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Selection of Suitable General Circulation Model and Future Climate Assessment of Kashmir Valley

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Abstract: Many impact studies require climate change information at a finer resolution than that provided by Global Climate Models (GCMs). Climate change scenarios developed from Global Climate Models (GCMs) are the initial source of information for estimating plausible future climate. However, the spatial resolution of GCMs is too coarse to resolve regional scale effect and to be used directly in local impact studies. Therefore, downscaling is required to develop climate scenarios of higher spatial resolutions. Also the simulated data for different GCMs is freely available at IPCC data distribution Centre, but to extract the data for a particular region and convert it to a user readable format, different software packages are required. This study presents a decision support tool to select a suitable GCM for any specific region, based on statistical parameters such as coefficient of determination (R^2), Mean Square Error (RMSE) and Mean Absolute Deviation (MAD). Linear Regression method is incorporated as a downscaling technique to project future climate scenarios. To demonstrate the application of the method, future air surface temperature and precipitation scenarios are projected for 21st century, using data for six meteorological stations for Kashmir Valley, India.
Keywords: Climate change; GCM; Downscaling

I. INTRODUCTION

Climate change is being recognized as a major threat to present day society because of its adverse impacts on ecosystem, agricultural productivity, water resources, socio-economy and sustainability in a global as well as regional basis. The Intergovernmental Panel on Climate Change (IPCC) in its fourth assessment report (AR4) states with very high confidence (90% probability of being correct) that human activities, since industrialization have caused the planet to warm by about 1^{o}C. With the doubling of carbon dioxide content in the atmosphere, this trend is projected to cause average global warming of around 3^{o}C compared to the pre-industrial level.

It is widely acknowledged that the direct outputs of climate change simulations from general circulation models (GCMs) are inadequate for assessing land-surface impacts on regional scales (DOE, 1996). This is primarily for two reasons: first, because the spatial resolution of GCMs (typically 50000 km^2) is often larger than that required for input to impacts models; and second, because of doubts about the reliability of some GCM output variables (particularly those, like precipitation, that are critically dependent on sub-grid-scale processes such as those involving clouds). This leads to a scale mismatch between the information that GCMs are able to supply most confidently and that which is generally required by the climate change impacts community (e.g. Hostetler, 1994). Consequently, statistical ‘downscaling’ techniques have emerged as a means of relating meso-scale GCM output (frequently atmospheric circulation data) to sub-grid-scale surface variables (such as precipitation), under the assumption that the former GCM outputs are more reliable than the latter. Statistical downscaling, therefore, is based on the assumptions that (i) suitable relationships can be developed between grid- and larger-scale versus grid- and smaller-scale predictor variables; (ii) these observed, empirical relationships are valid under future climate conditions; and (iii) the predictor variables in regression-based (or similar) downscaling methods.

Downscaling methods, as reviewed in Wilby and Wigley (1997) and more recently in Wilby et al. (2004) and Mearns et al. (2003), were divided into four general categories: regression methods (Hewitson andCrane, 1996;Wilby et al., 1999), weather pattern approaches (Yarnal et al., 2001), stochastic weather generators (Richardson, 1981; Racsko et al., 1991; Semenov and Barrow, 1997; Bates et al., 1998) and limited-area Regional Climate Models (RCMs, Mearns et al., 1995). Among these approaches, regression methods are regularly used because of their ease of implementation and their low computation requirements. Statistical downscaling is based on the fundamental assumption that regional climate is conditioned by the local physiographic characteristics as well as the large scale atmospheric state. Based on this assumption, large scale climate fields are related to local variables through a statistical model in which GCM simulations are used as input for the large scale atmospheric variables (or ‘‘predictors’’) to downscale the local climate variables (or ‘‘predictands’’) with the use of observed meteorological data. The major weaknesses of statistical downscaling methods are that the fundamental assumption on which they are based is not verifiable, i.e. the statistical relationships developed for the present day climate also hold under different forcing conditions of plausible future climate (Wilby et al., 2004), and they cannot explicitly describe the physical processes that affect climate. In spite of these limitations, these methods may be helpful for impact studies in heterogeneous environments (see for example the recent study of Dibike et al., 2007 and Gachon and Dibike, 2007, in coastline areas of northern Canada), and/or for generating large ensembles or transient scenarios. In this paper multiple linear regression method was used to downscale monthly temperature and precipitation of Kashmir valley and future climate was projected for 21st century.

II. STUDY AREA

The valley of Kashmir is called as the "paradise on earth". It has an approximate area of 15948 sq.km. The valley is a plain embedded in the midst of mountains lying in an oval shape , NW & SE between 33°-05' & 34°-07' north latitude and 74° and 75°-10' east longitude .The valley is 150 km long from NW to SE and on width it varies between 32 to 100 km. In elevation the valley varies from 2130 m above MSL (mean Sea level) down to 1585 m, with lowest portion along the north. Average height of the valley is 1850 m above the mean sea level, but the surrounding mountains which are perpetually snow-clad rise from 3000-4000m above the mean sea level. The valley of Kashmir is conveniently classed into a separate climatic region for its peculiarities in the variation of temperature, precipitation and humidity compared to other regions of India. Winter lasts up to March and is often severe. The mid–Mediterranean depressions called western disturbances blow over the Afghan frontier after passing over Iran and precipitate in the valley and its surrounding mountains in the form of snow. The influence of the south-west monsoon is minimal over Kashmir valley. The monsoon dies out of the south of the pir panjal ranges of the mountains and the summers have, therefore; very little in common with the general winds and pressures of India. In mid-summer the temperature ranges from 32°c to 35°c and sometimes even 37°c, and in winter it descends several degrees below freezing point. The mean temperature of the year is about 14°c.

III. DATA

Monthly precipitation and temperature data for six National Meteorological Observatory (NMO) stations namely Srinagar, Qazigund, Pahalgam, Kokernag, Kupwara and Gulmarg for the period 1970 to 2014 were obtained from India Meteorological Department (IMD), Pune.

The predictor data of the GCMs ; mslpas (mean sea level pressure), tempas (mean temperature at 2m), humas (specific humidity at 2m),relative humidity(rhum), zonal velocity(u), meridional velocity(v) were obtained from CGCM3,HADCM3 and ECHAM5 climate model ,for A1B scenario for the grid location of 32°58'42" N to 35°08'02" N (latitude) and 73°23'32" E to 75°35'57" E (longitude). The above mentioned predictor data were downscaled using MLR technique. For multiple linear regression (MLR) analysis the data set for the period 1970 -2010 was used for calibration and that of 2011- 2014 was used for validation purposes. The GCM data for the baseline period and the projection period were downloaded for selected GCM model and selected future scenario from Canadian Climate Data and Scenarios (CCDS) website http://ccds-dscc.ec.gc.ca/ and www.cccsn.ec.gc.ca/ .Table 1 shows the list of models used each driven by the SRE scenarios, to capture the possible range and trend of changes. The average of the mean monthly temperature and monthly precipitation totals recorded at the six meteorological stations were assumed to represent the basin wide averages. The MLR analysis was carried out to find the dependence relationship between temperature and precipitation and the appropriate GCM predictors.

A. *Multiple Linear Regression*

Multiple linear regression (MLR) attempts to model the relation between two or more independent variables (input) and the dependent variable (output) by fitting a linear equation to the observed data.

The regression model used for prediction is given in Equation below:

$$y = b_0 + b_1 x_{1+\dots} b_p x_p + \varepsilon$$

Where, B_0 is the intercept and B_i is the multiple regression coefficient of the dependent variable x_1 on the independent variable x_i with all other variables kept constant, y is the dependent (or response) variable, x is independent (or predictor) variable and $\mathcal{E}$ is the error term.

Multiple regression has three primary uses:

Understanding which input variables have the greatest effect on the output.

Knowing the direction of the effect of the input variable, e.g. increasing x_1 increases/decreases Y.

Using the model simulated to predict future values of the input variables when only the output variables are known.

To date it has been shown that multiple regression is able to establish that a set of independent variables contributes to the variance of a dependent variable to a significant extent. The significance of this contribution can be tested rigorously by the R^2 value, using the "dropping method". The importance can also be tested further by examining the beta weights attributed to each of the contributing and non-contributing variables.

In the MLR method three different GCMs were used under A1B scenario for projection of climate in Kashmir valley. Table 1shows selected GCMs and heir attributes.

Table 1. Selected GCM models and their attributes

Model	Centre Name	GCM Resolutions (Long.° vs. Lat.°)
CGCM3	Canadian Global climate model,version3	3.75×3.75
HadCM3	Hadley centre coupled model,version3	3.75×2.5
Echam5	ECMWF stands for European Centre for Medium-range Weather Forecasting Ham stands for Hamburg the place of development of its parameterisation package.	2.8×2.8

In order to evaluate different GCMs, the model outputs were compared based on different statistical parameters such as coefficient of determination (*R2*) and root mean square error (*RMSE*) are used.

1) *Root Mean Square Error (RMSE):* Alternatively known as the Root Mean Square Deviation (RMSD), the RMSE is commonly used to measure the difference between the values predicted by the model and the values observed. The RMSE with respect to an estimated variable X_{model} is defined as the square root of the mean squared error with:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

Where, *Xobs* is observed values and *Xmodel* is modeled/simulated values. The RMSE has been used to evaluate the model's performance for the validation period.

Another measure is the mean squared error (MSE),

$$RMSE = (MSE)^{\frac{1}{2}}$$

2) *Coefficient of Determination:* (denoted by R^2) is a key output of regression analysis. It is interpreted as the proportion of the variance in the dependent variable that is predictable from the independent variable.

The coefficient of determination R^2 for a linear regression model with one independent variable is:

$$R^2 = \frac{\left(\sum XY - n\overline{XY}\right)^2}{\left(\sum X^2 - n\overline{X}^2\right)\left(\sum Y^2 - n\overline{Y}^2\right)}$$

Where,
n is the number of observations
x is the value for independent variable
y is the value of dependant variable
$\bar{X}$ and $\bar{Y}$ are the mean of observations of independent and dependant variables respectively.

3) *Mean Absolute Deviation (MAD):* The Mean Absolute Deviation (MAD) of a set of data is the average distance between each data value and the mean. The median absolute deviation is a measure of statistical dispersion.

$$\text{MAD}=\frac{1}{n}\sum_{i=1}^{n}|x_i - \mu|$$

Where,

n = No. of observations
y_p = predicted value obtained the model
y_a = actual value.

The model having minimum RMSE, minimum MAD and maximum R^2 is considered as the best model.

Table 2: Selected predictor variables.

Model	Predictand	Predictor variables	Symbol
CGCM3/ HadCM3/ Echam5	Mean temperature	Mean temperature at 2m	Tempas
		Relative humidity at 2m	Rhum
		Surface zonal velocity	U
		Surface meridional velocity	V
	Precipitation	Mean sea level pressure	Mslpas
		Mean temperature at 2m	Tempas
		Surface zonal velocity	U
		Specific humidity at 2m	Humas

IV. RESULTS AND DISCUSSION

The GCMs showed good results while simulating the spatial variability of mean temperature. Every model had responded with a high value of R^2 (0.45-0.87), suggesting that they were accurate at representing the spatial pattern of variation. But all the models substantially underestimated the magnitude of precipitation in comparison to temperature. Hence GCMs simulate temperature to a much greater accuracy than precipitation. IPCC (2001b) report describes that no model can be considered as the best, therefore a couple of models should be used for climate change analysis. The validity of the model is assessed by projecting mean monthly temperature and precipitation for the past time period (1970-2010) relative to 2011-2013, and then analyzing the statistical relationship between observed and projected data for the same period. This analysis examined the degree to which the observed and projected mean monthly temperature and precipitation matches.

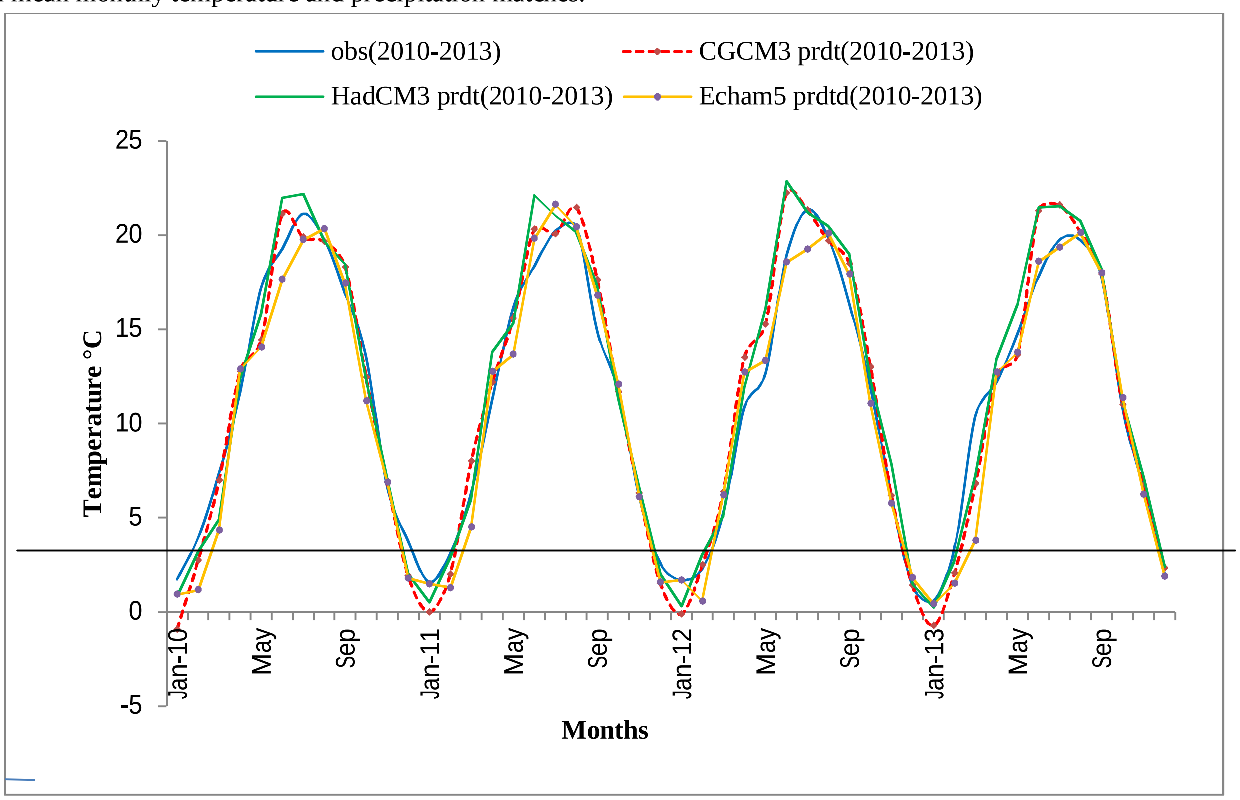

Figure 1. Validation of mean monthly temperature of Kashmir Valley for the period 2010-2013 using MLR.

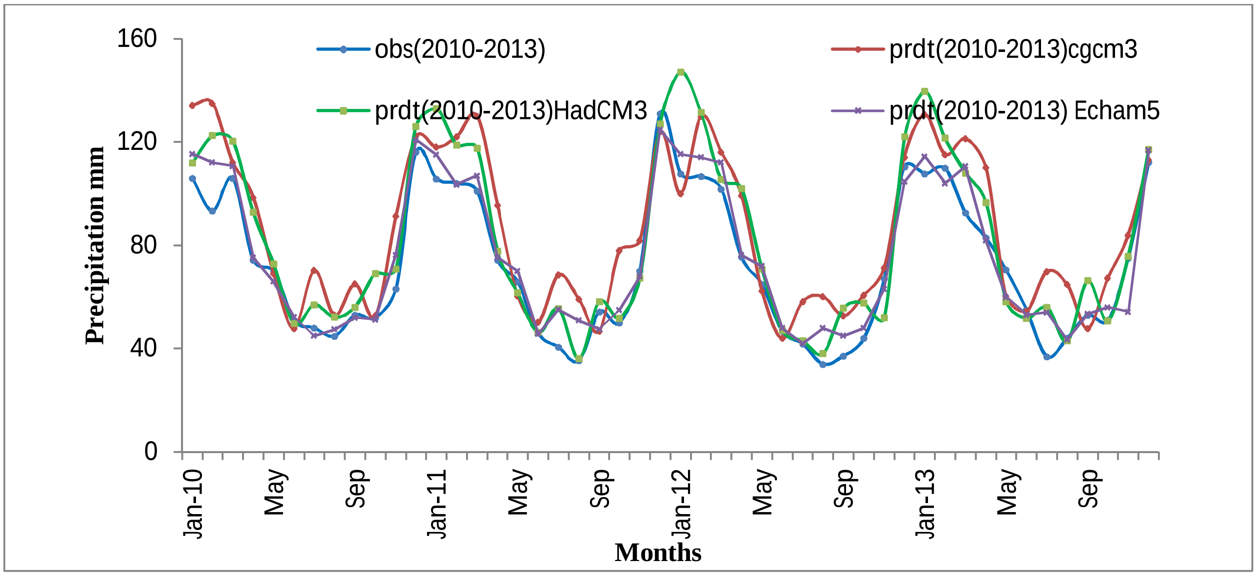

Figure 2. Validation of monthly total precipitation of Kashmir Valley for the period 2010-2013 using MLR.

Table 3. Comparison of results obtained by MLR for precipitation and temperature using CGCM3, HADCM3 and ECHAM5.

Variable	Parameter	CGCM3	HADCM3	ECHAM5
Precipitation	MSE	0.284225-10.76250	0.538008-12.94620	0.524925-19.41750
Temperature		0.0448-4.3685	0.3943-12.6593	0.0766-14.2766
Precipitation	RMSE	0.533128-3.280625	0.821029-3.598083	0.724517-4.406529
Temperature		0.2117-2.7484	0.6248-3.5580	0.2767-3.7784
Precipitation	R^2	0.57-0.84	0.48-0.78	0.45-0.67
Temperature		0.65-0.87	0.57-0.84	0.48-0.80
Precipitation	MAD	-2.825000-0.031402	-2.91624-1.42324	-4.32500-2.23125
Temperature		-2.6431 to 1.8484	-3.5254-1.5341	-1.2760-2.6736

From the statistical parameters of temperature and precipitation validation using MLR model, maximum value of MAD is for Echam5 and least for CGCM3 .Thus MSE and RMSE works out to be least for CGCM3 and is the best climate model selected. Thus Echam5 is the least accurate model and CGCM3 is the most accurate model selected.

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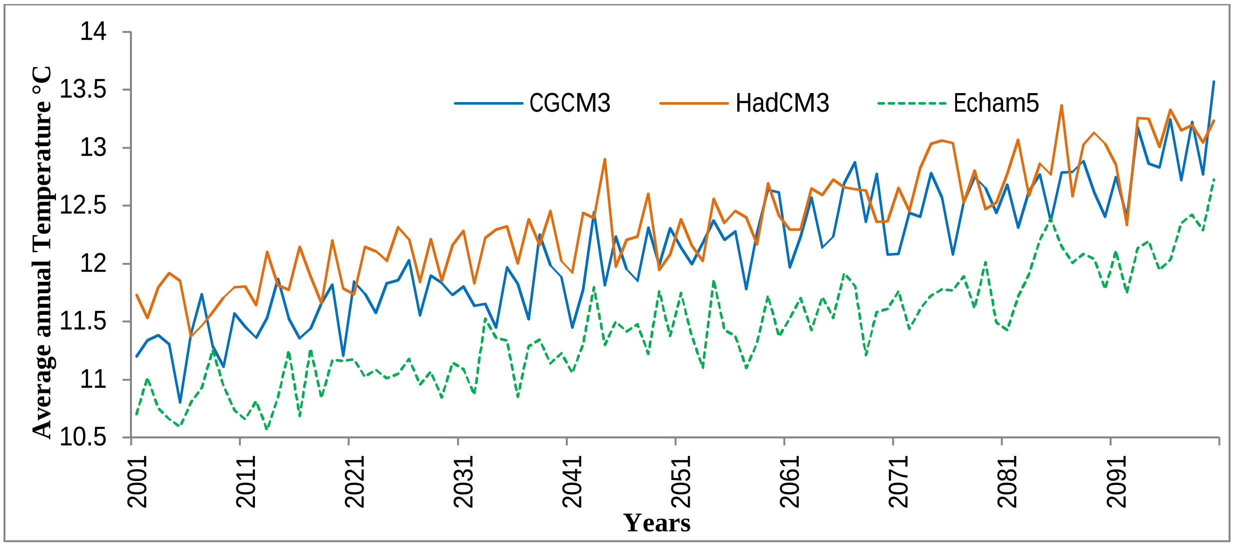


Figure 3.Variation of MLR predicted average annual temperature of Kashmir Valley during 21st century

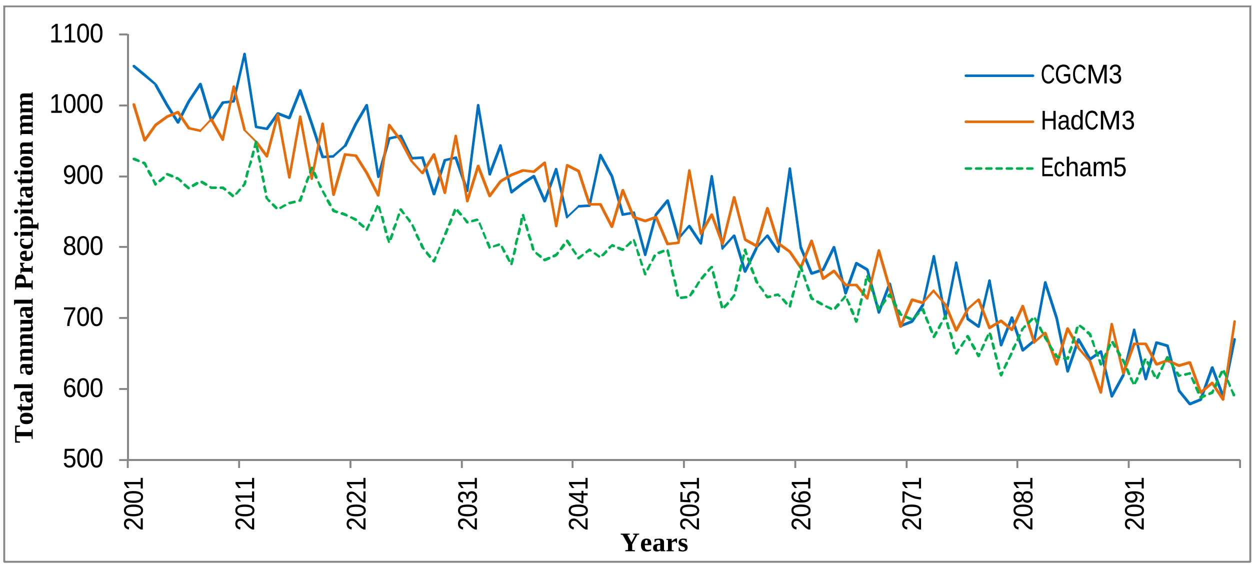


Figure 4. Variation of MLR predicted total annual Precipitation of Kashmir Valley during 21st century

V. CONCLUSIONS

The rainfall amounts generally show a decreasing trend throughout the year for the period 2001–2100 for all the three GCMs: CGCM3, HadCM3 and Echam5. The total annual precipitation will decrease by 36.53%,30.58°C and 36.27% respectively for CGCM3, HadCM3 and Echam5 models over 21st century in A1B scenario. The downscaled monthly mean temperature shows an increasing trend for the period 2001–2100 for all the three GCMs: CGCM3, HadCM3 and Echam5. The average annual temperature will increase by 2.37°, 1.50°C and 2.02°C respectively for CGCM3, HadCM3 and Echam5 models over 21st century in A1B scenario.

REFERENCES

[1] Bates, B.C., Charles, S.P., Hughes, J.P., 1998. Stochastic downscaling of numerical
[2] Crane, R.G., Hewitson, B.C., 1998. Doubled CO2 precipitation changes for the Susquehanna bsin: downscaling from the GENESIS general circulation model. International Journal of Climatology 18, 65e76.
[3] Dibike, Y., Gachon, P., St-Hilaire, A., Ouarda, T.B.M.J., Nguyen, V.T.V., 2007. Uncertainty analysis of statistically downscaled temperature and precipitation regimes in Northern Canada. Theoretical and Applied Climatology, doi:10.1007/s00704-007-0299-z.
[4] Gachon, P., Dibike, Y., 2007. Temperature change signals in northern Canada: convergence of statistical downscaling results using two driving GCMs. International Journal of Climatology 27, 1623e1641.
[5] Hewitson, B.C., Crane, R.G., 1996. Climate downscaling: techniques and application. Climate Research 7, 85e95.

[6] IPCC, 2001. In: 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., Johnson, C.A. (Eds.)]. Cambridge University Press, Cambridge, U.K. and New York, N.Y.,U.S.A., 881 pp.

[7] IPCC, 2007. Climate Change 2007. The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmenta Panel on Climate Change (IPCC), Summary for Policymakers. Available from: <http://www.ipcc.ch> (accessed 10.03.07).

[8] McCuen, R.H., 2003. Modeling Hydrologic Change. CRC press, pp. 261e263.

[9] Mearns, L.O., Giorgi, F., McDaniel, L., Shields, C., 1995. Analysis of daily variability of precipitation in a nested regional climate model: comparison with observations and doubled CO2 results. Global and Planetary Change 10, 55e78.

[10] Mearns, L.O., Giorgi, F., Whetton, P., Pabon, D., Hulme, M., Lal, M., 2003. Guidelines for Use of Climate Scenarios Developed from Regional Climate Model Experiments. Data Distribution Centre of the International Panel of Climate Change, 38 pp. Available from IPCC-DDC: http://www. ipcc-data.org/.

[11] Racsko, P., Szeidl, L., Semenov, M., 1991. A serial approach to local stochastic weather models. Ecological Modelling 57, 27e41.

[12] Richardson, C., 1981. Stochastic simulation of daily precipitation, temperature, and solar radiation. Water Resources Research 17, 182e190.

[13] Semenov, M.A., Barrow, E., 1997. Use of stochastic weather generator in the development of climate change scenarios. Climatic Change 35, 397e414.

[14] Wilby, R.L., Wigley, T.M.L., 1997. Downscaling general circulation model output: a review of methods and limitations. Progress in Physical Geography 21, 530e548.

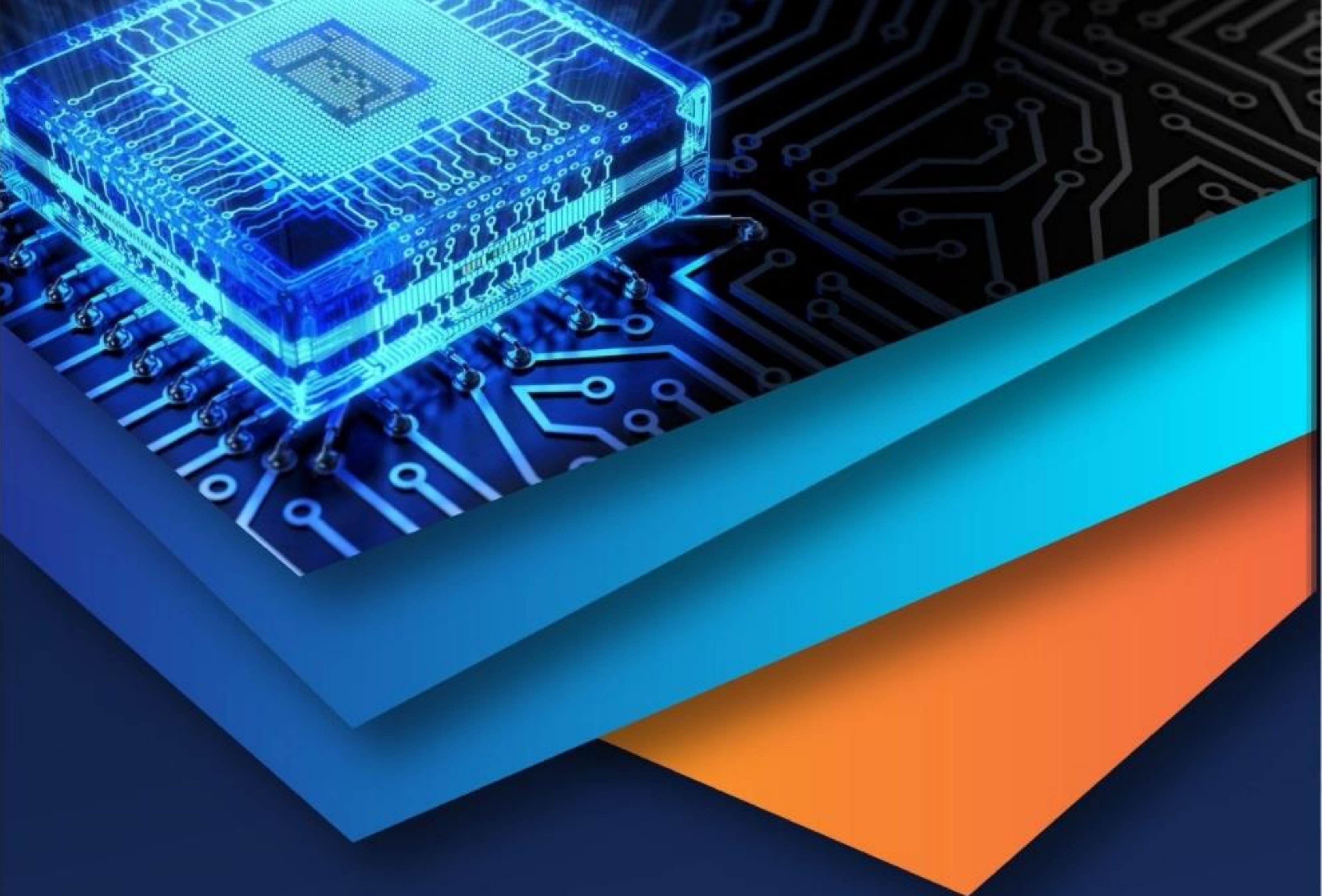
[15] Wilby, R.L., Dawson, C.W., Barrow, E.M., 2002. SDSM e a decision support tool for the assessment of regional climate change impacts. Environmental Modelling and Software 17, 147e159.

[16] Wilby, R.L., Hay, L.E., Leavesley, G.H., 1999. A comparison of downscaled and raw GCM output: implications for climate change scenarios in the San Juan River basin, Colorado. Journal of Hydrology 225, 67e91.

[17] Wilby, R.L., Wigley, T.M.E., 2000. Precipitation predictors for downscaling: observed and general circulation model relationships. International Journal of Climatology 20, 641e661.

[18] Wilby, R.L., Charles, S.P., Zorita, E., Timbal, B., Whetton, P., Mearns, L.O., 2004. Guidelines for use of climate scenarios developed from statistical downscaling methods, available from the DDC of IPCC TGCIA, 27 pp. Available from: IPCC-DDC: http://www.ipcc-data.org/

[19] Yarnal, B., Comrie, A.C., Frakes, B., Brown, D.P., 2001. Developments and prospects in synoptic climatology. International Journal of Climatology 21, 1923e1950.



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