

Temperature Change Scenarios over the Chilika Lagoon of India during 1901-2100

Lalu Das^{1*}, Monami Dutta¹, Jitendra Kumar Meher¹ and Javed Akhter²

¹Department of Agricultural Meteorology and Physics, Bidhan Chandra Krishi Viswavidyalaya
Mohanpur, Nadia, West Bengal, India

²Department of Physics, Jadavpur University, Kolkata – 700 032
✉ daslalu@yahoo.co.in

Received November 20, 2015; revised and accepted December 31, 2015

Abstract: Temperature change scenarios over the Chilika Lagoon of India for 200 years (1901-2100) were quantified by the observational data sets of the Climate Research Units (CRU) of UK as well as 39 numbers of GCMs simulations from the Couple Model Inter-comparison Project Phase 5 (CMIP5) through Mann Kendall trends analysis. Long-term trend during 1901-2005 over Chilka Lake indicates the highest warming in the pre-monsoon season (1.79°C) and lowest warming (1.09°C) was shown in both the winter and post-monsoon seasons while opposite warming trends i.e., the lowest warming was observed in pre-monsoon season and highest warming was shown in the winter season for recent four decades (1969-2009) data. The performance of the CMIP5 GCMs was evaluated over a target point of Chilika Lake. Twelve numbers of models were considered as a group of “better performing GCMs” on the basis of their ability to simulate the long-term trends as well as the mean seasonal correlation with observation. Quantile mapping technique is used for adjusting the bias for the selected GCMs. Improvement in the multi-model ensemble (MME) of bias corrected better performing models compared to MME of 39 GCMs was judged with the help of Taylor plot as well as using four different conventional statistical indices viz. correlation (r), index of agreement (d index), Nash-Sutcliffe efficiency (NSE) and root mean square error (RMSE). All the ensemble members commonly available in the four Representative Concentrations Pathways (RCPs) from the better performing selected models show a temperature change of 0.27-3.61°C, 0.38-3.98°C, 0.28-3.72°C, 0.33-3.41°C and 0.22-2.50°C in annual, winter, pre-monsoon, monsoon and post-monsoon seasons respectively at the end of 21st century over Chilika Lagoon.

Keywords: Chilika lagoon; Climate change scenarios; CMIP5 GCMs, RCPs.

Introduction and Overview about Chilika Lake

The terms “global warming and climate change” is presently recognized as a real environmental issue, which is being discussed in every section of stakeholders and government agencies. The effect of climate change is projected to be more dangerous over the mountain region and coastal belts of any continent. Even if we immediately stop the emission of greenhouse

gas (GHG), the amount of GHG already present in the atmosphere is enough to maintain the present rate of glaciers melting and accelerated rate of sea level rise (Raven et al., 2015).

The Chilika Lagoon is a shallow brackish-water inshore Lake located in the coastal area of Orissa state in India and connected with the Bay of Bengal through a narrow mouth during the later stages of the Pleistocene period according to geological evidence by Pascoe in 1964. The Split had grown in Chilika Lake

*Corresponding Author

due to abrupt changes in the morphology of the coast along north of the lake, strong shifting sand to the shore, long-shore drift and the presence or absence of river and tidal currents in different areas. The Chilika Lake is a brackish water lagoon (A lagoon is a shallow body of water separated from the large body of water by barrier land or reefs). It is the largest coastal lagoon in India and second largest lagoon in the world. It is also one of the largest tropical lagoons in the world, which has been marked as 'Category I' of the marine protected area and designated as Ramsar site in the Ramsar Convention of the Wetlands.

There are two outflows from Chilika and one inflow to Bay of Bengal like an old mouth at Arakhakuda and a new mouth at Satapada. The water of the Chilika Lake fluctuates seasonally and also during high and low tides; in addition, every year lake experiences maximum area of the submergence and emergence. The river is continuously becoming shallow; sandbanks and a number of islands are visible just above the surface because of the discharge of silt and sediments by river Daya, Bhargavi, Makra and Nuna. The shallow water body (average depth 2 m) is about 65 km in length, spreading from northeast to southwest parallel to the coastline with a variable breadth reaching 20 km. The area enclosed by water has reduced nearly 200 km², if we compare the result of Gupta et al. (2008) and Annandale and Kemp (1915). The area enclosed is 704 km² to 1020 km² according to the former, and 905 km² and 1165 km² as per the study conducted in early 1990s. Inside the Chilika Lake, there are some islands like Kalijai, Barakuda, Ghantasila, Nalaban etc. It is one of the hotspots of biodiversity in India with many near threatened, endangered and critically endangered species listed in the International Union for Conservation of Nature (IUCN).

The Nalaban island, where thousands of birds migrate during the winter season from the Caspian Sea, lake Baikal, Aral Sea, remote places of Russia, Mongolia, South Asia and Ladakh, has been declared as a "bird sanctuary" in the year 1973 under Indian Wildlife (protection) Act 1972. This place is one of the distinct places for tourism not only for Orissa but also for India. Scientists from different disciplines have carried out research in this lake pertain to water quality, plankton, benthos, fish and fishers, migratory birds and resident birds since the 20th century. Scientific study reveals that lake ecology has degraded particularly in the 1980s and 1990s due to the changes in the local oceanographic process, climate change including floods and droughts. As a result of environment degradation,

loss of biodiversity has occurred. These changes have affected the socio-economic and culture of the local people. Chilika is situated in the coastal regions in Bay of Bengal, which is considered as one of the six largest cyclone prone zones in the world. On an average, every year four to five cyclones strike the coastal regions of India (Shanmugasundaram et al., 2000).

According to a study by Gupta and Sharma (2000) coastal districts of Orissa have been hit by 11 severe cyclones and 55 cyclone storms with a probable maximum storm surge height between 3.2 m and 5.5 m in the last 120 years. These have affected the coast, water of the lake and disturbed the biological and socio-economic settings. The area of Chilika lagoon dominated by invasive plants has increased from 20 sq. km. in 1972 to 685 sq. km. in May 2000 (CDA, 2005). These changes reduce the area of fishing grounds in Chilika lagoon. Chilika government authority (CDA) reinforced the innovative hydrological interventions in collaboration with research institutes, NGOs and local people. The best part is that there was a dramatic improvement in the natural and social lagoon environment (CDA, 2005). Chilika lagoon is typically a tropical area with average annual maximum and minimum temperatures of 39.9°C and 14°C, respectively (CDA, 2008). According to the statistical fixed-point observations in two meteorological stations (Bhubaneswar and Puri), it was observed that the apparent warming trend has not been seen in Chilika lagoon. However, it seems especially in the hottest months, there was a slight warming trend of mean maximum and minimum temperature. Even a little change in water temperature can cause a disastrous effect on fish, living animals and plants in the Chilika Lake. Temperature study of the coastal area is very important for the animals and plants residing in the ocean. There are some studies over fisheries, fauna, flora, dolphins, environment, ecology, hydrology etc. but to the best of our knowledge none of the studies has yet focused on the detailed description about the past and future temperature simulations over Chilika Lake. The present study has been carried with the following objectives:

1. To assess the centennial scale seasonal temperature changes over Chilika Lake using CRU data.
2. To select a group of better performing models from the wide range of CMIP5 GCMs over the Lake.
3. To quantify the range of future temperature change at the end of the 21st century using different RCPs.

These results may be the basic climatic input for national level policy making and long-term decision taking.

Study Area

Chilika Lake is quite a large area situated in the east coast of India which is extended from 19°28'-19°54'N and 85°06'-85°35'E (Figure 1). Instead of taking the whole domain of lake we have considered a single point marked in red in Figure 1, in the middle of the lake of latitude 19.72N and longitude 85.32E over which temperature change of Chilika Lake is assessed.

Data

To evaluate the past temperature, we have used the data set of Climate Research Units (CRU), which contains monthly time series of precipitation, daily maximum and minimum temperatures, cloud cover, and other variables covering Earth's land areas for the period 1901-2012. The CRU data set is gridded to 0.5°×0.5 degree resolution, based on analysis of over 4000 individual weather station records in the globe. The data can be downloaded from the website <http://www.cru.uea.ac.uk/cru/data/hrg/>. The time period taken for past temperature analysis is from 1901 to 2005.

In the present study Intergovernmental Panel on Climate Change (IPCC) CMIP5 GCM models are used for past temperature assessment, model selection and future projection. We have downloaded the data from KNMI climate explorer from the website <http://climexp.knmi.nl>. In KNMI climate explorer the raw GCMs are being processed and the historical runs and the emission

scenarios are combined together as single file. Unlike raw GCMs, resolutions of these processed GCMs are same; all the GCMs are at 2.5° × 2.5° resolution.

For future climate assessment over the study area we have used the output of fifth assessment report (AR5) by IPCC, which was published in September 2013. In AR5, Representation Concentration Pathway (RCPs) for the first time has included the scenarios that explore the approach to climate change mitigation in addition to the traditional 'no climate policy scenarios'. Each RCP represents a different emission scenario including RCP 8.5 leading to a greater than 1370 PPM (Parts Per Million) CO₂ equivalent by 2100 with a continued rise post 2100, RCP 6.0 which stabilizes by 2100 at 850 PPM CO₂ equivalent by 2100 without overshoot, RCP4.5 which also stabilizes by 2100 but at 650 PPM CO₂ equivalent without overshoot and RCP2.6 which peaks at 490 PPM CO₂ equivalent before 2100 and then declines. We have considered three RCPs namely RCP2.6 (low), RCP4.5 (middle) and RCP8.5 (high) so that we can estimate a range of probable future temperature change over the Chilika Lake at the end of 21st century.

Methodology

CRU data is used for assessing the past centennial scale temperature change and IPCC CMIP5 GCM data has been used for future projection. There are more

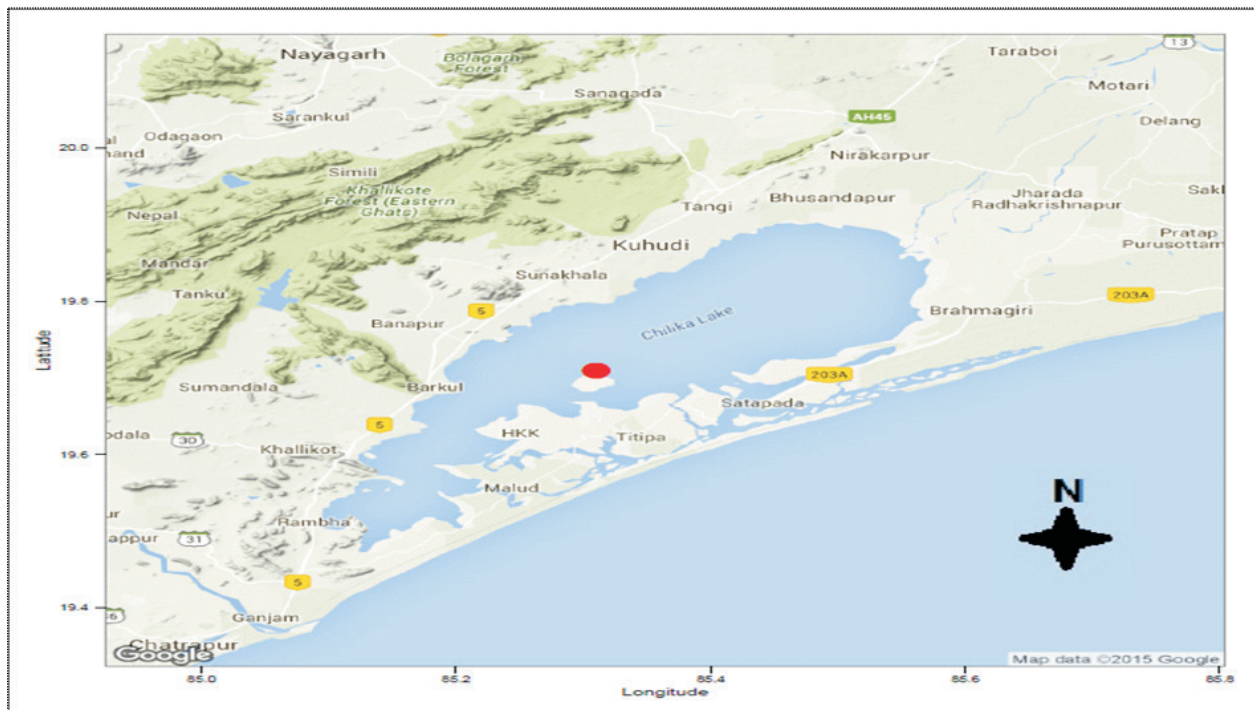


Figure 1: Study area covering the Chilika Lake located in the state of Orissa.

than forty GCM models available in KNMI climate explorer in CMIP5 historical runs, among which some models have the problem related to calendar year. After thorough checking of all models, we are left with 39 numbers of models, which were used for model evaluation. Both CRU and CMIP5 GCM data are interpolated to a point location with latitude 19.72°N and longitude 85.32°E over the middle of the Chilika Lake through bi-linear interpolation method. The bi-linear method uses a minimum of four nearest grid points from the domain and nearby areas. This method of interpolation has been used by Das and Lohar (2005) and Das et al. (2012) for assessing climate change over eastern part of India. For each GCM, the monthly-interpolated station time series were further converted into four well-defined seasonal time series namely winter (DJF), pre-monsoon (MAM), monsoon (JJAS) and post monsoon (ON) as well as annual time series. Mann-Kendall non parametric (Mitchell et al., 1966; Pant and Rupa Kumar, 1997) trends were calculated on annual, seasonal and monthly basis. This test has been widely used in the climatological analysis (Libiseller and Grimvall, 2002; Lazaro et al., 2001; Mirza et al., 1998; Karabulut et al., 2008). The test examines whether a random response variable monotonically increases or decreases with time. If a linear trend is present in a time series, then the true slope (change per unit time) can be estimated by using a simple nonparametric procedure developed by Sen (1968). This means linear model $f(t)$ can be described as

$$f(t) = Qt + B \quad (1)$$

where Q is the slope and B is a constant. To derive an estimate of the slope Q , the slopes of all data pairs are calculated.

$$Q_i = (x_j - x_k)/(j - k), i = 1, 2, \dots, N, j > k$$

If there are n values x_j in the time series we get as many as $N = n(n-1)/2$ slope estimates Q_i . The Sen's estimator of slope is the median of these N values of Q_i . The N values of Q_i are ranked from the smallest to the largest.

Mann-Kendall trends analysis indicates a monotonic increasing or decreasing trend in the time series. On the other hand non-parametric slope estimator is used to identify the trends. The values of the Sen's Slope are multiplied with 105 to get change in 105 years. The trends are calculated at 95% significant level. CRU data is used as "reference dataset" to select a group of better

performing models from 39 numbers of CMIP5 GCMs. These selected better performing models will be used for construction of future warming over Chilika Lake.

Model Evaluation

This section is dealing to identify suitable better performing GCMs from CMIP5 over Chilika Lake for the purpose of future projection. In IPCC in different CMIP project, produces a dozen of models to assess the past and future climate. Models number has increased from the IPCC first assessment report (FAR) to the fifth assessment report (AR5) via third and fourth assessment reports (TAR and AR4) and sometimes it is confusing which models should be considered for a specific study. Some scientists think, it is relevant to take ensemble mean of all the models instead of considering single model. Benestad (2002, 2005) used multi-model ensemble (MME) for downscaling over Europe. Duan and Phillips (2010) utilize MME in their study in spite of single GCM. In IPCC 2001, it was mentioned that it would be better to take MME of all models because single GCM can over estimate or under estimate. This situation will rise only if all the available models are considered randomly; however, situation might improve if we choose those models which are able to simulate the observation adequately, and then MME of that models will be considered.

According to Hulme (1992), it is advisable to evaluate the GCMs results with true observational data, which may be helpful to reduce the systematic errors/biases inherent in the GCMs. Tiwari et al. (2014) identified a group of models that can perform well over northern India. The study by Miao et al. (2014) reveals the performance of AR4 GCMs and their ensemble to simulate the global mean air temperature. Errasti et al. (2011) used averaged seasonal cycles and probability density functions (PDFs) to assess the performance of AR4 model over Iberian Peninsula. GCMs, the most popular, robust and widely used tool for global climate simulation, is used for past and future temperature simulation over the study area. Since there is no consensus method to identify good GCM models, seasonal cycle and long-term trend between models and observed are being used to determine a group of good performing models among 39 models in this particular paper. Seasonal temperature variation is due to change in position of the Earth relative to the Sun and seasonal cycle of particular latitude will be identical. Therefore if a model is able to represent the seasonal cycle

satisfactorily then it is supposed that it is also able to simulate the climate of that place to some extent.

Firstly, mean seasonal cycle between observation and model were plotted during 1901-2005 periods and correlations between them are calculated. A threshold value for the correlation was considered by taking the mean value of the correlation between observed and model; hereafter these will be known as mean seasonal correlation. The models, which have seasonal correlation values less than mean seasonal correlation, will be considered as bad models and will be excluded for future projection. Secondly, long-term trend of observation and GCM models were compared for annual and all seasons. Those models that have a positive trend in all seasons and in annual and simultaneously have threshold value greater than mean correlation was selected as a group of good models. Then multi model ensemble was constructed by simple averaging the models without giving any weightage to specific model. Keeping in mind, most of the GCMs have warm or cool bias compared to observations, we have corrected the bias for the selected group of models.

In the present study Quantile mapping using SSPLIN function is used for bias correction of GCMs. Quantile SSPLIN mapping fits a smoothing spline to the quantile-quantile plot of observed and modelled time series and uses the spline function to adjust the distribution of the modelled data to match the distribution of the observations (Gudmundsson, 2012). We have compared the multi-model ensemble (MME) using all 39 GCMs, 12 better performing models and bias corrected of better models with the help of Taylor diagram which visualize the improvement after selection of good and bias corrected models. Taylor plot is one of the way to judge the model performance, which provides a way to summarizing graphically how model or group of models simulations closely (or a set of patterns) matches observations (Taylor, 2001). The similarity between model simulation and observation is quantified in terms of their correlation (r), their centered root-mean-square-error (RMSE) and the amplitude of their standard deviations (STD). Three statistics of models simulations and observation are plotted on a polar graph style and the radial distances from the observation to the simulation/models are proportional to the STD, and the azimuthal positions give the correlation coefficient between the simulation and observation. The reason that each point in the two-dimensional space of the Taylor diagram can represent three different statistics

simultaneously (Centred RMSE, r and Std) is that these statistics are related by the following formula:

$$\text{RMSE}^2 = \sigma_F^2 + \sigma_O^2 - 2\sigma_F \sigma_O r \quad (2)$$

where σ_F and σ_O are the standard deviations of the simulations and observation respectively. It is expected that models will not be able to capture the exact pattern of the observation, but yet we were interested to see how far these models are able to simulate the observation based on Taylor plots. Temporal pattern is also estimated to further judge the models. Further, four statistical indices namely correlation, d -index, RMSE (Root Mean Square Error) and NSE (Nash-Sutcliffe Efficiency) were also used for comparing the MME of 39 models, good models and bias corrected models. Correlation measures the amount of linear relationship between the two variable under consideration and ranges from -1 to $+1$. Negative unit represents their opposite association, zero represents no linear association and positive unity represent similar association between the two variables under consideration. Das et al. (2012) also used d -index, also known as index of agreement, to compare the models with observation. The range of d -index varies from 0 to 1; closer values to unity represent better agreement with observation. Other two parameters are error index and NSE. The Nash-Sutcliffe efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information") (Nash and Sutcliffe, 1970). NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. Nash-Sutcliffe efficiencies range from Infinity to 1. Essentially, the closer to 1, the more accurate the model is. Root Mean Square Error (RMSE) between model and observation gives the standard deviation of the model prediction error. A smaller value indicates better model performance. The range to RMSE is from 0 to positive infinity. For future projection, we have considered all the common ensemble members of RCPs (RCP2.5, RCP4.5 and RCP8.5) of the better performing models and corrected the bias using Quantile mapping of SSPLIN technique. Similar to the past, MME and trends are calculated for future projection and is discussed in the next section and the formulae used for these four statistical indices are given in Table 1. For future projection we have considered all the ensemble members commonly available in each of the three RCPs (RCP2.5, RCP4.5 and RCP8.5) of the selected bias corrected better performing models.

Table 1: Formulae used to calculate statistical indices

Statistics	Formula	References
Correlation	$r = \frac{\sum_{i=1}^n (xi - \bar{x})(\sum yi - \bar{y})}{\sqrt{\sum_{n=1}^N (xi - \bar{x})^2 \sum_{n=1}^N (yi - \bar{y})^2}}$	Taylor (2001)
Index of agreement (<i>d</i> -index)	$d = 1 - \left(\frac{\sum_{n=1}^N (O_n - M_n)^2}{\sum_{n=1}^N (M_n - \bar{O} + O_n - \bar{O})^2} \right)$	Willmott (1981), Lagates and McCabe (1999)
RMSE	$[\sum_{n=1}^N (O_n - M_n)^2]^{\frac{1}{2}} / N$	Covery et al. (2002), Taylor (2001)
NSE	$1 - \frac{\sum (O_n - M_n)^2}{\sum (O_n - \bar{O}_n)^2}$	Nash and Sutcliffe (1970)

Results and Discussion

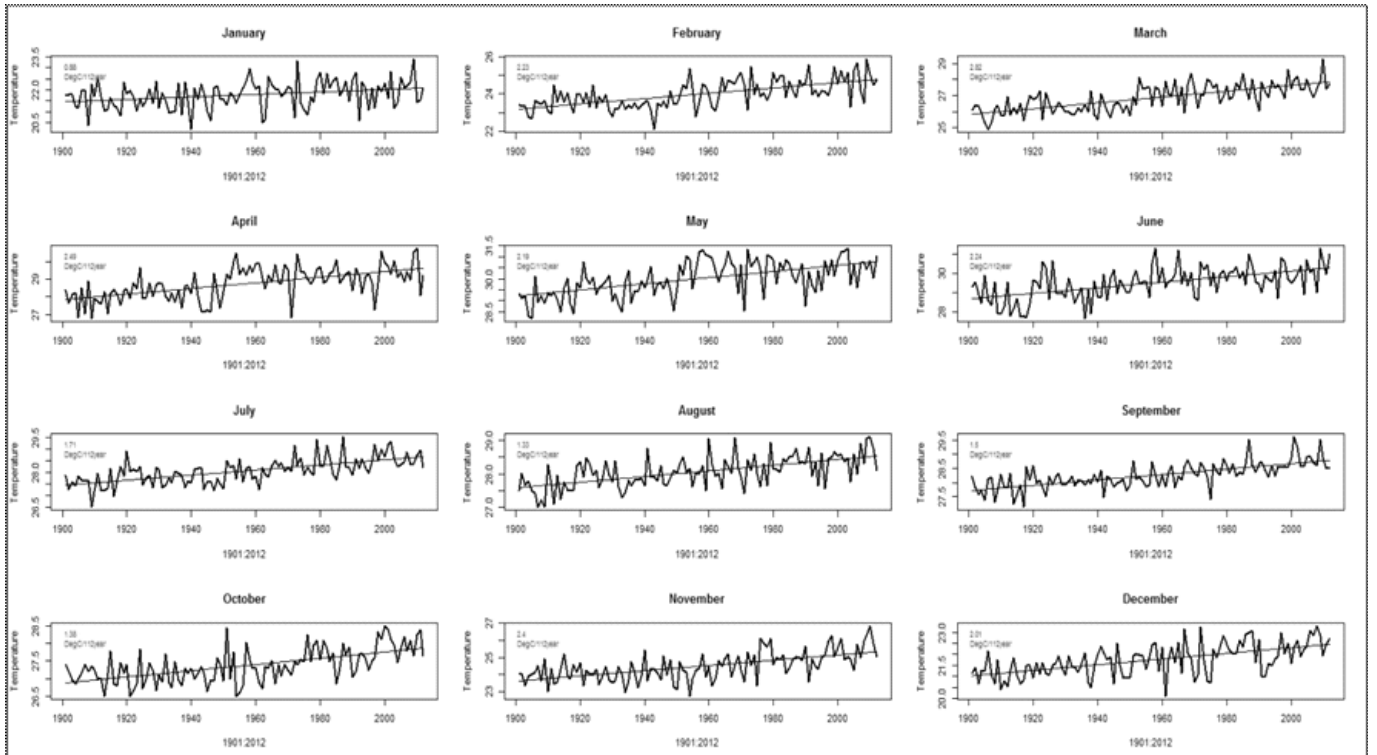
The observed mean monthly and seasonal temperature trends of Chilika Lake during 1901-2012 are estimated using regression analysis and results are displayed in Figure 2. Table 2 is summarization of trends during the period of 1901-2005 for the purpose of comparison of trends with model simulated trends. Slightly short period trends for recent four decades namely 1969-2009 was also calculated and the results were displayed in Table 1 for the purpose of comparison of results with other available literatures. It is to be

Table 2: Observed annual and seasonal trends over Chilika Lake

Time period	DJF	MAM	JJAS	ON	ANN
1901-2005	1.09	1.79	1.10	1.09	1.29
1969-2009	0.55	0.14	0.51	0.52	0.38

Bold letters represent significant values at 95% significant level.

mentioned that the available literature over different parts of India indicates the highest warming in the winter season. The similar highest warming in winter was also obtained in our present study using CRU

**Figure 2: Monthly variation of temperature over Chilika Lake during 1901-2012 using CRU Data.**

data for the recent four decades but long-term (1901-2005) data analysis indicates entirely opposite warming trends which reveals the highest warming in the pre-monsoon and winter warming was lowest. The highest temperature was observed in the month of March and lowest temperature change is observed in the month of January. Interestingly winter season has faced lowest temperature change whereas highest temperature change is observed in the pre-monsoon season. How the recent generation of GCMs (AR5) was able to reproduce the observed temperature over Chilika Lake was assessed by two criteria: firstly model performance was evaluated through the comparison of mean seasonal cycles and secondly by the comparison of long-term trends between observation and model simulation. Figure 3 displayed the mean seasonal cycle of observation and GCM simulations and its correlation values are displayed in Table 3. The value of mean seasonal correlation is 0.95 and those models, which have deceeded, below the mean seasonal correlation is marked in red colour. Among the 39 models, 12 models namely ACCESS1-3,

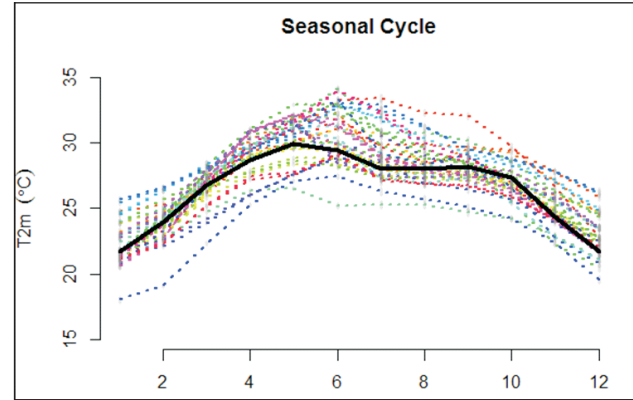


Figure 3: Comparison of seasonal cycles between observation and model simulation of 39 GCMs. Coloured dotted lines are model simulations of 39 GCMs and solid black line is observation.

bcc-csm1-1-m, CanESM2, CSIRO-Mk3-6-0, GISS-E2-H-CC, GISS-E2-H, GISS-E2-R-CC, GISS-E2-R, IPSL-CM5A-LR, IPSL-CM5b-LR, MIROC-ESM-CHEM, MIROC-ESM and MRI-CGCM3 were

Table 3: Variations of correlations of the mean seasonal cycles between the model simulation and observational data.

<i>Model</i>	<i>Correlation</i>	<i>Model</i>	<i>Correlation</i>
ACCESS1-0	0.97	NOAA	0.96
ACCESS1-3	0.92	GISS-E2-H-CC	0.93
bcc-csm1-1-m	0.92	GISS-E2-H	0.93
bcc-csm1-1	0.95	GISS-E2-R-CC	0.87
BNU-ESM	0.97	GISS-E2-R	0.86
CanESM2	0.91	HadGEM2-AO	0.97
CCSM4	0.98	inmcm4	0.95
CESM1-BGC	0.98	IPSL-CM5A-LR	0.93
CESM1-CAM5.1-FV2	0.99	IPSL-CM5B-LR	0.85
CESM1-CAM5	0.99	MIROC-ESM-CHEM	0.92
CESM1-FASTCHEM	0.98	MIROC-ESM	0.92
CESM1-WACCM	0.99	MIROC5	0.97
CMCC-CESM	0.99	MPI-ESM-LR	0.97
CMCC-CM	0.97	MPI-ESM-MR	0.96
CMCC-CMS	0.97	MPI-ESM-P	0.97
CNRM-CM5	0.96	MRI-CGCM3	0.94
CSIRO-Mk3-6-0	0.93	MRI-ESM1	0.95
EC-EARTH	0.97	NorESM1-M	0.97
FGOALS_g2	0.97	NorESM1-ME	0.97
FIO-ESM	0.97	Threshold value	0.95

Correlation are statistically significant at 95% level. Bold represents the models crossing the threshold value.

unable to reproduce the pattern of observed seasonal cycles satisfactorily. These models also showed lower correlations between observed mean seasonal cycles and observations; hence the above-mentioned 12 models were discarded for further analysis of future projection. Mann-Kendall linear trend for winter, pre monsoon, monsoon, post monsoon seasons and annual was constructed for both models and observed during the same period. The seasonal and annual trends of observation showed warming trends during 1901-2005 periods. If any model reproduce negative trends at least one season or annual scale, we directly discarded that model for further analysis of future trends estimation.

On doing the same, finally 12 numbers namely bcc-sm1, BNU-ESM, CCSM4, CESM1-BGC, CESM1-FASTCHEM, CESM1-WACCM, CMCC-CM, EC-EARTH, FGOALS_g2, FIO-ESM and MPI-ESM-LR were retained as those models fully reproduced the mean seasonal correlation satisfactorily and adequately reproduced the observed warming trends in four seasons as well as annual scale. Figure 4 shows the comparison of MMEs using (i) all 39 models, (ii) 12 better performing models and (iii) 17 bias corrected better performing models. Biases of 12 better performing models were corrected using the quantile SSPLIN mapping technique. Bias corrected models reflected improved performance compared to without bias correction as well as MME of all models. Temporal variation of three types of MME is presented in Figure 5. The black line is observation, the red line is MME of all models, the green line is MME of good models and the yellow line is MME of bias corrected models. The bias corrected MME i.e., the yellow line is not only able to capture the magnitude satisfactory but also able to capture the pattern of time series in early and late 20th century; however it is unable to capture the pattern in the middle period. Although there was a significant improvement from all model MME to bias corrected selected models MME.

Three types of MMEs namely all model MME, good models MME and bias corrected MME are evaluated by four statistical indices for four seasons and annual and is represented in Figures 6 (a-d) for correlation, *d*-index, NSE and RMSE respectively. After selection of good models and subsequent bias correction, decreasing value in correlation for winter and post-monsoon season was noticed, no improvement was identified in case of monsoon season although improvement was observed in annual and the pre-monsoon season. A steady

increasing value of *d*-index was observed for all seasons and annual scale (Figure 6 (b)). In annual, winter and monsoon seasons magnitude of *d*-index became twice upon bias correction compared to all models MME. The NSE ranges from 1 to negative infinity, closer value to 1 indicate better model. The magnitude of NSE upon bias correction became close to zero or one (Figure 6 (c)). Similarly significant improvement was observed in RMSE after bias correction in annual as well as in all seasons (Figure 6(d)). The non-parametric linear trend for all GCM models and its MME for all seasons and annual scale are determined and are given in Table 4. It is noted that the temperature changes in the monsoon, post monsoon and winter seasons are almost same magnitudes, which are well captured by the bias corrected better performing GCMs. GCMs are also able to capture the high warming in the pre-monsoon season to some extent.

The future warming/cooling projection over Chilika Lake was generated through three different Representative Concentrative Pathways (RCPs) namely RCP2.6, RCP4.5 and RCP8.5 and results are displayed in Table 5. It is to be further mentioned that all the 12 better performing GCMs were not commonly available in three RCPs, so we have considered all ensemble members commonly available in each RCP and finally MME are constructed using 18 ensemble members from RCP2.6, 17 members from RCP4.5 and 24 members from RCP8.5. Mann-Kendall trends of MMEs of ensemble members were calculated during 2006-2100 periods for winter, monsoon and annual basis and results are displayed in Table 5. Finally the temporal variation of the bias corrected MMEs for the historical period (1901-2005) as well as its future projection using three RCPs was displayed in Figure 7. All trends as presented in Table 5 and Figure 7 is significant at 95% level. The analysis of future trends using four different RCPs over Chilika Lake indicates a range of annual temperature change will be 0.27-3.61, whereas the range of seasonal temperature warming in winter, pre-monsoon, monsoon and post-monsoon are 0.38-3.98°C, 0.28-3.72°C, 0.33-3.41°C and 0.22-3.50°C respectively at the end of 21st century.

Conclusion

Analysis of past centennial scale warming or cooling over Chilika Lake indicates extensive higher rates of warming in different seasons and as well as in

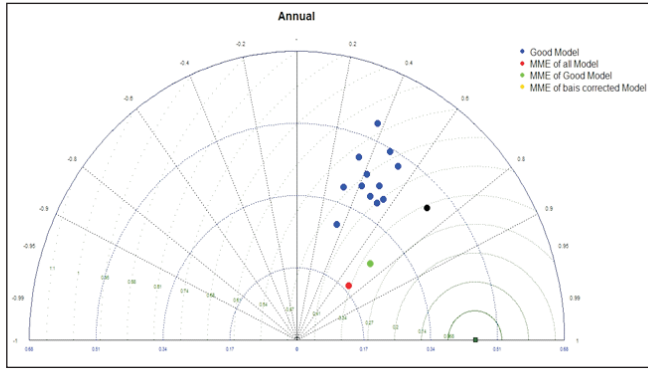


Figure 4: Taylor diagram representing the group of better performing models (blue dots) and their MME (green dot), MME of 39 numbers of GCMs (red dot) and MME of bias corrected better performing models (yellow dot).

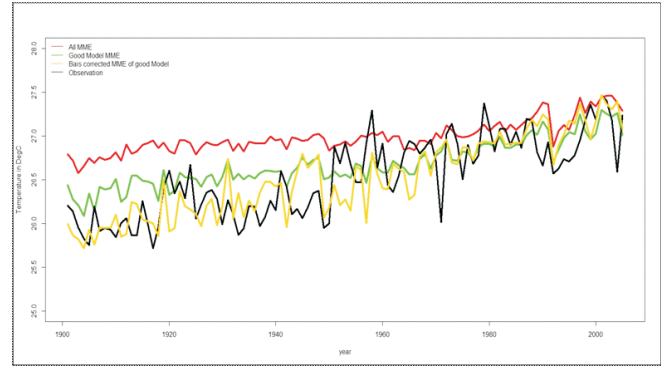


Figure 5: Temporal variation of MMEs comprising different combinations of models during 1901-2005.

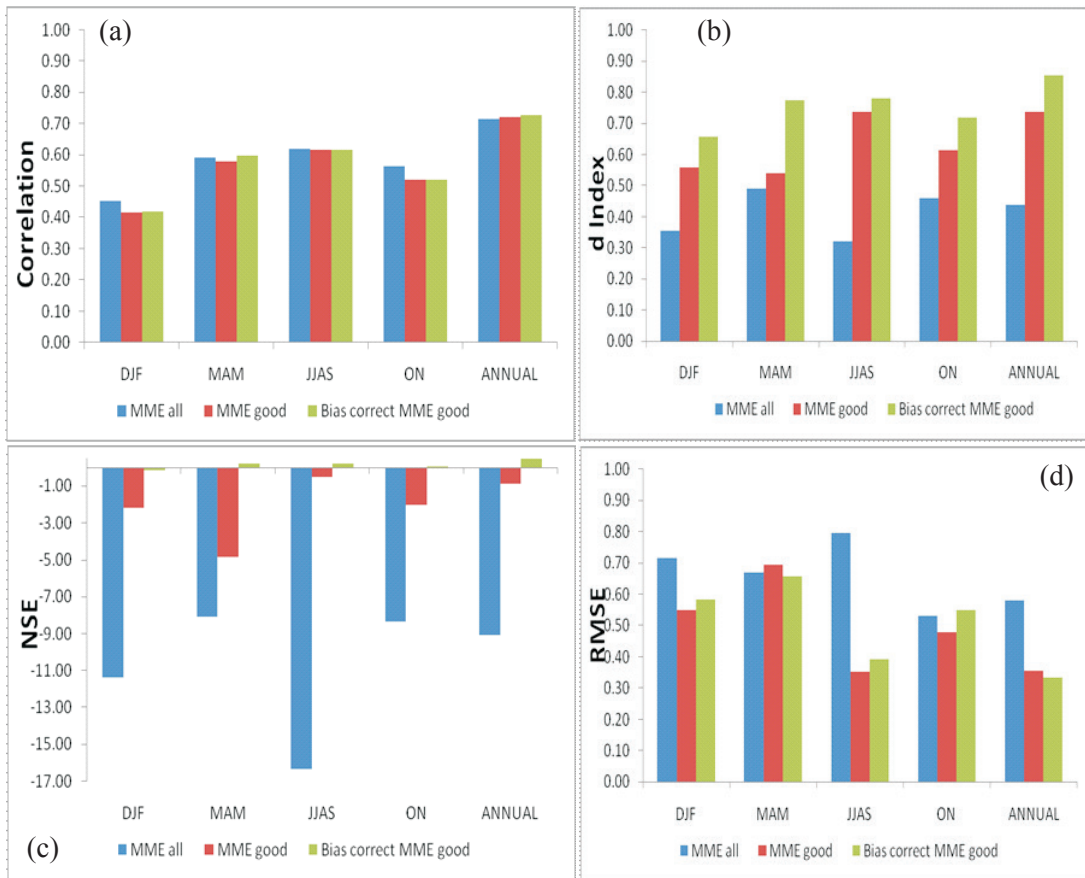


Figure 6: Variation of four statistical indices namely (a) correlation, (b) d index, (c) NSE and (d) RMSE for the MME comprises different combinations of models.

annual scale. The highest warming was noticed in the pre-monsoon season (1.79°C) followed by monsoon (1.10°C), post monsoon (1.09°C) and winter (1.09°C) seasons while the annual temperature shows a moderate warming of 1.29°C in the last century. On the other hand, in recent four decades, winter season is showing

highest warming (0.55°C) trend and lowest warming is in the pre-monsoon (0.14°C) season while warming in monsoon is 0.51°C and post-monsoon is 0.52°C during 1969-2009. 12 numbers of better performing models over Chilika were selected based on two criteria namely the comparison of mean seasonal cycles and long-term

Table 4: Variation of seasonal and annual non-parametric Mann Kendall linear trend for different models

<i>Model</i>	<i>Winter</i>	<i>Pre-monsoon</i>	<i>Monsoon</i>	<i>Post-monsoon</i>	<i>Annual</i>
ACCESS1-0	0.44	0.55	0.26	-0.03	0.37
ACCESS1-3	-0.41	0.19	0.21	0.16	0.02
bcc-csm1-1-m	0.44	0.39	0.41	0.49	0.44
bcc-csm1-1	0.60	0.55	0.76	0.51	0.61
BNU-ESM	0.66	1.04	0.66	0.35	0.75
CanESM2	1.02	0.93	0.90	0.86	0.96
CCSM4	0.51	1.19	0.92	0.80	0.86
CESM1-BGC	0.92	0.83	1.00	0.79	0.86
CESM1-CAM5.1-FV2	0.26	0.07	0.04	0.10	0.13
CESM1-CAM5	-0.13	0.33	-0.04	0.12	0.09
CESM1-FASTCHEM	0.77	1.05	1.00	0.82	0.94
CESM1-WACCM	1.04	1.08	1.02	1.10	1.06
CMCC-CESM	0.62	0.00	-0.03	0.06	0.09
CMCC-CM	1.01	0.92	0.79	0.86	0.86
CMCC-CMS	0.44	0.60	0.38	0.11	0.33
CNRM-CM5	0.72	0.67	0.41	0.33	0.51
CSIRO-Mk3-6-0	0.16	0.34	0.45	-0.18	0.26
EC-EARTH	0.53	0.55	0.53	0.55	0.50
FGOALS_g2	1.00	0.69	0.65	0.58	0.72
FIO-ESM	1.18	0.89	0.64	1.06	0.94
NOAA	0.46	0.68	0.57	0.47	0.53
GISS-E2-H-CC	0.59	0.30	0.19	0.32	0.35
GISS-E2-H	0.56	0.48	0.42	0.42	0.52
GISS-E2-R-CC	0.34	0.59	0.32	0.26	0.39
GISS-E2-R	0.40	0.58	0.66	0.43	0.56
HadGEM2-AO	0.19	0.58	0.42	0.04	0.30
inmcm4	0.46	0.86	0.61	0.54	0.64
IPSL-CM5A-LR	0.83	1.06	1.07	0.81	0.95
IPSL-CM5B-LR	0.76	0.61	0.77	0.54	0.70
MIROC-ESM-CHEM	0.90	1.19	0.71	0.75	0.88
MIROC-ESM	1.11	1.33	0.77	0.67	0.92
MIROC5	0.45	0.24	0.07	0.56	0.31
MPI-ESM-LR	0.54	0.95	1.00	1.25	0.92
MPI-ESM-MR	0.42	0.68	0.88	0.75	0.65
MPI-ESM-P	0.81	1.08	0.99	0.79	0.95
MRI-CGCM3	-0.78	0.24	0.02	-0.99	-0.21
MRI-ESM1	-1.08	0.06	-0.68	-0.62	-0.56
NorESM1-M	0.41	0.32	0.38	0.47	0.36
NorESM1-ME	0.24	0.58	0.06	0.49	0.34
Observation	1.06	1.79	1.10	1.09	1.29
MME of 39 GCMs	0.45	0.61	0.48	0.44	0.50
MME of 12 better GCMs	0.76	0.86	0.79	0.77	0.78
MME of bias corrected GCMs	1.34	2.27	1.33	1.55	1.44

MME 39 – Multi Model Ensemble of 39 models

MME of 12 better GCMs – Multi Model Ensemble of 12 better performing models

MME of bias corrected GCMs – Multi Models Ensemble of 12 bias corrected better performing models

Bold letters represent significant at 95%.

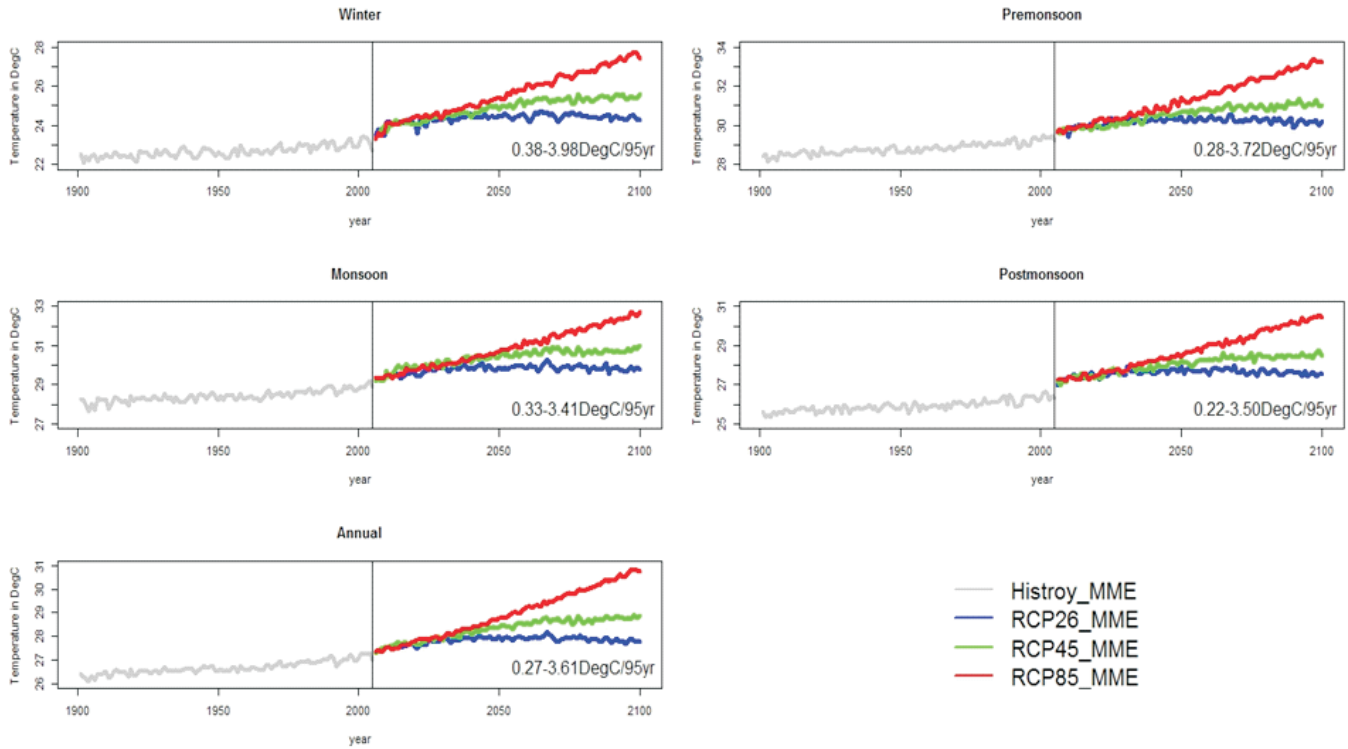


Figure 7: Annual and seasonal variation of temperatures changes over Chilika Lake during 1901-2100.

Table 5: Future seasonal and annual temperature trends simulated by MME of 18, 17 and 24 GCMs of RCPs 26, 45 and 85

<i>RCP26</i>	<i>DJF</i>	<i>MAM</i>	<i>JJAS</i>	<i>ON</i>	<i>Annual</i>
bcc-csm1-1	0.43	0.48	0.37	0.37	0.56
BNU-ESM	0.31	0.12	0.28	0.21	0.20
CCSM4	0.15	0.27	0.31	0.37	0.22
CCSM4	0.05	0.01	0.21	0.04	0.09
CCSM4	0.41	0.16	0.24	0.47	0.17
CCSM4	-0.01	0.03	0.24	0.06	0.09
CCSM4	0.07	0.05	0.18	0.20	0.19
CCSM4	0.15	0.17	0.23	0.66	0.27
EC-EARTH	0.91	0.17	0.42	0.23	0.38
EC-EARTH	0.39	0.38	0.36	0.25	0.45
FGOALS_g2	0.29	0.15	-0.21	0.04	0.05
FIO-ESM	0.00	0.01	0.02	0.02	0.06
FIO-ESM	-0.04	-0.02	0.07	-0.05	0.00
FIO-ESM	0.17	-0.03	0.13	0.03	0.07
MPI-ESM-LR	0.17	0.15	0.08	0.15	0.07
MPI-ESM-LR	0.19	0.35	0.27	0.00	0.19
MPI-ESM-LR	0.17	0.66	0.47	0.37	0.49
MPI-ESM-MR	0.21	0.03	0.32	0.01	0.19
MME	0.38	0.28	0.33	0.22	0.27

(Contd.)

(Table 5: *Contd.*)

<i>RCP45</i>	<i>DJF</i>	<i>MAM</i>	<i>JJAS</i>	<i>ON</i>	<i>Annual</i>
bcc-csm1-1	1.06	1.53	0.91	1.51	1.44
BNU-ESM	2.04	1.63	0.85	1.80	1.55
CCSM4	1.37	1.14	1.46	1.34	1.26
CCSM4	1.28	1.00	0.64	1.01	0.88
CCSM4	0.66	0.72	1.17	1.12	0.99
CCSM4	1.01	1.22	1.20	1.62	1.23
EC-EARTH	1.95	1.04	1.29	2.03	1.61
EC-EARTH	2.18	1.34	1.46	1.52	1.77
EC-Earth	1.77	0.98	1.43	1.59	1.35
EC-EARTH	2.27	1.06	1.46	1.29	1.61
EC-EARTH	1.90	1.56	1.47	1.62	1.74
FGOALS_g2	0.70	0.58	0.15	0.72	0.30
FIO-ESM	0.74	0.89	1.00	0.97	1.17
FIO-ESM	1.14	0.59	0.68	0.95	1.05
MPI-ESM-LR	0.92	1.70	0.64	1.41	1.01
MPI-ESM-MR	1.47	1.49	1.06	1.20	1.61
MPI-ESM-MR	1.81	0.69	0.88	0.73	1.71
MME	1.81	1.53	1.25	1.36	1.50

<i>RCP85</i>	<i>DJF</i>	<i>MAM</i>	<i>JJAS</i>	<i>ON</i>	<i>Annual</i>
bcc-csm1-1	4.07	3.68	2.72	0.00	3.96
BNU-ESM	4.23	3.75	2.96	0.00	4.12
CCSM4	4.05	3.48	3.63	0.92	3.85
CCSM4	3.31	3.12	3.31	1.03	3.87
CCSM4	3.91	3.27	2.87	0.94	3.73
CCSM4	3.78	3.16	3.44	1.05	3.63
CCSM4	3.54	2.77	3.26	0.95	3.63
CCSM4	4.08	3.27	3.32	1.00	3.89
EC-EARTH	4.13	3.75	3.41	1.05	4.12
EC-EARTH	4.27	3.60	3.42	1.02	3.85
EC-Earth	4.85	3.00	3.30	1.01	4.07
EC-EARTH	4.46	2.67	3.68	0.99	4.00
EC-EARTH	3.92	3.27	3.57	1.02	4.07
EC-EARTH	1.98	1.52	1.44	0.93	1.55
EC-EARTH	3.94	3.78	3.45	1.02	4.11
EC-EARTH	4.57	3.19	3.53	1.01	4.16
FGOALS_g2	3.28	2.30	0.96	0.03	2.67
FIO-ESM	3.92	3.44	3.61	0.46	4.23
FIO-ESM	3.21	2.97	3.29	0.00	3.73
FIO-ESM	3.45	2.65	3.54	0.04	3.77
MPI-ESM-LR	4.96	4.88	3.54	1.04	5.01
MPI-ESM-LR	4.73	4.67	3.00	1.10	4.60
MPI-ESM-LR	4.00	4.69	4.06	1.08	5.16
MPI-ESM-MR	5.06	4.29	3.35	1.05	4.65
MME	3.98	3.72	3.41	3.50	3.61

Bold letters represent significant at 95%.

trend between observation and GCMs simulation. The MME of better performing models with adjusted bias have provided better results compared to MME using all 39 models and better models without bias correction. The improvement in the results of MME of all, good and bias corrected models were judged using Taylor diagram, correlation, *d*-index, NSE and RMSE. After bias correction improvement was observed in correlation in annual and pre monsoon season whereas no improvement was found in winter and post monsoon season. However, gradual improvement in the statistical indices like *d*-index, NSE and RMSE was noticed after selection of good models and further bias correction. Trends estimated for the period 1901-2005 of bias corrected MMEs are 1.44°C, 1.34°C, 2.27°C, 1.33°C and 1.55°C for the annual, winter, pre-monsoon, monsoon and post monsoon seasons respectively. The results are close to the observed trends estimated from CRU data. In addition, MMEs were also able to capture the higher pre-monsoon warming and lower winter warming over Chilika. When dealing with climate models, it is recommended to use those models which are able to simulate the past trends satisfactorily.

Thus we have used 12 better performing bias corrected models, as a group or individually which are able to simulate the observed warming or cooling satisfactorily. MME of CMIP5 GCMs projects a wide range of future temperature changes over Chilika Lake for the winter, pre-monsoon, monsoon, post-monsoon and annual scale by 0.38-3.98°C, 0.28-3.72°C, 0.33-3.41°C, 0.22-3.50°C and 0.27-3.61°C respectively at the end of 21st century. In last century pre-monsoon seasons had shown more warming whereas projected temperature over Chilika showed that winter season temperature is going to be higher, followed by pre-monsoon, monsoon and post-monsoon seasons. Further assessing the reliable adequate warming/cooling trends over Chilika Lake can be generated through any suitable downscaling technique from wide range of GCMs simulations which is our future plan of research.

References

- Annandale, N. and Kemp, S., 1915. Introduction to the Fauna of the Chilika Lake. *Memories of India Museum*, **5**: 1-20.
- Benestad, R.E., 2002. Empirically Downscaled Multi-model Ensemble Temperature and Precipitation Scenarios for Norway. *Journal of Climate*, **15**: 3008-3027.
- Benestad, R.E., 2005. Climate change scenarios for northern Europe from multi-model IPCC AR4 climate simulations. *Geophysical Research Letters*, **32**: L17704, doi:10.1029/2005GL023401.
- CDA, 2005. Achievement report 2005. Chilika Development Authority, Bhubaneswar.
- CDA, 2008. About Chilika. <http://www.chilika.com/about.htm>. Cited 21 Dec 2008.
- Covey, C., Achuta Rao, K.M., Fiorino, M., Gleckler, P.T., Taylor, K.E. and Wehner, M.F., 2002. Intercomparison of climate data sets as a measure of observational uncertainty. Program for climate model diagnosis and intercomparison. UCRLID-147371, Lawrence Livermore National Laboratory, Livermore, CA.
- Das, L. and Lohar, D., 2005. Construction of climate change scenarios for a tropical monsoon region. *Climate Research*, **30**: 39-52.
- Das, L., Annan, J.D., Hargreaves, J.C. and Emori, S., 2012. Improvements over three generations of climate model simulations for eastern India. *Climate Research*, **51**(3): 201-216.
- Duan, Q.Y. and Phillips, T.J., 2010. Bayesian estimation of local signal and noise in multi-model simulations of climate change. *Journal of Geophysical Research*, **115**: D18123.
- Errasti, I., Ezcurra, A., Sáenz, J. and Ibarra-Berastegi, G., 2011. Validation of IPCC AR4 models over the Iberian Peninsula. *Theoretical and Applied Climatology*, **103**: 61-79.
- Gudmundsson, L., Bremnes, J.B., Haugen, J.E. and Engen-Skaugen, T., 2012. Technical Note: Downscaling RCM precipitation to the station scale using statistical transformations—A comparison of methods. *Hydrology and Earth System Sciences*, **16**: 3383-3390, doi:10.5194/hess-16-3383-2012.
- Gupta, G.V.M., Sarma, V.V.S.S., Robin, R.S., Saman, A.V., Kumar, M.J., Rakesh, M. and Subramanian, B.R., 2008. Influence of net ecosystem metabolism in transferring riverine organic carbon to atmospheric CO₂ in a tropical coastal lagoon (Chilika lake, India). *Biogeochemistry*, **87**: 265-285.
- Gupta, M.C. and Sharma, V.K., 2000. Orissa super cyclone 99. National Centre for Disaster Management, Delhi.
- Hulme, M., 1992. A 1951–80 global land precipitation climatology for the evaluation of general circulation models. *Climate Dynamics*, **7**(2): 57-72.
- Karabulut, M., Gürbüz, M. and Korkmaz, H., 2008. Precipitation and Temperature Trend Analyses in Samsun. *Int. Environmental Application & Science*, **3**(5): 399-408.
- Lazaro, R., Rodrigo, F.S., Gutierrez, L., Domingo, F. and Puigdefabregas, J., 2001. Analysis of a 30-year rainfall record (1967-1997) in semi-arid SE Spain for implications on vegetation. *Journal of Arid Environment*, **48**: 373-395.

- Legates, D.R. and McCabe Jr., G.J., 1999. Evaluating the Use of “Goodness-of-Fit” Measures in Hydrologic and Hydroclimatic Model Validation. *Water Resource Research*, **35**(1): 233-241.
- Libiseller, C. and Grimvall, A., 2002. Performance of partial Mann-Kendall test for trend detection in the presence of covariates. *Environmetrics*, **13**: 71-84.
- Miao, C., Duan, Q., Sun, Q., Huang, Y., Kong, D., Yang, T., Ye, A., Di, Z. and Gong, W., 2014. Assessment of CMIP5 climate models and projected temperature changes over Northern Eurasia. *Environment Research Letter*, 9 055007.
- Mirza, M., 2007. Climate change, adaptation and adaptive governance in the water sector in South Asia. Adaptation and Impacts Research Division (AIRD), Department of Physical and Environmental Sciences, University of Toronto at Scarborough, Scarborough, Ontario.
- Nash, J.E. and Sutcliffe, J.V., 1970. River flow forecasting through conceptual models, part I—A discussion of principles. *Journal of Hydrology*, **10**(3): 282-290.
- Pant, G.B. and Rupa Kumar, K., 1997. *Climates of South Asia: Behaviour studies in climatology*. Wiley, New York.
- Pascoe, E.H., 1964. *A manual of the Geology of India and Burma*. Vol 3. Geological Survey of India, Delhi.
- Raven, H.P., Hassenzehl, D.M. and Berg, L.R., 2015. *Environment* (Eighth edition). John Wiley and Sons, Inc.
- Sen, P.K., 1968. Estimates of the regression coefficient based on Kendall’s tau. *Journal of the American Statistical Association*, **63**: 1379-1389.
- Shanmugasundaram, J., Arunachalam, S., Gomathinayagam, S. and Lakshnaman, P., 2000. Cyclone damage to buildings and structures: A case study. *Journal of Wind Engineering and Industrial Aerodynamics*, **84**: 369-380 doi:10.1016/S0167-6105(99)00114-2.
- Taylor, K.E., 2001. Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research – Atmosphere*, **106**: 7183-7192.
- Tiwari, P.R., Kar, S.C., Mohanty, U.C., Kumari, S., Sinha, P., Nair, A. and Dey, S., 2014. Skill of precipitation prediction with GCMs over north India during winter season. *International Journal of Climatology*, DOI: 10.1002/joc.392.
- Willmott, C.J., 1981. On the validation of models. *Physical Geography*, **2**: 184-194.