Sejong University Advanced Hydrology Resources Lab.

A novel spatial downscaling approach for climate change assessment in regions with sparse ground data networks

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SEJONG UNIVERSITY

CONTENTS

TOPIC to discuss

01. Research Background

Research Background

A flavor of today's climate model results

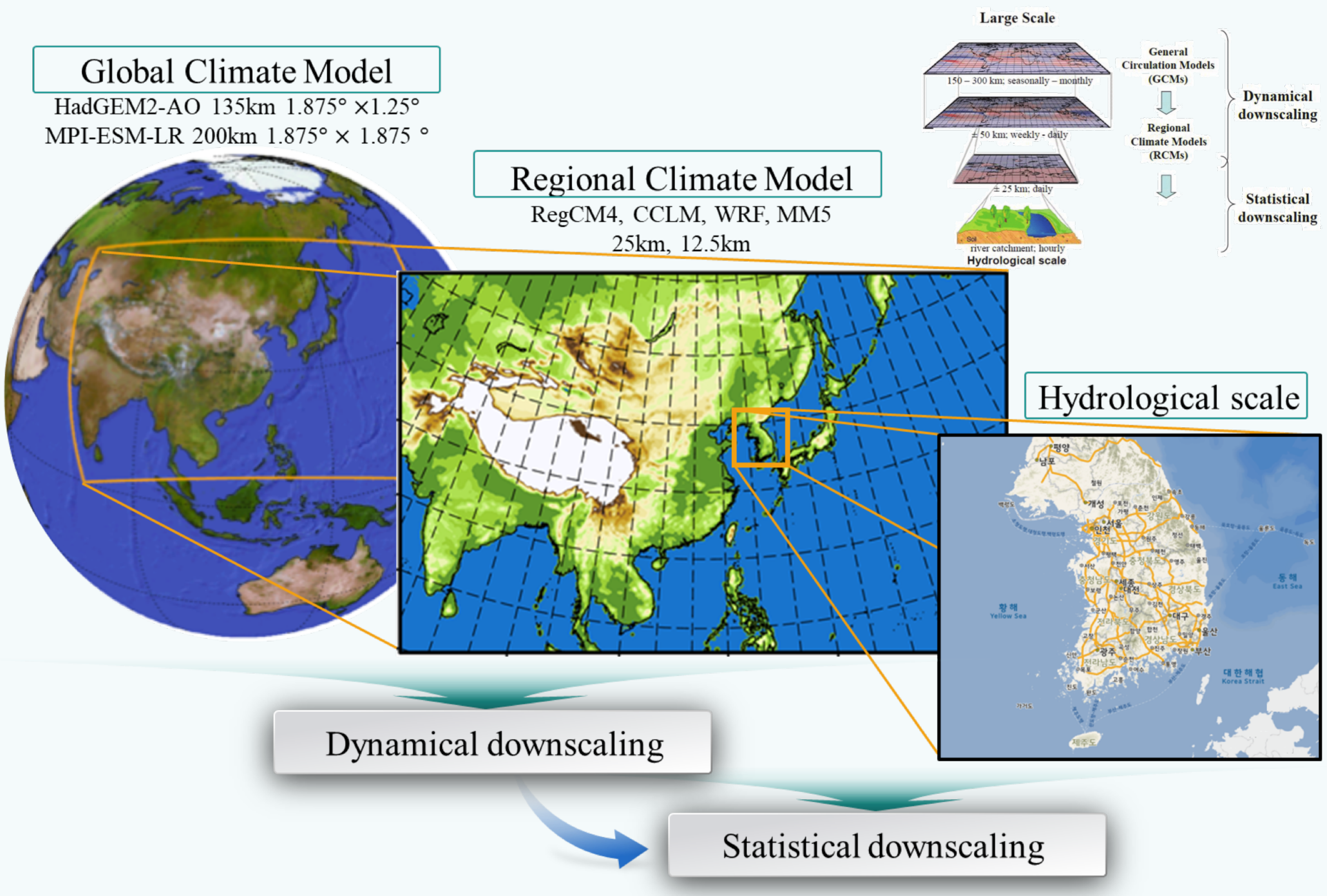
- ✓ Much better than 20 years ago in many respects
  - Much valuable work has been done in the entire modeling chain from climate to hydrology to impacts assessment
- ✓ However, how well do models reproduce seasonal/monthly/extreme precipitation?
  - Moments/Interannual Variability, Response to CO2?

Why We Need Downscaling- Some Justifications

- ✓ Even if GCM in the future are run at high resolution there will remain the need to "downscale" the results from such models to individual sites or localities for impact studies
- ✓ SD are commonly used to address the scale mismatch between coarse resolution GCM output and the regional or local catchment scales required for hydrological modeling

01. Research Background

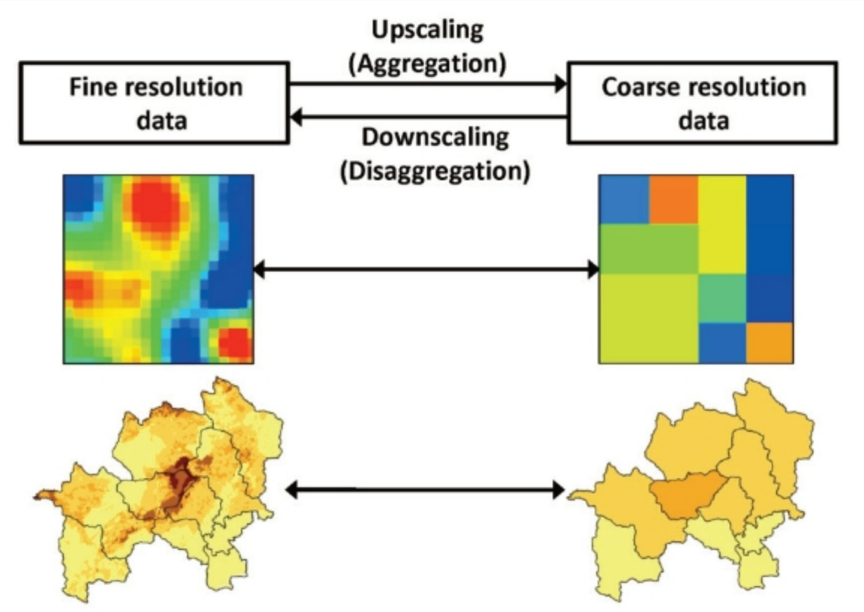
Research Background



01. Research Background

Research Background

Global Models → Re-gridding → Bias Correction → Spatial Downscaling



Quantile Mapping (QM)

Constructed Analogs
(CA; Hidalgo et al. 2008)

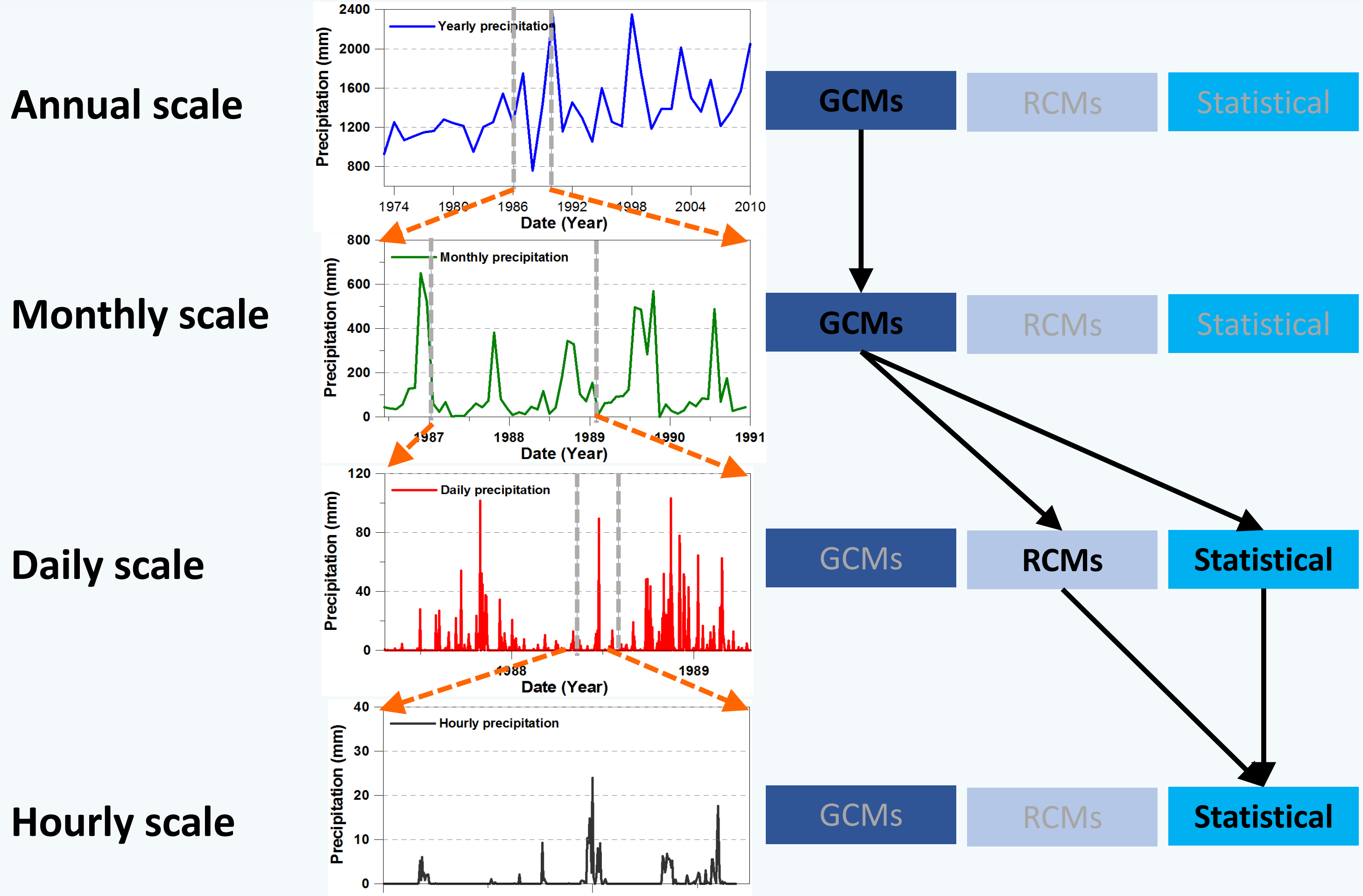
Bias Correction and Constructed Analogs
(BCCA; Maurer et al. 2010)

Multivariate Adapted Constructed analogs
(MACA; Abatzoglou & Brown 2012)

Bias Correction with Spatial Disaggregation
(BCSD; Wood et al. 2004)

01. Research Background

Research Background

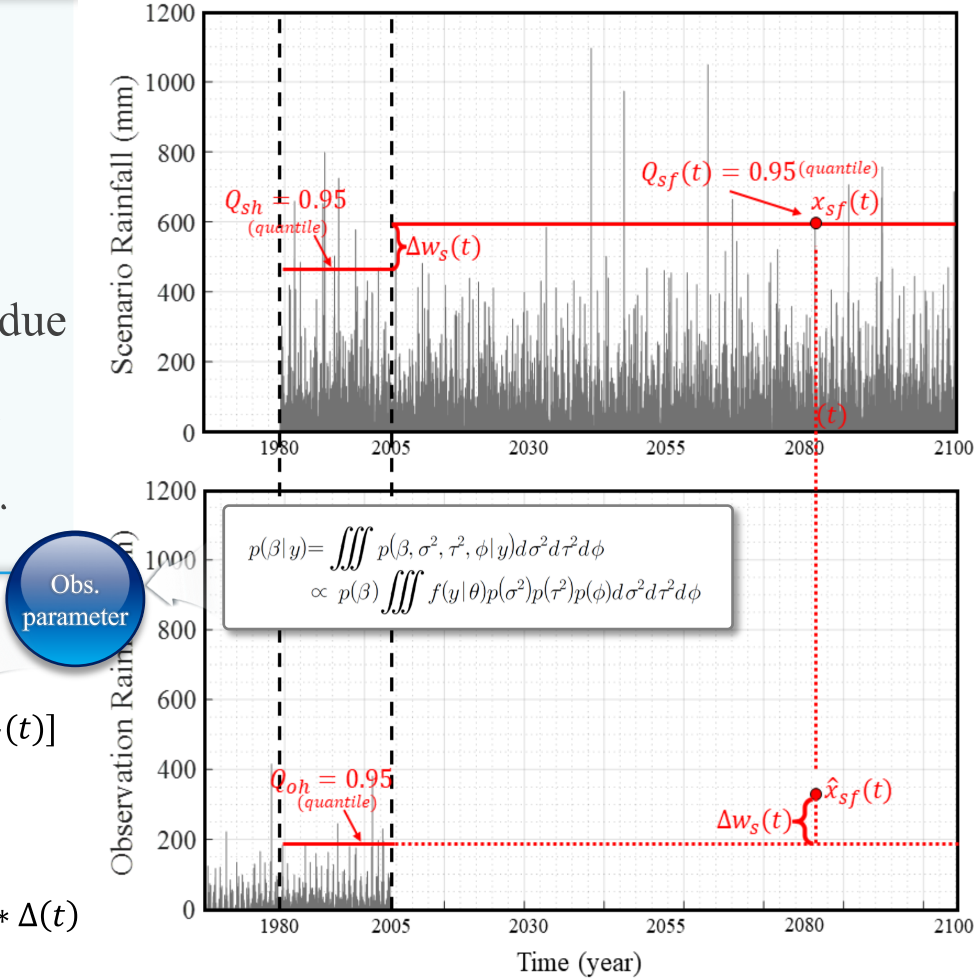


TOPIC to discuss

02. Methodologies

Quantile Delta Mapping (QDM) Approach

- QM does not preserve model-predicted changes (Maurer and Pierce, HESS, 2014)
- QDM has been widely adopted for bias-correction of the climate change scenarios due to its ability to preserve relative changes in quantiles over historical/future simulations.



Eq. 1

$$\tau_{s.f}(t) = F_{s.f}^{(t)}\left[x_{s.f}(t)\right] \quad \tau_{s.f}(t) \in \{0,1\}$$

Eq. 2

$$\Delta w_s(t) = \frac{x_{s.f}(t)}{F_{s.h}^{-1}[\tau_{s.f}(t)]}$$

Eq. 3

$$\hat{x}_{o.s.h.f}(t) = F_{o.h}^{-1}[\tau_{s.f}(t)]$$

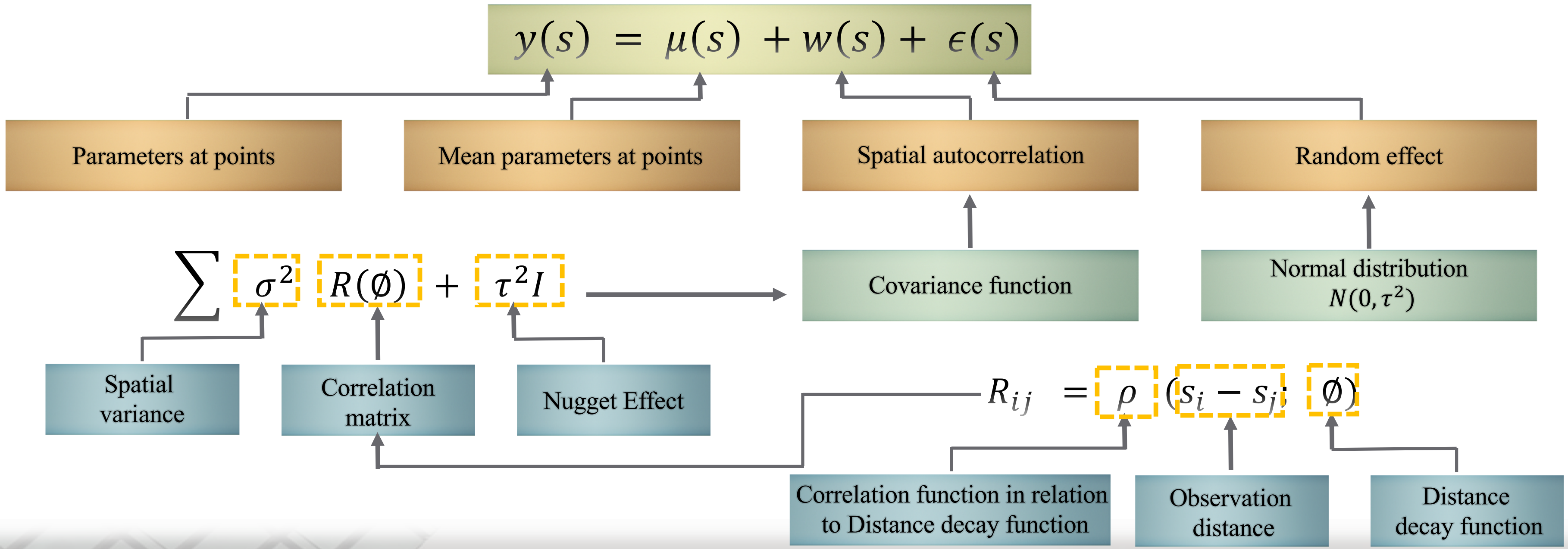
Eq. 4

$$\hat{x}_{s.f}(t) = \hat{x}_{o.s.h.f}(t) * \Delta(t)$$

02. Methodologies

Bayesian Kriging based SD-QDM (Quantile Delta Mapping)

- Kriging is a field of geostatistics that can be applied to geophysical data
- There are various types of Kriging such as Simple Kriging, Ordinary Kriging, Co-Kriging
- We have used the OK, which minimizes the error variance without biasing Kriging estimation equation.



02. Methodologies

Bayesian Kriging based SD-QDM (Quantile Delta Mapping)

- Kriging can be estimated with approaches such as Generalized Least Squares(GLS), Maximum Likelihood Estimation(MLE), and Bayesian inference.
- Bayesian inference was applied to quantify the uncertainty of spatial downscaling.
- If the Kriging parameter vector is $\theta = (\beta, \sigma^2, \tau^2, \phi)^T$, the likelihood function based on Bayes' theorem according to the prior probability distribution $p(\theta)$ can be calculated as $\mathrm{p}(\theta) = p(\beta)p(\sigma^2)p(\tau^2)p(\phi)$.
- The posterior distribution $p(\beta|y)$ requires integral calculation using a computer and can be estimated using the Markov Chain Monte Carlo.

Bayesian Inference

$$p(\theta|y) \propto p(y|\theta) \cdot p(\theta)$$

$\boldsymbol{\theta}$: Full parameter set

$\boldsymbol{y}$: Observed data

$\boldsymbol{p(\theta)}$: prior distribution of parameters

$\boldsymbol{p(y|\theta)}$: likelihood function of y

$$p(\beta|y) = \iiint p(\beta, \sigma^2, \tau^2, \phi|y)\, d\sigma^2 d\tau^2 d\phi$$

$$\propto p(\beta) \iiint f(y|\theta) p(\sigma^2) p(\tau^2) p(\phi)\, d\sigma^2 d\tau^2 d\phi$$

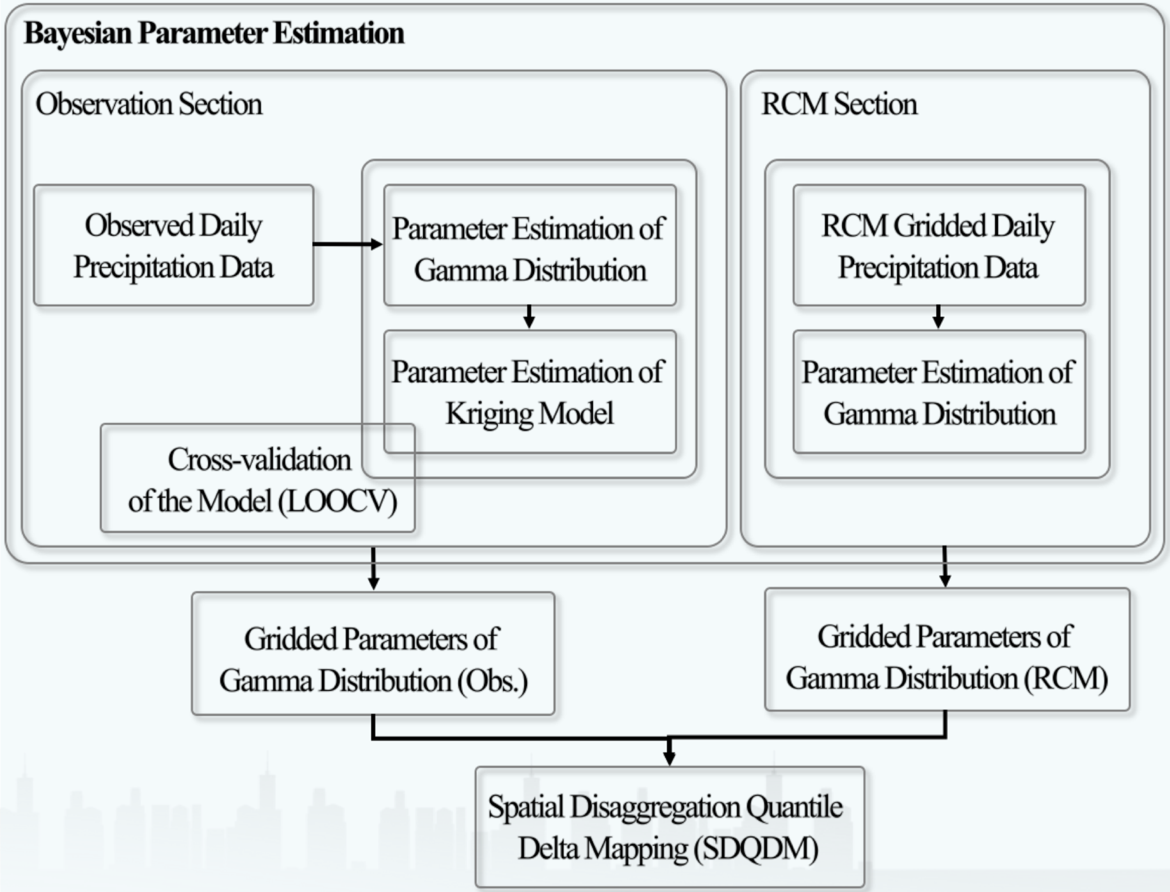
02. Methodologies

Bayesian Kriging based SD-QDM Flowchart

- *Can all parameters associated with the spatial downscaling and bias-correction be simultaneously estimated and interpolated at the desired points?*
- *Can the interpolation of the bias-correction parameters be more effective than the interpolation of the daily precipitation in the context of spatial downscaling and bias-correction?*
- *Can a Bayesian Kriging based bias-correction approach effectively reproduce spatial dependency over a network of weather stations in the interpolated parameters associated with bias-correction?*

02. Methodologies

Bayesian Kriging based SD-QDM Flowchart



$$F(x|k_{oh},\theta_{oh}) = \frac{1}{\theta^k \Gamma(k)} \int_0^x t^{k-1} e^{-t/\theta} dt$$

$$S \sim MVN(\mu, \tau^2 \Sigma)$$

$$\Sigma_{ij} = f(d_{ij}|\theta)$$

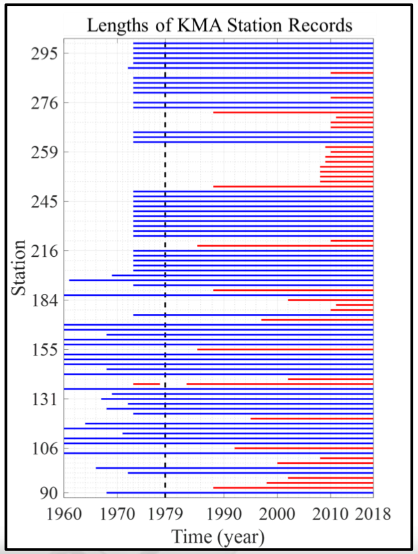
$$f(d_{ij}|\phi,\kappa) = exp\left[-(\phi \cdot d_{ij})^{\delta}\right]$$

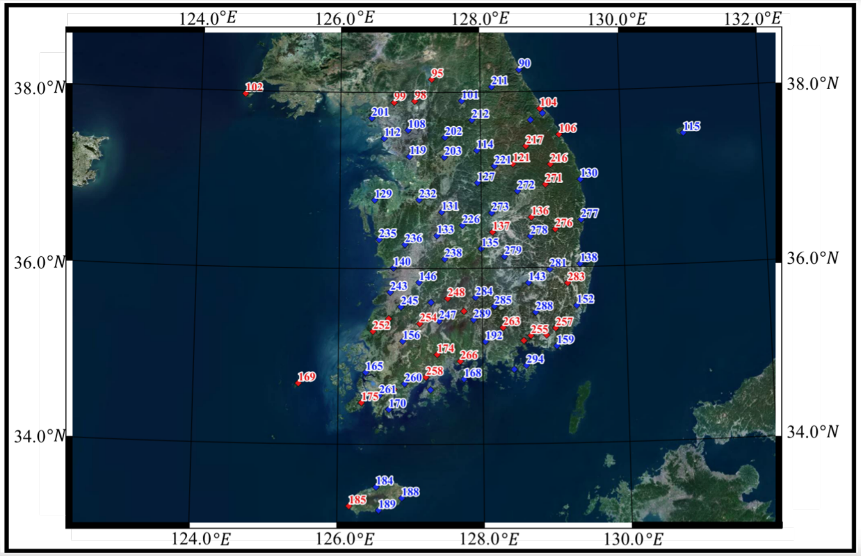
TOPIC to discuss

03. Data (Obs. / CC Scenario)

Historical Data - KMA

- The daily precipitation data was compiled from over 92 Automatic Synoptic Observation System (ASOS) across South Korea, operated by the KMA.
- Here, daily precipitation data at 60 weather stations with more than 45 years, ranging from 1973 to 2018, were finally selected for the subsequent analysis.
- In the present work, we explore a seasonal-varying model under the circumstances of high rainfall variability, without focusing on an annual basis model, in a more general context.



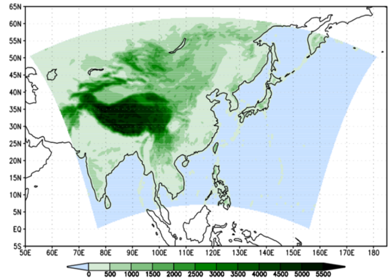


03. Data (Obs. / CC Scenario)

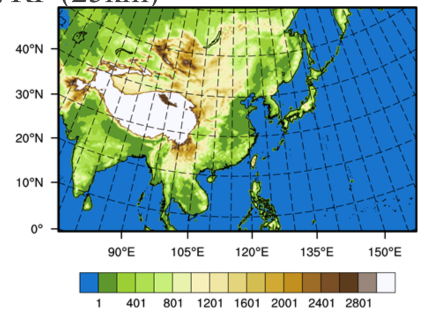
Climate Change scenario– CORDEX-RCMs

- The proposed model is applied to climate change scenarios simulated by three different RCMs employed in the Coordinated Regional Climate Downscaling Experiment-East Asia (CORDEX-EA), covering the entire East Asian areas, including South Korea.
- CORDEX is an internationally coordinated framework with the use of multiple RCMs for providing high-resolution climate change projections.
- In this study, the future precipitation simulation for 2006-2100 under the representative concentration pathways (RCP) 4.5 and 8.5 was used with the historical precipitation simulation for 1979-2005.
- The Bayesian Kriging based SD-QDM approach was applied to provide downscaled precipitation at finer scales of about 6.25km, 12.5km and 12.5km resolution for SNURCM, WRF, and CCLM, respectively, which is typically more relevant as input for hydrological model applications.

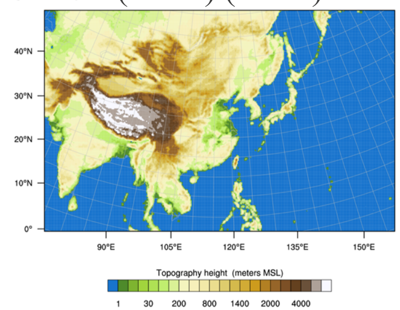
a) CCLM (25km)



b) WRF (25km)



c) SNU-RCM(MM5) (12km)



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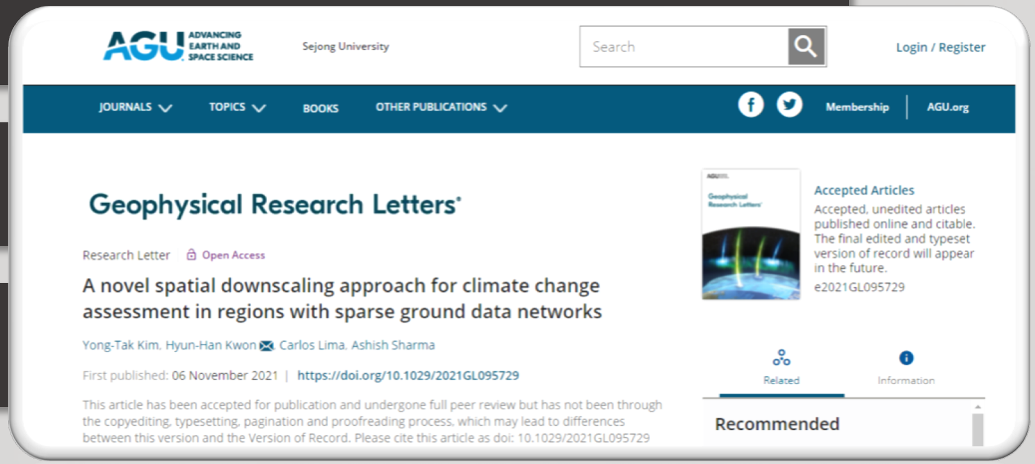
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A novel spatial downscaling approach for climate change assessment in regions with sparse ground data networks

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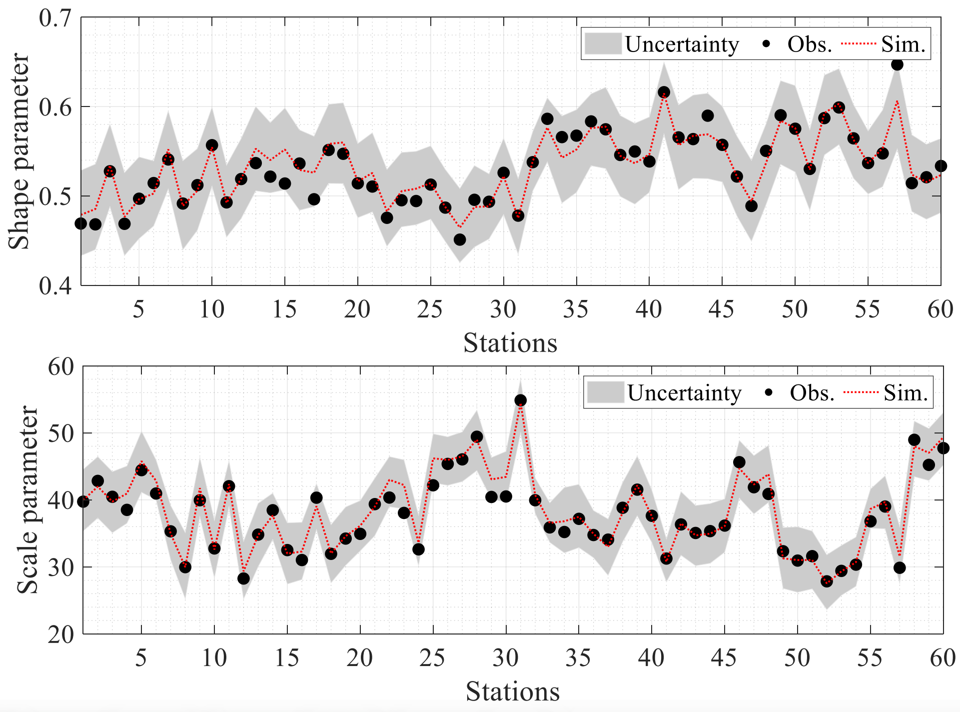
Related Information

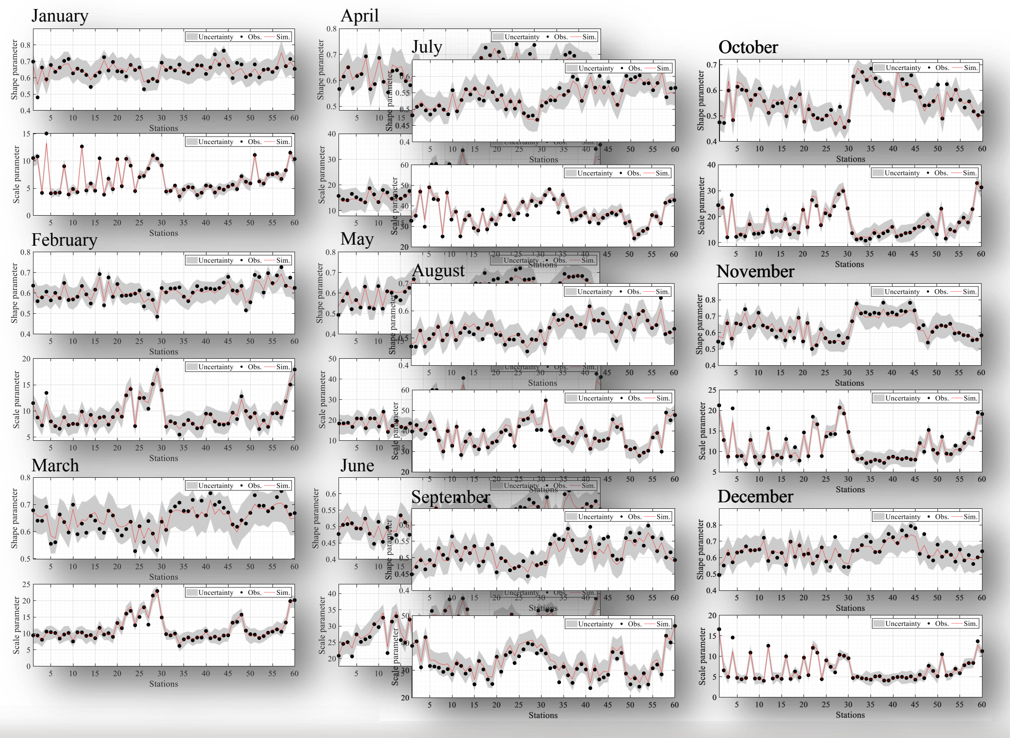
Recommended

04. Results & Discussion

Parameter Estimation and Cross Validation

- The cross-validated results and their 95% credible intervals (shaded region) of the Gamma parameters within a LOOCV assessment in August.
- The black-filled circles are the parameters estimated from observed precipitation, while the red-dotted lines represent the median values estimated from the predictive posterior distribution.
- The number on the X-axis represents the gauge code, summarized in the supplementary information.





04. Results & Discussion

Parameter Estimation and Cross Validation

- A seasonal-varying model under the LOOCV scheme is investigated, and the model performance
- Model performance of the proposed prediction model for both shape and scale parameters in terms of Nash–Sutcliffe Efficiency (NSE), Index-of-Agreement (IoA), correlation coefficient (CC) and Root Mean Square Error (RMSE)
- For the shape parameter, the model showed slightly lower performance in the spring season from February to April in terms of the NSE
- Still, the model predictability can be regarded as "Very good: NSE ≥ 0.7" according to the given criteria suggested by Kalin et al. (2010), and other performance measures are largely comparable to that of different seasons. For the scale parameter, the predicted parameters appear to be almost identical to that of the observed, confirming the efficacy of the model.

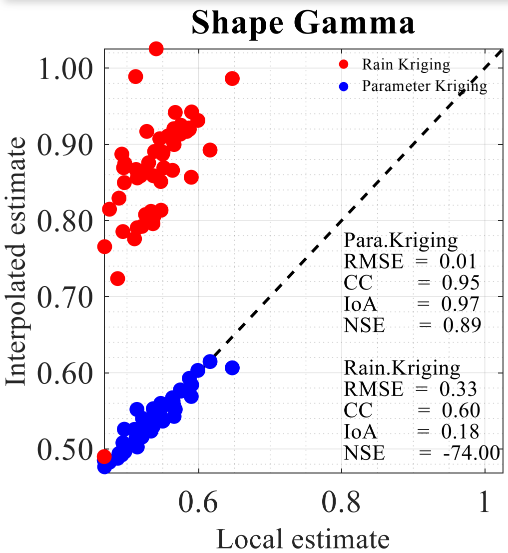
Mon	Shape Parameter				Mon	Scale Parameter			
	NSE	IoA	CC	RMSE		NSE	IoA	CC	RMSE
Jan	0.81	0.93	0.95	0.02	Jan	0.99	1.00	0.99	0.32
Feb	0.86	0.95	0.97	0.02	Feb	0.96	0.99	0.98	0.49
Mar	0.82	0.94	0.94	0.02	Mar	0.98	0.99	0.99	0.46
Apr	0.87	0.96	0.95	0.02	Apr	0.94	0.98	0.99	1.35
May	0.91	0.97	0.97	0.02	May	0.97	0.99	0.99	1.14
Jun	0.88	0.97	0.95	0.01	Jun	0.94	0.98	0.97	1.19
Jul	0.91	0.97	0.96	0.01	Jul	0.95	0.99	0.99	1.28
Aug	0.89	0.97	0.95	0.01	Aug	0.92	0.98	0.97	1.42
Sep	0.83	0.95	0.94	0.01	Sep	0.87	0.97	0.98	1.84
Oct	0.90	0.97	0.95	0.02	Oct	0.97	0.99	0.99	0.94
Nov	0.93	0.98	0.97	0.02	Nov	0.96	0.99	0.99	0.69
Dec	0.86	0.95	0.95	0.02	Dec	0.96	0.99	0.98	0.55

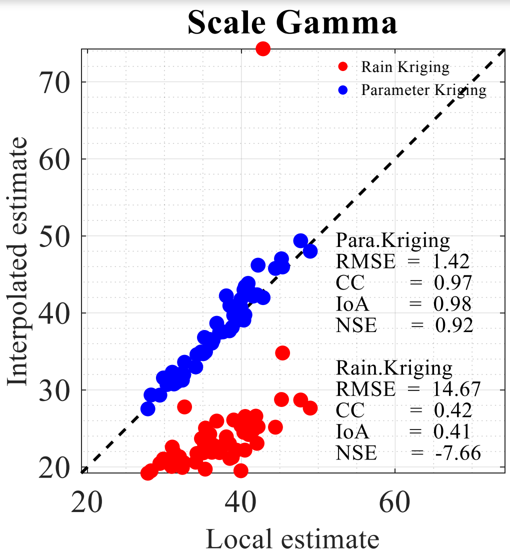
Statistics	Formula
Nash Sutcliffe efficiency (NSE)	$NSE = 1 - \frac{\sum_{i=1}^{N}(Obs_i - Sim_i)^2}{\sum_{i=1}^{N}(Obs_i - \overline{Obs})^2}$
Index of Agreement (IoA)	$IoA = 1 - \frac{\sum_{i=1}^{N}(Obs_i - Sim_i)^2}{\sum_{i=1}^{N}(\lvert Obs_i - \overline{Obs}\rvert + \lvert Sim_i - \overline{Obs}\rvert)^2}$
Correlation Coefficient (CC)	$CC = 1 - \frac{\sum_{i=1}^{N}(Obs_i - \overline{Obs})(Sim_i - \overline{Sim})}{\sqrt{\sum_{i=1}^{N}(Obs_i - \overline{Obs})^2}\sqrt{\sum_{i=1}^{N}(Sim_i - \overline{Sim})^2}}$
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Sim_i - Obs_i)^2}$

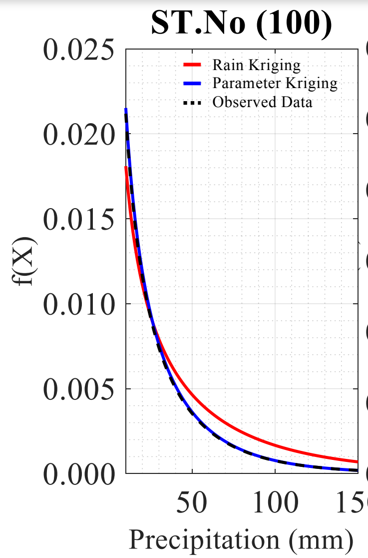
04. Results & Discussion

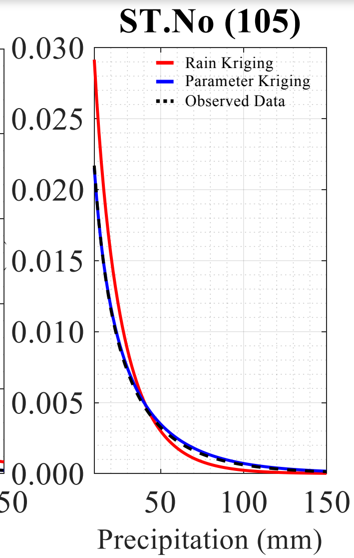
Parameter Estimation and Cross Validation

- Following the previous step, we investigated whether the grid generated by direct interpolating the gamma parameters can be more reliable than the grid obtained by first interpolating the observed daily precipitation onto the grid and thereafter estimating the gamma parameters over these points
- The directly interpolated gamma distribution parameters through the proposed Bayesian Kriging approach were then compared to the parameters obtained from the interpolated daily precipitation that will serve as a baseline model
- Note that daily precipitation was also interpolated by the Bayesian Kriging approach and all the results presented here were achieved under the LOOCV scheme
- It is clear that the proposed model outperformed the baseline model, which is based on the interpolated daily rainfall series



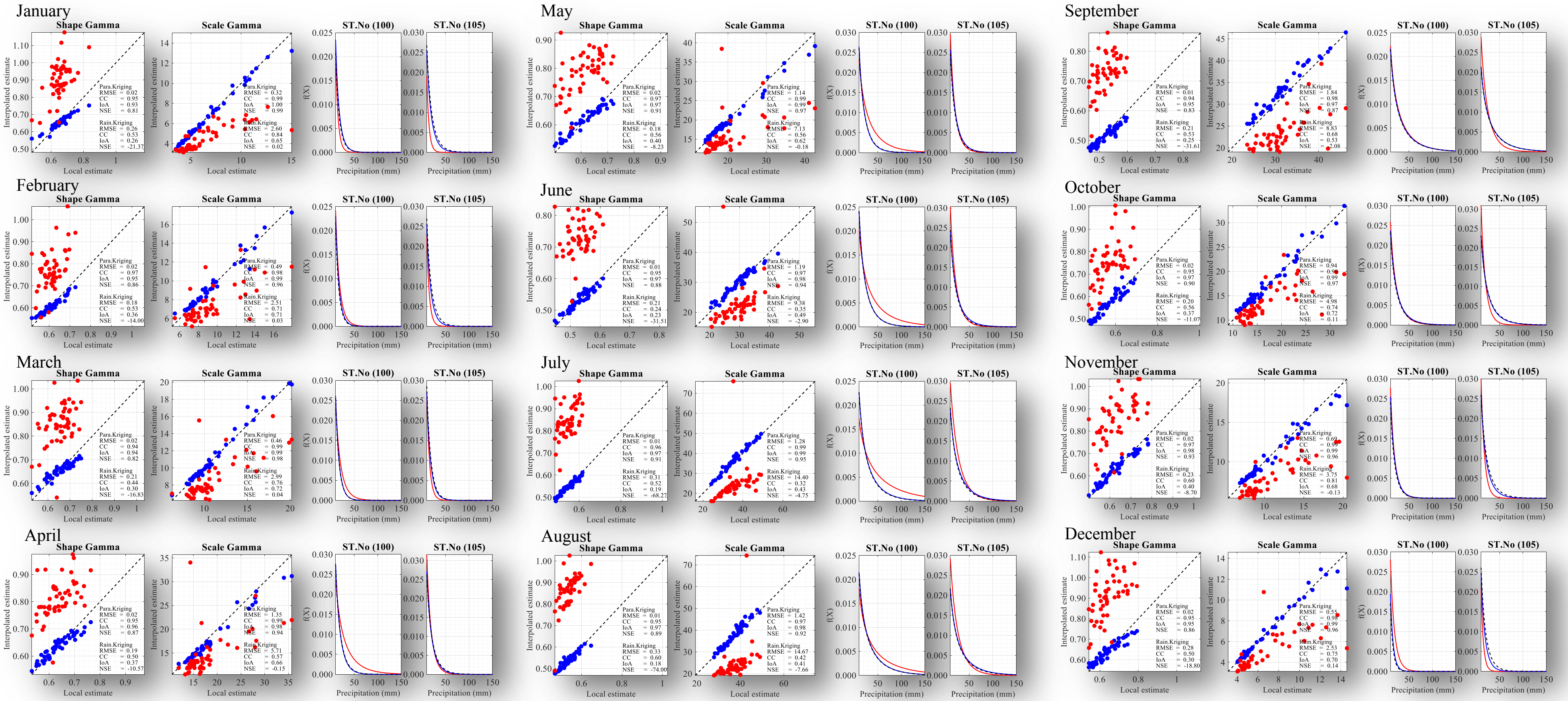






04. Results & Discussion

Parameter Estimation and Cross Validation

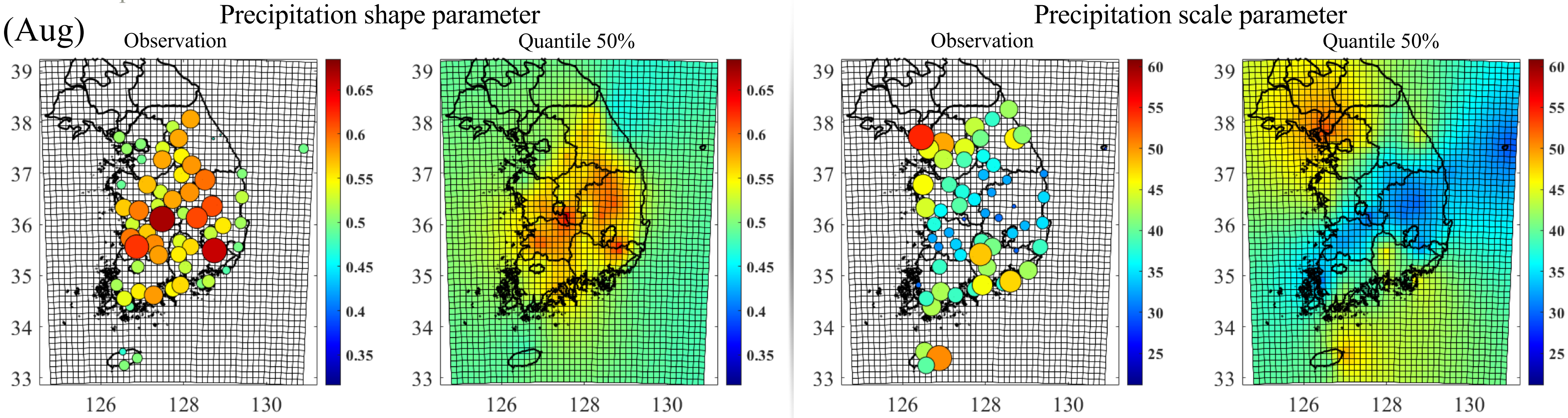


04. Results & Discussion

Interpolation of Parameters Using Bayesian Kriging Approach

- The relatively large shape parameters are identified in the southeastern regions, while relatively large scale parameter values are concentrated in the southern coastal area.
- On the other hand, the smaller shape parameters are mainly distributed in the mid-western region, while the lower scale parameter values are largely seen in the southern part of South Korea.
- Overall, the proposed Bayesian Kriging approach is capable of reproducing the main spatial patterns seen in the direct point estimates of both shape and scale parameters.

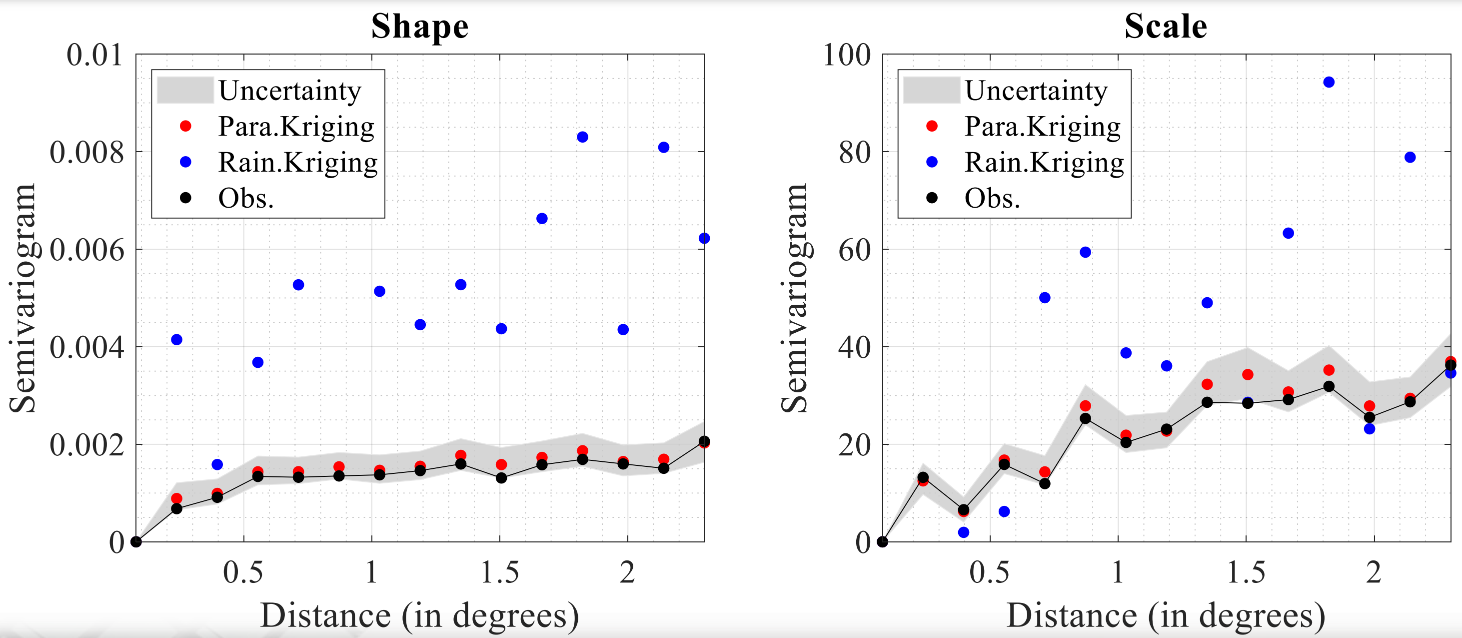
➢ Gamma parameters estimated from observed precipitation at weather stations (left panel) and gridded parameters (12.5km × 12.5km) obtained from the Bayesian Kriging approach (median estimates from the predictive posterior distribution). The estimates refer to the period 1979 – 2005



04. Results & Discussion

Interpolation of Parameters Using Bayesian Kriging Approach

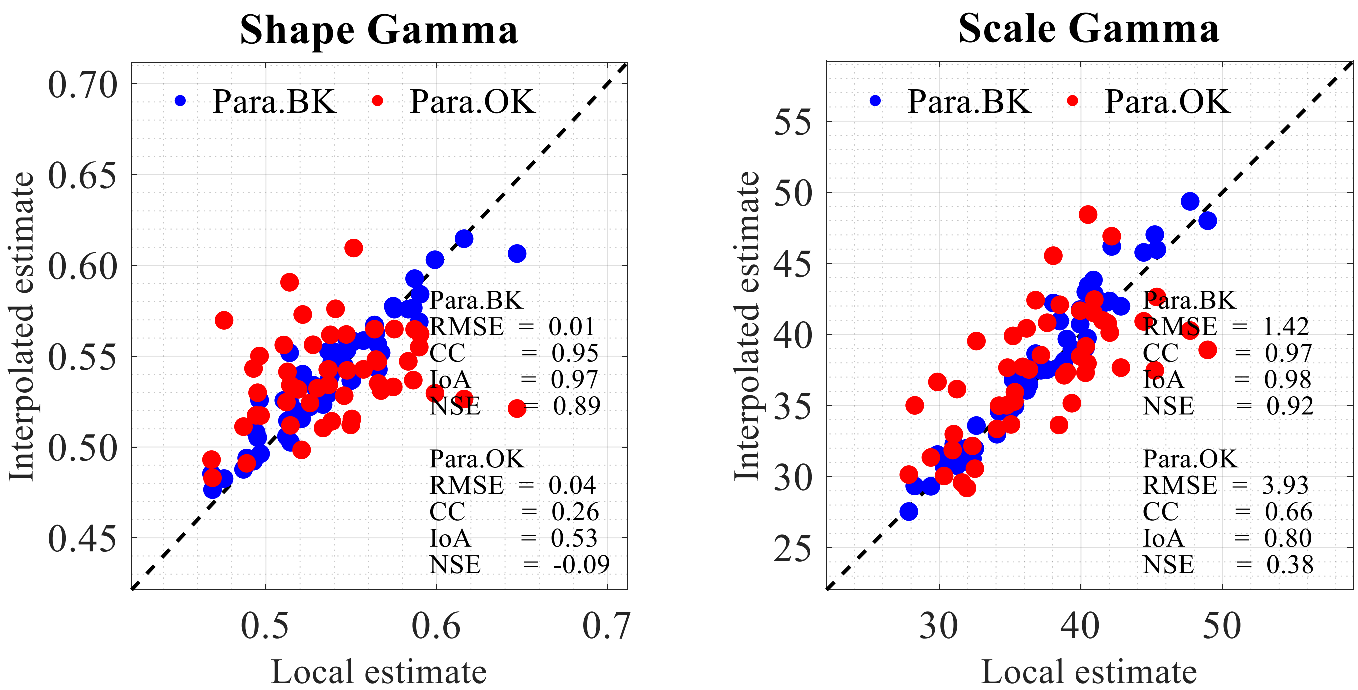
- This study further tested the efficacy of the model in effectively reproducing spatial dependency over a network of weather stations in the interpolated gamma parameters
- The semi-variogram of gamma parameters estimated from the posterior distributions obtained from the Bayesian Kriging approach was then compared to that obtained from local estimates based on gauged rainfall data.
- For August, the efficacy of the proposed model to reproduce the bias-correction parameters while preserving the spatial variability observed in the historical data-based estimates, where both semi-variograms are almost identical.
- The semi-variogram directly obtained from the interpolated precipitation is significantly biased from the observed one



04. Results & Discussion

Interpolation of Parameters Using Bayesian Kriging Approach

- Moreover, the Bayesian Kriging based SD-QDM model was compared with the ordinary Kriging approach, which is widely adopted in spatial interpolation.
- The results confirmed that the proposed approach showed better performance to estimate the Gamma distribution parameters in the context of cross-validation.



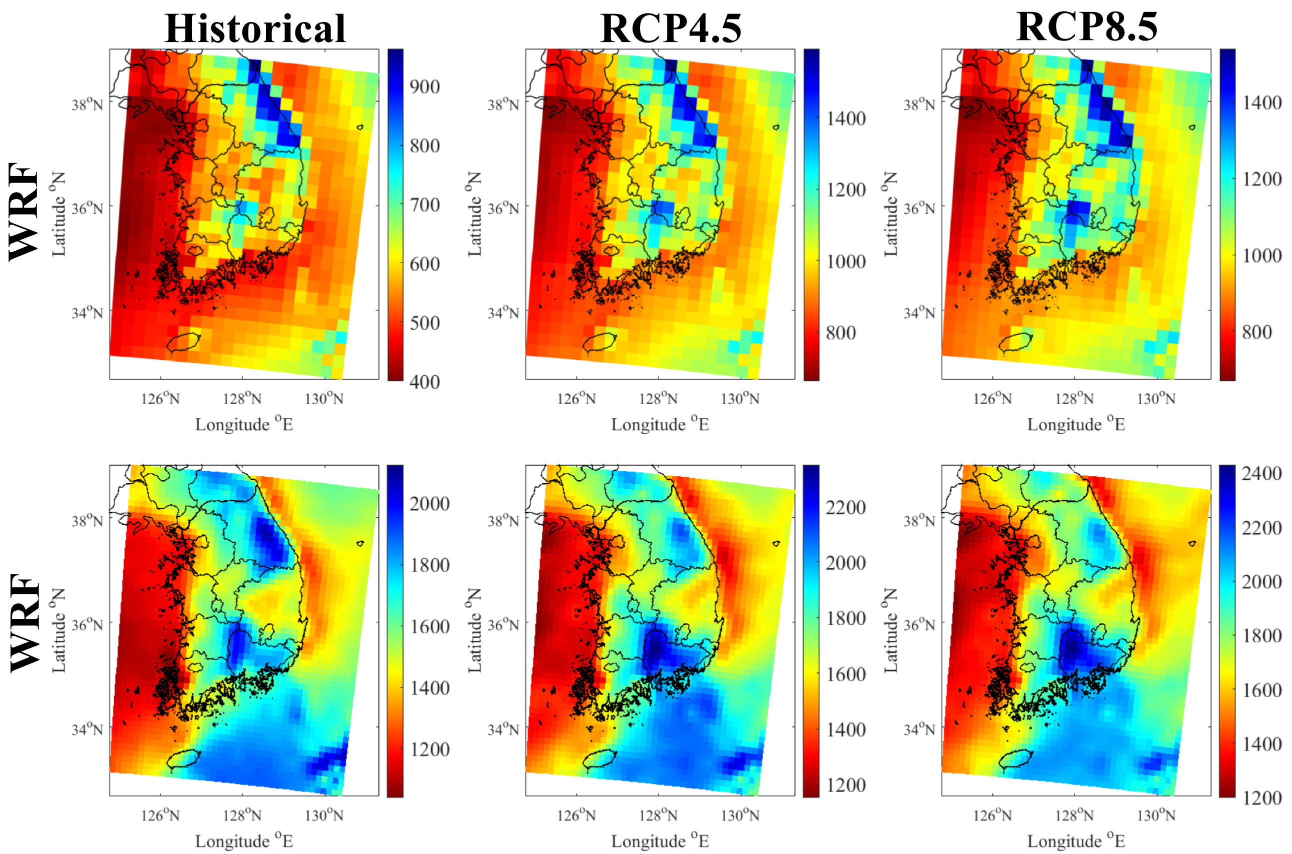
04. Results & Discussion

Spatial Downscaling of Climate Change Scenarios

In order to illustrate the use of the proposed Bayesian Kriging based SD-QDM approach, this work downscaled the historical and the future daily precipitation simulated by RCMs in the CORDEX-EA Phase 2 for 1979-2005 and 2006-2100.

- Mean annual precipitation compiled from WRF (25km×25km) without bias-correction.

- Spatially downscaled mean annual precipitation (12.5km×12.5km) from WRF (25km×25km) through the proposed Bayesian SD-QDM approach.



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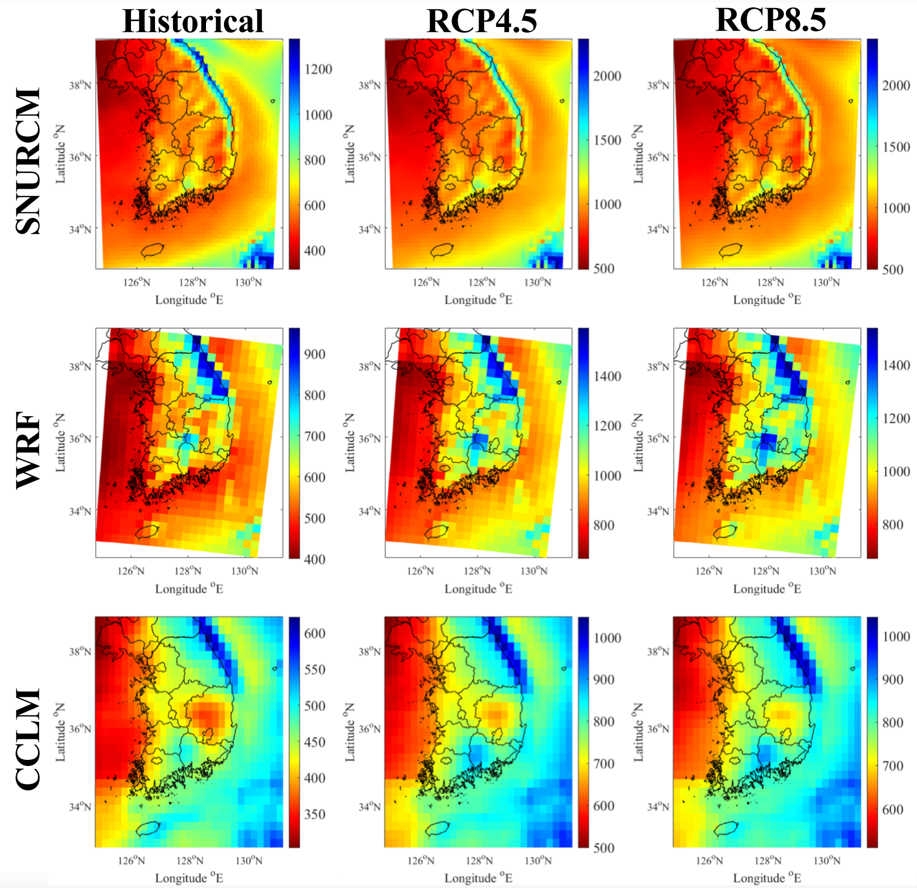
- Mean annual precipitation compiled from three RCMs (i.e., SNURCM, WRF and CCLM) without bias-correction.
- Here, the historical and the future daily precipitation are simulated by three different RCMs in the CORDEX-EA Phase 2 for 1979-2005 ("Historical") and 2006-2100 ("Future") under the RCP 4.5 and 8.5



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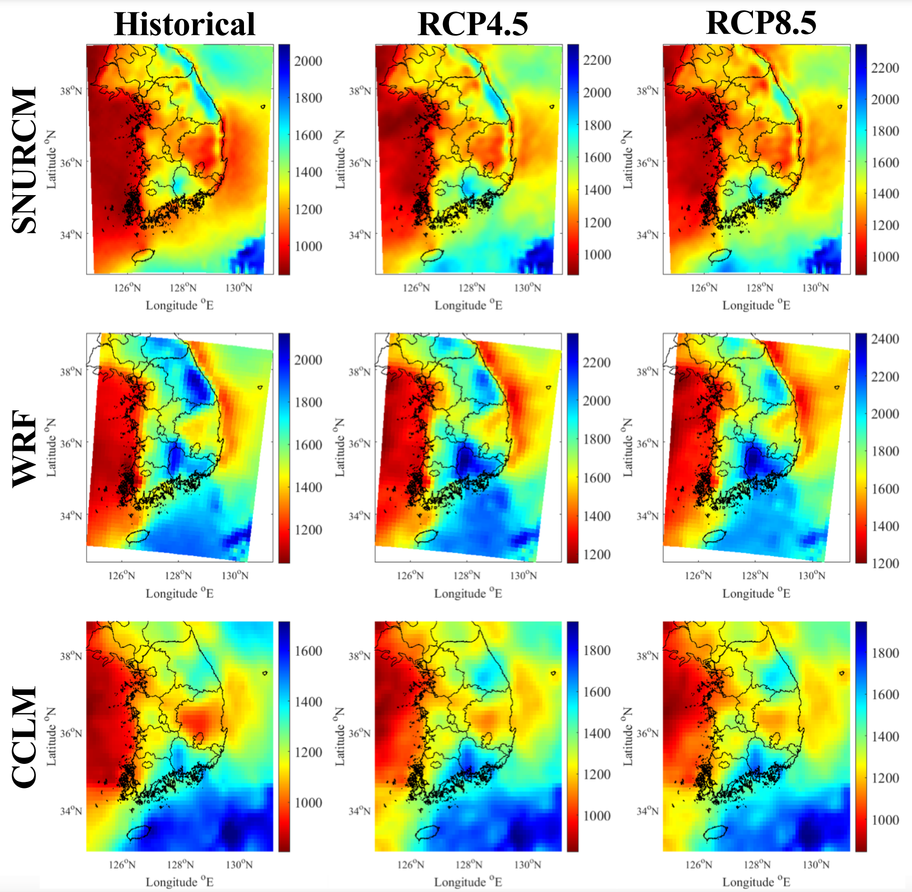
- Here, spatial downscaling was done at the fine grid by interpolating the pointwise estimation of QDM parameters onto the different grid points (or spatial resolutions) of three RCMs, with a resolution of 6.25km, 12.5km and 12.5km, for SNURCM, WRF and CCLM, respectively

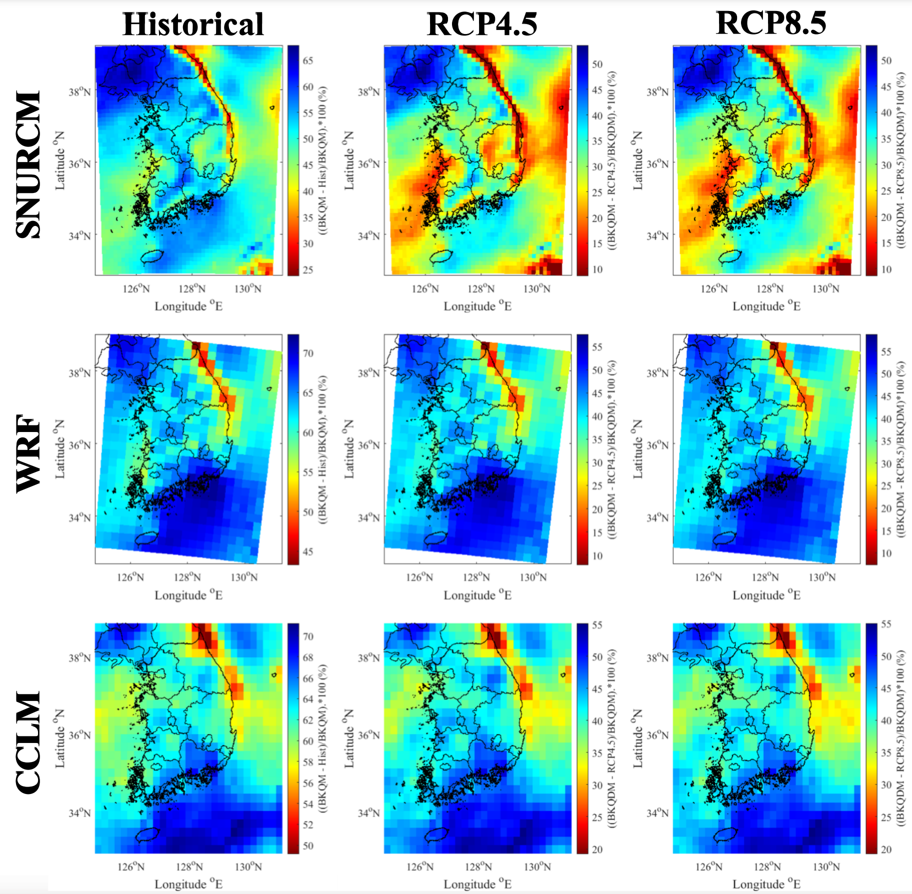


04. Results & Discussion

Spatial Downscaling of Climate Change Scenarios

- In order to illustrate the use of the proposed Bayesian Kriging based SD-QDM approach, this work downscaled the historical and the future daily precipitation simulated by RCMs in the CORDEX-EA Phase 2 for 1979-2005 and 2006-2100.

- Relative differences between the uncorrected precipitation from the three RCMs and the corrected precipitation



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05. Conclusion & Future Works

The key findings from this work are provided as follows:

- We investigated whether all parameters associated with the SD-QDM approach can be simultaneously estimated and gridded at the desired points within a Bayesian Kriging framework.
- Under the LOOCV scheme, we also found that the directly interpolated gamma parameters through the proposed Bayesian Kriging approach outperformed the baseline model based on interpolated daily rainfall, which produced a substantial bias that leads to an incorrect representation of the probability density function.
- Under these circumstances, the direct estimation of the distribution parameters from the interpolated daily precipitation for bias-correction and spatial downscaling should be cautious.
- This study further investigated whether spatial dependency over the interpolated gamma parameters can be effectively preserved.
- The results confirmed that the proposed model could effectively reproduce the spatial variability of parameters estimated from gauging stations, given that the semi-variogram of the interpolated parameters estimated from the Bayesian Kriging based SD-QDM approach was almost identical to that of the local parameters estimated from gauged rainfall data.

05. Conclusion & Future Works

Concluding Remarks

- The proposed Bayesian Kriging based SD-QDM approach could apply to various applications with different temporal scales in hydrometeorology to establish a spatial reference field to compare model simulations against.
- More specifically, the bias-correction and spatial downscaling for other climate variables, including temperature, soil moisture, solar radiation and wind field, rely on observed variables at the weather station (or grid points), limiting the full use of climate information obtained from the climate models.
- Although the proposed modeling framework provides an important basis for the spatial downscaling of climate model outputs, the variability of precipitation areal reduction factors are not fully incorporated and explored in this study.
- These aspects will be further investigated in future work.

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THANK YOU