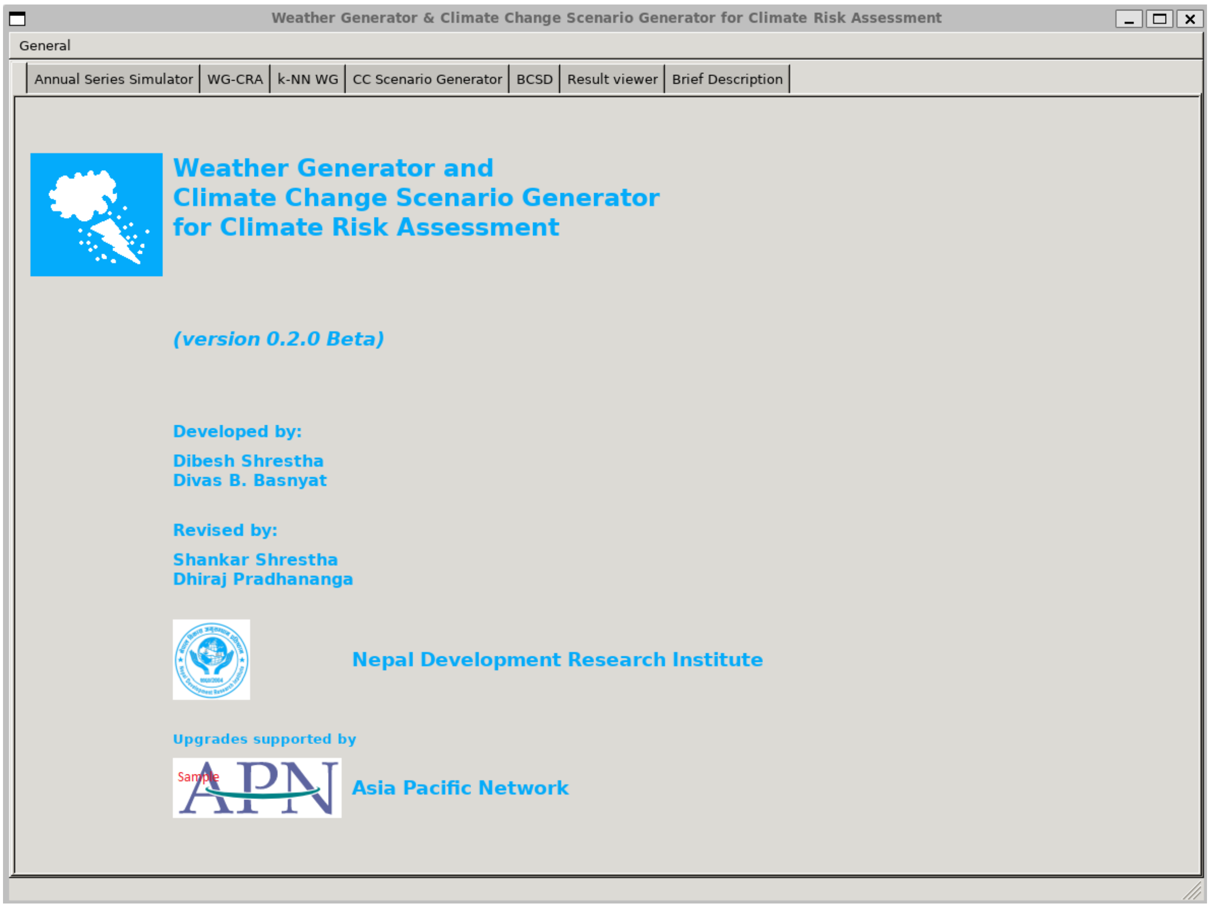
Draft Technical Report on:

Integration of the Bias Correction and Spatial disaggregation capability in "WEather generator and Climate Change Scenario Generator (WECCS-Gen)" tool



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1 Introduction to the WEather generator and Climate Change Scenario Generator tool

This tool – 'Weather Generator and Climate Change Scenario Generator (version 0.2.0)' has two parts:

(A) k-nearest neighbor (k-NN) based multisite multivariate weather generator. It is based on paper by Apipattanavis et al (2007) and Steinschneider and Brown (2013).
(B) Bias correction and Spatial Disaggregation (BCSD) for statistical downscaling of future climate projections. It is based research by Wood et al (2002) and Thrasher et al (2022).

Climate resiliency in WR infrastructures is needed by addressing uncertainties and future climate risks (ASCE, 2018) as it is very likely that heavy precipitation events will intensify and become more frequent in the future (IPCC, 2022). Major sources of uncertainty in is the climatic inputs from the global circulation models (GCMs) or regional climate models (RCMs) as they lack the required temporal and spatial resolution needed for impact studies at local scales (Fowler et al., 2007; Grotch and MacCracken, 1991). In such cases, a bottom-up, context-based CRA can serve as a decision support tool for WR development under uncertainty (Ray and Brown, 2015). Uncertainties of GCM projections and thus conclusions derived from them lack systematic risk analysis (Ray et al., 2018). Therefore, bottom-up or system-driven approaches like Decision Tree Framework (Ray and Brown, 2015), CRIDA (Mendoza et al, 2018) and Hydropower Sector Climate Resilience Guide (IHA, 2019) are adopted. These frameworks identify performance indicators of the hydro-system through stakeholders' consultation and run climate stress test to expose vulnerability and risk (Ray et al., 2018). This allows the decision-makers to adopt adaptive and resilience design of water resources infrastructures (Ray and Brown, 2015). Key step in the bottom-up climate risk assessment is to generate multiple realisations of the key climate variables (precipitation, temperature) and then generate the climate vulnerability domain of the selected performance indicator under scrutiny or test, for instance, streamflow, dry energy under various climatic realisations (Ray et al., 2018). This require generation of multiple climate realizations using tools like WECCS-Gen. It allows for altering the parameters like mean, coefficient of variation and transition probabilities of current climate and generate wide possible range of future scenarios (Steinschneider, and Brown 2013). In this aspect, the **first part of the tool (A**) 'k-nearest neighbor (k-NN) based multisite multivariate weather generator' becomes a handy tool to aid in climate stress test and CRA. The first part of the tool was developed in 2019 as part of inhouse development by Nepal Development Research Institute (NDRI).

The **second part (B) of the tool,** the main focus of the technical document, is directly related to the downscaling of the climate projections. This belongs to the top-down or GCM driven approach for climate risk studies. These are widely used in national and international context, like in the National Adaptation Plan of Nepal (MoFE, 2019), The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) and many other. In fact, it is common practice to use the climate models using ensemble (e.g. Whetton et al. (2012)) or envelope approach (e.g Lutz et al. (2016)) to address uncertainties. GCMs and RCMS are then treated using climate downscaling (like Wood et al., 2004) and bias correction (like quantile mapping in Gudmundsson et al., 2012) procedures to reduce biases and contextualise it to local conditions. Given the technical complexities involved in either simulating climate realizations or downscaling, this tool provides a and accessible platform to WR practitioners to facilitate CRA using either of the approaches. In this tool, **Bias correction and Sptial Disaggregation (BCSD)** described by Wood et al. (2002) and Thrasher et al. (2022) has been implemented with the Graphical User Interface. This is shown in the Figure 1. Development of the second part (B) has been supported by Asia Pacific Network (APN).

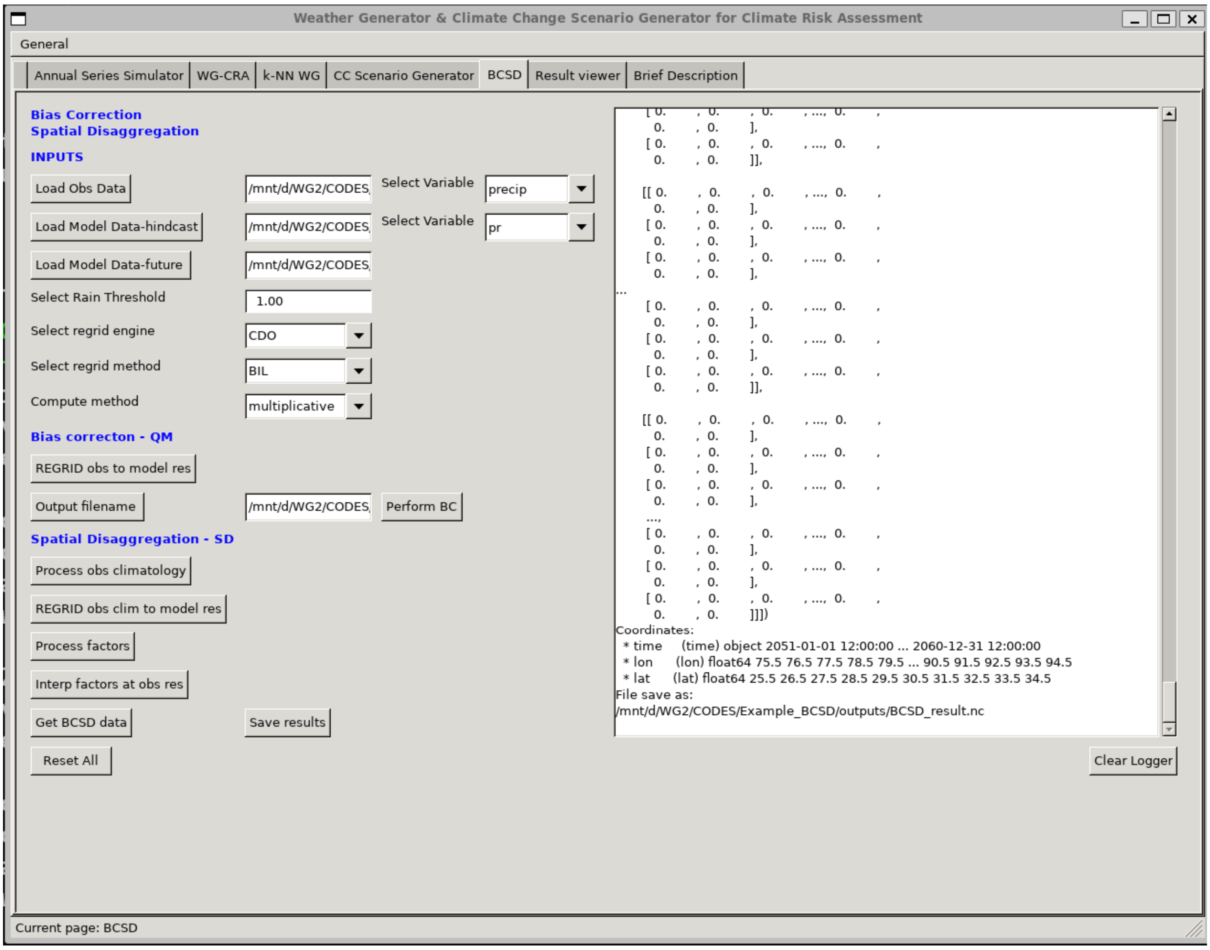

Figure 1: Graphical user interface of the Bias Correction and Spatial Disaggregation tool in the WECCS-Gen tool

2 Methodology for the Bias-Correction and Spatial Disaggregation (BCSD) tool

The approach of BCSD tool can be broadly divided into two parts: (A) Bias correction and (B) Spatial disaggregation. Tool was developed by following the approach described in Thrasher et al. (2022).

2.1 Bias Correction (BC)

Bias correction using Quantile Mapping (QM) has been implemented in BCSD tool. Biases in rainfall or temperatures or variables magnitude in General Circulation Models (GCMs) during the historical period against observation are corrected using the empirical quantile mapping method, a technique of mapping the probability distribution of rainfall of the GCMs with the probability distribution of the observed rainfall. Details of this procedure are described in Gudmundsson et al. (2012). The procedure is given by the following relationship:

$$X^{corr}_{future,t} = inverse\ ecdf\ ^{obs}_{reference}\left(ecdf^{Model}_{reference}\left(X^{Model}_{future,t}\right)\right),$$

where *ecdf* is the empirical cumulative distribution function for the reference time period, $X^{Model}_{future,t}$ is the raw GCM at time t in future, $ecdf^{Model}_{reference}$ is the empirical cumulative distribution function of GCM for the reference period, and $inverse\ ecdf\ ^{obs}_{reference}$ is the inverse empirical cumulative distribution function of the observed rainfall for the reference period. $X^{corr}_{future,t}$ is the corrected estimate of $X^{RModel}_{future,t}$. For any given future projection $X^{Model}_{future,t}$ in the x-axis, the probability is given by $ecdf^{Model}_{reference}$ (red curve). The bias-corrected value $X^{corr}_{future,t}$ is the value on x-axis corresponding to this probability on reference $ecdf\ ^{obs}_{reference}$ (black curve). For this study, the empirical cumulative distribution function is defined for each of the months.

Additional correction known as the “frequency adaption” was needed if the frequency of dry days in the reference period in the model (GCM) data was greater than the frequency of dry days in the observed data (Themeßl et al., 2012). In this study, corrections were made for the extra dry days to prevent artificial introduction of wet biases if any dry day is mapped as a wet day. Only the fraction

$$\Delta P_0 = \frac{ecdf^{Model}_{reference}(0) - \ ecdf^{obs}_{reference}(0)}{ecdf^{Model}_{reference}(0)}$$

of such dry-day cases with probability P_0 are corrected randomly by uniformly sampling a number between zero precipitation and the precipitation amount of $inverse\ ecdf^{obs}_{reference,t}(\ ecdf^{GCM}_{reference,t}(0))$.

Important points to be considered using QM using this tool:

A. The tool is implemented for the month-wise window rather than daily window (each daily GCM value using a +/− 15-day window).
B. QM doesn’t consider or correct for the trend. Separate treatment for trend (like detrending at the beginning and then apply BC and adding trend) is required in case of presence of trend like in temperature series.

Following steps were followed for the implementation of the bias correction using quantile mapping:

(A) At first the observations are interpolated to the resolution of the particular GCM model being processed.
(B) Data for observations and model hindcast are aggregated monthwise.
(C) Empirical cumulation distribution function (CDFs) were defined for observation dataset and model (hindcast) dataset for each of the month.
(D) Quantile mapping was carried as described above for the future data based on the CDFs.
(E) Bias correction is done at the GCM model resolution.

2.2 Spatial disaggregation (SD)

Spatial disaggregation was performed after the bias correction for the given variable was carried. This step is actually integrating the observation climatology with the relative changes in the future projections by GCM at each time step. This involves the following steps:

(A). At first, the observation climatology (mean of the values over the historical period for each day of the year). Smoothened version was produced using the Fast Fourier Transform (FFT) preserving the third harmonics as described in Thrasher et al (2022).

(B) The daily climatology is then regridded (interpolated at the GCM resolution).

(C) Multiplicative or additive factors are computed. In case of the variables like precipitation, the multiplication factors are computed by dividing the GCM values at each time step (day) by the daily observed climatology for given day of the year. In case of the variables like temperature, the additive factors are computed by subtracting daily observed climatology from the GCM values.

(D) Factors or residual fields which are computed at the GCM resolution are then interpolated back into the observation resolution.

(E) Finally, spatially disaggregated future projection are obtained by multiplying or addition of the factors at observation scale with the daily observation climatology.

This whole process then finally leads to the bias corrected and spatially disaggregated future projections.

2.3 Tool and codes availability

Currently the working draft version of the WECCS-Gen tool can be accessed through the following link:

Link 1: https://drive.google.com/drive/folders/1z3lfEN-TpnM4YMCZCZNSfAeujFrqxay0?usp=share_link

Link 2: https://ndri.org.np/ourproject/weather-generator-and-climate-change-scenario-generator-for-climate-risk-assessment/

The Github link will soon be created once the tool is revised and evaluated thoroughly.

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