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Statistical Downscaling of Precipitation Data from GCM to Regional Scale for Malaprabha Sub Basin

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***Abstract*— The Climate impact studies in hydrology often rely on climate change information at fine spatial resolution. However, general circulation models (GCMs), which are among the most advanced tools for estimating future climate change scenarios, operate on a coarse scale. Therefore the output from a GCM has to be downscaled to obtain the information relevant to hydrologic studies. In this paper, a support vector machine (SVM) approach is proposed for statistical downscaling of precipitation at monthly time scale. The effectiveness of this approach is illustrated through its application to Malaprabha Sub-basin in India. First, climate variables affecting spatio-temporal variation of precipitation in the study area are identified. SVM downscaling model is developed to downscale precipitation at a monthly scale. Further, the model is applied to downscale future precipitation data for the study area. Results show the increasing trend in precipitation for the future period. SVM is compared with the Artificial Neural Network (ANN) model and the performance is evaluated. It is shown that SVM is best suitable model for downscaling precipitation for the study area.**

Keywords: General Circulation Model(GCM), Support Vector Machine (SVM), Artificial Neural Network (ANN), Predictors.

I. Introduction

The change of condition of water between solid, fluid and gas includes exchange of heat which impacts atmospheric flow and global circulation of both water and heat [1]. The investigation of climatic framework requires a basic joining of exploratory methodologies that incorporate hydrological parts and its interrelationship which facilitate includes climatic variability, land spread change, watering system and stream direction and so on. A far reaching learning and comprehension of the different hydrological parts inside hydrological cycle is required to consider the impacts of these segments. Examination of these climatic frameworks and their linkages characterize the basic inquiries that the General Circulation Models (GCMs) are endeavoring to reply.

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General Circulation Models (GCM) are the numerical models created by considering the material science required in area surface, sea and barometrical procedures in type of an arrangement of direct also, non-direct incomplete differential conditions. They give us the data of future climatic variables up to coming 100 years considering the anthropogenic exercises however this data is accessible at such a coarse determination (around 300Kms matrix measure) that it can't be utilized straightforwardly for any investigation at neighborhood or local level [2], [3].

Downscaling is a method to get to the climatic data at different higher scales and use it in an effective way for further investigation at lower scales as required by water resource scientists and managers [4]. The utilization of downscaling is bound to the scale issues - spatial and temporal. Statistical and Dynamic are two climatic downscaling approaches [8].

The LS-SVM is a mainstream form of the SVM that has been utilized for arrangement and capacity estimation. The adaptation has been proposed by Suykens and Vandewalle (1999) [5]. The LS-SVM is a more rearranged adaptation of the SVM, safeguarding the first characteristics of SVM [6], yet has low computational expense and great speculation execution [9] . Not at all like the SVM that discovers arrangement by utilizing complex quadratic programming, the LS-SVM understands an arrangement of straight conditions. The LS-SVM is subjected to fairness requirements and the squared mistake terms. It is a more improved calculation not at all like the SVM where the model unpredictability (which is controlled by the quantity of concealed layers) takes after the raised enhancement issue. This empowers the LS-SVM to get prepared with far less exertion [7].

II. Study Area

The study area is the catchment of Malaprabha, Sub-basin of Krishna basin situated in Karnataka state of India. It has a zone of 2564 km^2 arranged somewhere around 15°30 N and 15°56 N latitudes and 74°12 E and 75°15 E longitudes. It gets a normal yearly precipitation of 1051 mm. It has a tropical rainstorm atmosphere where the majority of the precipitation is restricted to a couple of months of the storm season. The south–west (summer) storm has warm winds blowing from the Indian Ocean creating bounteous measure of precipitation amid June–September months. The Malaprabha Sub-basin is one of the real helps for the dry locales of north Karnataka. Malaprabha reservoir supplies water for watering system to the areas of northern Karnataka with an irrigable zone of 218191 hectares and the mean yearly precipitation in the repository order zone is 576 mm [11].

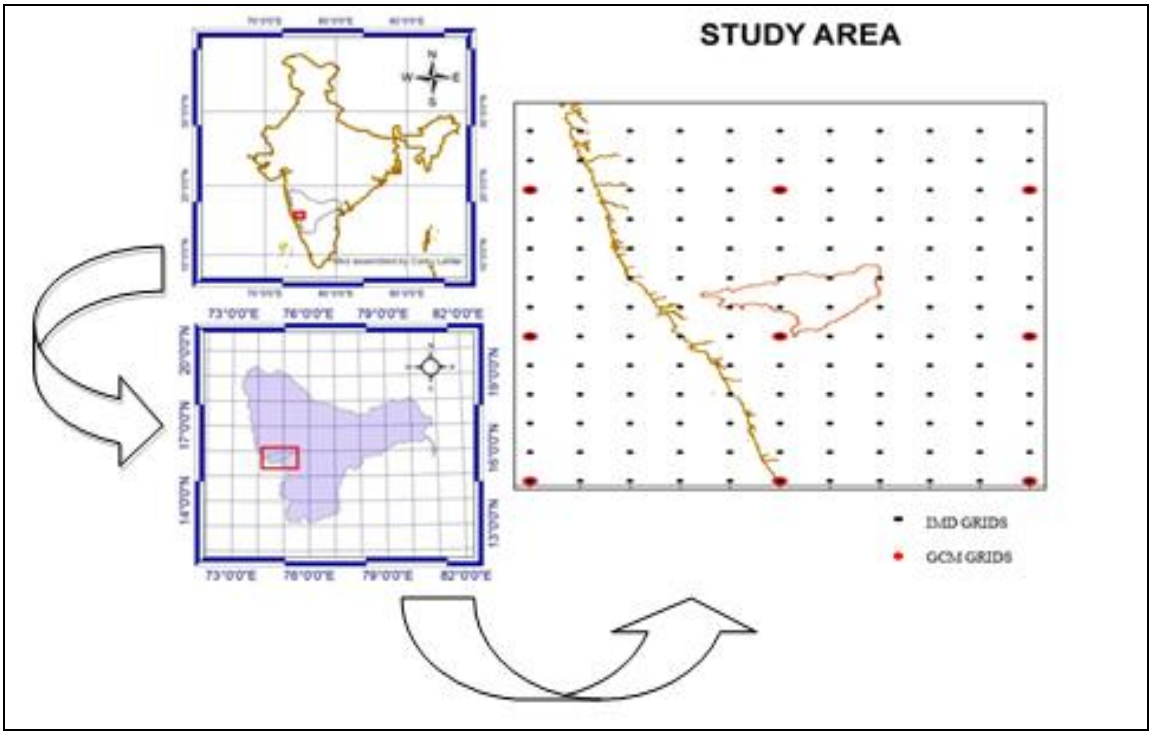

Fig. 1. Location map of the study region in Karnataka state of India.

III. DATA DESCRIPTION

Most recent AR5 report of IPCC has given different GCMs out of which CanCM4 at network size 2.5° X 2.5° created by Canadian Center for Climate Modeling and Analysis has been picked taking into account the ability score. It gives authentic information from 1961 to 2005 and also the information comprised of future predictions by emanation situations RCP4.5 from 2006 to 2035. The information was extracted to cover the whole Malaprabha Sub-basin with 3 x 3 framework focuses.

GCMs are accessible at coarse framework scale and ranges between 250Kms to 600Kms. These are scientific models created by considering material science required in area, sea and climatic forms in type of an arrangement of direct and nonlinear incomplete differential conditions. They anticipate climatic variables all around at coarse determination [12].

In fifth assessment report (AR5) of IPCC, four Representative Concentration Pathways (RCP's) were given and characterized by their aggregate radiative driving (total measure of human outflows of GHGs from all sources communicated in Watts per square meter) pathway and level by 2100. The Canadian GCM models have considered RCP4.5 as the future situation which speaks to adjustment without overshoot pathway to 4.5 W/m2 at adjustment after 2100.

The variables or the indicators gave by the CanCM4 GCM models incorporate atmospheric, area, maritime and ice variables and among them atmospheric variables have been considered here. Inside the atmospheric variables there are numerous variables and each of them is accessible at 22 pressure levels that are 1000, 925, 850, 700, 600, 500, 400, 300, 250, 200, 150, 100, 70, 50, 30, 2 , 10, 7, 5, 3, 2 and 1(in millibar).

The Indian Meteorological Department (IMD) observed gridded precipitation data for the Sub-basin is utilized for adjusting and approving the models to better determination. The precipitation data accessible at network size of 0.5° X 0.5° was changed over to monthly basis from daily. The IMD data is separated for January 1971 to December 2005.

IV. METHODOLOGY

The methodology presented below (see Figure 2) includes all the stages of downscaling the GCM data to regional scale. Here, CanCM4 is the GCM selected for the study and the variables are extracted using MATLAB programming. Screening of predictor variables is done using Pearson' coefficient. Two statistical methods (LS-SVM and ANN) are used for downscaling and are compared with each other.

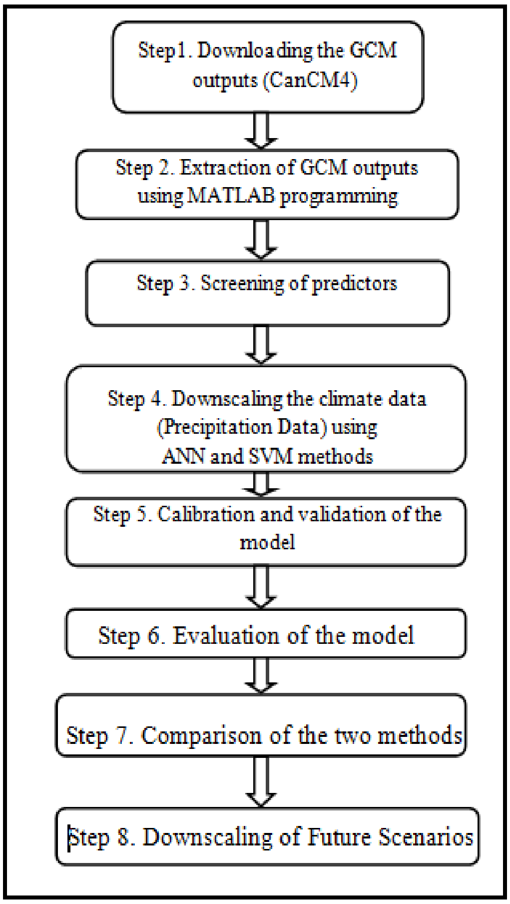

Fig. 2. Flowchart showing the methodology of the study

Watershed delineation was done using Soil and Water Assessment Tool (SWAT) model and GCM (CanCM4) grids of size 2.5^0 x 2.5^0 is been overlaid. 3 x 3 matrix of GCM grids is taken in to consideration which cover the study area (Figure 3). IMD grids of size 0.5^0 x 0.5^0 for precipitation are also been overlaid on the delineated Sub-basin. Three IMD stations (see Table 1) considered for downscaling i.e., S1, S2 and S3, cover the study area.

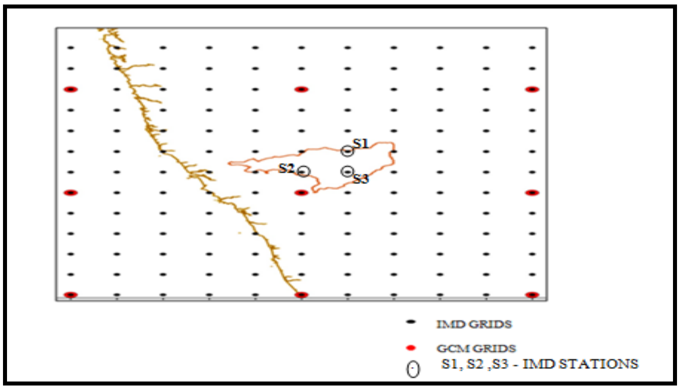

Fig. 3. IMD grids superimposed on GCM grids for Malaprabha Sub-Basin

Table 1. Location of downscaling points(coinciding IMD grids) for precipitation

Point	Latitude (North)	Longitude (East)
S1	16° 00' 00"	75° 00' 00"
S2	15° 30' 00"	75° 00' 00"
S3	15° 30' 00"	75° 30' 00"

V. SENSITIVITY ANALYSIS OF PREDICTORS

All the GCMs produces diverse reproductions for the future, considering the anthropogenic exercises and the discharge rates of Green House Gasses (GHG's). They all have their own particular suppositions and create distinctive variables or indicators which incorporate barometrical, soil, maritime and ice variables [13]. In this concentrate just the climatic indicators have been utilized. Inside the environmental variables there is extensive variety of variables relying upon the pressure levels. So there is a need to filter variables taking into account their significance to our study to get the likely indicators [14].

Variables chose ought to be such that taking after conditions are satisfied:

Data ought to be accessible for craved period

Selected GCM ought to be equipped for reproducing variable well

Predictor must show great connection with predictand

The variables or the indicators gave by the CanCM4 GCM models incorporate environmental, area, maritime and ice variables and among them climatic variables have been considered here. Inside the climatic variables there are numerous variables and each of them is accessible at 22 pressure levels that are 1000, 925, 850, 700, 600, 500, 400, 300, 250, 200, 150, 100, 70, 50, 30, 2 , 10, 7, 5, 3, 2 and 1(in millibar).

Karl Pearson's coefficient of relationship has been ascertained to decide the fitting indicators. The count of connection conceded from station to station contingent upon the nature and attributes of the barometrical flow variables and the predictand (for this situation, precipitation) to be downscaled. Just indicators which demonstrated sensible association with the predictand have been utilized as a part of the study.

Six predictor variables (ua, ta, zg, pr, rlds and hfls) were screened as potential predictors which impact the predictand (precipitation) for Malaprabha Sub-basin, based on the value ranges of Pearson's correlation coefficient. The r values show that only 6 out of 18 variables are most influencing the predictand for the Sub-basin under consideration.

VI. RESULTS AND DISCUSSIONS

The hyper parameters chosen are gamma equal to 700 and sigma square equal to 5 after a number of trails (Figure 4). As indicated by Figure 5, the model over-anticipated the low precipitation occasions and under-anticipated in the high precipitation occasions. The execution in this station might be because of the nearness of high precipitation occasions in the test data set, which may have created the model to measure its segments mistakenly (NOTE: Unlike ANN, SVM naturally alters weights relying upon the information and the yield).

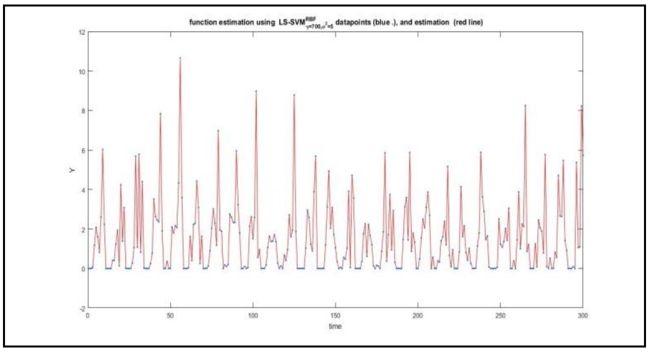

Fig. 4. Function estimation by LS-SVM

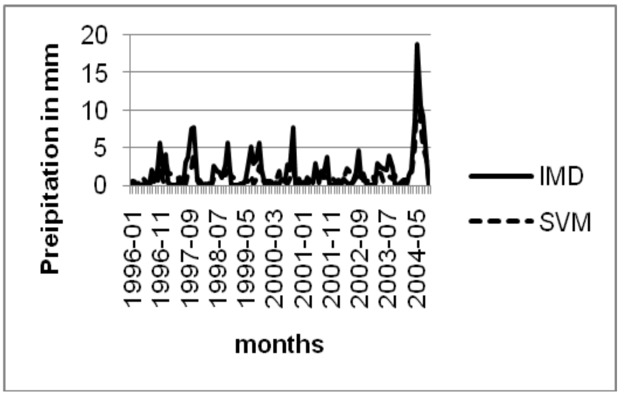

Fig. 5. Obtained precipitation from LS-SVM in mm

The performance of ANN was weaker in comparison with LS-SVM in case of downscaling of precipitation data. The R^2 values for LS-SVM and ANN are 0.745 and 0.448 respectively. This may be due to the uncertainties involved in GCM outputs, which are well considered in LS-SVM function estimation. Whereas in ANN, elimination of the uncertainties is not involved as ANN is only a training and validation process. Ill consideration of suitable inputs may also be the reason for weaker performance of ANN. The results of ANN proved weaker in comparison with LS-SVM with past researches (Tripathi et al., 2010). Hence ANN is not considered as a perfect model for downscaling future projections for the three stations. Table 2 gives the comparison of statistical models SVM and ANN with the IMD data.

VII. SUMMARY AND CONCLUSIONS

The essential targets of the examination was to downscale precipitation on a monthly basis at a regional level scale and produce precipitation data for a future time period. The exploration additionally centered around investigating different statistical downscaling procedures, drawing examinations amongst them and deciding the assessment criteria to survey the execution of a downscaling model.

Model effectively downscaled the precipitation data on a monthly basis. Training set was taken from 1971-1995 (and the hyper parameters were chosen as gamma 700 and $sigma^2$ as 5) and validation was accomplished for a time period of 1996-2005. Model performed well for all the three stations which were considered for downscaling in the Malaprabha Sub-basin.

Sensitivity examination was accomplished for determination of potential predictors which impact the predictand (precipitation for this situation). Karl Pearson's coefficient was utilized for performing the sensitivity analysis. Six predictor variables (ua, ta, zg, pr, rlds and hfls) were screened as potential predictors which impact the predictand (precipitation) for Malaprabha Sub-basin, based on the value ranges of Pearson's correlation coefficient. The r values show that only 6 out of 18 variables are most influencing the predictand for the Sub-basin under consideration. The variables which include both the thermodynamic and dynamic parameters and which have a physically meaningful relationship with the precipitation of the Sub-basin are chosen as the probable predictors.

Bias correction was finished by the technique for standardization which proficiently expelled the inclination in the data. Unlike temperature, the downscaled results for precipitation largely vary with the methods of downscaling as well as the seasons. Comparison of the two downscaling methods (LS-SVM and ANN) was accomplished for same training and test sets of data. LS-SVM turned out to be the best reasonable model when compared with ANN.

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