General Circulation Models (GCMs) Downscaling Techniques and Uncertainty Modeling for Climate Change Impact Assessment

J. Musau, J. Sang, J. Gathenya

***Abstract*—** Scientific literature on the assessment and projection of climate change impacts suggests that the rapidly changing climate conditions are causing far-reaching consequences on natural resources and agricultural production. Atmospheric general circulation models (GCMs) have been widely used to simulate the present climate and to predict future climatic change at the global-scale. However, the assessment and projection of climate change at regional and national scales requires high resolution and consistent climate data to ensure that the scale and accuracy of results will enable planning for adaptation. This data can be obtained by downscaling the simulated output from GCMs using the appropriate predictors. However, this process is characterized by uncertainty due projections generated with multiple GCMs. This paper provides a summary of research developments in the use of GCMs for the assessment and projection of climate change impacts. The different techniques which have been used to downscale GCM output for compatibility with regional and watershed models, their advantages and deficiencies are also discussed. Modeling approaches to address GCM uncertainties and uncertain future scenarios are discussed.

***Keywords*—** Climate change, Downscaling, General Circulation Models (GCMs), Uncertainty

I. INTRODUCTION

THE climate variability and change associated with rapid increase in atmospheric concentration of greenhouse gases (GHGs) is major concern at local and global levels due to its impacts on availability, supply and sustainability of ecosystem services [1]. The increased appreciation of the interactions between oceans, land and atmosphere has improved climate prediction [2]. Atmospheric general circulation models (GCMs) have been widely used in projection of future climatic under different emissions scenarios [3]. The application of these models increasingly elucidate advances in representation of important mean climate features, such as the large-scale distributions of atmospheric temperature, precipitation, radiation and wind, and of oceanic temperatures, currents and sea ice cover. In addition, GCMs have been used in reproducing observed features of current climate and its changes in the past [8].

However, the direct application of GCM output in climate impact studies is constrained by the mismatch with local scale models [9]. The GCMs output is very coarse hence significant local features and heterogeneities in the surface boundary conditions are filtered out in GCMs [11]. Therefore, interpolation of the conditions for different locations represented by a single grid point or very few grid points in a model and with very different climates is effective [14]. On the other hand, significant local-scale physical processes, such as radiative transfer, clouds, precipitation formation, and turbulent transports in the boundary layer, may not be well parameterized in some GCMs [15]. The lack of temporal and spatial specificity and accuracy in the application of GCMs at local scales has serious implications in weather and climate forecasts for natural resource management. To circumvent this challenge, impact analysis at local scale requires downscaling of GCM outputs. Downscaling can be applied to the spatial and temporal domains [19].

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II. DOWNSCALING TECHNIQUES

Any viable downscaling technique must consider the influence on local climate caused by regional forcings arising from orography, coast-lines, lakes, land surface characteristics among others [4]. Downscaling can be applied to the spatial and temporal domains [19]. The widely used downscaling techniques can be categorized into dynamic downscaling and statistical downscaling [21].

A. Dynamic downscaling

Dynamical downscaling involves regional models nested within the grids of the large-scale forecast models to simulate finer-scale physical processes [25]. In this downscaling method, domain size, lateral boundary conditions, and grid spacing play a significant role [30]. The high horizontal resolution of a RCM (~10–50 km) resolves the small-scale features with major influence on climatological variables as well as captures the spatial variability of model outputs [31]. These models have shown a relatively effectiveness in generating flood frequency curves as compared to those generated using observed input data[32].

According to Castro [33], dynamical downscaling can be categorized into four types. In type 1, numerical weather predictions involve specified initial conditions, lateral boundary conditions, re-analysis at regular intervals, and bottom boundary conditions such as terrain. In type 2, the prediction results are influenced by the lateral boundary conditions of reanalysis data and bottom boundary conditions.

However the initial atmospheric conditions in the interior of the model are forgotten. In type 3, lateral boundary conditions are obtained from GCMs forced with specified surface boundary conditions such as observed sea-surface temperature, sea ice coverage etc. In Type 4, a completely coupled earth system global climate model in which the atmosphere-ocean-biosphere and cryosphere are interactive is run without prescribed internal climate forcing.

The regional models can be applied in a variety of weather and climate conditions in a changing climate [26][34][35]. However, the high computational time and data requirements in this method limit simulations to single GCM outputs and brief time scales. In addition, three dimensional boundary and initial conditions as well as output bias correction measures are requisite for sufficient replication of conditions at the higher resolution [29].

B. Statistical downscaling

The theory and application of statistical downscaling has been documented widely in a plethora of publications [24][36]. In this approach, random or deterministic functions are used to transform large-scale features of the GCM (predictors) to station-scale meteorological series (predictands) based on established cross scale relationships. The relationships can take several forms such as: predictand as a function of the predictor(s), between predictors and the statistical distribution parameters of the predictand, or the frequencies of extremes of the predictand [10]. The relationships are then used to infer local scale variability and change based on the large-scale information. This approach is based on the premise that the local climate is function of overall atmospheric circulation as well as local topography, land-sea distribution and land use [39]. The statistical downscaling methods are based on three assumptions [13][22][40][41]:

(i*), The predictors are assumed to be relevant to local climate and realistically modeled by the host GCM.* Consequently, statistical downscaling will only provide reasonable information about local climate if the large scale predictors used realistically respond to the greenhouse gas forcing in the climate model [42]. However, although a model can credibly simulate the present climate, it is important to determine the variables and scales for which the model reflects reality [44]. This is because although tropospheric quantities such as temperature or geopotential height are intrinsic parameters in GCMs, derived variables may not be well represented [45]. In addition, though there is evidence GCMs can be considered skilful at several grid lengths, there is no theoretical level of spatial aggregation provided [46].

(ii) *The relationships between large-scale and local variables are assumed to remain valid under climate change.* Thus, the range of variations of the large-scale variable should encompass that from the statistical model for this assertion to be valid. If the time series used in training the statistical model are long enough, [7] and [36] agree that a range of large scale atmospheric structures will be observed including those which are more probable in an altered climate. On the other hand, [47] noted that a good match between the GCM simulations of future climate and the statistical model predictions indicate a good statistical model for using under climate change. However, [7] cautioned that the ability of the statistical model to realistically simulate the variability in the past should only enhance the level of confidence in the model but not strictly mean that it can be used for future conditions, since the statistical relationship may vary.

(iii) *The predictors employed are assumed to fully represent the climate change signal.* According to [41] this dependence relies on the size of the local area of interest, the time interval at the local scale, the large scale atmospheric variables considered, the large scale area considered, the resolution of the large scale predictors and the month or season under consideration.

Statistical downscaling methods are categorized into weather generators, transfer functions and weather typing schemes [4][10][48][50].

1) Transfer functions

This technique uses linear or nonlinear methods to infer the relationships between observed local climatic variables (predictands) and large-scale GCM output (predictors) [51]-[52]. The quantitative predictor-predictand relationship can be verified by use of multiple linear regressions [53], principal component analysis (PCA) [54], canonical correlation analysis (CCA) [55], artificial neural networks [12] and singular value decomposition (SVD) [56].

2) Weather typing

This method is based on classification of the large scale atmospheric structure into `weather types' and then associating local meteorological variables with each of these types [57]. Thus, the local variables are sensitively linked to large-scale atmospheric circulations. However, this method does not assume a continuous relationship between large-scale circulation and local climate and hence potential loss of information due to the coarse discretization of the predictor field [14][60]. Weather types can be objective by using clustering and classification algorithms or subjective by visually classifying synoptic situations [41][60]. Objective weather typing has been carried out based on ad-hoc or heuristic methods such as k-means [61], hierarchical clustering [62], fuzzy rules [63], or self-organized maps (SOMs) [64]. The weather classification procedures used include Principal Component Analysis (PCA) [66], cluster analysis [50], fuzzy rules [50] and analogue procedures.

3) Weather generators

In this technique, parameter values are perturbed according to the changes projected by climate models [67]. Due to their computational efficiency [70], weather generators allow for multi-model probabilistic projections or other impact assessments [71]. Although this approach has mainly focused on the daily time-scale, sub-daily models are also available. Weather generators have particularly been useful in provision of synthetic series of unlimited length, and filling missing values by imputation [72].

Weather generators have been used to produce time-series of precipitation frequency and intensity [69], maximum and minimum temperature [73], solar radiation [70], relative humidity and wind speed. The inclusion of other variables other than precipitation involves use of a multiple variable first-order autoregressive process to condition the variables on the occurrence of precipitation [36].

Weather generators can be distinguished based on parameterization, the assumed distributions and the suitability for particular application [74]. The two fundamental types are: the Markov chain approach and the spell –length approach [36]. The Markov chain approach involves a day-by-day change to the weather generator parameters based on daily variations in atmospheric circulation. Therefore, a random process is constructed which determines a day at a station as rainy or dry, based on the state of the previous day, following given probabilities [66][76]. In the spell–length approach, a probability distribution is fitted to the observed relative frequencies of wet and dry spell lengths [36][75]

Compared to dynamic downscaling, statistical downscaling methods have the following advantages and disadvantages [37]:

Table 1: Advantages and disadvantages of SD methods

Advantages: they are based on credible statistical procedures, (2) they are computationally inexpensive, (3) can be designed for specific purposes, and (4) they effectively integrate the observed data
Disadvantages: They assume stationarity of the predictor-predictand relationships (2) they involve long/reliable observed data series, and (3) the biases in the GCM affect the output

III. Selecting appropriate predictor variables

The selection of the predictor variables is of utmost significance in the statistical downscaling exercise. This requires a profound knowledge of the GCM model and the driving forces of local and regional scale meteorology [78]. The appropriate predictors are: (i) reliably simulated by GCMs, (ii) readily available from archives of GCM outputs, (iii) robustly interrelated with the predictands hence are statistically significant contributors to the variability in predictands, and (iv) they represent significant physical processes in the context of the enhanced greenhouse effect [50][79].

The circulation-based predictors have been widely used in the statistical downscaling [81]. The commonly used approach is summarizing the large-scale atmospheric circulation patterns into circulation indices which partition the movement of the atmosphere into zonal and meridional flow components as well as a vorticity component [39]. However, the circulation predictors are discrete variables rather than continuous, hence they do not represent the continuous properties of the climate system properly [83]. Therefore, additional variables which represent seasonality such as measurements of humidity, and vertical stability should be considered [12][18][85]. Alternatively, the downscaling technique can treat the seasons or months separately by estimating $\{f_i\ (y(i)|G(i)) : i = 1,\ldots,4\}$ where i represents the seasons, y(i) is a vector of observations for season i and G(i) is a matrix containing appropriate atmospheric data for season i [41].

The availability of reanalysis data sets has extensively augmented the number and multiplicity of candidate predictors [86]. Some of the predictors used in previous research are sea level pressure, vorticity, air flow indices, wind strength and direction, relative humidity and geosynthetic heights to predict temperature and precipitation [87]. As noted by [13], an objective comparison of different predictors and their spatial character is significant because the explanatory influence of any given predictor vary both in space and time. In addition, the influence of a predictor during the developing the downscaling function under present climates may or may not be very significant, but the changes in that predictor under a future climate may be significant in determining the climate change. Schubert [89] noted that under doubled atmospheric CO_2 conditions, changes in the radiative properties of the atmosphere are likely to dominate the local temperature changes compared to circulation changes.

IV. Predictor Standardization and transformation

Prior to the downscaling process, the potential predictors are prepared by re-gridding and standardization. The re-gridding is a requirement since the grid-spacing and/or coordinate systems of re-analysis data sets used for Statistical downscaling model calibration do not generally correspond to the grid-spacing of the GCM outputs [90]. For example, the grid-spacing NCEP/NCAR reanalyses data is 2.5º latitude by 2.5º longitude compared to CGCM1 (~3.7° latitude by 3.7° longitude) and the HadCM3 (2.5° latitude by 3.75° longitude). Hessami *et al.,* [90] interpolated NCEP/NCAR reanalysis grid to the GCM grids because GCM predictors were required for the climate change simulations and raw GCM information was essential for the down-scaling process.

Data standardization is carried out to minimize systematic biases in the mean and variance of simulated values relative to observed values or re-analysis data [10]. The procedure involves subtraction of the mean and division by the standard deviation of the predictor for a predefined baseline period. However, there may exist bias in other statistical parameters hence consideration of only the mean and standard deviation is not adequate.

Principal Component Analysis (PCA) is used for reduction of the dimensionality of the predictors and identification of modes of variability [91]. Ghosh and Mujumdar, [92] performed Principal Component Analysis (PCA) to transform a set of correlated N-dimensional predictors (N = 100) into a new set of N-dimensional uncorrelated vectors (called principal components) by linear combination, such that most of the information content of the original data set is stored in the first few dimensions of the new set. The authors observed that 98.1% of the information content (or variability) of the original predictors was represented by the first 10 Principal Components (PCs), which were then used in downscaling.

Cluster analysis uses measures of distance to relate and classify observations within a dataset. Schoof and Pryor [93] used hierarchical clustering whereby each observation was at first considered as a cluster, and then proximal clusters were merged based on intra- and inter-class similarity. The data resemblance was determined by Euclidean distance based on five algorithms which reflected the different ways distances between observations were measured: (i) single linkage (which used the minimum distance between two clusters), (ii) complete linkage (which used the maximum distance between observations in the two clusters), average linkage (which used either (iii) the average distance between observations in the two clusters or (iv) the average distance between points in the newly formed cluster), and (v) Ward's method.

V. Application of Artificial Neural Networks (ANNs)

ANNs have been used widely as an alternative to the linear regression models [22][45][94]. This technique has gained wide recognition owing to their potential in mapping complex, nonlinear and time-varying relationships between predictors and predictands [50][95]. The commonly used ANNs structures include multi-layer feed forward networks, self-organizing feature maps, Hopfield networks and counter propagation networks [96]. Application of ANNs involves three distinctive modes: training, validation and prediction [22].The commonly used learning algorithm is back propagation algorithms [98]. The back propagation learning algorithm repeatedly runs through the training data patterns, comparing the predicted values and the observed values [97]. The weights and thresholds are then optimized to reduce the current least mean square classification error to acceptable level for all data patterns [98]. This algorithm comprises of: the learning rate which determines how much the weights are allowed to change each time they are updated; and the momentum factor which determines how much the current weight change is affected by the previous weight change [95]. The weights of the neural network are adjusted as follows [93]:

$$W_{i,j}(\text{new}) = w_{i,j}(\text{old}) + \eta\delta_i o_j + \alpha[\Delta w_{i,j}(\text{old})]$$

Where: $W_{i,j}$ is the weight associated with the jth node in the ith layer, η is the momentum factor, α is the learning rate, o_j is the output from the jth output node, and δ_i is the error signal determined by:

$$\delta_i = (t_i - o_i)o_i(1-o_i)$$

Where t_i is the observed value for the ith output

In mapping mode, a sigmoid function is then applied to the weighted sum of values from all nodes in the hidden layer. The value of the mapping function is sent to the output nodes which perform the same calculation as the hidden nodes and produce the value of the dependent variable(s) [93].

VI. Uncertainty analysis

Given the limitations and uncertainties associated with application of GCMs in regional and local levels, objective selection of model type and structure is significant. GCMs vary in resolution, model formulations, parameterization and inherent biases [8][101]. Consequently, although they may concur on the direction of change in predictands, results between models can vary widely [102]. Greenhouse gas emission scenarios which present "storylines" of likely future climatic conditions based on assumed directions human population growth, economic development, and energy technology change have inherent uncertainties [104].

According to Mearns et al., [25], these uncertainties extend across the specification of alternative emissions futures, conversion of emissions to concentrations, conversion of concentrations to climate forcing, simulation of climate response to a given forcing, conversion of the model response into inputs for impact studies, and modeling impacts. Hence, the consideration of a range of models and emissions scenarios better reflects the uncertainty in the range of possible climate impacts [106].

The cascade of uncertainties in climate modeling is thus composed of emission scenario, GCM and downscaling uncertainties [107]. The development of emission scenarios is based on the projected socioeconomic and human behavior resulting in future greenhouse gas (GHG). Therefore, scenario uncertainties are associated with unpredictability of these developments [8]. GCM uncertainty, on the other hand, is associated with inadequate information and understanding of the governing geophysical processes in the simulation of the transient climate response by coupled AOGCMs for a given emission scenario [85]. The generation of high resolution climate change information from coarse resolution climate change results introduces its own uncertainty. This is because different regional models or statistical downscaling methods can yield different results even when conditioned by the same GCM [43].

The various approaches used in managing uncertainty are: the extremes (max/min) approach; the ensemble approach; and the validation approach. The extremes (max/min) approach involves consideration of the full range of possibilities presented by the approximately 72 GCMs in AR4. The ensemble approach generates a probabilistic range of climate change predictions by considering several models thus reducing the uncertainty associated with any individual model to give more robust estimates [74][108]. The probabilistic functions used in this approach can be developed by: (i) equal weighting of the results from different models [111] or (ii) incorporating the weighted average of the ensemble members [112]. The validation approach compares the historical climate observations over a thirty-year period from a global gridded dataset against all models to determine which ones reproduce the values best [114].

The major concern in managing the uncertainties is that 'only a small subset of the potential pathways through the cascade is explicitly modeled' [85]. Typically, only one source of uncertainty at a time is considered and the models are commonly viewed as being free of any uncertainties. However, techniques aimed at managing a range of possible sources of uncertainty are emerging. These include Bayesian methods [115], perturbed physics ensembles [116] and pattern scaling arguments [117].

VII. References

[1] Carter TR, Parry ML, Harasawa H, Nishioka S (1994) Intergovernmental panel on climate change technical guidelines for assessing clunate change impacts and adaptation. University College London and Center for Global Environmental Research, London

[2] Wood A, Leung L, Sridhar V, Lettenmaier D. (2004) Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Climatic Change 62: 189 – 216.

[3] Ghosh, S., and P. P. Mujumdar (2007b), Nonparametric methods for modeling GCM and scenario uncertainty in drought assessment, Water Resour. Res., 43, W07405,

[4] Murphy J. 1999. An evaluation of statistical and dynamical techniques for downscaling local climate. Journal of Climate 12: 2256 – 2284

[5] Houghton, J. T., Y. Ding, D.J. Griggs, M. Noguer, P. J. van der Linden, D. Xiaosu (Eds.). (2001) Climate Change 2001: the Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, UK. pp 944

[6] Surfleet C, Tullos D, Chang H, Jung I, (2012) Selection of hydrologic modeling approaches for climate change assessment: A comparison of model scale and structures. J. Hydrol. 464–465: 233–248

[7] Zorita, E., and H. von Storch. (1999) The analog method as a simple statistical downscaling technique: comparison with more complicated methods. / . Climate. 12: 2474-2489.

[8] IPCC (2007) IPCC fourth assessment report. Climate change 2007: Projections of future changes in climate. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds) Working group I intergovernmental panel on climate change, Cambridge Univ Press, Cambridge.

[9] Dibike YB, Gachon P, St-Hilaire A, Ouarda TBMJ, Nguyen VTV (2008) Uncertainty analysis of statistically downscaled temperature and precipitation regimes in Northern Canada. Theor Appl Climatol 91:149–170

[10] Wilby, R. L., S. P. Charles, E. Zorita, B. Timbal, P. Whetton, and L.O. Mearns (2004), Guidelines for use of climate scenarios developed from statistical downscaling methods, technical report, Data Distrib. Cent., Intergovt. Panel on Clim. Change, Norwich, UK

[11] Allen, M.R. and W.J. Ingram, (2002) Constraints on future changes in climate and the hydrological cycle, Nature. 419: 224-232.

[12] Jeong D. I., A. St-Hilaire, T. B. M. J. Ouarda, and P. Gachon (2012) Comparison of transfer functions in statistical downscaling models for daily temperature and precipitation over Canada, Stochastic Environmental Research and Risk Assessment, Vol 26, Issue 5, pp 633-653

[13] Wilby, R.L., T.M.L. Wigley. (2000) Precipitation predictors for downscaling: observed and general circulation model relationships. Int. J. Climatol. 20: 641-661.

[14] Chen J., P. Brissette, R Leconte (2012) Coupling statistical and dynamical methods for spatial downscaling of precipitation, Climatic Change, Vol 114, Issue 3-4, pp 509-526

[15] Khairoutdinov M, D. Randall, and C. Demott (2004), Simulations of the Atmospheric General Circulation Using a Cloud-Resolving Model as a Superparameterization of Physical Processes, Journal of the Atmospheric Sciences, Vol 62, pp 2136-2154

[16] Bretherton, C. S., R. Ferrari, and S. Legg, 2004: Climate Process Teams: A new approach to improving climate models. U.S. CLIVAR Variations, Vol. 2, No. 1, 1-6.

[17] Miura, H., H. Tomita, T. Nasuno, S. Iga, M. Satoh, and T. Matsuno, 2005: A climate sensitivity test using a global cloud resolving model under an aqua planet condition, Geophys. Res. Lett., 32, L19717, doi:10.1029/2005GL023672.

[18] Soden, B. J., , and I. M. Held, 2006: An assessment of climate feedbacks in coupled ocean–atmosphere models. J. Climate, 19, 3354–3360.

[19] Hansen, J.W., Indeje, M., (2004) Linking dynamic seasonal climate forecasts with crop simulation for maize yield prediction in semi-arid Kenya. Agric. For. Meteorol. 125, 143–157.

[20] Zhang X. (2005) Spatial downscaling of global climate model output for site-specific assessment of crop production and soil erosion, Agricultural and Forest Meteorology 135: 215–229

[21] Jones, R.G., Murphy, J.M. and Noguer, M. (1995) Simulation of climate change over Europe using a nested regional climate model. I. Assessment of control climate, including sensitivity to location of lateral boundaries. Quarterly Journal of the Royal Meteorological Society 121, 1413–50.

[22] Sailor DJ, Hu T, Li X, Rosen JN. (2000) A neural network approach to local downscaling of GCM output for assessing wind power implications of climate change. Renewable Energy, 19:359-378

[23] Schnur, R., and D. Lettenmaier, 1998: A case study of statistical downscscaling in Australia using weather classification by recursive partitioning. J. Hydrol. 212–123: 362–379

[24] Yates, D. S., S. Gangopadhyay, B. Rajagopalan, and K. Strzepek, (2003) A technique for generating regional climate using a nearest-neighbor algorithm. Water Resour. Res., 39, 1199, doi:10.1029/2002WR001769.

[25] Mearns, L. O., F. Giorgi, P. Whetton, D. Pabon, M. Hulme, and M. Lal (2003), Guidelines for use of climate scenarios developed from regional climate model experiments, technical report, Data Distrib. Cent., Inter-govt. Panel on Clim. Change, Norwich, U. K.

[26] Hay, L. E., M. P. Clark, R. L. Wilby, W. J. Gutowski, G. H. Leavesley, Z. Pan, R. W. Arritt, E. S. Takle, (2002) Use of Regional Climate Model Output for Hydrologic Simulations. J. Hydrometeor, 3, 571–590. doi: http://dx.doi.org/10.1175/1525-7541(2002)003<0571:UORCMO>2.0.CO;2

[27] Fowler, H. J. and Kilsby, C. G. (2007) Using regional climate model data to simulate historical and future river flows in northwest England, Climatic Change, 80, 337–367

[28] Graham, L. P., Andreasson, J., and Carlsson, B., (2007) Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods – a case study on the Lule River basin, Clim. Change, 81, 293–307

[29] Leander, R. and Buishand, T. A. (2007) Resampling of regional climate model output for the simulation of extreme river flows. J. Hydrol., 332, PP 487–496

[30] Xue et al., 2007: Assessment of Dynamic Downscaling of the Continental U.S. Regional Climate Using the Eta/SSiB Regional Climate Model, J. Climate, 20, 4172-4193

[31] Gutowski, W. J., Decker, S. G., Donavon, R. A., Pan, Z., Arritt, R. W., and Takle, E. S. (2003) Temporal-spatial scales of observed and simulated precipitation in central U.S. climate, J. Climate, 16, 3841–3847

[32] Kay AL, Jones RG, Reynard NS. (2006) RCM rainfall f or U K flood frequency estimation. II Climate change results. Journal of Hydrology 318: 163 – 172, DOI: 10.1016/j.jhydr ol.2005.06.0.13.

[33] Castro, C.L., R.A. Pielke Sr., and G. Leoncini, (2005) Dynamical downscaling: Assessment of value retained and added using the Regional Atmospheric Modeling System (RAMS). J. Geophys. Res. - Atmospheres, 110, No. D5, D05108, doi:10.1029/2004JD004721.

[34] Manoj Jha. (2004) Impacts of climate change on streamflow in the Upper Mississippi River Basin: A regional climate model perspective. *Journal of Geophysical Research* **109**:D9, Online publication date: 1-Jan-2004.

[35] Akhtar, M. and Ahmad, N. and Booij, M.J. (2009) Use of regional climate model simulations as input for hydrological models for the Hindukush-Karakorum-Himalaya region. Hydrology and Earth System Sciences, 13 (7). pp. 865-902. ISSN 1027-5606

[36] Karl, T. R., Wang, W. C., Schlesinger, M. E., Knight, R. W. and Portman, D., (1990) A method of relating general circulation model simulated climate to the observed climate, Part I: Seasonal statistics. Journal of Climate 3, 1053–1079.

[37] Wilby, R. L. and Wigley, T. M. L., (1997) Downscaling general circulation model output: A review of methods and limitations. Progress in Physical Geography 21, 530–548.

[38] Yarnal, B., Comrie, A. C., Frakes, B. and Brown, D. P., (2001) Review. Developments and prospects in synoptic climatology. International Journal of Climatology 21, 1923–1950.

[39] Linderson M, Achberger C, and Chen D, (2003), Statistical downscaling and scenario construction of precipitation in Scania, southern Sweden, Nordic Hydrology, Vol 35 (3) pp 261-278

[40] Yimer G, Jonoski A and Griensven A, (2009), Hydrological Response of a Catchment to Climate Change in the Upper Beles River Basin,

Upper Blue Nile, Ethiopia, Nile Basin Water Engineering Scientific Magazine, Vol.2, pp 49-59

[41] Leith N, (2005), Forecasting local scale precipitation under scenarios of global climate change: A literature review, www.ucl.ac.uk/statistics/research/Rainfall/FD2113_rpt1.pdf, Accessed 24/01/2013

[42] Leung, L. R., L.O. Mearns, F. Giorgi, R.L. Wilby 2003. Regional Climate Research, Bull Amer Meteorol Soc 84, 89–95.

[43] Murphy, J. 2000. Predictions of climate change over Europe using statistical and dynamical downscaling techniques, Int J Climatol 20(5), 489–501

[44] Oreskes N, Shrader-Frechette K, Belitz K, (1994) Verification, validation, and confirmation of numerical models in the earth sciences. Science. 263, 641–646. doi:10.1126/science.263.5147.641.

[45] Trigo RM, Palutikof JP (2001) Precipitation scenario over Iberia: a comparison between direct GCM output and different downscaling techniques. J Clim 14:4422–4446

[46] Coulibaly, Paulin, Yonas B. Dibike, François Anctil, 2005: Downscaling Precipitation and Temperature with Temporal Neural Networks. J. Hydrometeor, 6, issue 4, pp 483–496

[47] Busuioc, A., von Storch, H. and Schnur, R. (1999) Verification of GCM generated regional precipitation and of statistical downscaling estimates. J. Climate, 12, 258–272.

[48] Hewitson BC, Crane RG. (1992) Large-scale atmospheric controls on local precipitation in tropical Mexico. Geophys Res Lett; 19 (18)

[49] Kilsby, C.G., Jones, P.D., Burton, A., Ford, A.C., Fowler, H.J., Harpham, C., James, P., Smith, A., Wilby, R.L., (2007), A daily weather generator for use in climate change studies. Environ. Modell. Softw., 22, 1705-1719.

[50] Ghosh S, and Mujumdar P, (2008), Statistical downscaling of GCM simulations to streamflow using relevance vector machine, Advances in Water Resources 31, pp 132–146

[51] Hashmi MZ, Shamseldin AY, Melville BW (2011) Comparison of SDSM and LARS-WG for simulation and downscaling of extreme precipitation events in a watershed. Stoch Environ Res Risk Assess 25:475–484

[52] Guo J, Chen H, Xu C-Y, Guo S, Guo J (2011) Prediction of variability of precipitation in the Yangtze River Basin under the climate change conditions based on automated statistical downscaling. Stoch Environ Res Risk Assess. doi:10.1007/s00477-011-0464

[53] Winkler, J.A., Palutikof, J.P., Andresen, J.A. and Goodess, C.M. (1997) The simulation of daily temperature time series from GCM output: Part II: Sensitivity analysis of an empirical transfer function methodology. J. Climate, 10, 2514–2535.

[54] Huth R (2004) Sensitivity of local daily temperature change estimates to the selection of downscaling models and predictors. J Clim 17(3):640–652

[55] WASA (1998) Changing waves and storms in the Northeast Atlantic? Bull. Amer. Met. Soc., 79, 741–760.

[56] Von Storch, H., and F.W. Zwiers, (1999) Statistical Analysis in Climate Research, Cambridge University Press

[57] Cheng, Chad Shouquan, Guilong Li, Qian Li, Heather Auld, (2011b) A Synoptic Weather-Typing Approach to Project Future Daily Rainfall and Extremes at Local Scale in Ontario, Canada. J. Climate, 24, 3667–3685. Doi: http://dx.doi.org/10.1175/2011JCLI3764.1

[58] Stephenson, D. B., A. Hannachi, and A. O'Neill, (2004) On the existence of multiple climate regimes, Q. J. R. Meteor. Soc., 130, 583{605, doi:10.1256/qj.02.146.

[59] Philipp, A., P. M. Della-Marta, J. Jacobeit, D. R. Fere-day, P. D. Jones, A. Moberg, and H. Wanner, (2007) Long term variability of daily North Atlantic-European pressure pat-terns since 1850 classified by simulated annealing clustering, J. Climate, 20 (16), 4065-4095.

[60] Maraun, D., et al. (2010), Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user, Rev. Geophys. , 48, RG3003, doi:10.1029/2009RG000314.

[61] Plaut, G., and E. Simonnet, (2001) Large-scale circulation classification, weather regimes, and local climate over France, the Alps and Western Europe, Clim. Res., 17, 303-324.

[62] Casola, J., and J. Wallace, (2007) Identifying weather regimes in the wintertime 500-hPa geopotential height field for the Pacific-North American sector using a limited-contour clustering technique, J. Appl. Meteor. Climatol., 46, 1619-1630.

[63] Bardossy, A., I. Bogardi, and I. Matyasovszky, (2005) Fuzzy rule-based downscaling of precipitation, Theor. Appl. Clima-tol., 82, 119-129.

[64] Wehrens, R., and L. M. C. Buydens (2007), Self- and super-organizing maps in R: The kohonen package, J. Stat. Softw., 21 (5), 1-19.

[65] Leloup, J., M. Lengaigne, and J.-P. (2008) Boulanger, Twenti-eth century ENSO characteristics in the IPCC database, Clim. Dyn., 30, 277-291

[66] Hughes, J. P., D.P. Lettenmaier, and P. Guttorp, (1993) A stochastic approach for assessing the effect of changes in synoptic circulation patterns on gauge precipitation. Water Resour. Res., 29 (10), 3303–3315.

[67] Zhang X (2007) A comparison of explicit and implicit spatial downscaling of GCM output for soil erosion and crop production assessments, Climatic Change, Volume 84, Issue 3-4, pp 337-363

[68] Wilks D. S. (1999), Multisite downscaling of daily precipitation with a stochastic weather generator, Clim Res, Vol 11, pp 125–136

[69] Chen, Y. D., Chen, X., Xu, C.-Y., and Shao, Q., (2006) Downscaling of daily precipitation with a stochastic weather generator for the subtropical region in South China, Hydrol. Earth Syst. Sci. Discuss., 3, 1145-1183, doi:10.5194/hessd-3-1145-2006.

[70] Semenov M. A., R. J. Brooks, E. M. Barrow, and C. W. Richardson (1998) Comparison of the WGEN and LARS-WG stochastic weather generators for diverse climates, Clim Res, Vol. 10: pp 95–107

[71] Jones, P. D., C. Harpham, C. Kilsby, V. Glenis, and A. Burton, (2009) Projections of future daily climate for the UK from the Weather Generator, Tech. Rep. 1, UK Met Office.

[72] Yang, C., R. E. Chandler, V. S. Isham, and H. S. (2005) Wheater, Spatial-temporal rainfall simulation using generalized linear models, Wat. Resour. Res., 41, doi: 10.1029/2004WR003,739.

[73] Chen, J.,F. P. Brissette, R. Leconte (2011)Assessment and improvement of stochastic weather generators for simulation of minimum and maximum temparatures, Transactions of the ASABE. 54(5): 1627-1637.

[74] Fowler, H. J., S. Blenkinsop, and C. Tebaldi, (2007) Linking climate change modelling to impact studies: recent advances in downscaling techniques for hydrological modelling, Int. J. Climatol., 27, 1547-1578.

[75] Wilks, D. S., a nd R. L. Wilby (1999), The weather generation game: A review of stochastic weather models, Prog. Phys. Geogr., 23, 329 –357

[76] Lettenmaier, D., 1995: Stochastic Modeling of precipitation with applications to climate model downscaling. In: H. von Storch and A. Navarra (eds) "Analysis of Climate Variability: Applications of Statistical Techniques", Springer Verlag, 197–212 (ISBN 3-540-58918-X).

[77] Hughes, J.P., P. Guttorpi and S.P. Charles, (1999) A non-homogeneous hidden Markov model for precipitation occurrence. Appl. Statist., 48, 15–30.

[78] Hofer M, (2007), Statistical downscaling of NCEP/NCAR reanalysis data to air temperature and specific humidity above an outer tropical glacier surface, Thesis, University of Innsbruck

[79] Goyal, M. K., Ojha, C. S. P., and Burn, D. H. (2010). "An evaluation of decision tree algorithm as a downscaling tool: Application on a Lake Basin for an arid region in India." Tenth conference of Canadian Geophysical Union, *University of Guelph*, Ontario, Canada

[80] Goyal, M. K., and Ojha, C. S. P. (2012). "Downscaling of surface temperature for lake catchment in arid region in india using linear multiple regression and neural networks." *International Journal of Climatology*, John Wiley & Sons, DOI: 10.1002/joc.2286.

[81] Wilby R, Wigley T (1994) Stochastic weather type simulation for regional climate change impact assessment. Water Resour Res 30:3395–3403

[82] Hellstrom, C., Chen, D., Achberger, C. and Ra¨isa¨nen, J. (2001). A comparison of climate change scenarios for Sweden based on statistical and dynamical downscaling of monthly precipitation. Climate Res., 19, 45 – 55.

[83] Wilby, R.L., Wigley, T.M.L., Conway, D., Jones, P.D., Hewitson, B.C., Main, J. and Wilks, D.S. (1998) Statistical downscaling of general circulation model output: A comparison of methods. Water Resources Research, 34, 2995–3008.

[84] Yang W, Bárdossy A, Caspary H, (2010) Downscaling daily precipitation time series using a combined circulation and regression-based approach, Theoretical and Applied, vol. 102, no. 3, pp. 439-454

[85] Knutti R (2008), Should we believe model predictions of future climate change?, Philosophical Transactions Of The Royal Society, Vol: 366 (1885) pp 4647-4664, DOI: 10.1098/rsta.2008.0169

[86] Kalnay, E., et al, (1996) The NCEP/NCAR 40-Year Reanalysis Project. *Bull. Amer. Meteor. Soc.*, **77**, 437–471. doi: http://dx.doi.org/10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2

[87] Solman S, Nunez M (1999) Local estimates of global climate change: a statistical downscaling approach. Int J Climatol 19:835–861

[88] Sailor, D.J., Li, X., (1999) A semiempirical downscaling approach for predicting regional temperature impacts associated with climatic change. J. Climate 12, 103–114.

[89] Schubert, S. (1998) Downscaling local extreme temperature changes in south-eastern Australia from the CSIRO MARK2 GCM. Int. J. Climatol., 18, 1419–1438.

[90] Hessami M., P. Gachon, T. Ouarda, and A St-Hilaire, (2008), Automated regression-based statistical downscaling tool, Environmental Modeling & Software 23, pp 813-834

[91] Kannan S. and Ghosh S., (2010) Prediction of daily rainfall state in a river basin using statistical downscaling from GCM output, Stochastic Environmental Research and Risk Assessment, Vol 25, Issue 4, pp 457-474

[92] Ghosh S, and Mujumdar P. (2006) Future rainfall scenario over Orissa with GCM projections by statistical downscaling. Curr Sci; 90(3):396–404

[93] Schoof J. T. and Pryor S C., (2001) Downscaling Temperature and Precipitation: A Comparison of Regression-Based Methods and Artificial Neural Networks, Int. J. Climatol. 21: 773 – 790

[94] Chadwick, R., Coppola, E., and Giorgi, F. (2011) An artificial neural network technique for downscaling GCM outputs to RCM spatial scale, Nonlin. Processes Geophys., 18, 1013-1028

[95] Dibike, Y. B., and Coulibaly, P. (2006). "Temporal neural networks for downscaling climate variability and extremes." *Neural Networks*, 19(2), 135–144.

[96] Chiang Y, Chang C, Chang J, (2004) Comparison of static-feedforward and dynamic-feedback neural networks for rainfall-runoff modeling, Journal of Hydrology 290 (2004) 297–311

[97] Ghaffari A., Abdollahi H., Khoshayand M., Soltani I., Dadgar A., Rafiee M., (2006) Performance comparison of neural network training algorithms in modeling of bimodal drug delivery, International Journal of Pharmaceutics, Vol 327, Issues 1–2, pp 126-138, (http://www.sciencedirect.com/science/article/pii/S0378517306006338)

[98] Gupta K, and Singh Y, (2011) Analysis of Back Propagation of Neural Network Method in the String Recognition, International Journal of Computer Theory and Engineering vol. 3, no. 5, pp. 652-655.

[99] Nandy S, Sarkar P, and Das A, (2012) An Improved Gauss-Newtons Method based Back-propagation Algorithm for Fast Convergence, International Journal of Computer Applications, Vol 39(8):1-7

[100] Nawi N, Hamid N, Ransing R, Ghazali R; Salleh M, (2011) Enhancing Back Propagation Neural Network Algorithm with Adaptive Gain on Classification Problems. International Journal of Database Theory & Application, Vol. 4 Issue 2, pp 65-76

[101] Colman R., (2003), A comparison of climate feedbacks in general circulation models, Climate Dynamics 20: 865–873, DOI 10.1007/s00382-003-0310-z

[102] Matyasovszky, I., I. Bogardi, and L. Duckstein (1994), Comparison of two general circulation models to downscale temperature and precipitation under climate change, Water Resour. Res., 30(12), 3437–3448, doi:10.1029/94WR01781.

[103] Mearns, L. O., S. H. Schneider, S. L. Thompson, and L. R. McDaniel (1990), Analysis of climate variability in general circulation models: Comparison with observations and changes in variability in 2xCO2 experiments, J. Geophys. Res., 95(D12), 20469–20490, doi:10.1029/JD095iD12p20469.

[104] Foley A.M. (2010) Uncertainty in regional climate modeling: A review, Progress in Physical Geography, Vol 34, Issue 5, pp 647–670

[105] Smith, J.B. and M. Hulme, 1998: Climate change scenarios. In: UNEP Handbook on Methods for Climate Change Impact Assessment and Adaptation Studies [Burton, I., J.F. Feenstra, J.B. Smith, and R.S.J. Tol (eds.)], Version 2.0, United Nations Environment Programme and Institute for Environmental Studies, Vrije Universiteit, Amsterdam, pp. 3-1 - 3-40. Web address: http://www.vu.nl/english/o_o/instituten/IVM/research/climatechange/Handbook.htm

[106] IPCC (2001): Climate Change (2001): The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change [Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., van der Linden, P.J., Dai, X., Maskell, K. and C.A. Johnson (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 881pp.

[107] Stainforth D.A, Allen M.R, Tredger E.R, Smith L.A (2007) Confidence, uncertainty and decision-support relevance in climate predictions*. Phil. Trans. R. Soc. A.* 365*,* 2145–2161*.* doi:10.1098/rsta.2007.2074*.*

[108] Christensen, N. and Lettenmaier, D. P. (2006) A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River basin, Hydrol. Earth Syst. Sci. Discuss., 3, 3727-3770, doi:10.5194/hessd-3-3727-2006.

[109] Tebaldi C, Mearns L, Nychka D, Smith R (2004) Regional probabilities of precipitation change: a Bayesian analysis of multimodel simulations*. Geophys. Res. Lett.* 31*,* L24213 doi:10.1029/2004GL021276*.*

[110] Najac, J., J. Boé, and L. Terray, 2009: A multi-model ensemble approach for assessment of climate change impact on surface winds in France. Climate Dyn., 32, 615–634. doi:10.1007/s00382-008-0440-4.

[111] Palmer T.N, and Räisänen J (2002) Quantifying the risk of extreme seasonal precipitation events in a changing climate*. Nature.* 415*,* 512–514*.* doi:10.1038/415512a*.*

[112] Giorgi, F., and L. O. Mearns, 2003: Probability of regional climate change based on the reliability ensemble averaging (REA) method. Geophys. Res. Lett., 30.1629, doi:10.1029/2003GL017130

[113] Lopez A, Tebaldi C, New M, Stainforth D.A, Allen M.R, Kettleborough J (2006) Two approaches to quantifying uncertainty in global temperature changes. J. Clim. 19, 4785–4796.

[114] Samadi, S.Z.,Sagareswar, G. and Tajiki, M. (2010) 'Comparison of General Circulation Models: methodology for selecting the best GCM in Kermanshah Synoptic Station, Iran', Int. J. Global Warming, Vol. 2, No. 4, pp. 347–365

[115] Furrer R, Knutti R, Sain S.R, Nychka D.W, Meehl G.A (2007) Spatial patterns of probabilistic temperature change projections from a multivariate Bayesian analysis*. Geophys. Res. Lett.* 34*,* L06711 doi:10.1029/2006GL027754*.*

[116] Forest C.E, Stone P.H, Sokolov A.P, Allen M.R, Webster M.D (2002) Quantifying uncertainties in climate system properties with the use of recent climate observations*. Science.* 295*,* 113–117*.* doi:10.1126/science.1064419

[117] Stott P.A, Kettleborough J. (2002) Origins and estimates of uncertainty in predictions of twenty-first century temperature rise*. Nature.* 416*,* 723–726*.* doi:10.1038/416723a