STATISTICAL DOWNSCALING

Statistical Downscaling is largely preferred over a raw GCM because of its stochasticity, it can also reproduce the unique meteorological characteristics of the individual stations, with the use of lesser data as compared to dynamical methods such as nested or Regional Climate Models (Meenu et al., 2012). Statistical downscaling involves the use of a predictor and a predictand in which predictors are large scale climate variables and predictands are regional or local variables, used in the hydrological models. A statistical relationship between the predictor and predictand is established and it is assumed to be the same for the future scenarios. The main advantages of this technique over dynamic downscaling are (Fowler et al., 2007):

- It is comparatively cheap and computationally inexpensive and thus can be used for various GCM outputs
- It can be used for site-specific information, which is crucial while considering various scenarios of climate change
- It can be used to derive the parameters that are not deducible from RCMs
- It can be effortlessly and readily deployed to a different site
- It is based on standard statistical methods
- The observations made can be directly incorporated into methods

The GCM variables, such as sea level pressure, geopotential height, wind fields, absolute/relative humidity, temperature, etc., are used to derive the predictors used in statistical downscaling. Statistical downscaling is broadly classified as (Wilby et al., 1998):

- Weather Classification Schemes/Weather Typing Schemes
- Regression Models
- Weather Generators

Each classification covers a range of methods with the basic concept of predictor-predictand relationship. The most important step in statistical downscaling is the selection of predictors. The predictors used in statistical downscaling should be (Ghosh & Mujumdar, 2006):

(1) reliably simulated by GCMs

(2) easily accessible from GCM outputs

(3) Strongly correlated with hydrological variables of interest

It is also essential to define the location and the dimensions of the large scale predictor field for downscaling local weather variables. The smaller the predictor domain, the more direct the influence of the GCM on the downscaling scenario (Wilby et al., 2004). The broad classification of downscaling is given below, and their strengths and weaknesses are summarized in Table 1:

Weather Classification Schemes/Weather typing Schemes:

Weather classification/typing schemes, as the name suggests, classifies days into different weather groups, or in other words, it is the classification of local climate into different weather classes. The classification of days is defined using empirical orthogonal functions (EOFs) from pressure data, by indices from SLP data, by applying cluster analysis or fuzzy rules to atmospheric pressure fields. The weather classification thus generated is used to estimate climate change by evaluating the change in the frequency of these classes (Fowler et al., 2007; Wilby et al., 2004).

Regression Models:

The regression models use a transfer function to define the relationship between the predictand and predictor variable. The methods commonly used by regression models are multiple regression, canonical correlation analysis (CCA), and ANN. The limitation of this model is that the variance associated with the regression is under predicted. However, efforts have been made to overcome this problem by using approaches such as expanded downscaling and multi-site regression-based methods (Wilby et al., 2004)

Weather Generators:

Weather generators are stochastic models, in which the statistical properties of a local climate variable are reproduced or replicated (Wilby et al., 2004). They use a two-state first-order Markov chain and a gamma distribution for modeling the occurrence and the amount of precipitation respectively. Limitations of weather generators are that since they are generated using local climate relationships, they cannot be used for other climatic conditions and also that they underestimate inter-annual variability (Fowler et al., 2007).

Table 1: Summary of Strengths and weaknesses of main SD methods (Fowler et al., 2007)

Methods	Strengths	Weaknesses
Weather Classification Schemes/Weather typing Schemes (e.g. Analogue method, Hybrid approaches, Fuzzy classification, Self-organizing maps, Monte Carlo Methods)	• The surface climate is linked to hydrological variables in a physically interpretable manner • Versatile (can be applied to flooding, air quality, erosion, etc.) • Can be used for the analysis of extreme events	• Weather classification has to be done additionally • Circulation based schemes can be insensitive to future climate forcing • Intra-type variations may not be captured
Weather Generators (e.g. Markov chains, Stochastic models, Mixture modelling, Spell length methods)	• Production of large ensembles for uncertainty analysis or long simulations for extremes • Parameters can be interpolated using landscapes • Sub-daily information can be generated	• Future climate parameters are not accurately predicted • Unanticipated effects on secondary variables of changing precipitation parameters
Regression Methods (e.g. Linear regression, Neural networks, Canonical correlation analysis, Kriging)	• Can be easily applied • Employs a full range of available predictor variables • Off-the-shelf solutions and software available	• Observed variance is often poorly represented • May assume linearity and/or normality of data • Poor representation of extreme events

Data requirements:

The predictand estimation and its accuracy depends on the quality and length of the data series used in calibrating the model and the ability of the model to capture the variability of the observed data. Thus for statistical downscaling, observed predictor values of long duration are required. If observed climatological data are not available, reanalysis data can also be used. Reanalysis data are data obtained from high resolution climate models that are run using satellite and surface observations, collectively known as assimilated data. Reanalysis data can be obtained from National Centers for Environmental Prediction (NCEP), the European Centre for Medium Range Forecasting (ERA40), the North American Regional Reanalysis (NARR) project, and the Japanese 25 year Reanalysis (JRA25) project (Mujumdar & Nagesh Kumar, 2010).

Hydrologic extremes in Statistical modeling:

Statistical models are often unable to accommodate extreme events for which fewer observations are only available. The methods chosen for downscaling should be able to predict beyond the observations that are already available. Events such as floods and droughts have very less data record and are extremely difficult to project. Taking climate variability and short term extremes into account, enough emphasis has to be given to variability in temperature and precipitation. Rise in global temperature results in extreme rainfall, giving rise to flash floods in urban areas.

Predictor Screening:

The first and most important step in statistical downscaling is the selection of predictor variables. The predictors selected should be such that they are significant in predicting the future climate changes. The predictor selection can be different for different regions and there is no single method or procedure for the selection of right predictor variables. The predictor chosen must be well simulated by GCMs, with a strong correlation to the predictands. Mujumdar & Nagesh Kumar, 2010 provides a list of predictor variables and predictands used for different downscaling techniques, predictors including: Geopotential heights, Vorticity, Mean sea level pressure, Airflow indices, Surface temperature, Sea level pressure, Surface V- wind, Surface specific humidity, Specific humidity, Surface air temperature, Precipitation flux, Mean, maximum and minimum surface air temperatures, Surface U- and V- winds and corresponding predictands: Daily precipitation, Monthly mean temperature, Maximum temperature, Monthly mean, maximum and minimum temperature, Monthly mean precipitation. It is recommended to use moisture variables along with the atmospheric variables as atmospheric variables alone fail to capture the key precipitation mechanisms and also is found to be unsuccessful in reflecting the atmospheric humidity in warmer climate. When used in combination, the simulation runs of the GCM outputs converge, thus increasing the efficiency of the statistical and dynamical methods.

Statistical Downscaling: When to use:

Statistical Downscaling are generally preferred in heterogeneous environments, with complex topography, steep slopes, such as islands, mountains, land/sea contexts where in large scales are involved. It is used when information on extreme events such as floods and heat waves at sub-grid scale are required. Statistical Downscaling are of great help in developing countries where computational resources are not available and also when computational demands are low.

Statistical Downscaling: When not to use:

In cases where station data is not available for model calibration, Statistical Downscaling is not recommended. Also, Statistical Downscaling methods does not take land surface forcing into account, thus climate change scenarios produced does not represent the original conditions when land-surface scenario changes.

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