~Table 9~~ while Table 10~~Table 10~~ of the DKNNR model shows much smaller bias.

Also, the whole year data instead of the summer season data was tested for model fitting. Note that all the results presented above were with the summer season data (June-September) as mentioned in section 4 on the data description. The lag-1 cross-correlation is shown in Figure 9~~Figure 9~~ which indicates that the same characteristic was observed as for the summer season, such that the proposed DKNNR model preserved better the lagged cross-correlation than did the existing MONR model. Other statistics, such as correlation matrix and transition probabilities, exhibited the same results (not shown). Also, other seasons were tried but the estimated correlation matrix was not a positive semi-definite matrix and its inverse cannot be made for multivariate normal distribution in the MONR model. It was because the selected stations were close to each other (around 50-100 km) and produced high cross-correlation, especially in the occurrence during dry seasons. Special remedy for the existing MONR model should be applied, such as decreasing cross-correlation by force, but further remedy was not applied in the current study since it was not within the current scope and focus.

6.3. Adaptation to climate change

Model adaptability to climate change in hydro-meteorological simulation models is a critical factor, since one of the major applications of the models is to assess the impact of climate change. Therefore, we tested the capability of the proposed model in the current study by adjusting the probabilities of cross-over and mutation as in Eqs.(15)~~(15)~~ and (16)~~(16)~~. A number of variations can be made with different conditions.

In Figure 10~~Figure 10~~, the changes of transition and marginal probabilities are shown along with increasing the crossover probability P_{cr} from 0.01 to 0.2 with the condition that that the candidate value is one and the previous value is also one as in Eq. (15)~~(15)~~ for the selected 5 stations among the 12 stations (from station 1 to station 5, see Table 1~~Table 1~~ for the detail). The stations were limited in this analysis due to computational time. At each case 100 series were simulated. The average value of the simulated statistics is presented in the figure. It is obvious that the transition probability P_{11} increased as intentioned along with the increase of P_{cr} . As expected from Eq. (5)~~(5)~~, P_1 presents that the change of P_1 is highly related to P_{11}. However, the probability P_{01} fluctuated along with the increase of P_{cr}. Elaborate work to adjust all the probabilities is however required.

The changes in transition and marginal probabilities are presented in Figure 11~~Figure 11~~ with increasing mutation probability P_m from 0.01 to 0.2 under the condition that the candidate value is one so that the marginal probability P_1 increased. P_{01} also increased along with increasing P_1. The change of P11 was not related with other probabilities. The combination of the adjustment of P_{cr} and P_m with a certain condition to the previous state will allow the specific adaptation for simulating future climatic scenarios.

7. Conclusions

In the current study, a nonparametric simulation model, based on discrete KNNR and DKNNR, is proposed to overcome the shortcomings of the existing MONR model such as long stochastic simulation for the parameter estimation and underestimation of the lagged crosscorrelation between sites. ~~The proposed DKNNR model is compared with the existing MONR model.~~ Occurrence and transition probabilities and cross-correlation as well as lag-1 cross-correlation are estimated for both models. Better preservation of cross-correlation and lag-1 cross-correlation with the DKNNR model than the MONR model is observed. For some cases (i.e., the whole year data and other seasons than the summer season), the estimated cross-correlation matrix is not a positive semi-definite matrix so the multivariate normal simulation is not applicable for the MONR model because the tested sites are close to each other with high cross-correlation.

Results of this study indicate that the proposed DKNNR model reproduces the occurrence and transition probabilities fairly well and preserves the cross-correlations better than the existing MONR model. Furthermore, not much effort is required to estimate the parameters in the DKNNR model while the MONR model requires a long stochastic simulation just to estimate each parameter. Thus, the proposed DKNNR model can be a good alternative for simulating multisite precipitation occurrence.

We tested further enhancement of the proposed model for adapting climate change through modifying the mutation and crossover probability P_m and P_{cr} with the current and previous states. The results show that the current model has the capability to adapt to the climate change scenarios, but elaborate work is required however. Further study on improving the model adaptability to climate change will be followed in near future.

Also, the simulated multisite occurrence can be coupled with a multisite amount model to produce precipitation events, including zero values. Further development can be made for multisite amount models with a nonparametric technique, such as KNNR and bootstrapping.

Code and Data Availability

DKNNR code is written in Matlab and is available at the supplement.

The precipitation data employed in the current study is downloadable through http://www.weather.go.kr/weather/main.jsp

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Appendix A: Example of DKNNR

In this appendix, one example of DKNNR simulation is presented with observed dataset in Table A 1~~Table A 1~~ (i.e. $\mathbf{x}_i = [x_i^s]_{s\in\{1,S\}}$ for *i*=1,…,*n*; here *S*=12 and *n*=16). The upper part of the table presents the observed precipitation (unit: mm). Its occurrence data is presented in the bottom part of this table. The current precipitation occurrence $\mathbf{X}_c = [X_c^s]_{s\in\{1,\ldots,12\}}$ is shown in the second row of Table A 2~~Table A 2~~. The number of nearest neighbors $k = \sqrt{n} = \sqrt{16} = 4$ and the parameters for GA (i.e. P_c and P_m) are 0.1 and 0.01, respectively. The simulation can be made as follows:

(1) Estimate the distance D_i between $\mathbf{x}_i$ and $\mathbf{X}_c$ for i=1,…,n-1 as in Eq.(11)~~(11)~~. For example, for i=1,

$$D_1 = \sum_{s=1}^{S} \left| X_c^s - x_1^s \right| = |0-1| + |1-1| + ... + |0-1| = 6$$

All the estimated distances are shown in the last column of Table A 2~~Table A 2~~.

(2) The daily index values are sorted according to the smallest distances shown in the first two columns of Table A 3~~Table A 3~~. The sorted day indices and their corresponding distances are shown in the third and fourth columns of Table A 3~~Table A 3~~. Among k number of sorted indices, one is selected with the weight probability (see Eq.(12)~~(12)~~), which is shown in the last column of Table A 3~~Table A 3~~.

(3) Simulate a uniform random number (u) between 0 and 1. Say u=0.321. This value must be compared with the cumulative weighted probabilities in the last column of Table A 3~~Table A 3~~ as [0 0.48 0.72 0.88 1.0]. The corresponding day index is assigned as to where the simulated uniform number falls in the cumulative weighted probabilities, here [0 0.48]. Therefore, the selected day, p, is 14. The occurrences of the following day p+1=15 for 12 stations are selected as in the second row of Table A 4~~Table A 4~~.

(4) For GA mixture, another set must be chosen as in step (3). Say u=0.561, which falls in [0.48 0.72]. The second one should be selected. However, there are a number of days with the same distances. Specifically, six days have the same distances with D_i=4. In this case, one among all six days is selected with equal probability. Assume that p=4 is selected and the following occurrences are selected as shown in the third row of Table A 4~~Table A 4~~.

(5) With two sets, crossover and mutation process is performed as follows:

(5-1) Crossover: For each station, a uniform random number (ε) is generated and compared with P_c=0.1 here. Say ε =0.345, then skip since ε =0.345> P_c=0.1. For s=6, assume the generated random number, ε (=0.051)< P_c(=0.1) and then switch the 6th station value of Set 1 into the value of Set 2 (see Table A 4~~Table A 4~~). The occurrence state of X_{c+1}^{s} turns into 1 from 0 as shown in the fourth row of Table A 4~~Table A 4~~ as well as station 8.

(5-2) Mutation: For each station, a uniform random number (ε) is generated and compared with P_m=0.01. For s=12, assume ε =0.009< P_m=0.01 and switch the 12th station value of Set 1 with the one selected among all the observed 12th station values with equal probability (here the last column, s=12, of the bottom part of Table A 1~~Table A 1~~, [1 1 0 0 … 1]). The occurrence state of X_{c+1}^{12} turns into 0 from 1 as shown in the fourth column of Table A 4~~Table A 4~~.

(6) Repeat steps (1)-(5) until the target simulation length is reached.

References

Apipattanavis, S., Podesta, G., Rajagopalan, B., and Katz, R. W.: A semiparametric multivariate and multisite weather generator, Water Resources Research, 43, Artn W11401, 2007.

Beersma, J. J. and Buishand, A. T.: Multi-site simulation of daily precipitation and temperature conditional on the atmospheric circulation, Climate Research, 25, 121-133, 2003.

Brandsma, T. and Buishand, T. A.: Simulation of extreme precipitation in the Rhine basin by nearest-neighbour resampling, Hydrology and Earth System Sciences, 2, 195-209, 1998.

Buishand, T. A. and Brandsma, T.: Multisite simulation of daily precipitation and temperature in the Rhine basin by nearest-neighbor resampling, Water Resources Research, 37, 2761-2776, 2001.

Chau, K. W.: Use of meta-heuristic techniques in rainfall-runoffmodelling, Water (Switzerland), 9, 2017.

Fotovatikhah, F., Herrera, M., Shamshirband, S., Chau, K. W., Ardabili, S. F., and Piran, M. J.: Survey of computational intelligence as basis to big flood management: Challenges, research directions and future work, Engineering Applications of Computational Fluid Mechanics, 12, 411-437, 2018.

Frost, A. J., Charles, S. P., Timbal, B., Chiew, F. H. S., Mehrotra, R., Nguyen, K. C., Chandler, R. E., McGregor, J. L., Fu, G., Kirono, D. G. C., Fernandez, E., and Kent, D. M.: A comparison of multi-site daily rainfall downscaling techniques under Australian conditions, Journal of Hydrology, 408, 1-18, 2011.

Hughes, J. P., Guttorp, P., and Charles, S. P.: A non-homogeneous hidden Markov model for precipitation occurrence, Journal of the Royal Statistical Society. Series C: Applied Statistics, 48, 15-30, 1999.

Jeong, D. I., St-Hilaire, A., Ouarda, T. B. M. J., and Gachon, P.: A multi-site statistical downscaling model for daily precipitation using global scale GCM precipitation outputs, International Journal of Climatology, 33, 2431-2447, 2013.

Jeong, D. I., St-Hilaire, A., Ouarda, T. B. M. J., and Gachon, P.: Multisite statistical downscaling model for daily precipitation combined by multivariate multiple linear regression and stochastic weather generator, Climatic Change, 114, 567-591, 2012.

Katz, R. W.: Precipitation as a Chain-Dependent Process, Journal of Applied Meteorology, 16, 671-676, 1977.

Katz, R. W. and Zheng, X.: Mixture model for overdispersion of precipitation, Journal of Climate, 12, 2528-2537, 1999.

Lall, U. and Sharma, A.: A nearest neighbor bootstrap for resampling hydrologic time series, Water Resources Research, 32, 679-693, 1996.

Lee, T.: Multisite stochastic simulation of daily precipitation from copula modeling with a gamma marginal distribution, Theoretical and Applied Climatology, doi: 10.1007/s00704-017-2147-0, 2017. 1-10, 2017.

Lee, T.: Stochastic simulation of precipitation data for preserving key statistics in their original domain and application to climate change analysis, Theoretical and Applied Climatology, 124, 91-102, 2016.

Lee, T. and Ouarda, T. B. M. J.: Identification of model order and number of neighbors for k-nearest neighbor resampling, Journal of Hydrology, 404, 136-145, 2011.

Lee, T. and Ouarda, T. B. M. J.: Stochastic simulation of nonstationary oscillation hydro-climatic processes using empirical mode decomposition, Water Resources Research, 48, 1-15, 2012.

Lee, T., Ouarda, T. B. M. J., and Jeong, C.: Nonparametric multivariate weather generator and an extreme value theory for bandwidth selection, Journal of Hydrology, 452-453, 161-171, 2012.

Lee, T., Ouarda, T. B. M. J., and Yoon, S.: KNN-based local linear regression for the analysis and simulation of low flow extremes under climatic influence, Climate Dynamics, doi: 10.1007/s00382-017-3525-0, 2017. 1-19, 2017.

Lee, T. and Park, T.: Nonparametric temporal downscaling with event-based population generating algorithm for RCM daily precipitation to hourly: Model development and performance evaluation, Journal of Hydrology, 547, 498-516, 2017.

Lee, T., Salas, J. D., and Prairie, J.: An enhanced nonparametric streamflow disaggregation model with genetic algorithm, Water Resources Research, 46, 2010a.

Lee, T., Salas, J. D., and Prairie, J.: An Enhanced Nonparametric Streamflow Disaggregation Model with Genetic Algorithm, Water Resources Research, 46, W08545, 2010b.

Mehrotra, R., Srikanthan, R., and Sharma, A.: A comparison of three stochastic multi-site precipitation occurrence generators, Journal of Hydrology, 331, 280-292, 2006.

Prairie, J. R., Rajagopalan, B., Fulp, T. J., and Zagona, E. A.: Modified K-NN model for stochastic streamflow simulation, Journal of Hydrologic Engineering, 11, 371-378, 2006.

Rajagopalan, B. and Lall, U.: A k-nearest-neighbor simulator for daily precipitation and other weather variables, Water Resources Research, 35, 3089-3101, 1999.

St-Hilaire, A., Ouarda, T. B. M. J., Bargaoui, Z., Daigle, A., and Bilodeau, L.: Daily river water temperature forecast model with a k-nearest neighbour approach, Hydrological Processes, 26, 1302-1310, 2012.

Taormina, R., Chau, K. W., and Sivakumar, B.: Neural network river forecasting through baseflow separation and binary-coded swarm optimization, Journal of Hydrology, 529, 1788-1797, 2015.

Todorovic, P. and Woolhiser, D. A.: Stochastic model of n-day precipitation Journal of Applied Meteorology, 14, 17-24, 1975.

Wang, W. C., Xu, D. M., Chau, K. W., and Chen, S.: Improved annual rainfall-runoff forecasting using PSO-SVM model based on EEMD, Journal of Hydroinformatics, 15, 1377-1390, 2013.

Wilby, R. L., Tomlinson, O. J., and Dawson, C. W.: Multi-site simulation of precipitation by conditional resampling, Climate Research, 23, 183-194, 2003.

Wilks, D. S.: Multisite downscaling of daily precipitation with a stochastic weather generator, Climate Research, 11, 125-136, 1999.

Wilks, D. S.: Multisite generalization of a daily stochastic precipitation generation model, Journal of Hydrology, 210, 178-191, 1998.

Wilks, D. S. and Wilby, R. L.: The weather generation game: a review of stochastic weather models, Progress in Physical Geography, 23, 329-357, 1999.

Zheng, X. and Katz, R. W.: Simulation of spatial dependence in daily rainfall using multisite generators, Water Resources Research, 44, 2008.

Table 1. Information on 12 selected stations from Yeongnam province, South Korea.

Order	Station Number[†]	Name	Longitude	Latitude
1	138	Pohang	129.3797	36.0327
2	143	Daegu	128.6189	35.8850
3	152	Ulsan	129.3200	35.5600
4	159	Busan	129.0319	35.1044
5	162	Tongyeong	128.4356	34.8453
6	277	Youngdeok	129.4092	36.5331
7	278	Uisung	128.6883	36.3558
8	279	Gumi	128.3206	36.1306
9	281	Youngcheon	128.9514	35.9772
10	285	Hapcheon	128.1697	35.5650
11	288	Milyang	128.7439	35.4914
12	294	Geojae	128.6044	34.8881

[†] The station number indicates the identification number operated by Korea Meteorological Administration (KMA).

Table 2. Occurrence and transition probabilities of observed data and data simulated by DKNNR and MONR for 12 stations from Yeongnam province, South Korea, during the summer season. Note that 100 sets with the same record length as the observed data were simulated and the statistics of 100 sets were averaged.

	Obs			DKNNR			MONR		
	P11	P01	P1	P11	P01	P1	P11	P01	P1
S1	0.56	0.27	0.38	0.56	0.27	0.38	0.56	0.26	0.37
S2	0.56	0.27	0.38	0.58	0.26	0.38	0.57	0.25	0.37
S3	0.57	0.26	0.38	0.58	0.26	0.38	0.56	0.26	0.37
S4	0.58	0.25	0.37	0.58	0.25	0.37	0.57	0.24	0.36
S5	0.58	0.25	0.37	0.59	0.24	0.37	0.58	0.24	0.36
S6	0.52	0.25	0.34	0.50	0.24	0.33	0.52	0.24	0.33
S7	0.55	0.26	0.36	0.56	0.25	0.36	0.55	0.24	0.35
S8	0.56	0.25	0.37	0.57	0.25	0.37	0.57	0.24	0.36
S9	0.55	0.25	0.36	0.55	0.24	0.35	0.55	0.24	0.35
S10	0.58	0.25	0.38	0.59	0.24	0.37	0.57	0.23	0.35
S11	0.57	0.25	0.36	0.58	0.24	0.36	0.56	0.24	0.35
S12	0.59	0.25	0.38	0.59	0.25	0.38	0.59	0.25	0.37

Table 3. Cross-correlation of observed data for 12 stations from Yeongnam province, South Korea.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	1.00	0.70	0.70	0.64	0.58	0.70	0.65	0.63	0.75	0.64	0.66	0.59
S2	0.70	1.00	0.67	0.64	0.61	0.64	0.70	0.72	0.79	0.72	0.74	0.62
S3	0.70	0.67	1.00	0.75	0.68	0.61	0.57	0.57	0.68	0.67	0.74	0.70
S4	0.64	0.64	0.75	1.00	0.79	0.56	0.56	0.55	0.65	0.66	0.73	0.82
S5	0.58	0.61	0.68	0.79	1.00	0.51	0.54	0.55	0.61	0.65	0.70	0.87
S6	0.70	0.64	0.61	0.56	0.51	1.00	0.69	0.65	0.68	0.59	0.59	0.54
S7	0.65	0.70	0.57	0.56	0.54	0.69	1.00	0.78	0.71	0.65	0.63	0.55
S8	0.63	0.72	0.57	0.55	0.55	0.65	0.78	1.00	0.71	0.68	0.65	0.56
S9	0.75	0.79	0.68	0.65	0.61	0.68	0.71	0.71	1.00	0.68	0.71	0.62
S10	0.64	0.72	0.67	0.66	0.65	0.59	0.65	0.68	0.68	1.00	0.77	0.66
S11	0.66	0.74	0.74	0.73	0.70	0.59	0.63	0.65	0.71	0.77	1.00	0.70
S12	0.59	0.62	0.70	0.82	0.87	0.54	0.55	0.56	0.62	0.66	0.70	1.00

Table 4. Averaged cross-correlation of the 100 simulated series from the DKNNR model for 12 stations from Yeongnam province, South Korea.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	1.00	0.68	0.69	0.64	0.60	0.69	0.64	0.62	0.73	0.63	0.65	0.61
S2	0.68	1.00	0.67	0.63	0.62	0.63	0.68	0.72	0.77	0.74	0.73	0.63
S3	0.69	0.67	1.00	0.74	0.69	0.60	0.58	0.59	0.66	0.68	0.74	0.70
S4	0.64	0.63	0.74	1.00	0.79	0.55	0.55	0.56	0.62	0.65	0.71	0.81
S5	0.60	0.62	0.69	0.79	1.00	0.51	0.56	0.58	0.60	0.66	0.70	0.86
S6	0.69	0.63	0.60	0.55	0.51	1.00	0.68	0.64	0.65	0.59	0.58	0.53
S7	0.64	0.68	0.58	0.55	0.56	0.68	1.00	0.78	0.69	0.65	0.63	0.56
S8	0.62	0.72	0.59	0.56	0.58	0.64	0.78	1.00	0.70	0.69	0.67	0.58
S9	0.73	0.77	0.66	0.62	0.60	0.65	0.69	0.70	1.00	0.67	0.69	0.60
S10	0.63	0.74	0.68	0.65	0.66	0.59	0.65	0.69	0.67	1.00	0.77	0.67
S11	0.65	0.73	0.74	0.71	0.70	0.58	0.63	0.67	0.69	0.77	1.00	0.71
S12	0.61	0.63	0.70	0.81	0.86	0.53	0.56	0.58	0.60	0.67	0.71	1.00

Table 5. Averaged cross-correlation of 100 simulated series from the MONR model for 12 stations from Yeongnam province.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	1.00	0.63	0.67	0.58	0.54	0.66	0.62	0.60	0.68	0.55	0.62	0.53
S2	0.63	1.00	0.61	0.60	0.57	0.59	0.68	0.68	0.75	0.66	0.72	0.58
S3	0.67	0.61	1.00	0.71	0.67	0.57	0.56	0.53	0.65	0.61	0.71	0.69
S4	0.58	0.60	0.71	1.00	0.78	0.50	0.52	0.52	0.61	0.62	0.69	0.78
S5	0.54	0.57	0.67	0.78	1.00	0.48	0.51	0.53	0.57	0.62	0.67	0.81
S6	0.66	0.59	0.57	0.50	0.48	1.00	0.67	0.62	0.63	0.54	0.54	0.49
S7	0.62	0.68	0.56	0.52	0.51	0.67	1.00	0.75	0.70	0.61	0.62	0.52
S8	0.60	0.68	0.53	0.52	0.53	0.62	0.75	1.00	0.66	0.64	0.61	0.52
S9	0.68	0.75	0.65	0.61	0.57	0.63	0.70	0.66	1.00	0.63	0.69	0.57
S10	0.55	0.66	0.61	0.62	0.62	0.54	0.61	0.64	0.63	1.00	0.72	0.61
S11	0.62	0.72	0.71	0.69	0.67	0.54	0.62	0.61	0.69	0.72	1.00	0.66
S12	0.53	0.58	0.69	0.78	0.81	0.49	0.52	0.52	0.57	0.61	0.66	1.00

Table 6. The difference of RMSE of cross-correlation between MONR and DKNNR. Note that the positive value indicates that the DKNNR model better performs in preserving the cross-correlation, while a negative value (underlined) shows that the MONR model better performs.

MONR-DKNNR	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.000	0.014	0.004	0.013	0.012	0.012	0.008	0.005	0.024	0.031	0.011	0.035
S2	0.014	0.000	0.023	0.013	0.021	0.009	0.010	0.013	0.018	0.027	0.011	0.020
S3	0.004	0.023	0.000	0.015	0.004	0.014	0.003	0.022	0.009	0.028	0.011	0.004
S4	0.013	0.013	0.015	0.000	0.002	0.017	0.018	0.014	0.018	0.018	0.027	0.024
S5	0.012	0.021	0.004	0.002	0.000	0.014	0.021	0.014	0.015	0.013	0.015	0.012
S6	0.012	0.009	0.014	0.017	0.014	0.000	0.006	0.010	0.030	0.018	0.029	0.021
S7	0.008	0.010	0.003	0.018	0.021	0.006	0.000	0.005	0.008	0.024	0.012	0.023
S8	0.005	0.013	0.022	0.014	0.014	0.010	0.005	0.000	0.032	0.019	0.022	0.023
S9	0.024	0.018	0.009	0.018	0.015	0.030	0.008	0.032	0.000	0.019	0.005	0.027
S10	0.031	0.027	0.028	0.018	0.013	0.018	0.024	0.019	0.019	0.000	0.020	0.021
S11	0.011	0.011	0.011	0.027	0.015	0.029	0.012	0.022	0.005	0.020	0.000	0.022
S12	0.035	0.020	0.004	0.024	0.012	0.021	0.023	0.023	0.027	0.021	0.022	0.000

Table 7. Lag-1 cross-correlation of observed data for 12 stations from Yeongnam province, South Korea.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.29[‡]	0.26	0.30	0.27	0.24	0.29	0.26	0.24	0.27	0.26	0.28	0.26
S2	0.28	0.30	0.29	0.28	0.26	0.28	0.28	0.27	0.31	0.30	0.32	0.27
S3	0.28	0.26	0.31	0.30	0.27	0.27	0.25	0.24	0.27	0.27	0.30	0.27
S4	0.28	0.27	0.32	0.34	0.31	0.27	0.26	0.26	0.28	0.28	0.31	0.32
S5	0.29	0.28	0.32	0.35	0.34	0.27	0.27	0.26	0.29	0.29	0.33	0.35
S6	0.25	0.22	0.26	0.23	0.22	0.27	0.24	0.22	0.25	0.23	0.24	0.23
S7	0.25	0.26	0.27	0.25	0.25	0.28	0.29	0.27	0.27	0.27	0.28	0.26
S8	0.29	0.30	0.29	0.27	0.26	0.30	0.31	0.30	0.31	0.30	0.31	0.27
S9	0.29	0.29	0.30	0.29	0.27	0.29	0.27	0.27	0.30	0.30	0.31	0.28
S10	0.28	0.31	0.32	0.31	0.29	0.29	0.30	0.30	0.31	0.33	0.34	0.29
S11	0.27	0.29	0.31	0.30	0.27	0.27	0.27	0.27	0.29	0.30	0.32	0.29
S12	0.30	0.29	0.32	0.35	0.33	0.28	0.27	0.26	0.29	0.30	0.33	0.35

[‡] Shaded values represent~~s~~ lag-1 autocorrelation (i.e. the one lagged correlation for the same site).

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Table 8. The difference of RMSE of lag-1 cross-correlation between MONR and DKNNR. Note that a positive value indicates that the DKNNR model better performs in preserving lag-1 cross-correlation, while a negative value (underlined) shows that the MONR model better performs.

MONR- DKNNR	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.000	0.048	0.075	0.049	0.041	0.095	0.059	0.036	0.047	0.055	0.063	0.052
S2	0.070	0.000	0.079	0.057	0.046	0.104	0.068	0.047	0.066	0.058	0.073	0.047
S3	0.067	0.054	0.000	0.046	0.031	0.096	0.072	0.056	0.055	0.052	0.056	0.025
S4	0.086	0.075	0.083	0.002	0.037	0.117	0.089	0.077	0.078	0.062	0.077	0.040
S5	0.111	0.096	0.098	0.074	0.002	0.124	0.103	0.085	0.105	0.070	0.108	0.049
S6	0.039	0.024	0.060	0.038	0.043	-0.002	0.028	0.017	0.045	0.034	0.055	0.037
S7	0.055	0.045	0.077	0.061	0.062	0.084	0.000	0.023	0.051	0.052	0.071	0.064
S8	0.092	0.078	0.104	0.079	0.068	0.115	0.079	0.000	0.094	0.078	0.101	0.074
S9	0.060	0.052	0.084	0.066	0.056	0.106	0.057	0.056	0.001	0.069	0.076	0.064
S10	0.091	0.094	0.105	0.081	0.062	0.123	0.107	0.085	0.100	0.001	0.092	0.063
S11	0.064	0.061	0.071	0.057	0.033	0.109	0.084	0.063	0.062	0.043	-0.002	0.043
S12	0.121	0.099	0.096	0.077	0.036	0.130	0.101	0.086	0.107	0.082	0.109	0.003

~~[†]Underline represents a negative value implying that the MONR model better performs.~~

~~[‡]Shaded values represent lag-1 autocorrelation (i.e. the lagged-1 correlation for the same site).~~

Table 9. Bias of lag-1 cross-correlation of the generated data from the DKNNR model. Note that a positive value indicates the overestimation of lag-1 cross-correlation, while a negative value shows underestimation. Note that $Bias = 1/N\sum_{m=1}^{N}\Gamma_{m}^{G} - \Gamma^{h}$ and see Eq. (18) for the details of each term.

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	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.000	0.009	0.001	0.003	0.006	-0.002	0.010	0.011	0.006	0.010	0.010	0.006
S2	0.005	0.009	0.010	0.006	0.008	0.006	0.011	0.011	0.004	0.009	0.009	0.010
S3	0.002	0.010	0.001	-0.002	0.003	0.002	0.007	0.008	0.006	0.009	0.006	0.007
S4	0.006	0.009	0.004	0.001	0.007	0.003	0.008	0.008	0.009	0.010	0.010	0.005
S5	0.004	0.005	0.000	-0.001	-0.001	0.007	0.005	0.006	0.002	0.008	0.000	-0.001
S6	-0.002	0.006	0.000	0.002	-0.001	-0.002	0.004	0.003	0.002	0.005	0.004	0.001
S7	0.004	0.008	0.003	0.003	0.001	0.004	0.002	0.006	0.007	0.007	0.007	0.002
S8	0.000	0.005	0.004	0.001	0.004	-0.003	-0.003	0.000	0.001	0.004	0.006	0.003
S9	0.005	0.007	0.006	0.003	0.006	0.004	0.010	0.007	0.004	0.007	0.006	0.007
S10	0.003	0.005	0.001	-0.001	-0.001	0.001	0.001	0.001	0.003	0.000	0.002	0.001
S11	0.010	0.010	0.008	0.004	0.008	0.009	0.009	0.009	0.010	0.010	0.011	0.008
S12	0.003	0.006	0.001	-0.001	0.004	0.003	0.008	0.008	0.005	0.005	0.002	0.001

Table 10. Bias of lag-1 cross-correlation of the generated data from the Wilks model. Note that a positive value indicates the overestimation of lag-1 cross-correlation, while a negative value shows underestimation.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	-0.001	-0.062	-0.089	-0.063	-0.055	-0.106	-0.074	-0.052	-0.060	-0.070	-0.080	-0.067
S2	-0.084	0.000	-0.096	-0.072	-0.061	-0.117	-0.083	-0.063	-0.079	-0.072	-0.089	-0.063
S3	-0.080	-0.070	0.001	-0.059	-0.043	-0.110	-0.086	-0.072	-0.069	-0.066	-0.071	-0.037
S4	-0.100	-0.090	-0.097	-0.001	-0.048	-0.129	-0.103	-0.093	-0.093	-0.077	-0.092	-0.051
S5	-0.125	-0.110	-0.111	-0.087	-0.001	-0.138	-0.117	-0.100	-0.118	-0.084	-0.121	-0.060
S6	-0.053	-0.037	-0.074	-0.051	-0.057	-0.001	-0.039	-0.030	-0.060	-0.047	-0.070	-0.049
S7	-0.068	-0.058	-0.091	-0.077	-0.077	-0.098	-0.002	-0.038	-0.065	-0.065	-0.086	-0.079
S8	-0.106	-0.091	-0.119	-0.094	-0.084	-0.128	-0.093	0.001	-0.108	-0.091	-0.116	-0.088
S9	-0.074	-0.064	-0.098	-0.080	-0.070	-0.119	-0.072	-0.070	-0.001	-0.082	-0.091	-0.078
S10	-0.105	-0.107	-0.120	-0.096	-0.075	-0.136	-0.119	-0.097	-0.113	-0.001	-0.106	-0.076
S11	-0.078	-0.074	-0.085	-0.070	-0.047	-0.123	-0.097	-0.077	-0.076	-0.056	-0.001	-0.057
S12	-0.134	-0.112	-0.108	-0.088	-0.046	-0.142	-0.116	-0.101	-0.121	-0.095	-0.122	0.000

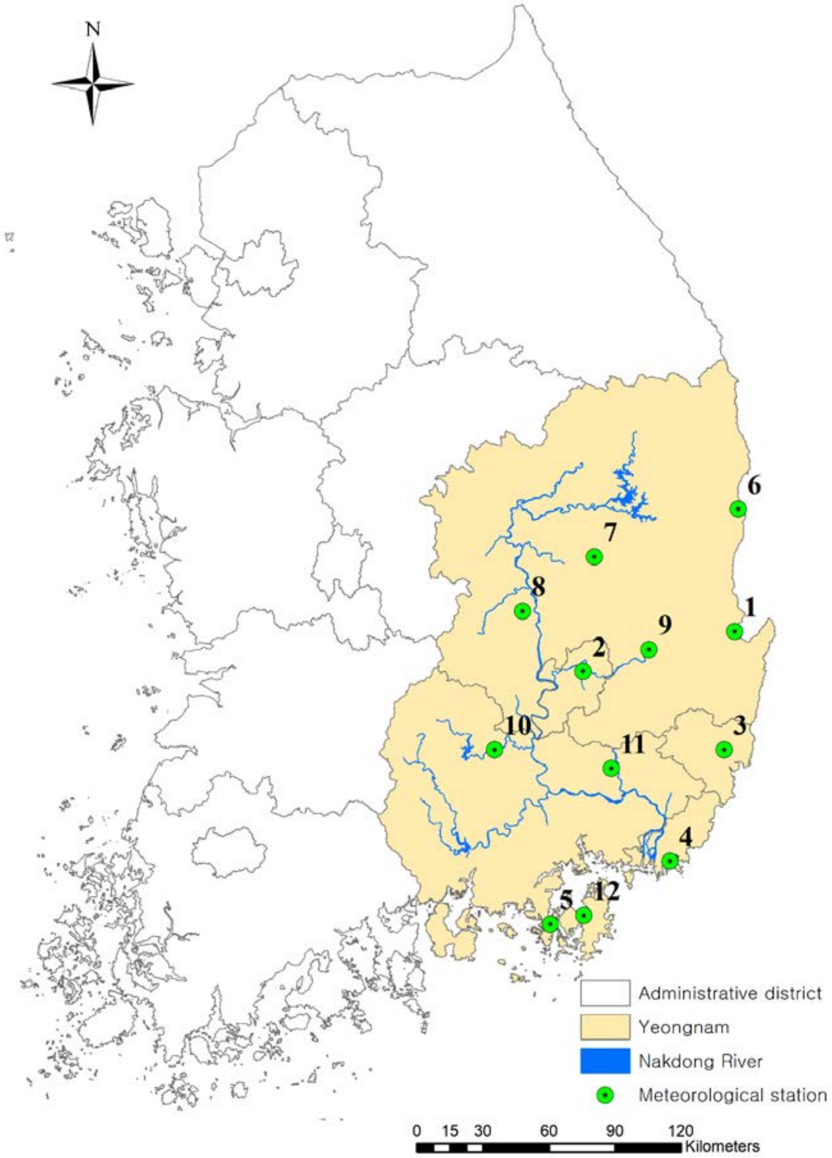

Figure 1. Locations of 12 selected weather stations at the Yeongnam province. See Table 1~~Table 1~~ for further information about the stations.

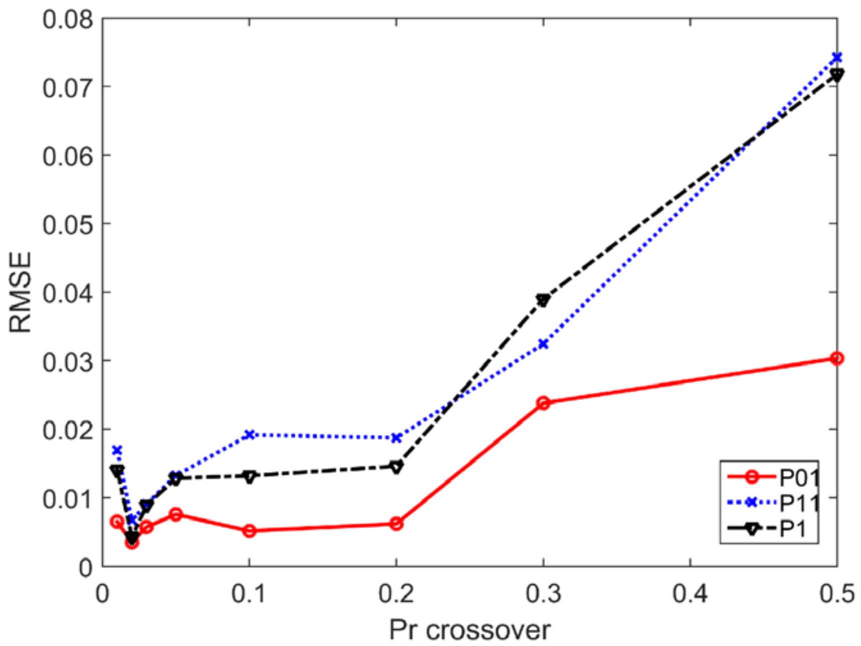

Figure 2. Testing for different probabilities of crossover Pcr. RMSE is estimated for all the tested 12 stations for each transition and limiting probability of the simulated data with the record length of 100,000.

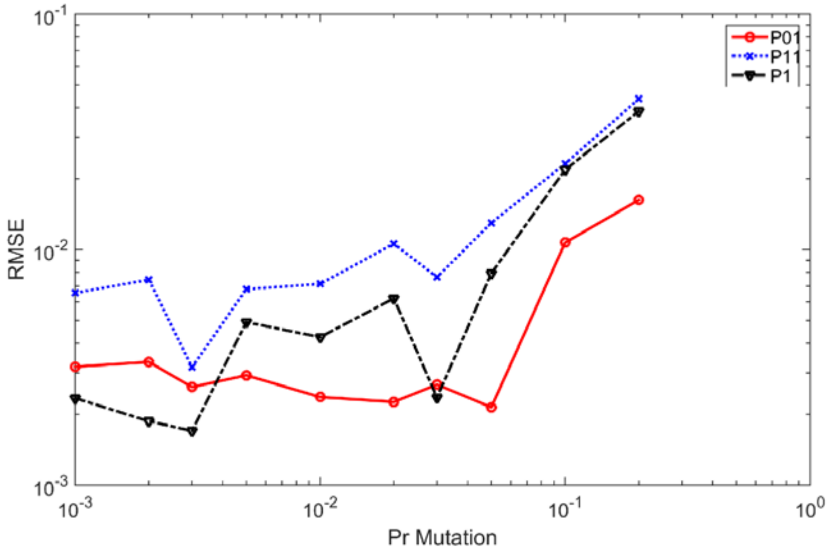

Figure 3. Testing for different probabilities of mutation P_m. RMSE is estimated for all the tested 12 stations for each transition and limiting probability of the simulated data with the record length of 100,000.

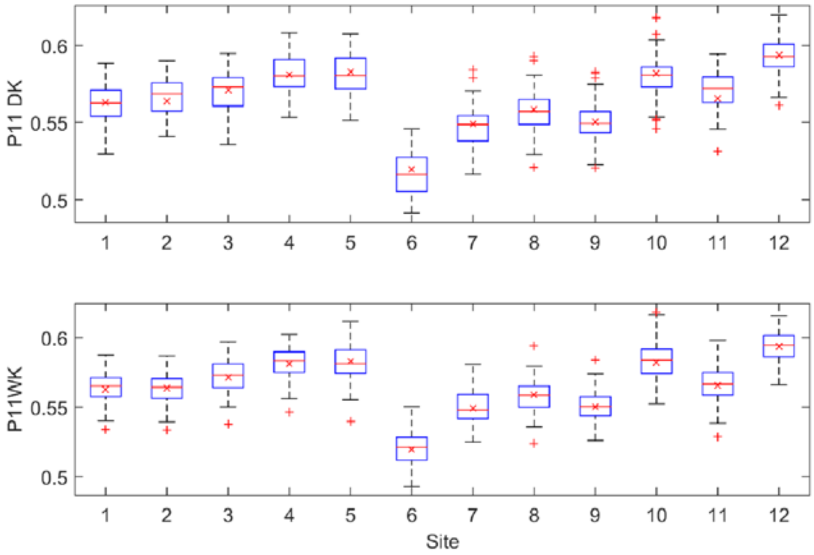

Figure 4. Boxplots of the P11 probability for the simulated data from the DKNNR model (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

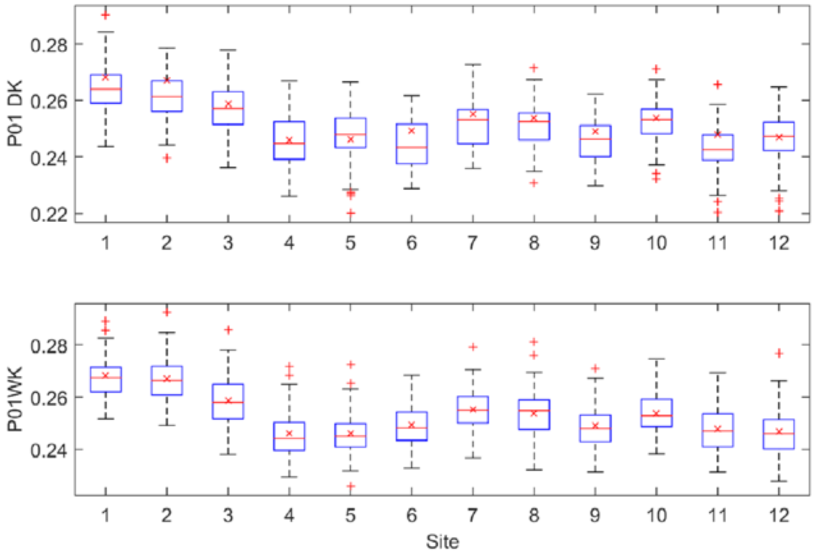

Figure 5. Boxplots of the P01 probability for the data simulated from the DKNNR model (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

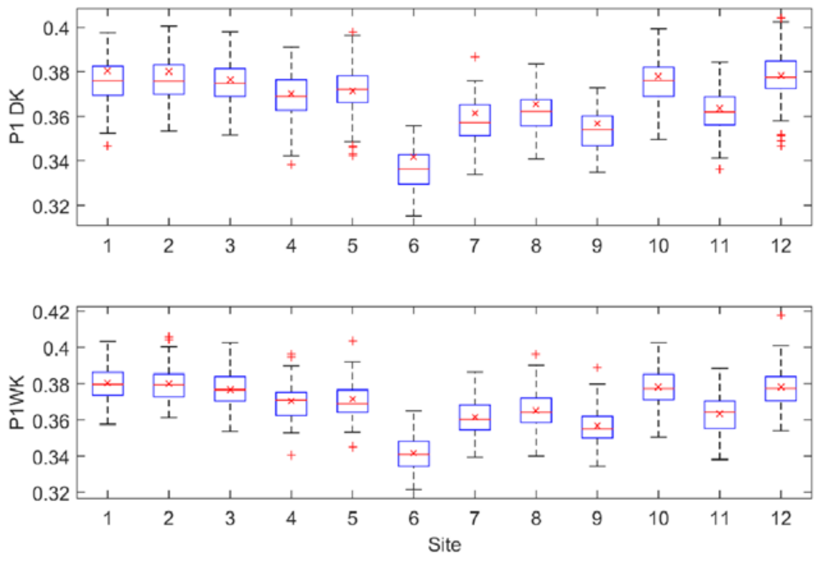

Figure 6. Boxplots of the P1 probability for the data simulated from the DKNNR model (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

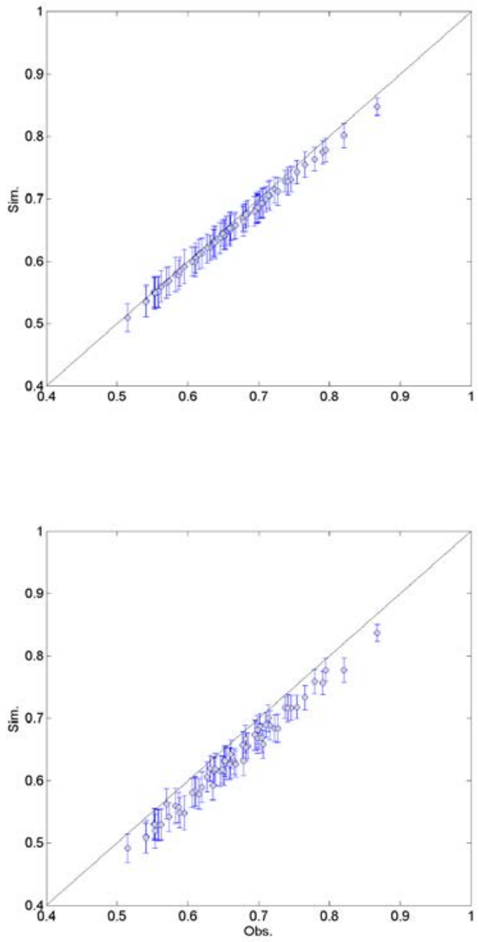

Figure 7. Scatterplot of cross-correlations between 12 weather stations for the observed data (X coordinate) and the generated data (Y coordinate) generated from the DKNNR model (top panel) and the MONR model (bottom panel). The cross-correlations from 100 generated series are averaged for the filled circle and the errorbars upper and lower extended lines indicate the range of 1.95×standard deviation.

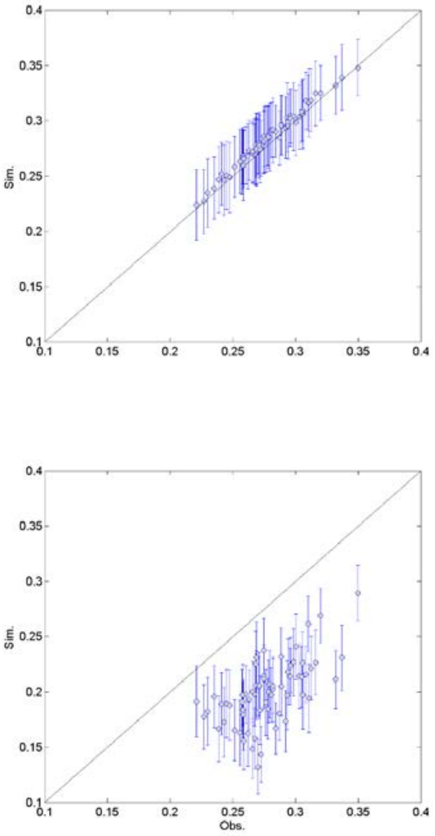

Figure 8. Scatterplot of lag-1 cross-correlations between 12 weather stations for the observed data (X coordinate) and the generated data (Y coordinate) generated from the DKNNR model (top panel) and the MONR model (bottom panel). The cross-correlations from 100 generated series are averaged for the filled circle and the errorbars upper and lower extended lines indicate the range of 1.95×standard deviation.

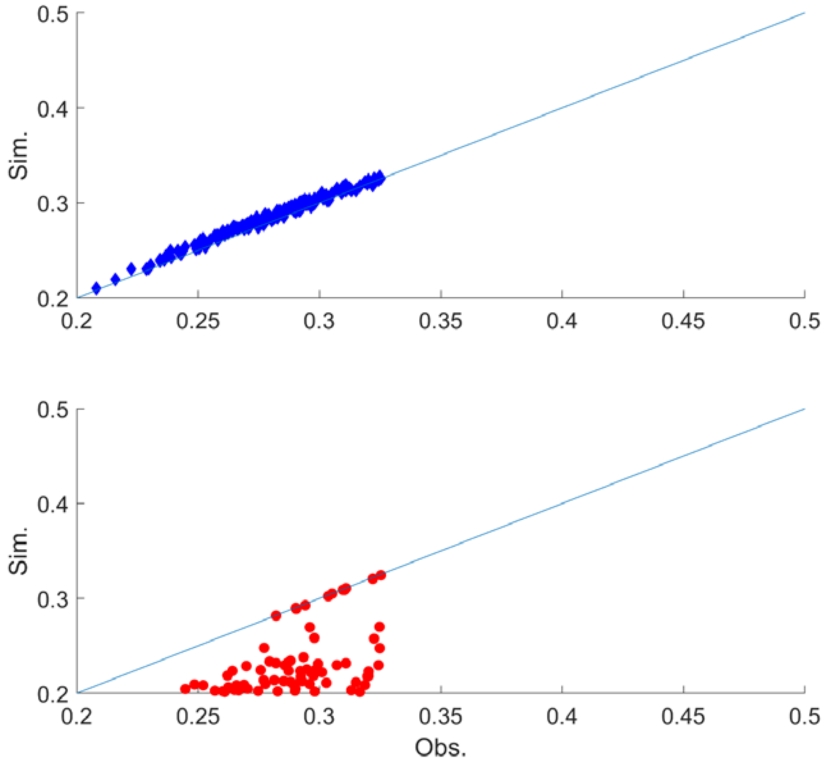

Figure 9. Scatterplot of lag-1 cross-correlations between 12 weather stations for the observed data (X coordinate) and the generated data (Y coordinate) generated from the DKNNR model (top panel) and the MONR model (bottom panel) with the whole year data not with the summer season. The cross-correlations from 100 generated series are averaged.

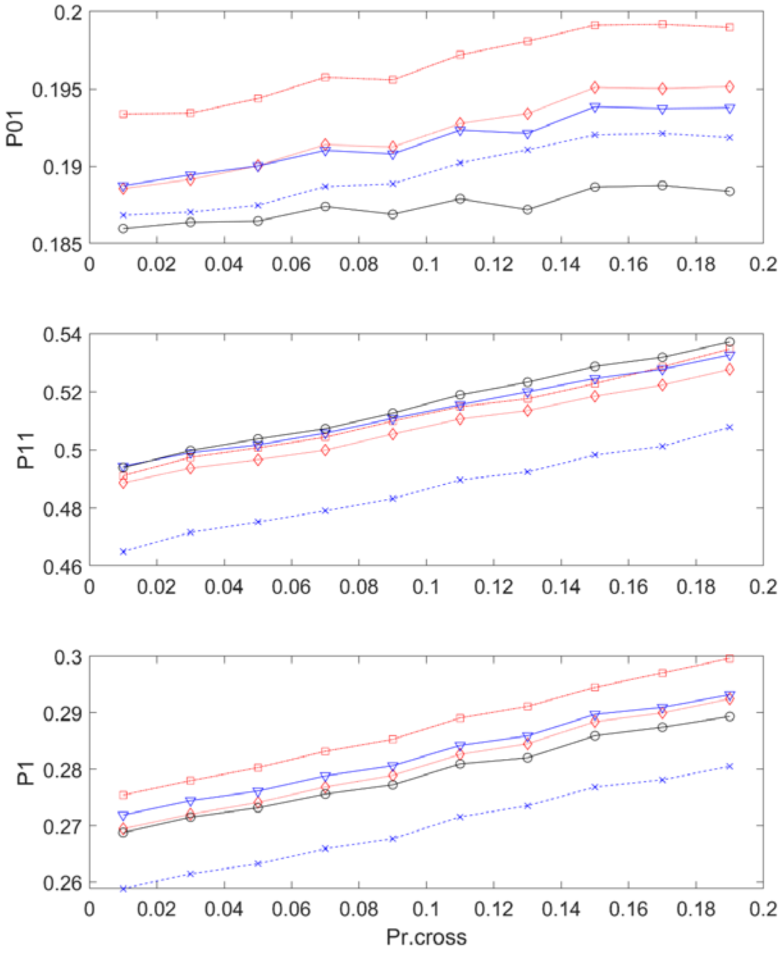

Figure 10. Transition probabilities and marginal distribution for the selected five stations along with changing the cross-over probability P_{cr} with the condition that the candidate value is one and the previous value is also one. See Eq.(15)~~(15)~~ for the detail.

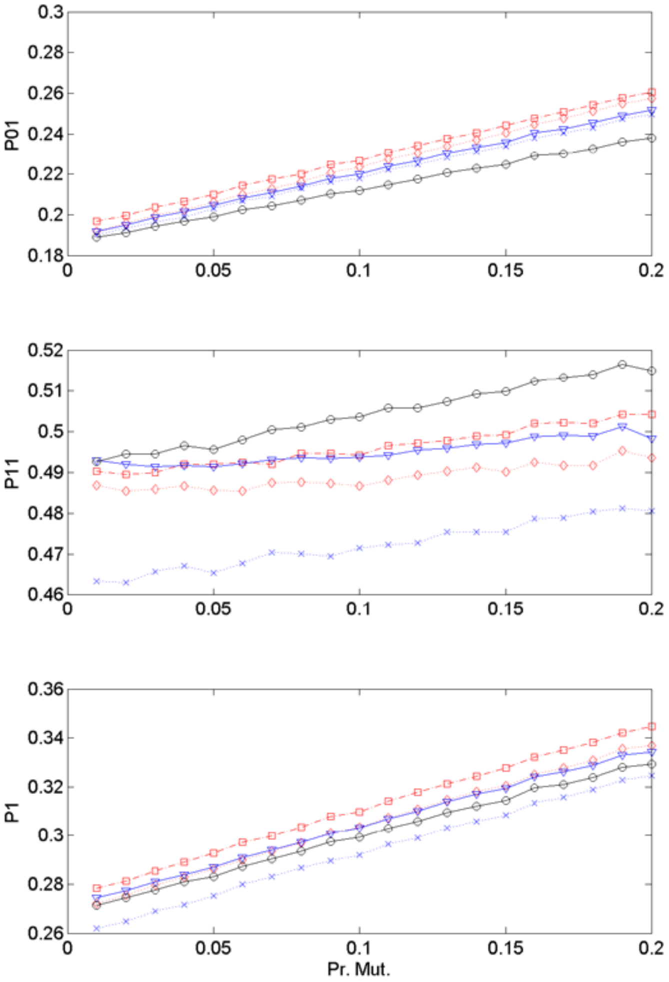

Figure 11. Transition probabilities and marginal distribution along with changing the cross-over probability with the condition that the mutation is processed only if the candidate value is one. See Eq.(16)~~(16)~~ for the detail.

Table A 1. Example dataset of daily rainfall with 12 weather stations and 16 days for measured rainfall (mm) in the upper part of this table and its corresponding occurrences in the bottom part of this table.

Day	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
1	2.0	2.9	1.2	0.0	0.0	1.8	4.0	8.9	2.0	4.6	1.3	0.6
2	52.6	39.8	47.2	17.4	11.8	31.0	30.0	33.7	52.0	57.8	37.0	17.5
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.2	1.0	1.4	1.9	12.3	0.0	0.0	0.0	0.7	3.1	3.5	8.1
6	14.8	0.2	0.8	0.2	5.0	0.0	0.0	18.0	0.0	0.0	0.6	3.1
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	0.0	1.0	0.0	0.4	0.0	3.8	0.0	0.1	0.0	0.0	0.0	0.0
11	7.1	6.4	12.8	12.8	13.6	2.3	2.0	5.4	6.0	7.3	16.4	20.3
12	0.0	0.0	0.0	0.0	5.5	0.0	0.0	0.0	0.0	0.0	0.0	4.3
13	10.0	1.6	11.6	14.3	1.5	5.4	0.0	0.0	2.5	0.0	2.7	16.1
14	2.3	0.0	0.7	0.0	0.0	1.4	0.0	0.0	0.0	0.0	0.0	0.0
15	31.5	4.3	30.6	12.7	14.4	25.8	3.5	0.8	5.0	2.7	6.5	20.3
16	37.0	7.8	30.1	11.2	9.6	36.8	2.5	4.7	13.5	1.7	10.1	14.1

Day	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
1	1	1	1	0	0	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1
3	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0
5	1	1	1	1	1	0	0	0	1	1	1	1
6	1	1	1	1	1	0	0	1	0	0	1	1
7	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0
10	0	1	0	1	0	1	0	1	0	0	0	0
11	1	1	1	1	1	1	1	1	1	1	1	1
12	0	0	0	0	1	0	0	0	0	0	0	1
13	1	1	1	1	1	1	0	0	1	0	1	1
14	1	0	1	0	0	1	0	0	0	0	0	0
15	1	1	1	1	1	1	1	1	1	1	1	1
16	1	1	1	1	1	1	1	1	1	1	1	1

Table A 2. Example dataset for estimating distances. The second row presents the current daily precipitation occurrences for 12 stations and the rows below show the absolute difference between the current occurrences (**Xc**) and the observed data in Table A 1~~Table A 1~~. The last column presents the distances in Eq. (11)~~(11)~~.

day	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	Dist
Xc	*0*	*1*	*1*	*0*	*0*	*1*	*1*	*0*	*0*	*0*	*0*	*0*	
1	1	0	0	0	0	0	0	1	1	1	1	1	**6**
2	1	0	0	1	1	0	0	1	1	1	1	1	**8**
3	0	1	1	0	0	1	1	0	0	0	0	0	**4**
4	0	1	1	0	0	1	1	0	0	0	0	0	**4**
5	1	0	0	1	1	1	1	0	1	1	1	1	**9**
6	1	0	0	1	1	1	1	1	0	0	1	1	**8**
7	0	1	1	0	0	1	1	0	0	0	0	0	**4**
8	0	1	1	0	0	1	1	0	0	0	0	0	**4**
9	0	1	1	0	0	1	1	0	0	0	0	0	**4**
10	0	0	1	1	0	0	1	1	0	0	0	0	**4**
11	1	0	0	1	1	0	0	1	1	1	1	1	**8**
12	0	1	1	0	1	1	1	0	0	0	0	1	**6**
13	1	0	0	1	1	0	1	0	1	0	1	1	**7**
14	1	1	0	0	0	0	1	0	0	0	0	0	**3**
15	1	0	0	1	1	0	0	1	1	1	1	1	**8**
16	1	0	0	1	1	0	0	1	1	1	1	1	**8**

Table A 3. Example for selecting one sequence for $\mathbf{X}_{c+1}$. The second row presents the distances in Table A 2~~Table A 2~~. The third and fourth columns show the sorted days and distances for the smallest distances to the largest in the second column. The fourth row presents the probabilities estimated with Eq. (12)~~(12)~~. Note that there are six days whose distances are the same with each other. In this case all the days are included and among six days, one is selected with equal probabilities.

Day	Dist.	Sorted Day	Sorted Dist	Prob
1	6	14	3	0.48
2	8	3	**4**	0.24
3	4	4	**4**	0.16
4	4	7	**4**	0.12
5	9	8	**4**	
6	8	9	**4**	
7	4	10	**4**	
8	4	1	6	
9	4	12	6	
10	4	13	7	
11	8	2	8	
12	6	6	8	
13	7	11	8	
14	3	15	8	
15	8	16	8	
16	8	5	9	

Table A 4. Example for GA mixture for $\mathbf{X}_{c+1}$. The second and third rows present two selected sets, while the third row shows the final set for $\mathbf{X}_{c+1}$ with the crossover at S6 and S8 and the mutation for S12.

	Assigned day, *p*	Selected day, *p*+1	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
Set1	14	**15**	1	0	0	1	1	0	0	1	1	1	1	1
Set2	4	**5**	1	0	0	1	1	1	1	0	1	1	1	1
Final			1	0	0	1	1	1	0	0	1	1	1	**0**

Discrete k-nearest neighbor resampling for simulating multisite precipitation occurrence and adaption to climate change

: Discrete KNNR for Multisite Occurrence (DKMO version1.0) - model development

Keywords: daily precipitation, discrete, k-nearest neighbor, Markov chain, multisite, occurrence

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Abstract

Stochastic weather simulation models are commonly employed in water resources management agricultural applications, forest management, transportation management, and recreational activities. ~~The data simulated by these models, such as precipitation, temperature, and wind, are used as input for hydrological and agricultural models.~~ Stochastic simulation of multisite precipitation occurrence is a challenge because of its intermittent characteristics as well as spatial and temporal cross-correlation. Although ~~T~~the multisite occurrence model with standard normal variate (MONR) has been used for preserving key precipitation statistics and contemporaneous correlation, ~~but~~ it ~~can~~ does not reproduce lagged crosscorrelation between stations so ~~and~~ long stochastic simulation is ~~therefore~~ required. ~~to estimate its parameters.~~ Employing a nonparametric technique, k-nearest neighbor resampling (KNNR)~~,~~ and coupling it with Genetic Algorithm (GA), this study proposes a novel simulation method for multisite precipitation occurrence, overcoming the shortcomings of the ~~existing~~ MONR model. The ~~proposed~~ novel discrete version of KNNR (DKNNR) model ~~is~~ was developed and its modification for the study of climatic change adaptation was tested. ~~compared with an existing parametric model, called multisite occurrence model with standard normal variate (MONR).~~ The datasets simulated from both the DKNNR model and the MONR model ~~are~~ were evaluated ~~tested~~ using a number of statistics, such as occurrence and transition probabilities as well as temporal and spatial cross-correlations. Results showed that the proposed DKNNR model ~~can be a good alternative for~~ simulated ~~ing~~ multisite precipitation occurrence, ~~while~~ preserving the lagged crosscorrelation between sites. ~~and simulating multisite occurrence from a simple and direct procedure without no parameterization. We also tested the~~ When climate change was considered, ~~model capability to adapt climate change. It is shown that~~ the model performed satisfactorily, but ~~is capable but~~ further improvement is required to more

accurately simulate ~~have~~ specific variations of the occurrence probability. ~~due to climate change. Combining with the generated occurrence, the multisite precipitation amount can then be simulated by any multisite amount model.~~

~~2.~~ Introduction

Stochastic simulation of weather variables has been employed for water resources management, hydrological design, agricultural irrigation~~applications~~, forest management, transportation planning and evacuation~~management~~, recreation activities, filling-~~—~~in missing historical data, simulating data, extending observed records, ~~simulating data,~~ and simulating different weather conditions. Stochastic simulation models play a key role in producing weather sequences, while preserving the statistical characteristics of observed data. A number of stochastic weather simulation models have been developed using parametric and nonparametric approaches (Lee, 2017; Lee et al., 2012; Wilby et al., 2003; Wilks, 1999; Wilks and Wilby, 1999).

Parametric approaches simulate ~~summarize the~~ statistical characteristics of observed weather data with a set of parameters ~~set~~that are determined by fitting (Jeong et al., 2012; Lee, 2016; Zheng and Katz, 2008), whereas ~~.~~in ~~The parameters fitted with observed weather data are employed in simulation. In~~ nonparametric approaches, historical analogs with current conditions are searched, following the weather simulation data (Buishand and Brandsma, 2001; Lee et al., 2012). ~~Furthermore, c~~Combinations of parametric and nonparametric approaches ~~models~~ have also been proposed (Apipattanavis et al., 2007; Frost et al., 2011).

Among weather variables, ~~the~~ precipitation ~~variable~~ possesses intermittency and zero values between precipitation events, which make it difficult ~~and~~ to properly reproduce the events ~~m is difficult and remains a challenge~~ (Beersma and Buishand, 2003; Hughes et al., 1999; Katz and Zheng, 1999). To overcome the problem of intermittency and zero values~~Due to this difficulty~~, precipitation is simulated separately from other variables. The main method for reproducing intermittency has been the multiplication of precipitation occurrence and an amount as $Z=X\cdot Y$, where X is the occurrence (binary as either 0 or 1) and Y is the amount (Jeong et al., 2013; Lee and

Park, 2017; Todorovic and Woolhiser, 1975). The spatial and temporal dependence in the occurrence and amount of precipitation introduces further complexity in multisite simulation.

Wilks (1998) presented a multisite simulation model for the occurrence process (i.e. *X*) using the standard normal variable that is spatially dependent, representing the relation between the occurrence variable and the standard normal variable with simulation data. Originally, the occurrence of precipitation had been simulated with a discrete Markov Chain (MC) model (Katz, 1977). Compared to the MC model that requires~~ing~~ a significant number of parameters for ~~to~~ generating~~e~~ multisite occurrence, the multisite occurrence model proposed by Wilks (1998) transforms the standard normal variate and simulates the sequence with multivariate normal distribution, and then back-transforms the multivariate normal sequence to the original domain. The model is able to reproduce the contemporaneous multisite dependence structure and lagged dependence only for the same site but it ~~while~~ requires ~~ing~~ a complex simulation process to estimate parameters for each site and is ~~being~~ unable to preserve lagged dependence between sites.

~~Meanwhile,~~ Lee et al. (2010a) proposed a nonparametric-based stochastic simulation model for hydrometeorological variables. Their model ~~y~~ overcame the shortcomings of a previous nonparametric simulation model (Lall and Sharma, 1996), called k-nearest neighbor resampling (KNNR) but ~~such that~~ the simulated data do ~~can~~not produce patterns different from those of the observed data (Brandsma and Buishand, 1998; Mehrotra et al., 2006; St-Hilaire et al., 2012). In addition to ~~this~~ KNNR, Lee et al. (2010a) used a meta-heuristic ~~algorithm~~ Genetic Algorithm (GA) that led to the reproduction of similar populations by mixing the simulated datasets. While ~~the~~ KNNR is employed to find ~~similar~~ historical analogues of multisite occurrence similar to the current status of a simulation series, GA is applied to use its skill to generate a new descendant from the historical parent chosen with the KNNR. In this procedure, the multisite occurrence of

~~the~~ precipitation ~~variable~~ can be simulated while preserving spatial and temporal correlations. ~~Note that m~~Meta-heuristic techniques, such as ~~to~~ GA, have been popularly employed in a number of hydrometeorological applications (Chau, 2017; Fotovatikhah et al., 2018; Taormina et al., 2015; Wang et al., 2013). Although a number of variants of KNNR-GA have ~~since~~ been applied (Lee et al., 2012; Lee and Park, 2017), ~~. N~~none of them ~~se models~~ can simulate ~~adopt the~~ multisite occurrence of ~~in~~ precipitation whose characteristics are binary and temporally and spatially related.

Therefore, this ~~in the current~~ study ~~we~~ proposes a ~~novel~~ stochastic simulation method for multisite occurrence of ~~the~~ precipitation ~~variable~~ with the KNNR-GA based nonparametric approach that (1) simulates multisite occurrence with a simple and direct procedure without parameterization of all the required occurrence probabilities; and (2) reproduces the complex temporal and spatial correlation between stations as well as the basic occurrence probabilities. ~~Note that t~~The proposed nonparametric model is compared with the ~~most~~ popular ~~ly employed~~ model proposed by Wilks (1998). Even though the multisite occurrence data generated from the Wilks ~~is~~ model ~~(Wilks, 1998)~~ preserves various statistical characteristics of the observed data well, significant underestimation of lagged cross-correlation still exists. Furthermore, the relation between standard normal variable and occurrence variable relies on long stochastic simulation.

The paper is organized as follows. The next section presents the ~~a~~ mathematical background of existing multisite occurrence modeling and section discusses ~~. T~~the modeling procedure. ~~is discussed in section 3.~~ The study area and data are reported in section 4. The model ~~is~~ application is presented ~~ed~~ in section 5. Results of the proposed model are discussed in section 6, and summary and conclusions are presented in section 7.

~~3.~~1. Background

~~3.1.~~1.1. Single site occurrence modeling

Let X_t^s represent the occurrence of daily precipitation for a location *s* (*s*=1,…, *S*) on day *t* (*t*=1,…, *n*; *n* is the number observed days) and let X_t^s be either zero for dry day or one for wet day. The first order Markov chain model for X_t^s is defined with the assumption that the occurrence probability of a wet day is fully defined by the previous day as

$$\Pr\left\{X_t^s = 1 \mid X_{t-1}^s = 0\right\} = p_{01}^s \tag{1}$$

$$\Pr\left\{X_t^s = 1 \mid X_{t-1}^s = 1\right\} = p_{11}^s \tag{2}$$

Also $p_{00}^s = 1 - p_{01}^s$ and $p_{10}^s = 1 - p_{11}^s$, since the summation of zero and one should be unity with the same previous condition. This consists of a transition probability matrix (TPM) as

$$TPM^s = \begin{bmatrix} p_{00}^s & p_{01}^s \\ p_{10}^s & p_{11}^s \end{bmatrix} = \begin{bmatrix} 1 - p_{01}^s & p_{01}^s \\ 1 - p_{11}^s & p_{11}^s \end{bmatrix} \tag{3}$$

The marginal distributions of TPM (i.e. p_0 and p_1) can be expressed with TPM and its condition of $p_0 + p_1 = 1$ as:

$$p_0^s = \frac{p_{01}^s}{1 + p_{01}^s - p_{11}^s} \tag{4}$$

$$p_1^s = \frac{1 - p_{11}^s}{1 + p_{01}^s - p_{11}^s} \tag{5}$$

Note that p_1 represents the probability of precipitation occurrence for a day, while p_0 does non-occurrence. The lag-1 autocorrelation of precipitation occurrence is the combination of transition probabilities as:

$$\rho_1(s,s) = p_{11}^s - p_{01}^s \qquad (6)$$

The simulation can be done by comparing TPM with a uniform random number (u_t^s) as

$$X_t^s = \begin{cases} 1 & \text{if } u_t^s \le p_{i1}^s \\ 0 & \text{otherwise} \end{cases} \qquad (7)$$

where p_{i1}^s is the selected probability from TPM regarding the previous condition i (i.e. either 0 or 1). Wilks (1998) suggested a different method using a standard normal random number w_t^s ~N[0,1] as

$$X_t^s = \begin{cases} 1 & \text{if } w_t^s \le \Phi^{-1}(p_{i1}^s) \\ 0 & \text{otherwise} \end{cases} \qquad (8)$$

where Φ^{-1} indicates the inverse of the standard normal cumulative function Φ.

~~3.2.~~1.2. Multisite occurrence modeling

Wilks (1998) suggested a multisite occurrence model using a standard normal random number (here, denoted as MONR) that is spatially dependent but serially independent. The correlation of the standard normal variate for a site pair of q and s can be expressed as:

$$\tau(q,s) = corr[w_t^q, w_t^s] \qquad (9)$$

Also, the correlation of the original occurrence variate is

$$\rho(q,s) = corr[X_t^q, X_t^s] \qquad (10)$$

Once the correlation of the standard normal variate is known, the simulation of multisite precipitation occurrence is straightforward. Multivariate standard normal distribution is used with a ~~the~~ parameter set of [**0**, **T**] where **0** is the zero vector (*S*x1) and **T** is the correlation matrix with the elements of $\tau(q,s)$ for $q \in \{1,...,S\}$ and $s \in \{1,...,S\}$.

Since direct estimation of $\tau(q,s)$ is not feasible~~applicable~~, a simulation technique is used to estimate $\tau(q,s)$ from $\rho(q,s)$. A long sequence of the occurrences~~ process~~ is simulated with different values of $\tau(q,s)$ and its corresponding correlation of the original domain $\rho(q,s)$ is estimated with the simulated long sequence by the inverse standard normal cumulative function (i.e. $\mathbf{\Phi}^{-1}$). A curve between $\tau(q,s)$ and $\rho(q,s)$ is derived from this long simulation with the MONR model and is employed for ~~the~~ parameter estimation for a real application.

4~~.~~2. DKNNR

~~4.1.~~2.1. DKNNR modeling procedure

In the current study, a novel multisite simulation model for discrete occurrence of precipitation variable with k-nearest neighbor resampling (KNNR) technique (Lall and Sharma, 1996; Lee and Ouarda, 2011; Lee et al., 2017) for a discrete case (denoted as Discrete KNNR; DKNNR) is proposed by combining a mixture mechanism with Genetic Algorithm (GA).

Provided the number of nearest neighbors, *k*, is known, the discrete k-nearest neighbor resampling with genetic algorithm is done as follows:

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(1) Estimate the distance between the current (i.e. time index: c) multisite occurrence X_c^s and the observed multisite occurrence x_i^s. Here, the distance is measured for i=1,…, n-1 as

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$$D_i = \sum_{s=1}^{S} \left| X_c^s - x_i^s \right| \qquad (11)$$

(2) Arrange the estimated distances from step (1) in ascending order, select the first k distances (i.e., the smallest k values), and reserve the time indices of the smallest k distances.

(3) Randomly select one of the stored k time indices with the weighting probability given by

$$w_m = \frac{1/m}{\sum_{j=1}^{k} 1/j}\ , \qquad m = 1,\ldots,k \qquad (12)$$

(4) Assume the selected time index from step (3) as p. Note that there are a number of values that have the same distance as the selected D_p, since D_p is a natural number between 0 and S. For example, if S=2 and X_c^1=0 and X_c^2=1, the two sequences have the same D=1 as [x_i^1=0 and x_i^2=0] and [x_i^1=1 and x_i^2=1]. In this case, a random selection procedure is required to take into account the cases with the same quantity. One particular time index is randomly selected with ~~the~~ equal probabilities among the time indices of the same distances. Note that instead of the random selection, one can always use the first one. In such a case, only one historical combination of multisite occurrences will be selected.

(5) Assign the binary vector of the proceeding index of the selected time as $\mathbf{x}_{p+1} = [x_{p+1}^{s}]_{s\in\{1,S\}}$. Here, p is the finally selected time index from step (4).

(6) Execute the following steps for GA mixing if GA mixing is subjectively selected. Otherwise, skip this step.

(6-1) Reproduction: Select one additional time index using steps (1) through (4) and denote this index as p*. Obtain the corresponding precipitation occurrence values, $\mathbf{x}_{p^*+1} = [x_{p^*+1}^{s}]_{s\in\{1,\ldots,S\}}$. The subsequent two GA operators employ the two selected vectors, $\mathbf{x}_{p+1}$ and $\mathbf{x}_{p^*+1}$. This reproduction process is a mating process by finding another individual that has similar characteristics to the current one $\mathbf{x}_{p+1}$. With this procedure, a vector ~~to~~ similar to the current vector will be mated and will produce a new descendant.

(6-2) Crossover: Replace each element x_{p+1}^{s} with $x_{p^*+1}^{s}$ at probability P_{cr}, i.e.,

$$X_{c+1}^{s} = \begin{cases} x_{p^*+1}^{s} & \text{if } \ \varepsilon < P_{cr} \\ x_{p+1}^{s} & \text{otherwise} \end{cases} \tag{13}$$

where ε is a uniform random number between 0 and 1. From this crossover, a new occurrence vector whose elements are similar to the historical ones is generated.

(6-3) Mutation: Replace each element (i.e., each station, s=1,…, S) with one selected from all the observations of this element for i=1,…, n with probability P_m, i.e.,

$$X_{c+1}^{s} = \begin{cases} x_{\xi+1}^{s} & \text{if } \ \varepsilon < P_{m} \\ x_{p+1}^{s} & \text{otherwise} \end{cases} \tag{14}$$

where $x^{s}_{\xi+1}$ is selected from $[x_i^s]_{i\in\{1,\ldots,n\}}$ with equal probability for i=1,…, n and ε is a uniform random number between 0 and 1. This mutation procedure allows to generate a multisite occurrence combination that is totally different from the historical records. Without this procedure, ~~always similar~~ multisite occurrences always similar to historical combinations are generated, which is not feasible for a simulation purpose.

(7) Repeat steps (1)-(6) until the required data are generated.

The selection of the number of nearest neighbors (k) has been investigated by Lall and Sharma (1996) and Lee and Ouarda (2011). A simple selection method was applied in the current study as $k=\sqrt{n}$. For hydrometeorological stochastic simulation, this heuristic approach of k selection has been employed (Lall and Sharma, 1996; Lee and Ouarda, 2012; Lee et al., 2010b; Prairie et al., 2006; Rajagopalan and Lall, 1999). One can use generalized cross-validation (GCV) as shown in Sharma and Lall (1996) and Lee and Ouarda 2011 by treating this simulation as a prediction problem. However, the current multisite occurrence simulation does not necessarily require an accurate value prediction and not much difference ~~o~~in simulation using the simple heuristic approach has been ~~is~~ reported. Also, this heuristic approach of k selection has been popularly employed for hydrometeorological stochastic simulations (Lall and Sharma, 1996; Lee and Ouarda, 2012; Lee et al., 2010b; Prairie et al., 2006; Rajagopalan and Lall, 1999).

In Appendix A, an example of the DKNNR simulation procedure is explained in detail.

~~4.2.~~2.2. Adaptation to climate change

The capability of model to take climate change into account is critical. For example, the marginal distributions and transition probabilities in Eqs. (5)~~(5)~~ and (3)~~(3)~~ can change in future climate scenarios. It is known that nonparametric simulation models have a difficulty to adapt to climate change, since the models employ in general the current observation sequences. However, the proposed model in the current study possesses the capability to adapt to the variations of probabilities by tuning the crossover and mutation probabilities in P_{cr} (13)~~(13)~~ and P_m (14)~~(14)~~ , adding the condition when applied.

For example, the probability of P_{11} can be increased with the cross-over probability P_{cr} by adding the condition to increase the probability of P_{11} as:

$$X_{c+1}^{s} = \begin{cases} x_{p^*+1}^{s} & \text{if } \varepsilon < P_{cr} \ \& \ x_{p^*+1}^{s} = 1 \ \& \ X_{c}^{s} = 1 \\ x_{p+1}^{s} & \text{otherwise} \end{cases} \tag{15}$$

It is obviously possible to increase the probability of P_1 by removing the condition of $X_c^s = 1$.

In addition, further adjustment can be made with the mutation process in Eq. (14)~~(14)~~ as

$$X_{c+1}^{s} = \begin{cases} x_{\xi+1}^{s} & \text{if } \varepsilon < P_{m} \text{ and } x_{\xi+1}^{s} = 1 \\ x_{p+1}^{s} & \text{otherwise} \end{cases} \tag{16}$$

This adjustment of adding the condition $x_{\xi+1}^{s} = 1$ can increase the marginal distribution as much as $P_m \times P_1$. This has been tested in a ~~the~~ case study.

~~5.~~3. Study area and data description

For testing the occurrence model, 12 weather stations were selected from Yeongnam province which is located in the southeastern part of South Korea, as shown in Figure 1~~Figure 1~~. Information on longitude and latitude (fourth and fifth columns) as well as order index and the identification number (first and second columns) of these stations operated by Korea Meteorological Administration with the area name (third column) is shown ~~at~~in Table 1~~Table 1~~. The employed precipitation dataset presents strong seasonality, since this area is dry from late fall to early autumn and humid and rainy during the remaining ~~st~~ seasons, especially ~~o~~in summer. The employed stations are not far from each other, at most 100 km apart, and not much high mountains are located in the current study area. Therefore, this region can be considered as a homogeneous region (Lee et al., 2007).

Figure 1~~Figure 1~~ illustrates the locations of the selected weather stations. All the stations are inside Yeongnam province which consists of two different regions as north and south Gyeongsang as well as the self-governing cities of Busan, Daegu, and Ulsan. Most of the Yeongnam region is drained to Nakdong River. To validate the proposed model appropriately, test~~ed~~ sites must be highly correlated with each other as well as have significant temporal relation. The ~~employed~~ stations inside the Yeongnam area cover one of the most important watersheds, the Nakdong River basin, where the Nakdong ~~r~~River passes through the entire basin and its hydrological assessments for agriculture and climate change have ~~s the~~a particular value in flood control and water resources management such as floods and droughts.

It is important to analyze the impact of weather conditions for planning agricultural operations and water resources management, especially during the summer season, because around 50-60 percent of the annual precipitation occurs during the summer season from June to September. The length of daily precipitation data record ranges from 1976 to 2015 and the summer season record was employed, since a large number of rainy days occur~~s~~ during summer and it is important to preserve these characteristics. Also, the whole year dataset was tested and other seasons were further applied but the correlation coefficient was relatively high and its correlation matrix estimated was not a positive semi-definite matrix for the MONR model.

~~6.~~4. Application

To analyze the performance of the proposed DKNNR model, the occurrence of precipitation was simulated. The DKNNR simulation was compared with that of the MONR model. For each model, 100 series of daily occurrence with the same record length were simulated. The key statistics of observed data and each generated series, such as transition probabilities (P_{11}, P_{01} , and P_1) and cross-correlation (see Eq.(10)~~(10)~~), were determined. The MONR model underestimated the lag-1 cross-correlation, as indicated by Wilks (1998). In the current study, this statistic was analyzed, since a synoptic scale weather system often results in lagged cross-correlation for daily precipitation data (Wilks, 1998). It was formulated as

$$\rho_1(q,s) = corr[X_{t-1}^{q}, X_{t}^{s}] \qquad (17)$$

Statistics from 100 generated series were evaluated by the root mean square error (RMSE) expressed as~~ below~~:

$$RMSE = \left(\frac{1}{N} \sum_{m=1}^{N} (\Gamma_m^G - \Gamma^h)^2 \right)^{1/2} \qquad (18)$$

where N is the number of series (here 100), Γ_m^G is the statistic estimated from the m^{th} generated series, while Γ^h is the statistic for the observed data. Note that lower RMSE indicates better performance representing the summarized error of a given statistic of generated series from the statistic of the observed data.

The 100 simulated statistic values were illustrated with boxplots to show their variability as shown in Figure 5~~Figure 4~~ - Figure 7~~Figure 6~~. The box of boxplot represents the interquartile range (IQR) ranging 25 percentile to 75 percentile. The whiskers extend to up and down 1.5×IQR. Data beyond the whiskers (1.5×IQR) are indicated by a plus sign (+). The horizontal line inside the box represents the median of the data. The statistics of the observed data are denoted by a cross (x). The closer a cross is to the horizontal line inside the box, the better the simulated data from a model reproduces the statistical characteristics of the observed data.

~~The roles of crossover probability P_{cr} (Eq. (13)) and mutation probability P_m (Eq.(14)) were studied by Lee et al. (2010b). In the current study, we further tested to select an appropriate parameter set of these two parameters with the simulated data from the DKNNR model and the record length of 100,000. RMSE (Eq. (18)) of the three transition and limiting probabilities (P_{11}, P_{01}, and P_1) between the simulated data and the observed was used, since those probabilities are key statistics that the simulated data must be met with the observed and no parameterization on these probabilities has been made for the current DKNNR model. The results are shown in Figure 2 and Figure 3 for P_{cr} and P_m, respectively. For P_{cr} in Figure 2, the probability of 0.02 shows the smallest RMSE in all transition and limiting probabilities. The RMSE of P_m in Figure 3 shows a slight fluctuation along with P_m. However, all three probabilities (P_{11}, P_{01}, and P_1) have relatively small RMSEs in P_m =0.003. Therefore, the parameter set 0.02 and 0.003 is chosen for P_{cr} and P_m, respectively, and employed in the current study.~~

~~7.~~5. Results

5.1. GA mixing and its probability selection

The roles of crossover probability P_{cr} (Eq. (13)) and mutation probability P_m (Eq.(14)) were studied by Lee et al. (2010b). In the current study, we further tested by ~~to~~ selecting an appropriate parameter set of these two parameters with the simulated data from the DKNNR model and the record length of 100,000. RMSE (Eq. (18)) of the three transition and limiting probabilities (P_{11}, P_{01}, and P_1) between the simulated data and the observed was used, since those probabilities are key statistics that the simulated data must match ~~be met~~ with the observed data and no parameterization of~~n~~ these probabilities ~~h~~was ~~been~~ made for the current DKNNR model. ~~The~~ ~~r~~Results are shown in Figure 2 and Figure 3 for P_{cr} and P_m, respectively. For P_{cr} in Figure 2, the probability of 0.02 shows the smallest RMSE in all transition and limiting probabilities. The RMSE of P_m in Figure 3 shows a slight fluctuation along with P_m. However, all three probabilities (P_{11}, P_{01}, and P_1) have relatively small RMSEs in P_m =0.003. Therefore, the parameter set 0.02 and 0.003 ~~i~~was chosen for P_{cr} and P_m, respectively, and employed in the current study. We also tested the simulation without the GA mixing procedure (results not shown). The results showed that no better result could ~~an~~ be found from the simulation wihtout GA mixing. The necessity of the GA mixing is further discussed in the following.

We further tested and discussed why the GA mixing is necessary in the proposed DKNNR model as follows. For example, assume that three weather stations are considered and observed data only has the occurrence cases of 000, 001,011,010, 011,100,111 among 2^3=8 possible cases. In other words, no patterns for 110 and 101 is found in the observed data. Note that 0 is dry day and 1 is rainy (or wet) day. The KNNR is a ~~the~~ resampling process in that the simulation data is

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resampled from the observation. Therefore, no new patterns such as 110 and 101 can be found in the simulated data.

This can be problematic for the simulation purpose in that one of the major simulation purposes is to simulate sequences that might possibly happen in future. The wet (1) or dry (1 0?) for multisite precipitation occurrence is decided by the spatial distribution of a precipitation weather system. A humid air mass can be distributed randomly relying on wind velocity and direction as well as surrounding air pressure. In general, any combinations of wet and dry stations can be possible, especially when the simulation continues infinitely. Therefore, the patterns of ~~the~~ simulated data must be allowed to have any possible combinations, here 4096 even if it has not been observed from the historical records. Also, its probability to have this new pattern must ~~be~~ not be high since it has not been observed in the historical records and this can be taken into account by low probability of the crossover and mutation.

서식 있음: 강조

This drawback of the KNNR model frequently happens in multisite occurrence as the number of stations increases. Note that the number of patterns increases as 2^n where *n* is the number of stations. If *n*=12, then 4096 cases must be observed. However, among 4096 cases, observed cases are limited, since the number of data is limited. The GA process can mix two candidate patterns to produce new patterns. For example, in the three station case, ~~,~~ a new pattern 101 can be produced from two observed occurrence candidates of 001 and 100 by the crossover of the first value of ~~the~~ 001 to the first value of 100 (i.e. 001 →101), which is not in the observed data.

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Note that the data employed in the case study are 40 years and 122 days (summer months) in ~~at~~ each year. The total number of the observed data is 4880 and the number of possible cases is

4096. We checked how many of possible cases are not found in the observed data. The result shows that 3379 cases are not observed at all for the entire cases as shown in Figure 4.

We further investigated how many ~~of~~ new patterns are generated with the probabilities P_{cr}=0.02, P_m=0.001 by ~~of~~ the proposed GA mixing. The generated data for 100 sequences from DKNNR with the GA mixing shows that the number 3379 was reduced to 1200, which is not in the dataset among the 4096 possible patterns. Therefore, more than 2000 new patterns were simulated with the GA mixing process. The KNNR model without the GA mixing does not produce any new patterns in the 100 sequences with the same length of the historical data.

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~~7.1.~~5.2. Occurrence and transition probabilities

The data simulated from the proposed DKNNR model and the existing MONR model were analyzed. The estimated transition probabilities (P_{11} and P_{01} in Eq. (3)~~(3)~~) as well as the occurrence probability (P_1 in Eq. (5)~~(5)~~) are shown in Table 2~~Table 2~~ and Figure 5~~Figure 4~~ - Figure 7~~Figure 6~~ for the observed data and the data generated from the DKNNR and MONR models. In Table 2~~Table 2~~, the observed statistic shows that P_{11} is always higher than P_{01} and P_1 is between P_{11} and P_{01}. Site 6 shows the lowest P_{11} and P_1 and site 12 shows the highest P_{11}.

As shown in Figure 5~~Figure 4~~, the probability P_{11} of the observed data shows that sites 6, 7, 8, and 9 located in the northern part of the region exhibited lower consistency (i.e. consecutive rainy days) than did the other sites, while sites 5 and 12 had higher probability of P_{11} than did other sites. Both models preserved well the observed P_{11} statistic. It seems that the MONR model had a slightly better performance, since this statistic is parameterized in the model as shown in ~~the~~ section 2.2 and that is the same for P01 and P1 as shown in Figure 6 and Figure 7. Note that the

MONR model employed the transition probabilities in simulating rainfall occurrence, while DKNNR model did not. The occurrence probability P_1 can be described with the combination of transition probabilities as in Eq. (5)~~(5)~~. Even though the transition probabilities were not employed in simulating rainfall occurrence, the DKNNR model preserved this statistic fairly well.

In ~~Among~~ the DKNNR modeling procedure, the simple distance measurement in Eq. (11) allows to preserve ~~ing~~ transition probabilities in that the following multisite occurrence is resampled from the historical data whose previous states of multisite occurrence (x_i^s) are similar to the current simulation multisite occurrence (X_c^s). This summarized distance (D_i) is an essential tool in the proposed DKNNR modeling. The condition of the current weather system is memorized and the system is conditioned on simulating the following multisite occurrence with the distance measurement like a precipitation weather system dynamically changes but often it impacts the system of the following day.

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As shown in Figure 6~~Figure 5~~, the P_{01} probability showed a slightly different behavior such that sites 1, 2, and 3 located in the middle part of the Yeongnam province showed a higher probability than did other sites. A slight underestimation was seen for sites 2 and 11 but it was not critical, since its observed value with a cross mark was close to the upper IQR representing 75 percentile.

The behavior of P_1 was found to be the same as that of the P_{11} probability. It can be seen in Figure 7~~Figure 6~~ that no significant underestimation is seen for the DKNNR model (top panel). The P_1 statistic was fairly preserved by both DKNNR and MONR models. Note that the MONR model parameterized the P_1 statistic through the transition probabilities as in Eq. (5)~~(5)~~, while

DKNNR model did not. Although the DKNNR model used almost no parameters for simulation, the P_1 statistic was preserved fairly well.

~~7.2.~~5.3. Cross-correlation

Cross-correlation is a measure of relationship between sites. The preservation of cross-correlation is important for the simulation of precipitation occurrence and is required in the regional analysis for water resources management or agricultural applications. Furthermore, lagged cross-correlation is also essential as much as is cross-correlation (i.e. contemporaneous correlation). For example, the amount of streamflow for a watershed from a certain precipitation event is highly related with lagged cross-correlation.

Daily precipitation occurrence, in general, shows the strongest serial correlation at lag-1 and its correlation ~~is~~ decays~~ed~~ as the lag~~s~~ gets longer. This is because a precipitation weather system moves according to the surrounding pressure and wind direction that dynamically change within a day or week. Therefore, we analyzed the lag-1 cross-correlation in the current study as the representative lagged correlation structure.~~It is accepted that precipitation is not significantly correlated with that for more than one day. Therefore, only lag-1 cross-correlation was analyzed in the current study.~~

The cross-correlation of observed data is shown in Table 3~~Table 3~~. High cross-correlation among grouped sites, such as sites 6, 7, and 8 (northern part) and sites 3, 4, and 5 as well as 12 (southeast coastal area, 0.68-0.87), was found. As expected, sites 5 and 12 had the highest cross-correlation (0.87) due to ~~the~~ proximity. The northern sites and coastal sites showed low cross-correlation. This observed cross-correlation was well preserved in the data generated from both DKNNR and MONR models, as shown in Figure 8~~Figure 7~~ as well as Table 4~~Table 4~~ and Table

5~~Table 5~~. However, consistently slight but significant underestimation of cross-correlation was seen for the data generated by the MONR model (see the bottom panel of Figure 8~~Figure 7~~). Note that the errobars are extended to upper and lower lines of the circles to 1.95×standard deviation. The difference of RMSE in Table 6~~Table 6~~ showed this characteristic, as most of the values were positive, ~~to be~~ indicating that the proposed DKNNR model performed better for cross-correlation.

The lag-1 cross-correlation of observed data, as shown in Table 7~~Table 7~~, ranged from 0.22-0.35. The lag-1 cross-correlation for the same site (i.e. $\rho_1(q,s)$, q=s) was autocorrelation and was highly related with P_{01} and P_{11} as in Eq. (6)~~(6)~~. All the lag-1 cross-correlations exhibited similar magnitudes even for autocorrelation. This implies that the lag-1 cross-correlation among the selected sites was as strong as the autocorrelation and as much as the transition probabilities P_{01} and P_{11}, thereof.

The observed lag-1 cross-correlations were well preserved in the data generated by the DKNNR model, as shown in the top panel of Figure 9~~Figure 8~~, while the MONR model showed significant underestimation, as seen in the bottom panel of Figure 9~~Figure 8~~. The difference of RMSE shown in Table 8~~Table 8~~ reflects this behavior. In the bottom panel of Figure 9~~Figure 8~~, some of the lag-1 cross-correlations were well preserved, that was aligned with the base line. From Table 8~~Table 8~~, the MONR model reproduced the autocorrelations well with the shaded values. It is because the lag-1 autocorrelation was indirectly parameterized with the transition probabilities of P_{11} and P_{01} as in Eq. (6)~~(6)~~. Other than this autocorrelation, the lag-1 cross-correlation was not reproduced well with the MONR model. This shortcoming was mentioned by Wilks (1998). Meanwhile, the proposed DKNNR model preserved this statistic without any parameterization.

We further tested the performance measurements of MAE and Bias. The estimates showed that MAE had no difference from RMSE. In addition, Bias of the lag-1 correlation presented~~s~~ significant negative values implying its underestimation for the simulated data of the MONR model as shown in Table 9~~Table 9~~, while Table 10~~Table 10~~ of the DKNNR model showed~~s~~ a much smaller bias.

Also, the whole year data instead of the summer season data was tested for model fitting. Note that all the results presented above were for ~~with~~ the summer season data (June-September) as mentioned in section 4 on ~~the~~ data description. The lag-1 cross-correlation is shown in Figure 10~~Figure 9~~ which indicates that the same characteristic was observed as for the summer season, such that the proposed DKNNR model preserved better the lagged cross-correlation than did the existing MONR model. Other statistics, such as correlation matrix and transition probabilities, exhibited the same results (not shown). Also, other seasons were tried but the estimated correlation matrix was not a positive semi-definite matrix and its inverse cannot be made for multivariate normal distribution in the MONR model. It was because the selected stations were close to each other (around 50-100 km) and produced high cross-correlation, especially in the occurrence during dry seasons. Special remedy for the existing MONR model should be applied, such as decreasing cross-correlation by force, but further remedy was not applied in the current study since it was not within the current scope and focus.

~~7.3.~~5.4. Adaptation to climate change

Model adaptability to climate change in hydro-meteorological simulation models is a critical factor, since one of the major applications of the models is to assess the impact of climate change. Therefore, we tested the capability of the proposed model in the current study by adjusting the probabilities of cross-over and mutation as in Eqs.(15)~~(15)~~ and (16)~~(16)~~. A number of variations can be made with different conditions.

In Figure 11~~Figure 10~~, the changes of transition and marginal probabilities are shown along with increasing the crossover probability P_{cr} from 0.01 to 0.2 with the condition that that the candidate value is one and the previous value is also one as in Eq. (15)~~(15)~~ for the selected 5 stations among the 12 stations (from station 1 to station 5, see Table 1~~Table 1~~ for details). The stations were limited in this analysis due to computational time. In ~~At~~ each case 100 series were simulated. The average value of the simulated statistics is presented in the figure. It is obvious that the transition probability P_{11} increased as intent~~ion~~ed along with the increase of P_{cr}. As expected from Eq. (5)~~(5)~~, P_1 presents that the change of P_1 is highly related to P_{11}. However, the probability P_{01} fluctuated along with the increase of P_{cr}. Elaborate work to adjust all the probabilities is however required.

The changes in transition and marginal probabilities are presented in Figure 12~~Figure 11~~ with increasing mutation probability P_m from 0.01 to 0.2 under the condition that the candidate value is one so that the marginal probability P_1 increased. P_{01} also increased along with increasing P_1. The change of P11 was not related with other probabilities. The combination of the adjustment of P_{cr} and P_m with a certain condition to the previous state will allow the specific adaptation for simulating future climatic scenarios.

Climate change, however, may refer to a larger phenomenon, which cannot be addressed directly through modifying only the marginal and transition probabilities as in the current study. Further modeling development on systematically varying temporal and spatial cross-correlations is required to properly address the climate change of the regional precipitation system.

~~8.~~6. Conclusions

In the current study, the discrete version of a nonparametric simulation model, based on ~~discrete~~ KNNR~~ and DKNNR~~, is proposed to overcome the shortcomings of the existing MONR model such as long stochastic simulation for ~~the~~ parameter estimation and underestimation of the lagged crosscorrelation between sites as well as testing the adaptability for climatic change. Occurrence and transition probabilities and cross-correlation as well as lag-1 cross-correlation are estimated for both models. Better preservation of cross-correlation and lag-1 cross-correlation with the DKNNR model than the MONR model is observed. For some cases (i.e., the whole year data and other seasons than the summer season), the estimated cross-correlation matrix is not a positive semi-definite matrix so the multivariate normal simulation is not applicable for the MONR model, because the tested sites are close to each other with high cross-correlation.

Results of this study indicate that the proposed DKNNR model reproduces the occurrence and transition probabilities fairly ~~well~~ and preserves the cross-correlations better than the existing MONR model. Furthermore, not much effort is required to estimate the parameters in the DKNNR model, while the MONR model requires a long stochastic simulation just to estimate each parameter. Thus, the proposed DKNNR model can be a good alternative for simulating multisite precipitation occurrence.

We tested further the enhancement of the proposed model for adapting to climate change by ~~through~~ modifying the mutation and crossover probabilities~~y~~ P_m and P_{cr}. The results showed that the proposed DKNNR model has the capability to adapt to the climate change scenarios, but further elaborate work is required to find the best probability estimation for climate change. Also, only the marginal and transition probabilities cannot address the climate change of regional

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precipitation. The variation of temporal and spatial cross-correlation structure must be considered to properly address the climate change of the regional precipitation system. Further study on improving the model adaptability to climate change will be followed in the near future.~~We tested further the enhancement of the proposed model for adapting to climate change through modifying the mutation and crossover probability P_m and P_{cr} with the current and previous states. The results show that the current model has the capability to adapt to the climate change scenarios, but elaborate work is required, however. Further study on improving the model adaptability to climate change will be followed in the near future.~~

Also, the simulated multisite occurrence can be coupled with a multisite amount model to produce precipitation events, including zero values. Further development can be made for multisite amount models with a nonparametric technique, such as KNNR and bootstrapping.

Code and Data Availability

DKNNR code is written in Matlab and is available as a supplement.

The precipitation data employed in the current study is downloadable through http://www.weather.go.kr/weather/main.jsp

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Appendix A: Example of DKNNR

In this appendix, one example of DKNNR simulation is presented with observed dataset in Table A 1~~Table A 1~~ (i.e. $\mathbf{x}_i = [x_i^s]_{s\in\{1,S\}}$ for i=1,…,n; here S=12 and n=16). The upper part of the table presents the observed precipitation (unit: mm). Its occurrence data is presented in the bottom part of this table. The current precipitation occurrence $\mathbf{X}_c = [X_c^s]_{s\in\{1,\ldots,12\}}$ is shown in the second row of Table A 2~~Table A 2~~. The number of nearest neighbors $k = \sqrt{n} = \sqrt{16} = 4$ and the parameters for GA (i.e. P_c and P_m) are 0.1 and 0.01, respectively. Simulation can be made as follows:

(1) Estimate the distance D_i between $\mathbf{x}_i$ and $\mathbf{X}_c$ for i=1,…,n-1 as in Eq.(11)~~(11)~~. For example, for i=1,

$$D_1 = \sum_{s=1}^{S} \left| X_c^s - x_1^s \right| = |0-1| + |1-1| + ... + |0-1| = 6$$

All the estimated distances are shown in the last column of Table A 2~~Table A 2~~.

(2) The daily index values are sorted according to the smallest distances shown in the first two columns of Table A 3~~Table A 3~~. The sorted day indices and their corresponding distances are shown in the third and fourth columns of Table A 3~~Table A 3~~. From ~~Among~~ the k number of sorted indices, one is selected with the weight probability (see Eq.(12)~~(12)~~), which is shown in the last column of Table A 3~~Table A 3~~.

(3) Simulate a uniform random number (u) between 0 and 1. Say u=0.321. This value must be compared with the cumulative weighted probabilities in the last column of Table A 3~~Table A 3~~ as [0 0.48 0.72 0.88 1.0]. The corresponding day index is assigned as to where the simulated uniform number falls in the cumulative weighted probabilities, here [0 0.48].

Therefore, the selected day, *p*, is 14. The occurrences of the following day *p*+1=15 for 12 stations are selected as in the second row of Table A 4~~Table A 4~~.

(4) For GA mixture, another set must be chosen as in step (3). Say *u*=0.561, which falls in [0.48 0.72]. The second one should be selected. However, there are a number of days with the same distances. Specifically, six days have the same distances with D_i=4. In this case, one among all six days is selected with equal probability. Assume that *p*=4 is selected and the following occurrences are selected, as shown in the third row of Table A 4~~Table A 4~~.

(5) With two sets, crossover and mutation process is performed as follows:

(5-1) Crossover: For each station, a uniform random number (ε) is generated and compared with P_c=0.1 here. Say ε =0.345, then skip since ε =0.345> P_c=0.1. For *s*=6, assume the generated random number, ε (=0.051)< P_c(=0.1) and then switch the 6th station value of Set 1 into the value of Set 2 (see Table A 4~~Table A 4~~). The occurrence state of X_{c+1}^{s} turns into 1 from 0 as shown in the fourth row of Table A 4~~Table A 4~~ as well as station 8.

(5-2) Mutation: For each station, a uniform random number (ε) is generated and compared with P_m=0.01. For *s*=12, assume ε =0.009< P_m=0.01 and switch the 12th station value of Set 1 with the one selected among all the observed 12th station values with equal probability (here the last column, *s*=12, of the bottom part of Table A 1~~Table A 1~~, [1 1 0 0 … 1]). The occurrence state of X_{c+1}^{12} turns into 0 from 1 as shown in the fourth column of Table A 4~~Table A 4~~.

(6) Repeat steps (1)-(5) until the target simulation length is reached.

References

Apipattanavis, S., Podesta, G., Rajagopalan, B., and Katz, R. W.: A semiparametric multivariate and multisite weather generator, Water Resources Research, 43, Artn W11401, 2007.

Beersma, J. J. and Buishand, A. T.: Multi-site simulation of daily precipitation and temperature conditional on the atmospheric circulation, Climate Research, 25, 121-133, 2003.

Brandsma, T. and Buishand, T. A.: Simulation of extreme precipitation in the Rhine basin by nearest-neighbour resampling, Hydrology and Earth System Sciences, 2, 195-209, 1998.

Buishand, T. A. and Brandsma, T.: Multisite simulation of daily precipitation and temperature in the Rhine basin by nearest-neighbor resampling, Water Resources Research, 37, 2761-2776, 2001.

Chau, K. W.: Use of meta-heuristic techniques in rainfall-runoffmodelling, Water (Switzerland), 9, 2017.

Fotovatikhah, F., Herrera, M., Shamshirband, S., Chau, K. W., Ardabili, S. F., and Piran, M. J.: Survey of computational intelligence as basis to big flood management: Challenges, research directions and future work, Engineering Applications of Computational Fluid Mechanics, 12, 411-437, 2018.

Frost, A. J., Charles, S. P., Timbal, B., Chiew, F. H. S., Mehrotra, R., Nguyen, K. C., Chandler, R. E., McGregor, J. L., Fu, G., Kirono, D. G. C., Fernandez, E., and Kent, D. M.: A comparison of multi-site daily rainfall downscaling techniques under Australian conditions, Journal of Hydrology, 408, 1-18, 2011.

Hughes, J. P., Guttorp, P., and Charles, S. P.: A non-homogeneous hidden Markov model for precipitation occurrence, Journal of the Royal Statistical Society. Series C: Applied Statistics, 48, 15-30, 1999.

Jeong, D. I., St-Hilaire, A., Ouarda, T. B. M. J., and Gachon, P.: A multi-site statistical downscaling model for daily precipitation using global scale GCM precipitation outputs, International Journal of Climatology, 33, 2431-2447, 2013.

Jeong, D. I., St-Hilaire, A., Ouarda, T. B. M. J., and Gachon, P.: Multisite statistical downscaling model for daily precipitation combined by multivariate multiple linear regression and stochastic weather generator, Climatic Change, 114, 567-591, 2012.

Katz, R. W.: Precipitation as a Chain-Dependent Process, Journal of Applied Meteorology, 16, 671-676, 1977.

Katz, R. W. and Zheng, X.: Mixture model for overdispersion of precipitation, Journal of Climate, 12, 2528-2537, 1999.

Lall, U. and Sharma, A.: A nearest neighbor bootstrap for resampling hydrologic time series, Water Resources Research, 32, 679-693, 1996.

Lee, T.: Multisite stochastic simulation of daily precipitation from copula modeling with a gamma marginal distribution, Theoretical and Applied Climatology, doi: 10.1007/s00704-017-2147-0, 2017. 1-10, 2017.

Lee, T.: Stochastic simulation of precipitation data for preserving key statistics in their original domain and application to climate change analysis, Theoretical and Applied Climatology, 124, 91-102, 2016.

Lee, T. and Ouarda, T. B. M. J.: Identification of model order and number of neighbors for k-nearest neighbor resampling, Journal of Hydrology, 404, 136-145, 2011.

Lee, T. and Ouarda, T. B. M. J.: Stochastic simulation of nonstationary oscillation hydro-climatic processes using empirical mode decomposition, Water Resources Research, 48, 1-15, 2012.

Lee, T., Ouarda, T. B. M. J., and Jeong, C.: Nonparametric multivariate weather generator and an extreme value theory for bandwidth selection, Journal of Hydrology, 452-453, 161-171, 2012.

Lee, T., Ouarda, T. B. M. J., and Yoon, S.: KNN-based local linear regression for the analysis and simulation of low flow extremes under climatic influence, Climate Dynamics, doi: 10.1007/s00382-017-3525-0, 2017. 1-19, 2017.

Lee, T. and Park, T.: Nonparametric temporal downscaling with event-based population generating algorithm for RCM daily precipitation to hourly: Model development and performance evaluation, Journal of Hydrology, 547, 498-516, 2017.

Lee, T., Salas, J. D., and Prairie, J.: An enhanced nonparametric streamflow disaggregation model with genetic algorithm, Water Resources Research, 46, 2010a.

Lee, T., Salas, J. D., and Prairie, J.: An Enhanced Nonparametric Streamflow Disaggregation Model with Genetic Algorithm, Water Resources Research, 46, W08545, 2010b.

Lee, Y.-S., Heo, J.-H., Nam, W., and Kim, K.-D.: Application of Regional Rainfall Frequency Analysis in South Korea(II): Monte Carlo Simulation and Determination of Appropriate Method, Journal of the Korean Society of Civil Engineers, 27, 101-111, 2007.

Mehrotra, R., Srikanthan, R., and Sharma, A.: A comparison of three stochastic multi-site precipitation occurrence generators, Journal of Hydrology, 331, 280-292, 2006.

Prairie, J. R., Rajagopalan, B., Fulp, T. J., and Zagona, E. A.: Modified K-NN model for stochastic streamflow simulation, Journal of Hydrologic Engineering, 11, 371-378, 2006.

Rajagopalan, B. and Lall, U.: A k-nearest-neighbor simulator for daily precipitation and other weather variables, Water Resources Research, 35, 3089-3101, 1999.

St-Hilaire, A., Ouarda, T. B. M. J., Bargaoui, Z., Daigle, A., and Bilodeau, L.: Daily river water temperature forecast model with a k-nearest neighbour approach, Hydrological Processes, 26, 1302-1310, 2012.

Taormina, R., Chau, K. W., and Sivakumar, B.: Neural network river forecasting through baseflow separation and binary-coded swarm optimization, Journal of Hydrology, 529, 1788-1797, 2015.

Todorovic, P. and Woolhiser, D. A.: Stochastic model of n-day precipitation Journal of Applied Meteorology, 14, 17-24, 1975.

Wang, W. C., Xu, D. M., Chau, K. W., and Chen, S.: Improved annual rainfall-runoff forecasting using PSO-SVM model based on EEMD, Journal of Hydroinformatics, 15, 1377-1390, 2013.

Wilby, R. L., Tomlinson, O. J., and Dawson, C. W.: Multi-site simulation of precipitation by conditional resampling, Climate Research, 23, 183-194, 2003.

Wilks, D. S.: Multisite downscaling of daily precipitation with a stochastic weather generator, Climate Research, 11, 125-136, 1999.

Wilks, D. S.: Multisite generalization of a daily stochastic precipitation generation model, Journal of Hydrology, 210, 178-191, 1998.

Wilks, D. S. and Wilby, R. L.: The weather generation game: a review of stochastic weather models, Progress in Physical Geography, 23, 329-357, 1999.

Zheng, X. and Katz, R. W.: Simulation of spatial dependence in daily rainfall using multisite generators, Water Resources Research, 44, 2008.

Table 1. Information on 12 selected stations from Yeongnam province, South Korea.

Order	Station Number[†]	Name	Longitude	Latitude
1	138	Pohang	129.3797	36.0327
2	143	Daegu	128.6189	35.8850
3	152	Ulsan	129.3200	35.5600
4	159	Busan	129.0319	35.1044
5	162	Tongyeong	128.4356	34.8453
6	277	Youngdeok	129.4092	36.5331
7	278	Uisung	128.6883	36.3558
8	279	Gumi	128.3206	36.1306
9	281	Youngcheon	128.9514	35.9772
10	285	Hapcheon	128.1697	35.5650
11	288	Milyang	128.7439	35.4914
12	294	Geojae	128.6044	34.8881

[†] The station number indicates the identification number operated by Korea Meteorological Administration (KMA).

Table 2. Occurrence and transition probabilities of observed data and data simulated by DKNNR and MONR for 12 stations from Yeongnam province, South Korea, during the summer season. Note that 100 sets with the same record length as the observed data were simulated and the statistics of 100 sets were averaged.

	Obs			DKNNR			MONR		
	P11	P01	P1	P11	P01	P1	P11	P01	P1
S1	0.56	0.27	0.38	0.56	0.27	0.38	0.56	0.26	0.37
S2	0.56	0.27	0.38	0.58	0.26	0.38	0.57	0.25	0.37
S3	0.57	0.26	0.38	0.58	0.26	0.38	0.56	0.26	0.37
S4	0.58	0.25	0.37	0.58	0.25	0.37	0.57	0.24	0.36
S5	0.58	0.25	0.37	0.59	0.24	0.37	0.58	0.24	0.36
S6	0.52	0.25	0.34	0.50	0.24	0.33	0.52	0.24	0.33
S7	0.55	0.26	0.36	0.56	0.25	0.36	0.55	0.24	0.35
S8	0.56	0.25	0.37	0.57	0.25	0.37	0.57	0.24	0.36
S9	0.55	0.25	0.36	0.55	0.24	0.35	0.55	0.24	0.35
S10	0.58	0.25	0.38	0.59	0.24	0.37	0.57	0.23	0.35
S11	0.57	0.25	0.36	0.58	0.24	0.36	0.56	0.24	0.35
S12	0.59	0.25	0.38	0.59	0.25	0.38	0.59	0.25	0.37

Table 3. Cross-correlation of observed data for 12 stations from Yeongnam province, South Korea.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	1.00	0.70	0.70	0.64	0.58	0.70	0.65	0.63	0.75	0.64	0.66	0.59
S2	0.70	1.00	0.67	0.64	0.61	0.64	0.70	0.72	0.79	0.72	0.74	0.62
S3	0.70	0.67	1.00	0.75	0.68	0.61	0.57	0.57	0.68	0.67	0.74	0.70
S4	0.64	0.64	0.75	1.00	0.79	0.56	0.56	0.55	0.65	0.66	0.73	0.82
S5	0.58	0.61	0.68	0.79	1.00	0.51	0.54	0.55	0.61	0.65	0.70	0.87
S6	0.70	0.64	0.61	0.56	0.51	1.00	0.69	0.65	0.68	0.59	0.59	0.54
S7	0.65	0.70	0.57	0.56	0.54	0.69	1.00	0.78	0.71	0.65	0.63	0.55
S8	0.63	0.72	0.57	0.55	0.55	0.65	0.78	1.00	0.71	0.68	0.65	0.56
S9	0.75	0.79	0.68	0.65	0.61	0.68	0.71	0.71	1.00	0.68	0.71	0.62
S10	0.64	0.72	0.67	0.66	0.65	0.59	0.65	0.68	0.68	1.00	0.77	0.66
S11	0.66	0.74	0.74	0.73	0.70	0.59	0.63	0.65	0.71	0.77	1.00	0.70
S12	0.59	0.62	0.70	0.82	0.87	0.54	0.55	0.56	0.62	0.66	0.70	1.00

Table 4. Averaged cross-correlation of the 100 simulated series from the DKNNR model for 12 stations from Yeongnam province, South Korea.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	1.00	0.68	0.69	0.64	0.60	0.69	0.64	0.62	0.73	0.63	0.65	0.61
S2	0.68	1.00	0.67	0.63	0.62	0.63	0.68	0.72	0.77	0.74	0.73	0.63
S3	0.69	0.67	1.00	0.74	0.69	0.60	0.58	0.59	0.66	0.68	0.74	0.70
S4	0.64	0.63	0.74	1.00	0.79	0.55	0.55	0.56	0.62	0.65	0.71	0.81
S5	0.60	0.62	0.69	0.79	1.00	0.51	0.56	0.58	0.60	0.66	0.70	0.86
S6	0.69	0.63	0.60	0.55	0.51	1.00	0.68	0.64	0.65	0.59	0.58	0.53
S7	0.64	0.68	0.58	0.55	0.56	0.68	1.00	0.78	0.69	0.65	0.63	0.56
S8	0.62	0.72	0.59	0.56	0.58	0.64	0.78	1.00	0.70	0.69	0.67	0.58
S9	0.73	0.77	0.66	0.62	0.60	0.65	0.69	0.70	1.00	0.67	0.69	0.60
S10	0.63	0.74	0.68	0.65	0.66	0.59	0.65	0.69	0.67	1.00	0.77	0.67
S11	0.65	0.73	0.74	0.71	0.70	0.58	0.63	0.67	0.69	0.77	1.00	0.71
S12	0.61	0.63	0.70	0.81	0.86	0.53	0.56	0.58	0.60	0.67	0.71	1.00

Table 5. Averaged cross-correlation of 100 simulated series from the MONR model for 12 stations from Yeongnam province.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	1.00	0.63	0.67	0.58	0.54	0.66	0.62	0.60	0.68	0.55	0.62	0.53
S2	0.63	1.00	0.61	0.60	0.57	0.59	0.68	0.68	0.75	0.66	0.72	0.58
S3	0.67	0.61	1.00	0.71	0.67	0.57	0.56	0.53	0.65	0.61	0.71	0.69
S4	0.58	0.60	0.71	1.00	0.78	0.50	0.52	0.52	0.61	0.62	0.69	0.78
S5	0.54	0.57	0.67	0.78	1.00	0.48	0.51	0.53	0.57	0.62	0.67	0.81
S6	0.66	0.59	0.57	0.50	0.48	1.00	0.67	0.62	0.63	0.54	0.54	0.49
S7	0.62	0.68	0.56	0.52	0.51	0.67	1.00	0.75	0.70	0.61	0.62	0.52
S8	0.60	0.68	0.53	0.52	0.53	0.62	0.75	1.00	0.66	0.64	0.61	0.52
S9	0.68	0.75	0.65	0.61	0.57	0.63	0.70	0.66	1.00	0.63	0.69	0.57
S10	0.55	0.66	0.61	0.62	0.62	0.54	0.61	0.64	0.63	1.00	0.72	0.61
S11	0.62	0.72	0.71	0.69	0.67	0.54	0.62	0.61	0.69	0.72	1.00	0.66
S12	0.53	0.58	0.69	0.78	0.81	0.49	0.52	0.52	0.57	0.61	0.66	1.00

Table 6. The difference of RMSE of cross-correlation between MONR and DKNNR. Note that the positive value indicates that the DKNNR model better performs in preserving the cross-correlation, while a negative value (underlined) shows that the MONR model better performs.

MONR-DKNNR	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.000	0.014	0.004	0.013	0.012	0.012	0.008	0.005	0.024	0.031	0.011	0.035
S2	0.014	0.000	0.023	0.013	0.021	0.009	0.010	0.013	0.018	0.027	0.011	0.020
S3	0.004	0.023	0.000	0.015	0.004	0.014	0.003	0.022	0.009	0.028	0.011	0.004
S4	0.013	0.013	0.015	0.000	0.002	0.017	0.018	0.014	0.018	0.018	0.027	0.024
S5	0.012	0.021	0.004	0.002	0.000	0.014	0.021	0.014	0.015	0.013	0.015	0.012
S6	0.012	0.009	0.014	0.017	0.014	0.000	0.006	0.010	0.030	0.018	0.029	0.021
S7	0.008	0.010	0.003	0.018	0.021	0.006	0.000	0.005	0.008	0.024	0.012	0.023
S8	0.005	0.013	0.022	0.014	0.014	0.010	0.005	0.000	0.032	0.019	0.022	0.023
S9	0.024	0.018	0.009	0.018	0.015	0.030	0.008	0.032	0.000	0.019	0.005	0.027
S10	0.031	0.027	0.028	0.018	0.013	0.018	0.024	0.019	0.019	0.000	0.020	0.021
S11	0.011	0.011	0.011	0.027	0.015	0.029	0.012	0.022	0.005	0.020	0.000	0.022
S12	0.035	0.020	0.004	0.024	0.012	0.021	0.023	0.023	0.027	0.021	0.022	0.000

Note that no negative value can be found implying that the DKNNR model preserves the crosscorrelation better than the MONR model.

Table 7. Lag-1 cross-correlation of observed data for 12 stations from Yeongnam province, South Korea.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.29[‡]	0.26	0.30	0.27	0.24	0.29	0.26	0.24	0.27	0.26	0.28	0.26
S2	0.28	0.30	0.29	0.28	0.26	0.28	0.28	0.27	0.31	0.30	0.32	0.27
S3	0.28	0.26	0.31	0.30	0.27	0.27	0.25	0.24	0.27	0.27	0.30	0.27
S4	0.28	0.27	0.32	0.34	0.31	0.27	0.26	0.26	0.28	0.28	0.31	0.32
S5	0.29	0.28	0.32	0.35	0.34	0.27	0.27	0.26	0.29	0.29	0.33	0.35
S6	0.25	0.22	0.26	0.23	0.22	0.27	0.24	0.22	0.25	0.23	0.24	0.23
S7	0.25	0.26	0.27	0.25	0.25	0.28	0.29	0.27	0.27	0.27	0.28	0.26
S8	0.29	0.30	0.29	0.27	0.26	0.30	0.31	0.30	0.31	0.30	0.31	0.27
S9	0.29	0.29	0.30	0.29	0.27	0.29	0.27	0.27	0.30	0.30	0.31	0.28
S10	0.28	0.31	0.32	0.31	0.29	0.29	0.30	0.30	0.31	0.33	0.34	0.29
S11	0.27	0.29	0.31	0.30	0.27	0.27	0.27	0.27	0.29	0.30	0.32	0.29
S12	0.30	0.29	0.32	0.35	0.33	0.28	0.27	0.26	0.29	0.30	0.33	0.35

[‡] Shaded values represent lag-1 autocorrelation (i.e. the one lagged correlation for the same site).

Table 8. The difference of RMSE of lag-1 cross-correlation between MONR and DKNNR. Note that a positive value indicates that the DKNNR model better performs in preserving lag-1 cross-correlation, while a negative value (underlined) shows that the MONR model better performs.

MONR- DKNNR	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.000	0.048	0.075	0.049	0.041	0.095	0.059	0.036	0.047	0.055	0.063	0.052
S2	0.070	0.000	0.079	0.057	0.046	0.104	0.068	0.047	0.066	0.058	0.073	0.047
S3	0.067	0.054	0.000	0.046	0.031	0.096	0.072	0.056	0.055	0.052	0.056	0.025
S4	0.086	0.075	0.083	0.002	0.037	0.117	0.089	0.077	0.078	0.062	0.077	0.040
S5	0.111	0.096	0.098	0.074	0.002	0.124	0.103	0.085	0.105	0.070	0.108	0.049
S6	0.039	0.024	0.060	0.038	0.043	-0.002	0.028	0.017	0.045	0.034	0.055	0.037
S7	0.055	0.045	0.077	0.061	0.062	0.084	0.000	0.023	0.051	0.052	0.071	0.064
S8	0.092	0.078	0.104	0.079	0.068	0.115	0.079	0.000	0.094	0.078	0.101	0.074
S9	0.060	0.052	0.084	0.066	0.056	0.106	0.057	0.056	0.001	0.069	0.076	0.064
S10	0.091	0.094	0.105	0.081	0.062	0.123	0.107	0.085	0.100	0.001	0.092	0.063
S11	0.064	0.061	0.071	0.057	0.033	0.109	0.084	0.063	0.062	0.043	-0.002	0.043
S12	0.121	0.099	0.096	0.077	0.036	0.130	0.101	0.086	0.107	0.082	0.109	0.003

Table 9. Bias of lag-1 cross-correlation of the generated data from the DKNNR model. Note that a positive value indicates the overestimation of lag-1 cross-correlation, while a negative value shows underestimation. Note that $Bias = 1/N\sum_{m=1}^{N}\Gamma_m^G - \Gamma^h$ and see Eq. (18)~~(18)~~ for the details of each term.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	0.000	0.009	0.001	0.003	0.006	-0.002	0.010	0.011	0.006	0.010	0.010	0.006
S2	0.005	0.009	0.010	0.006	0.008	0.006	0.011	0.011	0.004	0.009	0.009	0.010
S3	0.002	0.010	0.001	-0.002	0.003	0.002	0.007	0.008	0.006	0.009	0.006	0.007
S4	0.006	0.009	0.004	0.001	0.007	0.003	0.008	0.008	0.009	0.010	0.010	0.005
S5	0.004	0.005	0.000	-0.001	-0.001	0.007	0.005	0.006	0.002	0.008	0.000	-0.001
S6	-0.002	0.006	0.000	0.002	-0.001	-0.002	0.004	0.003	0.002	0.005	0.004	0.001
S7	0.004	0.008	0.003	0.003	0.001	0.004	0.002	0.006	0.007	0.007	0.007	0.002
S8	0.000	0.005	0.004	0.001	0.004	-0.003	-0.003	0.000	0.001	0.004	0.006	0.003
S9	0.005	0.007	0.006	0.003	0.006	0.004	0.010	0.007	0.004	0.007	0.006	0.007
S10	0.003	0.005	0.001	-0.001	-0.001	0.001	0.001	0.001	0.003	0.000	0.002	0.001
S11	0.010	0.010	0.008	0.004	0.008	0.009	0.009	0.009	0.010	0.010	0.011	0.008
S12	0.003	0.006	0.001	-0.001	0.004	0.003	0.008	0.008	0.005	0.005	0.002	0.001

Table 10. Bias of lag-1 cross-correlation of the generated data from the Wilks model. Note that a positive value indicates the overestimation of lag-1 cross-correlation, while a negative value shows underestimation.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	-0.001	-0.062	-0.089	-0.063	-0.055	-0.106	-0.074	-0.052	-0.060	-0.070	-0.080	-0.067
S2	-0.084	0.000	-0.096	-0.072	-0.061	-0.117	-0.083	-0.063	-0.079	-0.072	-0.089	-0.063
S3	-0.080	-0.070	0.001	-0.059	-0.043	-0.110	-0.086	-0.072	-0.069	-0.066	-0.071	-0.037
S4	-0.100	-0.090	-0.097	-0.001	-0.048	-0.129	-0.103	-0.093	-0.093	-0.077	-0.092	-0.051
S5	-0.125	-0.110	-0.111	-0.087	-0.001	-0.138	-0.117	-0.100	-0.118	-0.084	-0.121	-0.060
S6	-0.053	-0.037	-0.074	-0.051	-0.057	-0.001	-0.039	-0.030	-0.060	-0.047	-0.070	-0.049
S7	-0.068	-0.058	-0.091	-0.077	-0.077	-0.098	-0.002	-0.038	-0.065	-0.065	-0.086	-0.079
S8	-0.106	-0.091	-0.119	-0.094	-0.084	-0.128	-0.093	0.001	-0.108	-0.091	-0.116	-0.088
S9	-0.074	-0.064	-0.098	-0.080	-0.070	-0.119	-0.072	-0.070	-0.001	-0.082	-0.091	-0.078
S10	-0.105	-0.107	-0.120	-0.096	-0.075	-0.136	-0.119	-0.097	-0.113	-0.001	-0.106	-0.076
S11	-0.078	-0.074	-0.085	-0.070	-0.047	-0.123	-0.097	-0.077	-0.076	-0.056	-0.001	-0.057
S12	-0.134	-0.112	-0.108	-0.088	-0.046	-0.142	-0.116	-0.101	-0.121	-0.095	-0.122	0.000

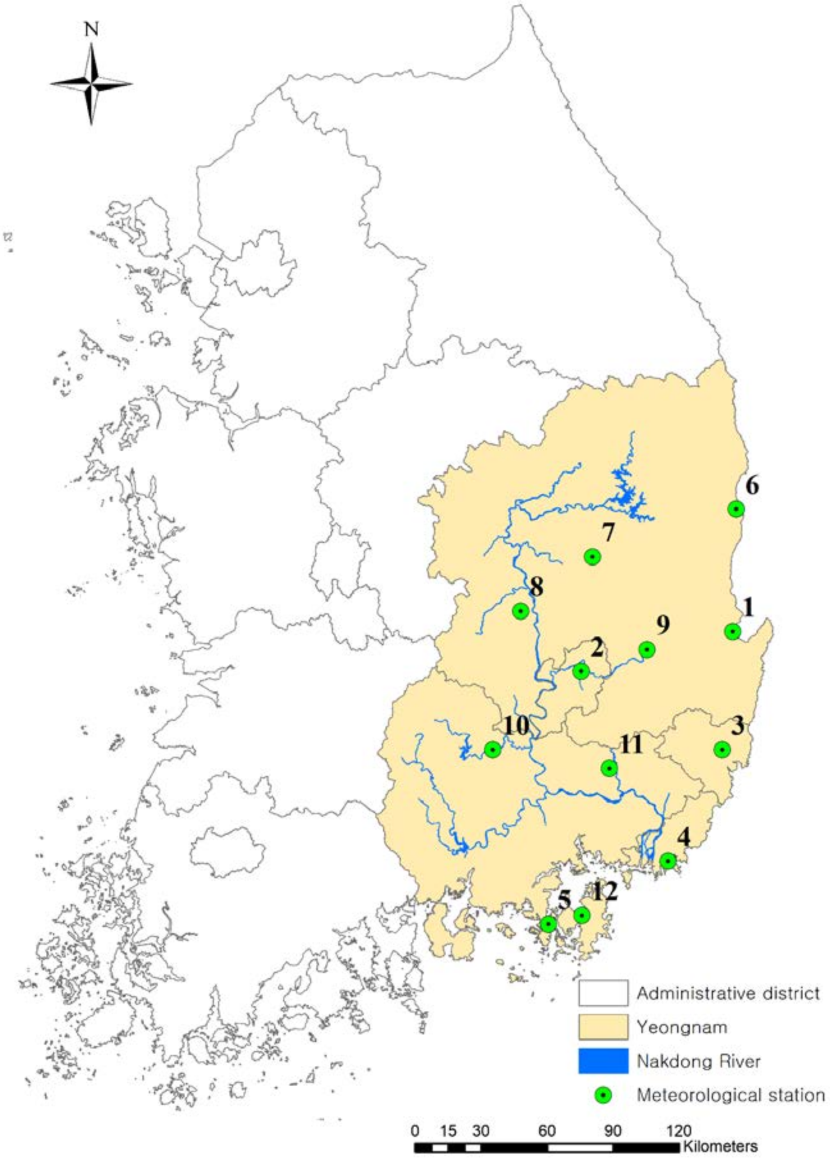


Figure 1. Locations of 12 selected weather stations at the Yeongnam province. See Table 1~~Table 1~~ for further information about the stations.

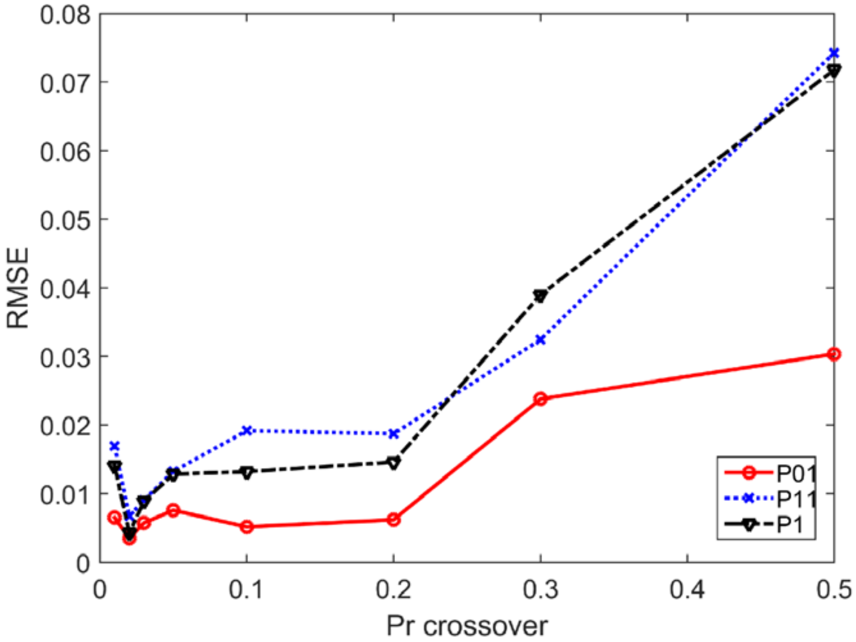


Figure 2. Testing for different probabilities of crossover Pcr. RMSE is estimated for all the tested 12 stations for each transition and limiting probability of the simulated data with the record length of 100,000.

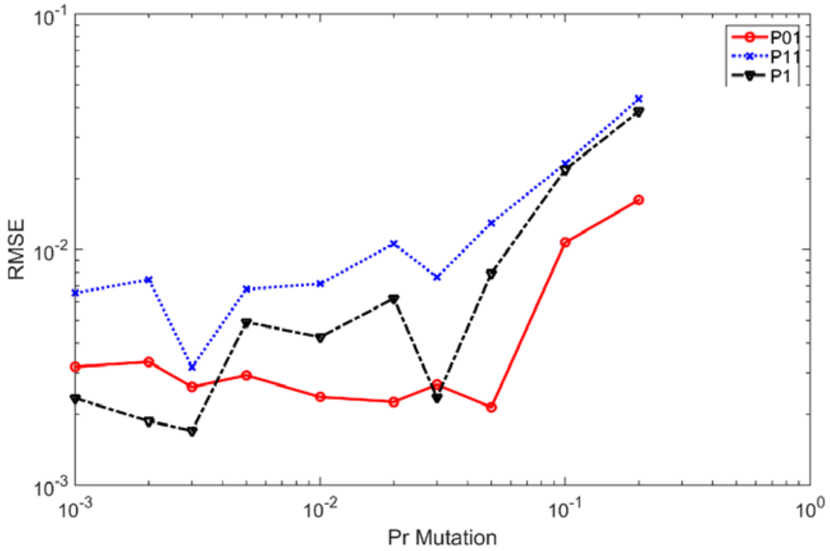


Figure 3. Testing for different probabilities of mutation P_m. RMSE is estimated for all the tested 12 stations for each transition and limiting probability of the simulated data with the record length of 100,000.

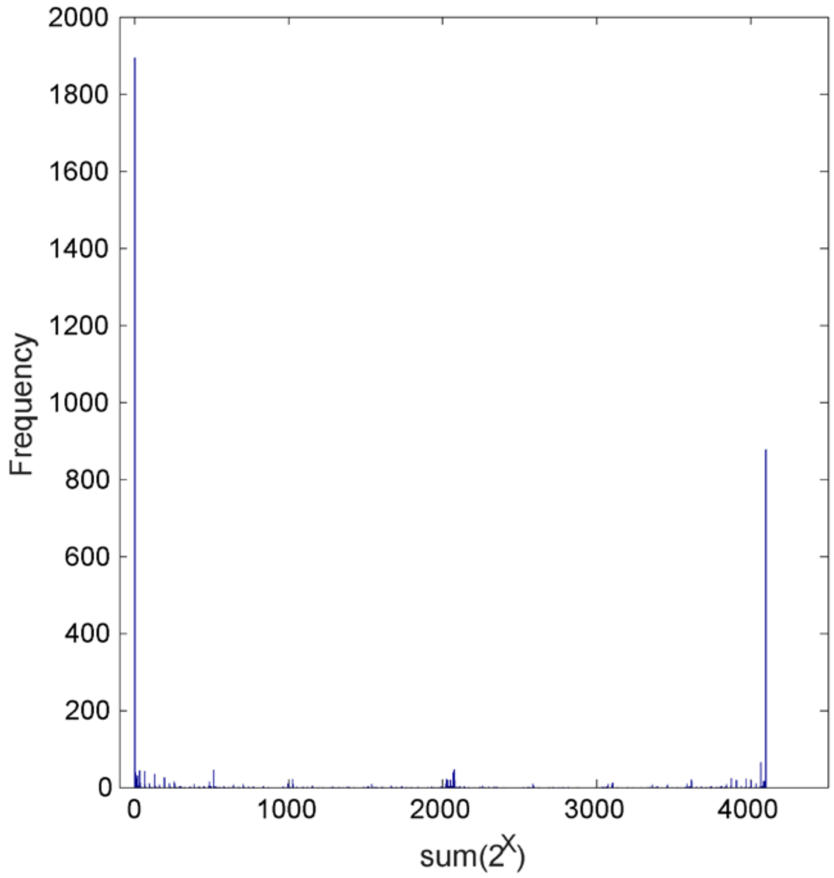


Figure 4. Frequency of the observed patterns among all the possible cases (2^{12}=4096). The X coordinate indicates each pattern with the numbering of the binary number system. All zero (0) and all one (4095) has the largest and second largest numbers of frequency as 1894 and 877, respectively as expected meaning all dry and all wet stations. Note that the bars are very sporadic indicating a number of occurrence patterns are not observed.

서식 있음: 위 첨자

서식 있음: 영어(캐나다)

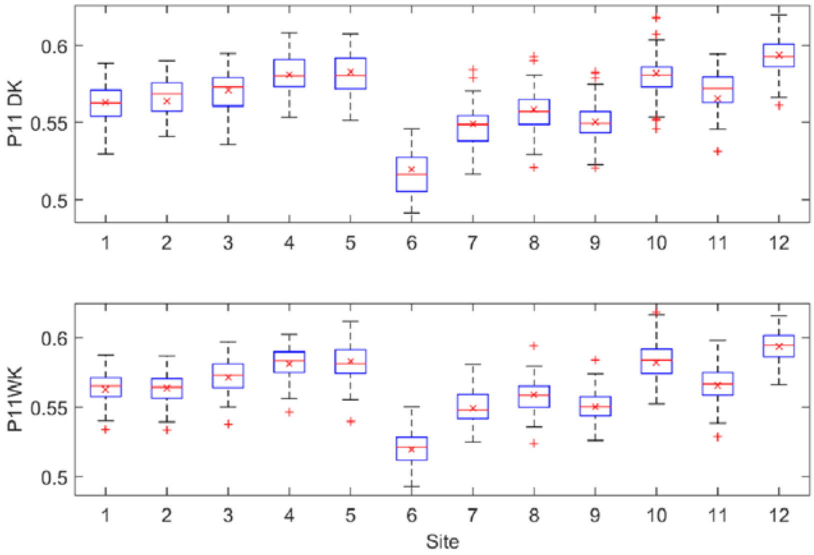


Figure 5. Boxplots of the P11 probability for the simulated data from the DKNNR model (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

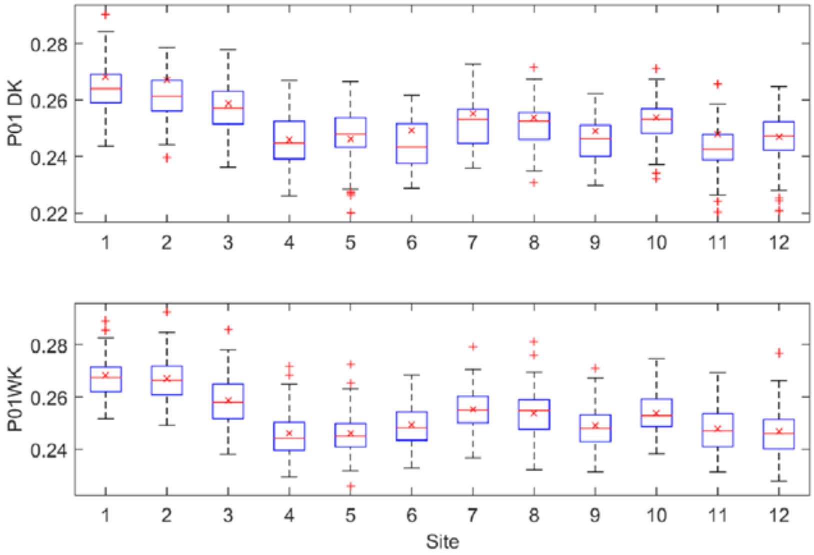


Figure 6. Boxplots of the P01 probability for the data simulated from the DKNNR model (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

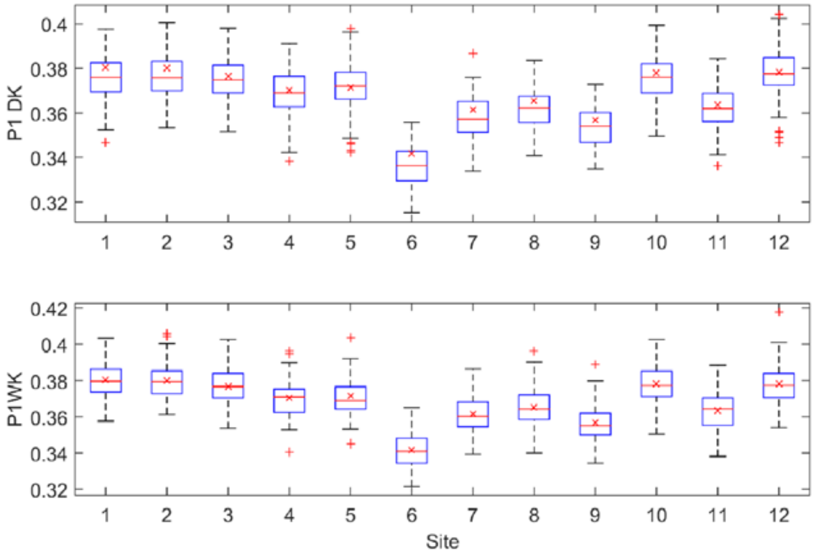


Figure 7. Boxplots of the P1 probability for the data simulated from the DKNNR model (top panel) and the MONR model (bottom panel) as well as the observed (x marker) for the 12 selected weather stations from the Yeongnam province.

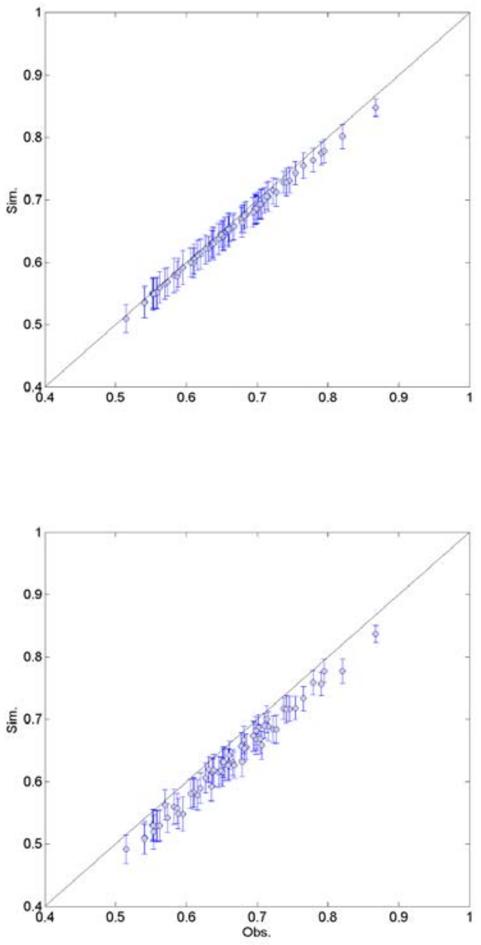


Figure 8. Scatterplot of cross-correlations between 12 weather stations for the observed data (X coordinate) and the generated data (Y coordinate) generated from the DKNNR model (top panel) and the MONR model (bottom panel). The cross-correlations from 100 generated series are averaged for the filled circle and the errorbars upper and lower extended lines indicate the range of 1.95×standard deviation.

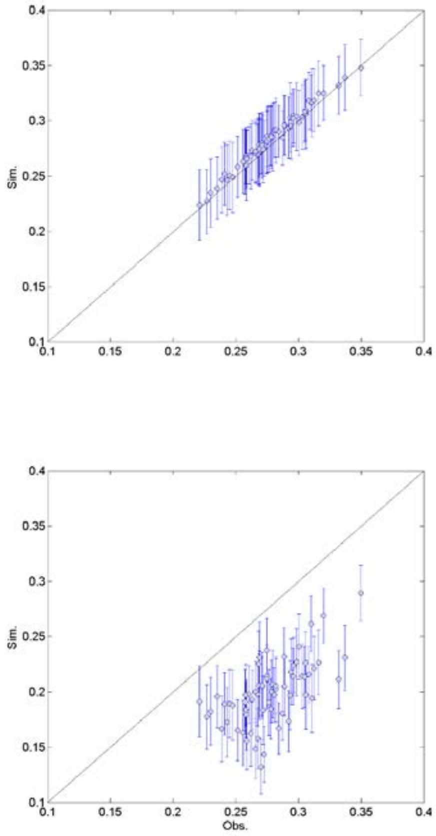


Figure 9. Scatterplot of lag-1 cross-correlations between 12 weather stations for the observed data (X coordinate) and the generated data (Y coordinate) generated from the DKNNR model (top panel) and the MONR model (bottom panel). The cross-correlations from 100 generated series are averaged for the filled circle and the errorbars upper and lower extended lines indicate the range of 1.95×standard deviation.

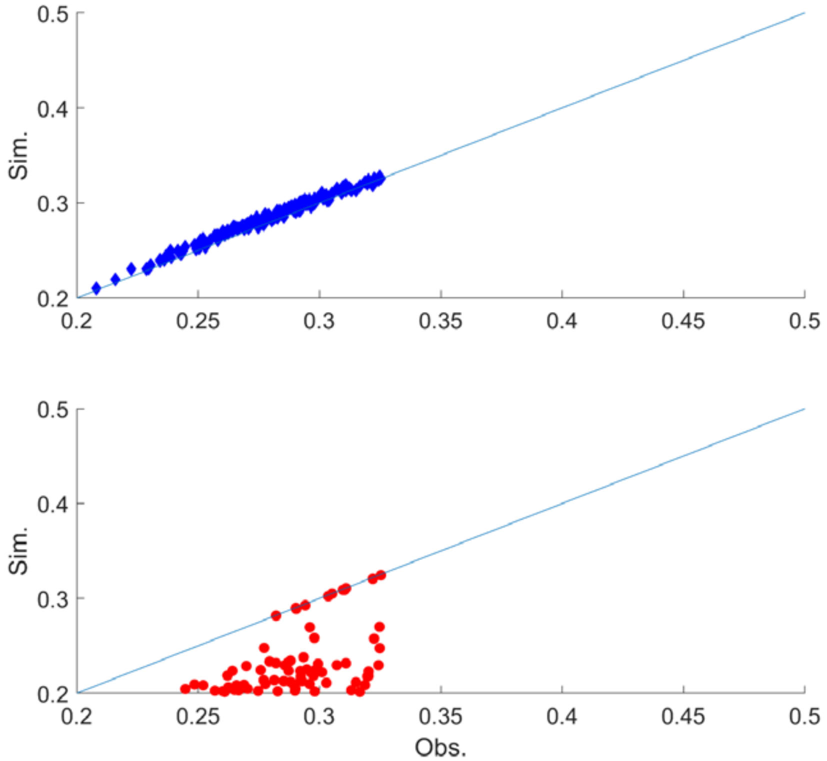
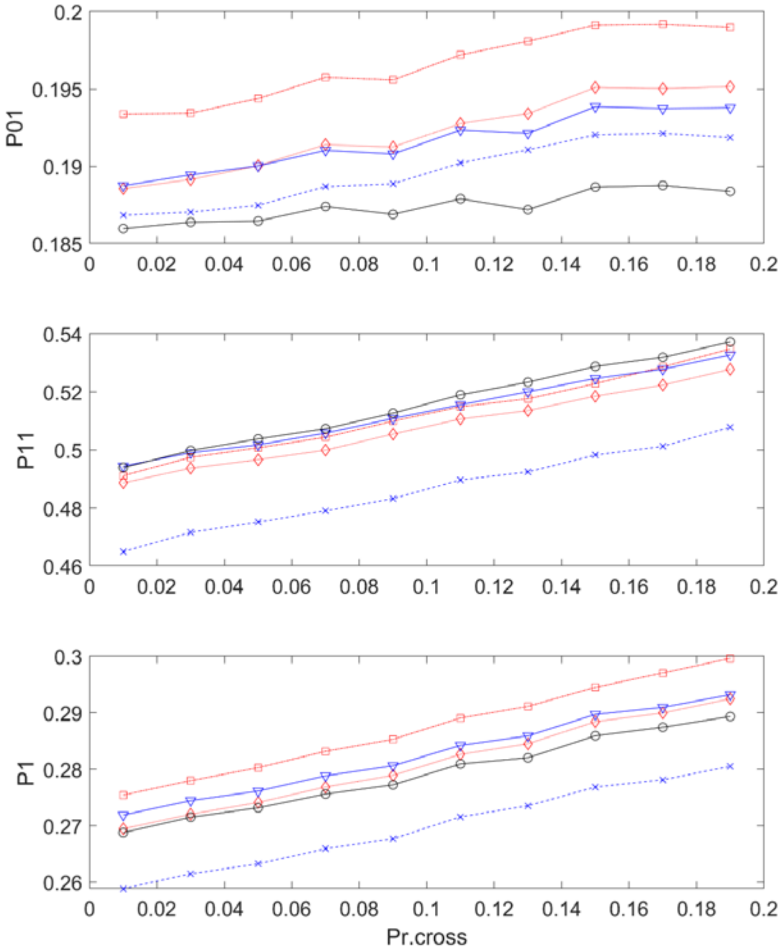


Figure 10. Scatterplot of lag-1 cross-correlations between 12 weather stations for the observed data (X coordinate) and the generated data (Y coordinate) generated from the DKNNR model (top panel) and the MONR model (bottom panel) with the whole year data not with the summer season. The cross-correlations from 100 generated series are averaged.



794

795 Figure 11. Transition probabilities and marginal distribution for the selected five stations along
796 with changing the cross-over probability P_{cr} with the condition that the candidate value is one
797 and the previous value is also one. See Eq.(15)~~(15)~~ for the detail.
798

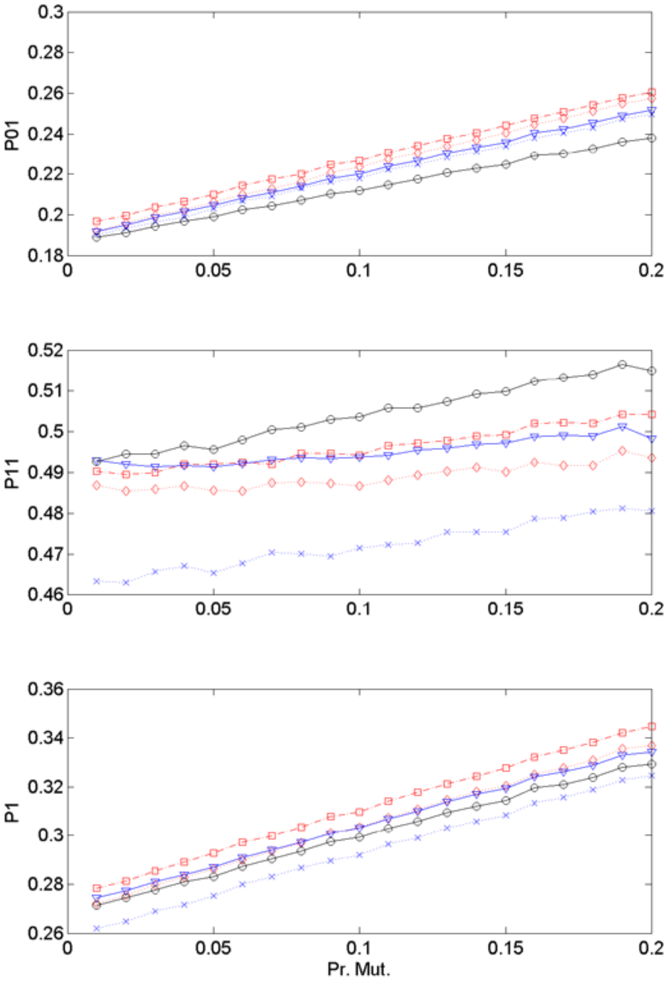


Figure 12. Transition probabilities and marginal distribution along with changing the cross-over probability with the condition that the mutation is processed only if the candidate value is one. See Eq.(16)~~(16)~~ for the detail.

Table A 1. Example dataset of daily rainfall with 12 weather stations and 16 days for measured rainfall (mm) in the upper part of this table and its corresponding occurrences in the bottom part of this table.

Day	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
1	2.0	2.9	1.2	0.0	0.0	1.8	4.0	8.9	2.0	4.6	1.3	0.6
2	52.6	39.8	47.2	17.4	11.8	31.0	30.0	33.7	52.0	57.8	37.0	17.5
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.2	1.0	1.4	1.9	12.3	0.0	0.0	0.0	0.7	3.1	3.5	8.1
6	14.8	0.2	0.8	0.2	5.0	0.0	0.0	18.0	0.0	0.0	0.6	3.1
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	0.0	1.0	0.0	0.4	0.0	3.8	0.0	0.1	0.0	0.0	0.0	0.0
11	7.1	6.4	12.8	12.8	13.6	2.3	2.0	5.4	6.0	7.3	16.4	20.3
12	0.0	0.0	0.0	0.0	5.5	0.0	0.0	0.0	0.0	0.0	0.0	4.3
13	10.0	1.6	11.6	14.3	1.5	5.4	0.0	0.0	2.5	0.0	2.7	16.1
14	2.3	0.0	0.7	0.0	0.0	1.4	0.0	0.0	0.0	0.0	0.0	0.0
15	31.5	4.3	30.6	12.7	14.4	25.8	3.5	0.8	5.0	2.7	6.5	20.3
16	37.0	7.8	30.1	11.2	9.6	36.8	2.5	4.7	13.5	1.7	10.1	14.1

Day	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
1	1	1	1	0	0	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1
3	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0
5	1	1	1	1	1	0	0	0	1	1	1	1
6	1	1	1	1	1	0	0	1	0	0	1	1
7	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0
10	0	1	0	1	0	1	0	1	0	0	0	0
11	1	1	1	1	1	1	1	1	1	1	1	1
12	0	0	0	0	1	0	0	0	0	0	0	1
13	1	1	1	1	1	1	0	0	1	0	1	1
14	1	0	1	0	0	1	0	0	0	0	0	0
15	1	1	1	1	1	1	1	1	1	1	1	1
16	1	1	1	1	1	1	1	1	1	1	1	1

Table A 2. Example dataset for estimating distances. The second row presents the current daily precipitation occurrences for 12 stations and the rows below show the absolute difference between the current occurrences (**Xc**) and the observed data in Table A 1~~Table A 1~~. The last column presents the distances in Eq. (11)~~(11)~~.

day	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	Dist
Xc	*0*	*1*	*1*	*0*	*0*	*1*	*1*	*0*	*0*	*0*	*0*	*0*	
1	1	0	0	0	0	0	0	1	1	1	1	1	**6**
2	1	0	0	1	1	0	0	1	1	1	1	1	**8**
3	0	1	1	0	0	1	1	0	0	0	0	0	**4**
4	0	1	1	0	0	1	1	0	0	0	0	0	**4**
5	1	0	0	1	1	1	1	0	1	1	1	1	**9**
6	1	0	0	1	1	1	1	1	0	0	1	1	**8**
7	0	1	1	0	0	1	1	0	0	0	0	0	**4**
8	0	1	1	0	0	1	1	0	0	0	0	0	**4**
9	0	1	1	0	0	1	1	0	0	0	0	0	**4**
10	0	0	1	1	0	0	1	1	0	0	0	0	**4**
11	1	0	0	1	1	0	0	1	1	1	1	1	**8**
12	0	1	1	0	1	1	1	0	0	0	0	1	**6**
13	1	0	0	1	1	0	1	0	1	0	1	1	**7**
14	1	1	0	0	0	0	1	0	0	0	0	0	**3**
15	1	0	0	1	1	0	0	1	1	1	1	1	**8**
16	1	0	0	1	1	0	0	1	1	1	1	1	**8**

Table A 3. Example for selecting one sequence for $\mathbf{X}_{c+1}$. The second row presents the distances in Table A 2~~Table A 2~~. The third and fourth columns show the sorted days and distances for the smallest distances to the largest in the second column. The fourth row presents the probabilities estimated with Eq. (12)~~(12)~~. Note that there are six days whose distances are the same with each other. In this case all the days are included and among six days, one is selected with equal probabilities.

Day	Dist.	Sorted Day	Sorted Dist	Prob
1	6	14	3	0.48
2	8	3	**4**	0.24
3	4	4	**4**	0.16
4	4	7	**4**	0.12
5	9	8	**4**	
6	8	9	**4**	
7	4	10	**4**	
8	4	1	6	
9	4	12	6	
10	4	13	7	
11	8	2	8	
12	6	6	8	
13	7	11	8	
14	3	15	8	
15	8	16	8	
16	8	5	9	

Table A 4. Example for GA mixture for $\mathbf{X}_{\mathbf{c+1}}$. The second and third rows present two selected sets, while the third row shows the final set for $\mathbf{X}_{\mathbf{c+1}}$ with the crossover at S6 and S8 and the mutation for S12.

	Assigned day, *p*	Selected day, *p*+1	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
Set1	14	**15**	1	0	0	1	1	0	0	1	1	1	1	1
Set2	4	**5**	1	0	0	1	1	1	1	0	1	1	1	1
Final			1	0	0	1	1	1	0	0	1	1	1	**0**