The following material is based on the work of R Meenu, 'Assessment of hydrologic impacts of climate change in Tunga-Bhadra river basin, India with HEC-HMS and SDSM', published in Hydrological Processes, 2013.

STATISTICAL DOWNSCALING USING SDSM 4.2

Introduction:

Projections from General Circulation models (GCMs) cannot be used directly for hydrological models, as their spatial resolution is too coarse. To surpass this limitation of directly using GCM outputs in hydrological models, downscaling methods are used (explained in earlier sections). Statistical downscaling methods are downscaling methods that ascertain an empirical relationship between large scale variables generated by Global Climate Model (GCMs) at grid box scale (regional or global) and local climate variables at sub-grid scales. Statistical downscaling methods are preferred as they have the following advantages over the use of raw GCM variables:

i. Statistical downscaling models are stochastic
ii. They can reproduce the unique meteorological characteristics of the individual stations
iii. They are less data intensive than dynamical methods

Statistical Downscaling Models (SDSM) is a regression based downscaling model, which develops quantitative relationships between predictors and predictands. The predictors are GCM variables, for example, Geopotential height, Mean Sea Level Pressure, and predictands are temperature, precipitation, etc.

Methodology:

Pre-processing:

The predictors are standardized before downscaling in order to minimize biases in the mean and variance of GCM atmospheric fields relative to observations or reanalysis data. The data is re-gridded to conform to the spacing of the GCM model grid.

Statistical Downscaling:

Statistical downscaling establishes empirical relationships between GCM resolution climate variables and local hydrological variables:

$$R = F(L)$$

R: Predictand (a local climate variable)

L: Predictor (a set of large scale climate variable)

F: Deterministic/Stochastic function (conditioned by predictor L and determined empirically from historical data and observations.)

Meenu et al. 2013, downscaled Maximum and Minimum temperature and daily mean areal precipitation for four sub-basins in the Tunga-Bhadra catchment. SDSM 4.2 was used in which primary step was to conduct a quality control check of the parameters to be downscaled. Quality control check is performed using codes and outliers, before model calibration to find the errors in the data records, specifically, missing data. The predictor variable, mean temperature lagged by one day (t_lag) is generated using the Transform feature, i.e:

L = t_lag

Precipitation distribution is found to be skewed and to make it normal, the fourth root transformation is applied to the original series. The corrected distribution is then subjected to regression analysis. The predictor screening is carried out using the results obtained in the seasonal correlation analysis, partial correlation analysis and scatter plots. The model structure is specified as monthly and downscaling process can be conditional or unconditional. The Maximum and Minimum temperature are modeled as unconditional processes, whereas precipitation is modeled as a conditional process. The amount of local precipitation is correlated with the occurrence of wet days. In the downscaling process of temperatures, in order to include an auto regressive term in the regression equation, Auto-regression option is also selected. Inter-variable correlations for the sub-periods (annual, seasonal or monthly), is found using correlation analysis. The predictors are then selected, based on the correlation values and scatterplots, which are suitable for downscaling the temperatures and daily precipitation values.

The calibration is performed by the model by taking one predictand and a set of possible predictors and estimating parameters of multiple regression equations by using an optimization algorithm (ordinary least squares). For every month, the model generates different model parameters. The regression model is then calibrated using 11 years of data and validated using another 10 years of data, out of the 30 years data available. The post model analysis can be done with the help of summary screen, which lists, the percentage of explained variance, stand error for the models, and Durbin-Watson statistic for each month. Regression model is finalized when the explained variance and SE values are found to be satisfactory.

For each variable, around 5 ensemble components are processed using weather generators thus the calibrated models are validated using independent data. The downscaled scenarios and the observed climate data can be compared in SDSM 4.2 using the summary statistics and frequency analysis screen. The observed and synthetic data are then subjected to statistical analysis using variable mean, maximum, minimum, variance, percent wet days and dry day spells, which are computed on monthly, seasonal or annual basis. The monthly statistics generated by the *Summary statistics* screen is then plotted using *Compare results* screen. Performance evaluation of the model for precipitation is done using mean daily precipitation, daily precipitation variability for each month, monthly average percentage of wet days and dry spell lengths, while calibrating and validating downscaling models for precipitation. Performance evaluation of the regression models for temperature is carried out by comparing mean values of observed and simulated data.

The Scenario Generator generates the downscaled synthetic daily weather series, provided the atmospheric predictor variables, which are obtained as output from GCM HadCM3, for both present and future climate experiments. Using the corresponding set of predictor variables for the A2 and B2 scenarios of the HadCM3 model, for every single climate model, five ensemble members are downscaled. The year length of HadCM3 is 360 days, and the downscaled variables will also have each year with 360 days. As the hydrological model year length is 365 days, in order to input the downscaled variables, it is essential to convert the SDSM outputs to 365 days a year format and it has to be done outside the model. The downscaled variables from the SDSM for the future are analyzed and future projections are generated. The maximum and minimum monthly temperature, mean areal daily rainfall, for the baseline period and for the future years, 2020, 2050 and 2080s are estimated and compared. The monthly rainfall, percent of wet days, and dry spell length are also projected for the future time periods.

Calibration and validation of SDSM:

The values of variance (E), coefficient of determination (R^2), and standard error (SE) for the maximum and minimum air temperature, and daily precipitation shows that the model can explain 60-66% of the variance in maximum and minimum air temperature but only 20% of the variance in daily precipitation. Also, there is a good correspondence between the observed and NCEP simulated maximum and minimum temperature throughout the year during the validation period. The low value of variance and coefficient of determination shows that model is comparatively inefficient in downscaling local precipitation from regional scale predictor variables. For the validation period, the statistical regression model estimates of daily precipitation with the observed series in terms of bias, shows that the downscaling model produces lower estimates of percent wet days and dry spell length. On the other hand, downscaling model estimated higher values for daily mean precipitation as compares to the observed values. As far as variance is concerned, the statistic or bias alone cannot weigh the efficiency of the precipitation regression model. The average daily precipitation, average monthly precipitation, average monthly percent of wet days, average monthly dry spell lengths, and monthly variance in precipitation can also be used to assess the performance of the model while calibrating and validating the model. Precipitation downscaling using SDSM gave inefficient results. Alternatively, Support Vector Machine (SVM) is adopted to downscale the mean areal precipitation of the sub-basins.

Projections of temperature based on downscaling:

The maximum and minimum temperature for the future periods is found to increase in both A2 and B2 scenarios. However, the increase is found to be more for maximum daily temperature in sub-basins 2 and 3 under A2 scenario by 1, 2.1, and 3.4°C in 2020, 2050, and 2080 respectively. The diurnal variations were found to have low ranges in winter months and higher ranges in the month of July and August in sub-basin 1 and 4. In the sub-basin 2, the diurnal range is increased throughout the year.

Projections of daily mean areal precipitation based on downscaling:

The projection of SDSM shows that the precipitation in the JJAS period in all sub-basins was more in the A2 scenario, compared to B2. It is estimated that in the 2080s the precipitation in the

JJAS period in sub-basin 2, will have an increase of 75% and 58% for A2 and B2 scenarios respectively. In sub-basin 4, the projection is found to increase by 15% in 2020, 28% in 2050 and 35% in 2080.

Summary:

The statistical downscaling model, SDSM 4.2, was found to be very efficient in for downscaling maximum and minimum temperature, but performed poorly for the daily mean and areal precipitation. The variance and R^2 value of daily precipitation shows the inefficiency of SDSM in downscaling local daily precipitation from regional scale predictor variables. The statistical properties of the precipitation data also limit the efficiency of the model in downscaling precipitation. The future projection of temperature indicates a rise in the maximum and minimum air temperature compared to the baseline period. For maximum temperature, the increase is larger for A2 scenario than B2 scenario (Meenu et al., 2013).

REFERENCES:

Meenu, R., Rehana, S., & Mujumdar, P. P. (2013). Assessment of hydrologic impacts of climate change in Tunga-Bhadra river basin, India with HEC-HMS and SDSM. *Hydrological Processes*, *27*(11), 1572–1589. https://doi.org/10.1002/hyp.9220