Chapter–3

Climate of Chilka Lake through Empirical Statistical Downscaling

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3.1. Introduction: Chilka Lake: An overview

'Chilka' means a Land covered with water. Chilka Lake, a tropical coastal lake, is connected through a 32 km long narrow channel with the Bay of Bengal, is geographically situated at the east coast of India (Lat 19.19-19.54 ^{0}N, Lon 85.06-85.35 ^{0}E) (Figure 1). It is also a brackish water (0.5 to 30 gm salt per liter) lagoon, spread over the Ganjam, Khurda and Puri districts of Odisha state in eastern India. It is attributed as the second largest lagoon in the world next to New Caledonia of southern pacific. The lagoon gains a size of ~1165 km^2 during monsoon and contracts up to an area of ~950 km^2 during summer. Maximum length and breadth of the lagoon are 65 km and 20 km respectively. The lagoon is shallow with a mean depth of 1.7m. Geographically it is known to have two major regions, viz., the outer channel and the main area. The lagoon comprises four distinctive ecological zones 1) the North Sector- influenced mainly by fresh water most of the year, 2) the central sector corresponds to mixing of both fresh and saline

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water, 3) the Southern sector is isolated with deep waters constituted of mixed waters of fresh, saline and wind, and 4) the Outer channel completely renewed by oceanic waters during dry season and flooded with fresh water during monsoon season.

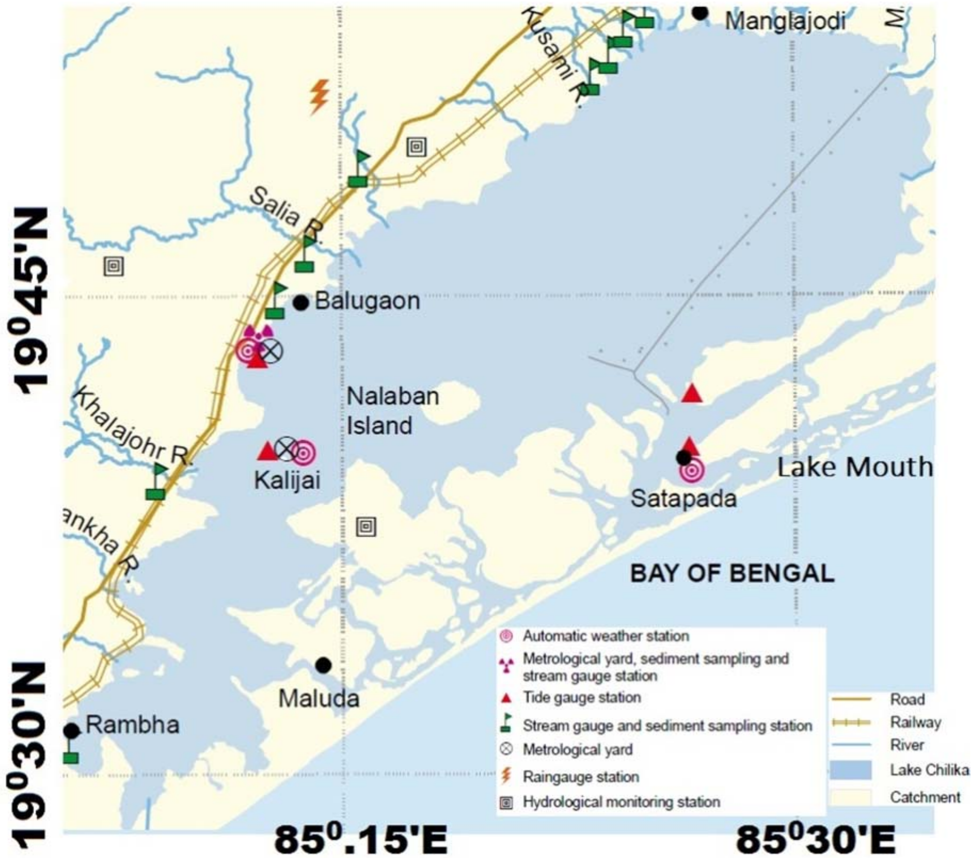

Figure 1: Map of Chilka Lake catchment area (Chilka news letter, 2013)

Like other coastal water bodies, the Chilka Lake is rich with biodiversity and is one of the hotspot of tourism in India. There are islands like Parikuda, Maluda, Rajhans and the rocky island of Goddess Kalijai lie scattered over the lake. ‘Nalbana Island’ in Chilka Lake is declared as a bird sanctuary in 1973 under Wildlife Protection Act.

3.2. Climatology of Chilka Lake

The catchment of the lagoon falls under a tropical climate region. The average annual temperature of the lagoon lies between 39.9^{0}C and 14.0^{0}C. The lagoon experiences Southwest and Northeast monsoons during June to September and November to December respectively. December to January is the winter month and during this time, cold wave conditions prevail for a couple of weeks due to Western disturbances in North India. March to May is the summer season which is popularly known as premonsoon season. In the inland hilly tract, the climate is comparatively drier with higher temperature during the summer season and slightly cooler in winter. The period from June to September is the monsoon season while October and November months are the post monsoon transition months. The annual average rainfall in the catchment is 1238.8 mm with 72 rainy days (Chilka Development Authority). The rainfall generally decreases from northeast to southwest. Monsoon rainfall contributes about 75% of the annual rainfall. In general the wind speed is high during the month of March to July and is calm during the winter season. The wind speed mostly from North and north easterly direction and during monsoon month it is mostly southerly and southwesterly direction due the influence of the Southwest monsoon and the wind speed varies from 5.3 to 16.0 km/hour. We have generated the detailed climate change scenarios for precipitation using both of CMIP3 and CMIP5 GCMs but in case of temperature the scenarios were constructed using only CMIP5 GCMs. The results are presented in the section 3.3.1 and 3.3.2 respectively

3.3. Climate Change and Global Circulation Models

Climate change is a global issue and its diversity makes it more composite. Prior to 1980s our understanding about climate change was rudimentary. Intergovernmental panel on climate change popularly known as IPCC came forth as an apex scientific body to produce report on global climate related issue in 1988 by the cooperative leadership of World Meteorological Organization (WMO) and United Nations Environment Programme (UNEP). It was setup with the aim to provide unified scientific, technical and socio-economic information concerning human induced climate change, its potential impact and adaptation and mitigation strategy to the scientific and non-scientific community. After 19-years of its establishmenti.e. in 2007 the IPCC was honored with the highest intellectual award-The Nobel Peace prize for its efforts to build up and disseminate greater knowledge about manmade climate change, and to lay the foundations for the measures that are needed to counteract such change. IPCC does not carry out any specific research work nor does it monitor the climate change but it assesses the scientific literatures published by the scientific community, which include peer-reviewed and non-peer reviewed sources. Till now IPCC have published five comprehensive assessment reports, first assessment report (FAR) was published in the year 1990 with a supplementary report in 1992. Subsequently the second (SAR), third (TAR), fourth (AR4) and the fifth assessment reports (AR5) were published in the year 1995, 2001, 2007 and 2014 respectively. Along with observed climate change information IPCC is also publishing special reports on specific topics. The Special Report on Emission Scenarios (SRES) published by IPCC contains ‘scenarios’ of future change in greenhouse gases (GHG) and sulfur dioxide. The SRES scenarios were first published in 2001 along with the TAR. SRES scenarios are used to project future changes in climate, for surface variable (global mean precipitation and temperature), radiation variable, ocean, ice and upper air components . Like SRES, IPCC has come up with a wide range of possible changes in future anthropogenic GHG emissions scenarios during 2014 along with the AR5known as Representative Concentration Pathways (RCP).There are several General Circulation Models (GCMs) reported by various countries to the IPCC which represents different climatic information. These climatic information are generate by mathematical models used to simulate the present climate and projection to future climate with forcing by GHG and aerosols. Now a days GCMs are used as an important tool in assessing the climate change in global scale as well as in regional scale. It is widely accepted that present day GCMs are able to simulate the large-scale atmospheric state in a realistic manner and are adequate tool to predict large scale climate change.

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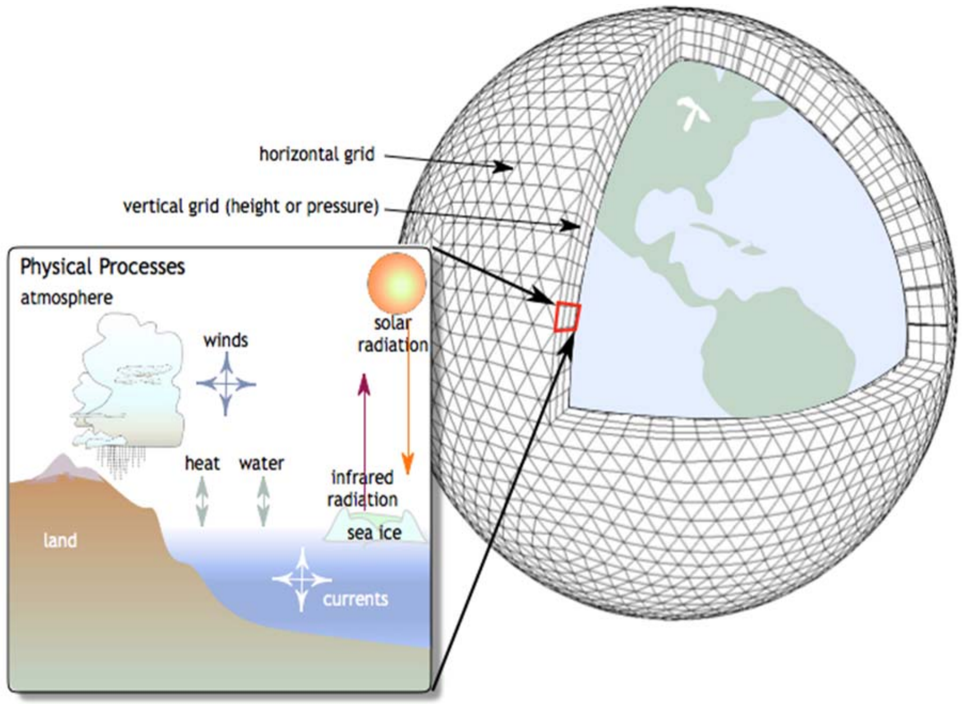

Figure 2: Structure of a climate model and the physical processes incorporated in a climate model

3.3.1 General Circulation Models (GCMs)

Models are the dummy representation of the real object. A climate model is as a mathematical representation of the climate system based on physical, biological and chemical principles . Heterogeneity of climate makes it challenging for our understanding so, climate models evolved as an attempt to describe the physical world (e.g. its chemistry, physics, fluid dynamics, biology) within a mathematical and numerical framework and developed to test our understanding in comparison with observations. Climate Models can make predictions about future state of the atmosphere. GCMs are evolved from the very first assessment report of IPCC to the present assessment report and have the potential to provide topographic and physically consistent estimates of regional climate change which are required in impact analysis. GCMs illustrate our climate using three dimensional grids over the globe (See Figure 2). The horizontal resolution of GCMs varies between 150 to 600 km, 10 to 20 vertical layers in the atmosphere and sometimes almost 30 layers in the ocean. The finest horizontal resolution in the recent assessment report i.e. AR5 is 0.5^0 x 0.5^0.

3.3.2 Building of General Circulation Model

Just like an architect who sketches the structure of a building to understand and predict its behavior, the climatologist builds a computer-based model (See Figure 3) of the climate system to understand and predict its behavior.

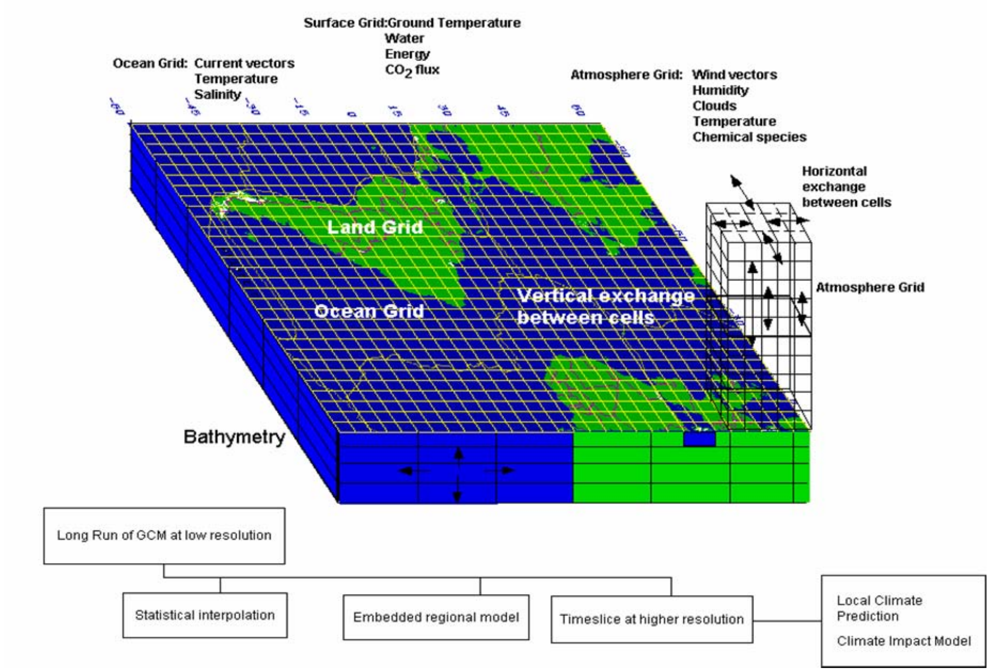

Figure 3: Structure of a typical General Circulation Model

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Every group of climate modellers come up with a different representation of the climate processes that explains the choice of initial, boundary and parameter condition assumptions. GCMs are based on well-established physical principles and have been demonstrated to reproduce observed features of past and future climate changes. The GCMs divides the atmosphere, ocean and earth into grids and are formed by a set of differential equations that describe fluid motion, radiative transfer, earth energy balance approach etc.

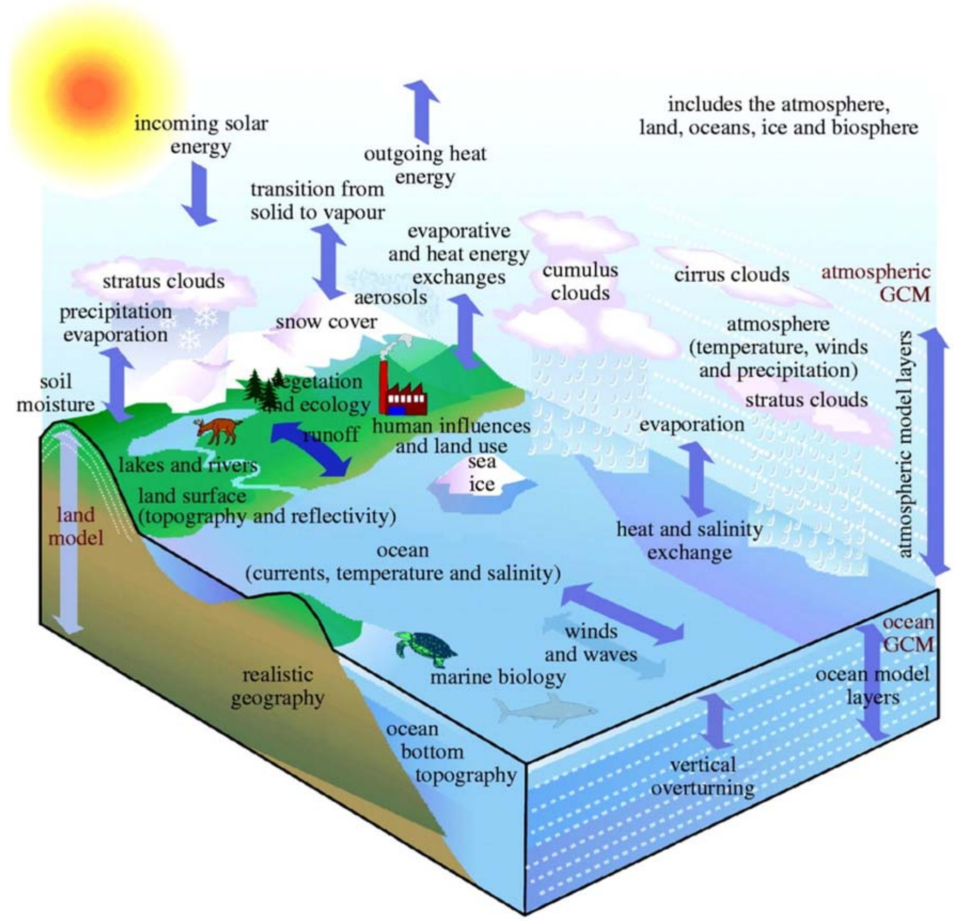

Figure 4: Schematic of the components of the NCAR Community Climate System Model, which is supported by the National Science Foundation (NSF) and the Department of Energy (DOE). Adapted from Kevin Trenberth (NCAR)

Each grid contains the calculated value of the various climatic variables like water vapor and cloud atmospheric interactions, direct and indirect effects of aerosols on radiation and precipitation, changes in snow cover and sea ice, the storage of heat in soils and oceans, surfaces fluxes of heat and moisture, and large-scale transport of heat and water by the atmosphere and oceans etc (See Figure 4).The calculated values of climatic variable in each grid are nothing but the solution of the differential equations. The GCMs again are designed in such a way that the time steps involved are the function of grid size therefore, the finer the resolution the shorter the interval between two set of calculated values. For example, a model with a 100 km horizontal resolution and 20 vertical levels would typically use a time-step of 10–20 minutes.

Following are the list of fundamental equations that is used to solve the climate models:

1. Conservation of energy (first law of thermodynamics)
2. Conservation of momentum (Newton’s second law of motion)
3. Conservation of mass (the continuity equation)
4. Ideal gas law (atmosphere only)

It is a demanding fact among researchers that the models must also be able to handle shorter-term fluctuations such as those associated with El Nino Southern Oscillations (ENSO). Recent developments in climate modeling, which take into account not only superficial processes at the interface of ocean and atmosphere but also those acting deep inside the ocean, have produced considerable improvement. An oceanic GCM typically requires

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very high spatial resolution to capture eddy processes associated with the major ocean currents, bottom topography and basin geometry.

In the context of Chilka Lake, climate change is expected to have implications for many of its wetland features. More intense rainfall spells are also projected in a warmer atmosphere, increasing the probability of extreme rainfall events. State level assessments based on downscaling of global circulation models (GCM) also confirm the trend. A decline in rainfall during the dry period (September–February) is projected along with an increase in summer and monsoon rainfall coupled with an increase in maximum rainfall. An increased incidence of hydrological extremes is projected. Basin level assessments of impacts of climate change on hydrology also indicate an increasing variability of flows within Mahanadi River. The basin is predicted to receive comparatively higher level of precipitation in future and a corresponding increase in evapo-transpiration and water yield. Given the fact that much of the river flows are concentrated during the months of monsoon, enhanced flows would exacerbate flood conditions as well as pose a serious risk to the current flood regulation infrastructure. Changes are also predicted in the coastal processes. The Bay of Bengal has recorded the maximum annual sea level rise of 2.42 – 4.87 mm within the Indian coast. Sea level rise has implications for salinity as well as livelihoods of coastal communities in Chilka. A key response strategy in Chilka management is to assess the vulnerability of Chilka to these changes through scenarios, and develop an adequate response strategy to secure wise use. The GCMs could not be used unambiguously over a small catchment like Chilka due to their coarse resolution which makes them limited for the impact assessment. So, getting climate information at local scale with high reliability from GCMs can be achieved if somehow we can incorporate a downscaling of coarser resolution information to the finer resolution. In the subsequent sections we will discuss about how downscaling can be achieved using the GCMs.

3.3.3 Climate of Chilka Lake from GCMs simulations:

3.3.3.1 Precipitation change Chilka Lake: For analysis of past and future projection of precipitation over the Chilka Lake, different data sources are used which includes fifteen number of GCMs from the Coupled Model Intercomparison Project phase three (CMIP3), high resolution ($1^0 \times 1^0$) gridded rainfall data from Indian Meteorological Department (IMD), high resolution ($0.5^0 \times 0.5^0$) gridded precipitation data (**CRU TS3.21**) fromClimatic Research Unit (CRU) and high resolution ($0.5^0 \times 0.5^0$) gridded precipitation data (**GPCC V6.0**) from Global Precipitation Climatology Centre (GPCC). Two different time periods namely 1901-2000 and 2001-2099 are considered for the analysis of precipitation for past and future respectively. Trend and percentage change of rainfall over the lake was studied for both the time periods using each of the dataset. As the data sets are in gridded format, the precipitation time series for each of the dataset over the lake was calculated by the method of bilinear interpolatation technique. Trend analysis was carried out using the non-parametric Mann-Kendall trend test where the Sen's slope represents the actual magnitude of the trend. The percentage change of precipitation over the lake were estimated by multiplying the Sen's slope with the period length and divided by the long mean precipitation of the corresponding season. Long term trend and percentage change of rainfall were analysed for both the time period. In case of future projection of precipitation, the percentage change was calculated by considering the past long term past data as reference period.

The results obtained from the analysis shows that, the past/observed (IMD) long term precipitation has non-significant increasing trend in annual and all the seasons except the post-monsoon (October-November). Similar results were also obtained from the CRU and GPCC data. The trend analysis of past precipitation for each of the seasons are mentioned in Table 1. Annual rainfall has shown highest increasing trend (87 mm/100yr) in IMD data sets but, in case of CRU and GPCC the trend is nearly 70 and 29 mm/100 year respectively. The monsoon (June to September) season has shown an increasing trend of almost 65 mm/100yr for both the IMD and CRU datasets, only the post-monsoon season has only shown a similar decreasing trend (-10 mm/100yr) for all the three data sets of IMD, CRU and GPCC. Most of the GCMs were failed to simulate an increasing trend of precipitation over the Chilka Lake. The GCMs which could able to simulate an increasing annual, monsoon and pre-monsoon trend in the past are CCCMA-T63, CSIRO-MK3.0, INGV-ECHAM4 and IPSL. Almost half of the GCMs in each season are simulated similar trend as observed data but the other half failed to do so. A seasonal cycle analysis of those GCMs which are showing similar trend as observed is helpful in finding the suitable set of GCMs for downscaling of precipitation over the Chilka Lake. It is found that four GCMs namely CCCMA-T63, INGV-ECHAM4, MPI

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and UKMO-HadCM3 are the suitable GCMs for simulating observed annual precipitation over the Chilka Lake (Analysis is not shown here).

Table 1: Long term trend along with Sen's slope (mm/100year) of precipitation over Chilka Lake for the period 1901-2000.

Bold letters: 90% confidence level

GCM ID	Sen's Slope/100year (mm)				
	Annual	**MAM**	**JJAS**	**ON**	**DJF**
BCCR	-36.8	16.6	-9.2	-41.0	1.3
CCCMA-1	-5.2	-10.3	-14.1	12.4	-3.6
CCCMA-t63	81.9	**21.7**	1.8	19.8	**20.1**
CNRM	-106.6	**-38.7**	-34.0	-7.7	-44.1
CSIRO-MK3.0	30.1	26.8	26.5	-1.9	-1.5
GFDL-CM2.0	**-209.1**	-0.6	**-184.0**	-27.4	3.3
GISS	-50.0	-0.4	-22.7	-8.2	0.8
INGV-ECHAM4	165.5	8.9	**119.0**	35.0	5.6
INM	60.9	-1.6	-13.3	21.6	-3.2
IPSL	42.2	16.8	44.9	-5.5	11.9
MIROC-H	**-248.7**	3.4	**-158.5**	**-82.9**	-3.4
MIROC-M	-115.6	**-8.9**	10.9	**-77.8**	-4.7
MPI	76.8	-1.8	54.5	37.9	-5.0
MRI	-60.0	27.0	**-78.5**	-4.6	1.4
UKMO-HadCM3	119.7	-4.0	**99.0**	23.2	-4.7
IMD1	87.5	19.9	67.8	-10.3	3.2
CRU-0.5	70.4	18.8	64.6	-10.0	-5.7
GPCC-0.5	28.6	19.6	1.1	14.3	4.1

Future projection of precipitation over the Chilka Lake shows a more consistent result, where most of the GCMs are showing significant increasing trend of precipitation for Annual, Pre-Monsoon and Monsoon

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season. In case of post-monsoon and winter (December, January, and February) majority of the GCMs are showing decreasing trend. The trend analysis of future precipitation for each of the seasons are mentioned in Table 2. A seasonal cycle analysis and trend comparison with the observed data for the evaluation of the GCMs shows that, BCCR, CCCMA-1, CCCMA-t63, CNRM-CM3, INGV-ECHAM4, MIROC-H, MIROC-M, UKMO-HadCM3 are the suitable set of GCMs to downscale annual rainfall over the Chilka Lake (analysis not shown here). The increasing trend of annual precipitation varies from a minimum of 38.0 mm/99 year to a maximum of 333.3 mm/99yr showing a greater uncertainty among the GCMs in simulating the observed precipitation. In monsoon season six GCMs are projected a significant (90% level) increasing trend which varies from 151.4 mm/99yr to 283.5 mm/99yr.

Table 2: Long term trend along with Sen's slope (mm/100year) of precipitation over Chilka Lake for the period 2001-2099.

Bold letters: 90% confidence level.

GCM ID	Sen's Slope/99year (mm)				
	ANU	MAM	JJAS	ON	DJF
BCCR	**137.4**	-14.7	35.1	**90.5**	30.2
CCCMA-1	**97.8**	**47.3**	33.9	-1.8	5.9
CCCMA-t63	87.7	**25.8**	17.1	16.5	**26.1**
CNRM	42.2	**-43.7**	**175.2**	-47.9	-31.1
CSIRO-MK3.0	95.1	4.8	56.4	**-5.2**	**-4.6**
GFDL-CM2.0	**-156.7**	-2.8	**-213.2**	**64.4**	0.0
GISS	**243.9**	**7.7**	**197.3**	21.0	13.7
INGV-ECHAM4	167.4	11.2	42.3	81.2	2.8
INM	**172.9**	-4.2	**283.5**	-33.0	-31.5

IPSL	**-251.3**	**-10.4**	**-178.6**	**-54.5**	**-13.9**
MIROC-H	**333.3**	-9.6	**223.3**	41.9	**12.9**
MIROC-M	**256.0**	7.4	**151.4**	**92.7**	-19.6
MPI	61.7	2.1	26.8	-43.2	-0.3
MRI	38.0	**40.2**	-24.9	1.3	-0.5
UKMO-HadCM3	**206.3**	-2.0	**244.4**	-32.2	-6.7

Percentage change of observed annual and monsoon precipitation in the time period 1901-2000 shows 7 to 8% (IMD) increase over 100 year period. The pre-monsoon season has received a higher percentage of rainfall over the 100 year period with an increase of almost 22% whereas the post-monsoon has shown a 3.6% decrease of rainfall over the years. Half of the GCMs are showing the rainfall has increased over the 100 year in different seasons whereas the other half showing the precipitation has decreased over the Chilka Lake during 1901-2000. The percentage change of precipitation for each of the GCMs during the past time period is mentioned in Table 3. Overall increasing or decreasing of precipitation during the past time period for the GCMs varies in between 10-30%. In case of future projection of GCMs the results shows that, the Lake will receive 5-25% of precipitation during annual, pre-monsoon, and monsoon season as compared to the past rainfall. In case of winter and post-monsoon most of the GCMs simulated a decrease of rainfall over the Chilka Lake. The percentage change of precipitation for each of the GCMs during the future time period are mentioned in Table 4.

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Table 3: Percentage change of precipitation over Chilka Lake for the period 1901-2000.

1901-2000	% change of rainfall (1901-2000)				
	ANNUAL	MAM	JJAS	ON	DJF
BCCR	-2.60	13.57	-1.10	-13.45	0.83
CCCMA-1	-0.36	-9.53	-1.29	6.54	-7.38
CCCMA-t63	4.57	16.32	0.14	6.89	28.36
CNRM	-5.77	-15.61	-3.69	-1.68	-19.74
CSIRO-MK3.0	3.91	7.90	6.87	-7.91	-7.18
GFDL-CM2.0	-14.86	-3.38	-15.54	-15.28	12.88
GISS	-5.64	-0.78	-3.91	-4.55	1.07
INGV-ECHAM4	11.07	6.46	12.78	9.89	7.64
INM	4.03	-4.05	-1.20	10.72	-2.03
IPSL	5.72	28.42	11.85	-2.43	16.10
MIROC-H	-16.36	4.82	-13.44	-35.25	-9.79
MIROC-M	-8.45	-29.33	1.15	-26.36	-4.92
MPI	7.02	-1.97	6.75	22.50	-18.40
MRI	-11.14	28.49	-18.94	-29.39	10.50
UKMO-HadCM3	8.46	-9.58	8.81	12.13	-8.17
IMD1	7.10	21.73	8.36	-3.57	7.76
CRU-0.5	5.06	19.28	6.28	-4.46	-13.74
GPCC-0.5	2.35	19.55	0.14	5.51	9.70

Table 4: percentage change of precipitation over Chilka Lake for the period 2001-2099

GCM ID	% change (2001-2099) with respect to 1901-2000				
	ANU	MAM	JJAS	ON	DJF
BCCR	9.6	-11.9	4.2	29.4	19.1
CCCMA-1	6.7	43.3	3.1	-1.0	11.9

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CCCMA-t63	4.8	19.2	1.3	5.7	36.4
CNRM	2.3	-17.4	18.9	-10.4	-13.8
CSIRO-MK3.0	12.2	1.4	14.5	-21.4	-21.9
GFDL-CM2.0	-11.0	-15.4	-17.8	35.5	0.0
GISS	27.2	14.8	33.6	11.5	18.2
INGV-ECHAM4	11.1	8.1	4.5	22.7	3.8
INM	11.3	-10.5	25.2	-16.2	-19.8
IPSL	-33.7	-17.4	-46.7	-23.8	-18.6
MIROC-H	21.7	-13.5	18.7	17.6	36.7
MIROC-M	18.5	24.0	15.8	31.1	-20.3
MPI	5.6	2.3	3.3	-25.4	-1.1
MRI	7.0	42.0	-5.9	8.5	-3.7
UKMO-HadCM3	14.4	-4.9	21.5	-16.7	-11.5

3.3.2 Temperature change Chilka Lake

Past Temperature change: Past temperature change was assessed through the historical runs of 54 GCMs from the IPCC CMIP5. We have chosen a location (Lat: 19.71^{o}N and Long: 85.31^{o}E), which is within the domain of Chilika lake, then each GCMs outputs were interpolated to each location through bi-linear interpolation techniques. The results shows that annual temperature changes for selected GCMs ranges 0.12 to 1.05^{o}C during the last century (analysis is not shown in here). It is also to be noted the multiple model ensemble using 54 models indicate a nominal change (0.48^{o}C/ 106 years) over the Chilka Lake. It is also observed that some GCMs were unable to reproduce the warming trend of observation.

Future Temperature change: The future temperature change over Chilka Lake is for four Representation Concentration Pathways (RCPs) assessed from 107 ensemble members from more than 54 GCMs available in CMIP5

The analysis or calculative part for future change is similar to that of analysis for the past. RCP26 is the lowest scenarios, which describe that the greenhouse gas concentration peaks at around 420 ppm and begins to reduce slowly towards 360 ppm by 2300. Two stabilization scenario RCP45 (low-high scenario) and RCP60 (medium high scenario) pictorize that greenhouse gas concentrationstabilizes about 540 ppm by 2100 and the medium-high scenario greenhouse gas concentration reaches about 670 ppm by 2100 and stabilize at around 750 ppm thereafter. The Temperature change according to each GCMs are assessed for fours RCPs for annual and four seasons namely pre monsoon, Monsoon, post monsoon and winter and resulted are displayed in the Table 6.

Table 6: Future temperature over Chilka using CMIP5 models during 2006-2100

	RCP26			**RCP45**			**RCP60**			**RCP85**		
Model	**ANN**	**JJAS**	**DJF**	**ANN**	**JJAS**	**DJF**	**ANN**	**JJAS**	**DJF**	**ANN**	**JJAS**	**DJF**
ACCESS1-0	NA	NA	NA	2.38	2.15	2.47	NA	NA	NA	4.68	4.06	5.39
ACCESS1-3	NA	NA	NA	2.29	2.22	2.34	NA	NA	NA	4.43	4.54	4.52
bcc-csm1-1	0.82	0.32	0.87	1.43	1.03	1.69	1.84	1.35	2.21	3.45	2.74	4.13
bcc-csm1-1-m	0.84	0.66	0.52	1.12	0.99	1.39	1.58	1.44	1.52	NA	NA	NA
BNU-ESM	1.00	0.47	0.50	1.83	1.24	2.25	NA	NA	NA	3.77	3.24	4.08
CanESM2	1.43	1.38	1.19	1.86	2.00	2.11	NA	NA	NA	4.47	4.78	4.56

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CanESM2	1.37	1.07	0.92	1.83	1.59	2.22	NA	NA	NA	4.20	4.11	4.24
CanESM2	1.43	0.94	0.93	1.90	1.74	2.19	NA	NA	NA	4.53	4.48	4.81
CanESM2	1.43	1.11	1.17	NA	NA	NA	NA	NA	NA	4.14	4.11	4.30
CanESM2	1.40	1.41	0.89	NA	NA	NA	NA	NA	NA	4.27	3.87	4.61
CCSM4	1.03	0.30	0.48	1.54	1.28	2.03	1.97	1.91	1.72	3.73	3.46	4.09
CCSM4	0.90	0.36	0.11	1.19	0.97	1.50	1.90	1.84	1.98	3.46	3.31	3.62
CCSM4	0.94	0.51	0.48	1.00	1.02	0.98	2.21	1.94	2.42	3.59	3.27	3.83
CCSM4	0.88	0.28	0.08	1.27	1.34	1.15	2.01	1.88	2.27	3.54	3.27	3.90
CCSM4	0.97	0.17	0.31	NA	NA	NA	2.22	1.92	2.25	3.50	3.14	3.65
CCSM4	0.94	0.44	0.28	NA	NA	NA	2.15	2.26	2.03	3.62	3.41	3.89
CESM1-BGC	NA	NA	NA	1.10	0.94	1.28	NA	NA	NA	3.13	3.02	3.16
CESM1-CAM5	0.95	1.22	1.35	2.45	2.25	3.05	2.92	2.83	3.21	4.35	4.02	4.87
CESM1-CAM5	1.04	1.29	1.03	NA	NA	NA	2.88	2.67	3.26	4.35	4.04	4.92
CESM1-CAM5	1.07	1.24	1.27	NA	NA	NA	2.95	2.87	3.29	NA	NA	NA
CMCC-CM	NA	NA	NA	NA	NA	NA	NA	NA	NA	5.33	4.99	5.89
CMCC-CMS	NA	NA	NA	NA	NA	NA	NA	NA	NA	5.45	5.41	5.99
CNRM-CM5	0.81	0.10	1.41	1.49	1.16	1.96	NA	NA	NA	3.01	2.75	3.23

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CNRM-CM5.1	NA	NA	NA	NA	NA	NA	NA	NA	NA	3.19	2.76	3.58
CNRM-CM5.2	NA	NA	NA	NA	NA	NA	NA	NA	NA	3.15	2.69	3.45
CNRM-CM5.3	NA	NA	NA	NA	NA	NA	NA	NA	NA	3.35	2.98	3.60
CSIRO-Mk3-6-0	1.11	1.74	1.52	2.84	2.52	3.33	NA	NA	NA	3.12	2.61	3.66
CSIRO-Mk3-6-0	1.04	1.29	1.57	2.76	2.41	3.15	2.76	2.43	3.16	4.72	4.18	5.26
CSIRO-Mk3-6-0	1.13	1.42	2.32	2.47	2.01	2.89	2.34	1.91	2.70	4.50	3.78	5.36
CSIRO-Mk3-6-0	1.09	1.34	1.68	2.82	2.05	3.65	2.35	1.61	2.83	4.63	3.97	5.58
CSIRO-Mk3-6-0	1.07	1.14	1.45	2.74	2.32	3.30	2.56	1.76	3.47	4.87	4.10	5.73
CSIRO-Mk3-6-0	1.04	1.24	1.55	2.74	2.37	3.25	2.28	1.64	2.69	4.68	3.81	5.38
CSIRO-Mk3-6-0	1.05	1.03	1.88	2.82	2.52	3.32	2.65	2.04	3.49	4.69	4.07	5.34
CSIRO-Mk3-6-0	1.08	1.65	1.17	2.74	2.45	3.26	2.52	1.77	3.12	4.79	4.11	5.70
CSIRO-Mk3-6-0	1.00	1.71	1.70	NA	NA	NA	2.71	2.31	3.29	4.82	4.19	5.61
CSIRO-Mk3-6-0	1.02	1.50	1.85	NA	NA	NA	2.79	2.42	3.34	4.58	3.76	5.36
CSIRO-Mk3-6-0.9	NA	NA	NA	NA	NA	NA	2.59	2.49	2.86	4.69	4.08	5.04
EC-EARTH	0.91	0.42	1.01	1.71	1.23	2.51	NA	NA	NA	3.82	3.37	4.15
EC-EARTH	0.93	0.34	0.72	1.75	1.39	2.20	NA	NA	NA	3.75	3.37	3.92

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EC-Earth	NA	NA	NA	1.55	1.26	1.93	NA	NA	NA	3.72	3.28	4.37
EC-EARTH.2	NA	NA	NA	1.90	1.40	2.47	NA	NA	NA	3.70	3.53	4.12
EC-EARTH.3	NA	NA	NA	1.83	1.36	2.48	NA	NA	NA	3.61	3.43	3.89
EC-EARTH.4	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.55	1.28	2.13
EC-EARTH.5	NA	NA	NA	NA	NA	NA	NA	NA	NA	3.74	3.39	3.91
EC-EARTH.6	NA	NA	NA	NA	NA	NA	NA	NA	NA	3.75	3.41	4.28
FGOALS_g2	0.70	-0.23	0.53	0.77	0.34	1.02	NA	NA	NA	2.28	1.31	3.18
FIO-ESM	0.81	0.16	0.14	1.24	1.34	1.15	1.68	1.76	1.52	3.75	3.91	3.77
FIO-ESM	0.81	0.20	-0.10	1.14	1.02	1.31	1.64	1.36	1.77	3.20	3.15	3.12
FIO-ESM	0.77	0.23	0.14	NA	NA	NA	1.62	1.43	1.77	3.34	3.54	3.36
NOAA	1.33	1.60	1.68	2.80	2.80	2.88	3.07	3.31	2.86	5.32	5.22	5.84
NOAA	0.63	0.08	-0.42	NA	NA	NA	1.69	1.90	1.19	3.44	3.25	3.53
NOAA	0.81	0.00	-0.09	NA	NA	NA	1.95	2.05	1.61	3.69	3.65	4.09
GISS-E2-H	0.68	0.39	0.29	1.25	1.03	1.32	1.38	1.19	1.48	2.71	2.25	3.29
GISS-E2-H	0.64	0.63	0.30	1.09	0.90	1.37	1.85	1.93	1.94	2.84	2.71	3.47

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GISS-E2-H	0.84	0.09	0.67	1.06	0.86	1.31	1.78	1.78	2.02	2.81	2.26	3.59
GISS-E2-H.3	NA	NA	NA	0.82	0.53	0.91	1.36	1.03	1.71	NA	NA	NA
GISS-E2-H.4	NA	NA	NA	1.34	1.08	1.59	1.34	0.77	1.98	NA	NA	NA
GISS-E2-H.5	NA	NA	NA	1.73	1.58	2.09	1.48	0.94	2.02	NA	NA	NA
GISS-E2-R	0.57	0.04	0.25	1.09	0.98	1.31	NA	NA	NA	2.18	1.61	2.81
GISS-E2-R	0.45	-0.05	-0.20	0.80	0.34	1.17	NA	NA	NA	2.13	1.56	2.81
GISS-E2-R	0.64	0.54	0.40	0.93	0.88	1.07	NA	NA	NA	2.46	1.73	3.11
GISS-E2-R.3	NA	NA	NA	0.71	0.57	1.02	NA	NA	NA	NA	NA	NA
GISS-E2-R.4	NA	NA	NA	1.03	0.78	1.43	NA	NA	NA	NA	NA	NA
GISS-E2-R.5	NA	NA	NA	1.16	0.99	1.34	NA	NA	NA	NA	NA	NA
GISS-E2-R.6	NA	NA	NA	1.21	1.20	1.32	NA	NA	NA	NA	NA	NA
GISS-E2-R.7	NA	NA	NA	1.49	1.09	1.85	NA	NA	NA	NA	NA	NA
GISS-E2-R.8	NA	NA	NA	1.35	1.09	1.66	NA	NA	NA	NA	NA	NA
GISS-E2-R.9	NA	NA	NA	1.46	1.15	1.59	NA	NA	NA	NA	NA	NA
GISS-E2-R-CC	NA	NA	NA	1.01	0.89	1.25	NA	NA	NA	NA	NA	NA
HadGEM2-AO	0.63	0.69	0.87	2.23	1.54	2.81	2.68	2.30	2.70	4.66	3.95	5.05

HadGEM2-ES	0.64	0.62	0.72	2.60	2.22	2.78	NA	NA	NA	4.69	3.79	5.31
HadGEM2-ES	0.64	0.64	0.49	2.62	2.35	2.75	2.97	2.88	2.89	4.93	4.34	5.35
HadGEM2-ES	0.78	1.24	1.75	2.61	2.45	2.57	2.62	2.23	2.44	4.66	4.23	4.78
HadGEM2-ES	0.67	1.35	1.29	NA	NA	NA	2.81	2.19	3.13	4.86	4.19	5.08
HadGEM2-ES.3	NA	NA	NA	NA	NA	NA	NA	NA	NA	4.80	4.37	5.15
inmcm4	NA	NA	NA	1.26	1.11	1.48	NA	NA	NA	3.05	2.45	3.77
IPSL-CM5A-LR	1.31	0.94	0.87	2.23	2.13	2.18	2.37	2.37	2.23	4.73	4.63	4.49
IPSL-CM5A-LR	1.24	0.64	0.80	2.07	1.70	2.28	2.42	2.38	2.26	4.70	4.49	4.65
IPSL-CM5A-LR	1.28	0.86	0.91	2.11	1.74	2.43	NA	NA	NA	4.78	4.65	4.41
IPSL-CM5A-LR	1.30	0.85	0.59	NA	NA	NA	NA	NA	NA	4.68	4.49	4.43
IPSL-CM5A-MR	1.11	0.66	0.60	1.18	0.89	1.28	NA	NA	NA	4.69	4.55	4.40
IPSL-CM5B-LR	NA	NA	NA	1.61	1.20	2.09	NA	NA	NA	3.24	2.96	3.41
MIROC5	0.78	0.48	1.13	1.74	1.27	2.04	1.88	1.53	2.26	3.22	2.53	3.92
MIROC5	0.79	0.66	1.11	NA	NA	NA	1.90	1.66	2.27	3.50	2.89	4.04
MIROC5	0.79	0.78	1.13	NA	NA	NA	1.98	1.75	2.12	3.32	2.65	3.91
MIROC-ESM	1.01	0.65	1.13	NA	NA	NA	2.81	2.45	3.11	5.00	4.42	5.32

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MIROC-ESM-CHEM	1.04	0.35	0.27	1.56	1.22	1.85	2.95	2.80	2.99	5.46	4.94	6.04
MPI-ESM-LR	1.11	0.36	0.56	NA	NA	NA	NA	NA	NA	4.79	4.36	5.35
MPI-ESM-LR	1.10	0.55	0.54	NA	NA	NA	NA	NA	NA	4.61	4.58	4.75
MPI-ESM-LR	1.06	0.68	0.72	NA	NA	NA	NA	NA	NA	4.78	4.63	5.16
MPI-ESM-MR	1.00	0.54	0.36	1.70	1.58	1.98	NA	NA	NA	4.39	4.07	5.03
MPI-ESM-MR.1	NA	NA	NA	1.96	1.59	2.44	1.75	1.83	1.63	NA	NA	NA
MRI-CGCM3	0.36	0.82	-0.03	NA	NA	NA	NA	NA	NA	3.65	3.39	3.96
NorESM1-M	0.76	0.65	0.66	1.20	1.25	1.05	1.81	1.98	1.68	3.58	3.56	3.51
NorESM1-ME	0.76	0.45	0.84	1.48	1.32	1.50	1.89	2.04	1.52	3.32	3.13	3.12
MME	**0.95**	**0.73**	**0.82**	**1.71**	**1.45**	**2.00**	**2.21**	**1.98**	**2.39**	**3.98**	**3.59**	**4.34**

We have observed that temperature over Chilka Lake is likely to be increased by each of the GCMs with varying magnitudes at the end of 21st. All the ensemble member of the models of four RCP is assessed separately and is given in Table 6. Literature review reveals that individual model may sometimes over estimate or under estimate compare to true observation, so we have calculate the multi model ensemble of all the available models for a particular RCPs. In general values of multi model are considered to be more reliable thanthe result from a single GCM. However it is always better to consider a set of good performing model for any impact assessment study. Multiple Model Ensemble (MME) shows that the annual mean temperature of Chilka lake will increase from 0.95^{o}C to 3.98 ^{O}C at the end of 21st century. is The stude reveals that the winter warming will be more(0.82-4.34 ^{O}C) compared to monsoon(0.73-3.59^{O}C).

3.4 Downscaling

'Scaling' means transforming a quantity measured at one scale so that it applies at some different scale. There are two types of scaling one is upscaling/aggregation and the other is downscaling. Upscaling is often a form of extrapolation to a larger extent or coverage and downscaling applies to a narrower or finer scale. In this book we will only focus on downscaling in details.A lot of useful information can be derived from GCMs without the need of downscaling to be undertaken, but it is recognized that sometimes it is necessary to try and add value to a scenario by making it more applicable for finer resolution studies. Scenarios constructed at the original GCM resolution may lead to problems if there is a large discontinuity between adjacent grid boxes – this is particularly apparent at the land-ocean boundary, and sometimes for neighboring land grid boxes. The ocean response to a change in forcing is damped compared to that of the land, due to its large thermal inertia, so the changes seen over the ocean are generally smaller (in the case of temperature) than those over the land. The coarse resolution of the grid boxes may result in a box being designated as ocean, when it does in fact contain some land area in reality (Barrow, CCIS Project). The methods used to convert GCM outputs into local meteorological variables are usually referred to as downscaling techniques which can give more reliable information for local and regional scale.

Downscaling tries to bridge the spatial gap between what GCMs can deliver and what society/business/stakeholders require for decision-making (See Figure 5). It is well known that there are strong physical linkages between climate on the large scale and weather on the local scale (Liu and Fan, 2012). Downscaling has emerged as a potential tool to relate atmospheric circulation patterns to surface variables for forecasting, for studying climate variability and for predicting regional climates in the context of climate change.For the purposes of downscaling, it is better to use GCM variables which do not exhibit large scale variations, for example, mean sea level pressure. It is better to use primary GCM variables, i.e., those variables which are used by the model to determine other climate variables (for example mean surface air temperature and precipitation etc). In GCM precipitation is less likely to be simulated, since it is a parameterized variable. From late 19th century the idea of downscaling as evolved after release of IPCC’s first and second assessment report. From then scientist are trying to cascade down the GCM information to the local and regional scale.

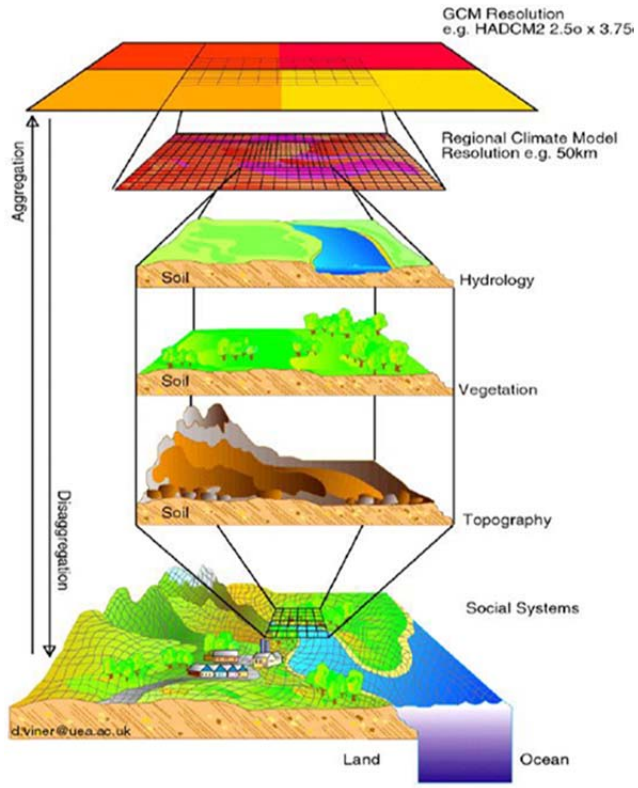

Figure 5: Schematic of Downscaling from a higher resolution GCM

3.4.1 Types of Downscaling: The different type of downscaling include**namely:** Simple Downscaling**, and** Dynamic Downscaling**. As for example Simple Downscaling is** one of the early and simple methods for downscaling is to obtaining finer resolution data by interpolates the coarse resolution data. This doesn't add any value to the scenarios - the change fields are simply being smoothed so that the discontinuities between adjacent grid boxes are not as large. However, this method introduces a false geographical precision to the scenario estimates. Delta method of downscaling comes under the simple downscaling approach.

3.4.1.1 Delta Method: In this method of downscaling Differences between GCM future and historical period are added to historical monthly or daily observations. Delta method is conceptually very simple and has been widely applied in studies related to water planning, particularly prior to the second assessment report (SAR) published by the IPCC. Delta method evolved as an efficient tool for regional scale downscaling prior to IPCC's SAR when the resolution of GCMs were typically very low and they were only capable of simulating regional scale changes in temperature (T) and precipitation (P) (e.g. Lettenmaier*et al*. 1999). It is the most commonly used method in UK water industry assessments up to 2009. A common application of the delta method will apply monthly changes in climatic variables from a GCM, calculated at the regional scale, to the same set of climatic variables observed at a station or gridded records that are the inputs to a hydrologic model. The meteorological variables from the GCMs simulation are typically averaged over an historic period from a control simulation and a future period from a scenario simulation to estimate the changes. Multiplicative perturbations are used for precipitation to avoid potential sign problems (i.e. the potential to calculate negative precipitation using an additive approach), and additive perturbations are used with temperature to avoid problems with temperature not being on an absolute scale (i.e. the centigrade scale is zero at the freezing point of water at standard pressure, not at absolute zero).

3.4.1.2 Advantage and Limitation of the delta method: With this approach, the errors associated with the baseline period in the historical and future climate data are substantially reduced (Wang et al. 2012). In this method observed patterns of spatio-temporal variability from the gridded observations are retained (See Figure 6), and comparison between observation and future projection is straightforward and easily interpreted. For example, particular flood years in the observed record can be directly compared in the historic and future simulations. Delta method facilitates a direct comparison of different GCMs with different error statistics, different patterns of spatial and temporal variability, etc. A key drawback of the delta method is that potential changes in the variability or time series behavior of temperature and precipitation are not captured by this approach.

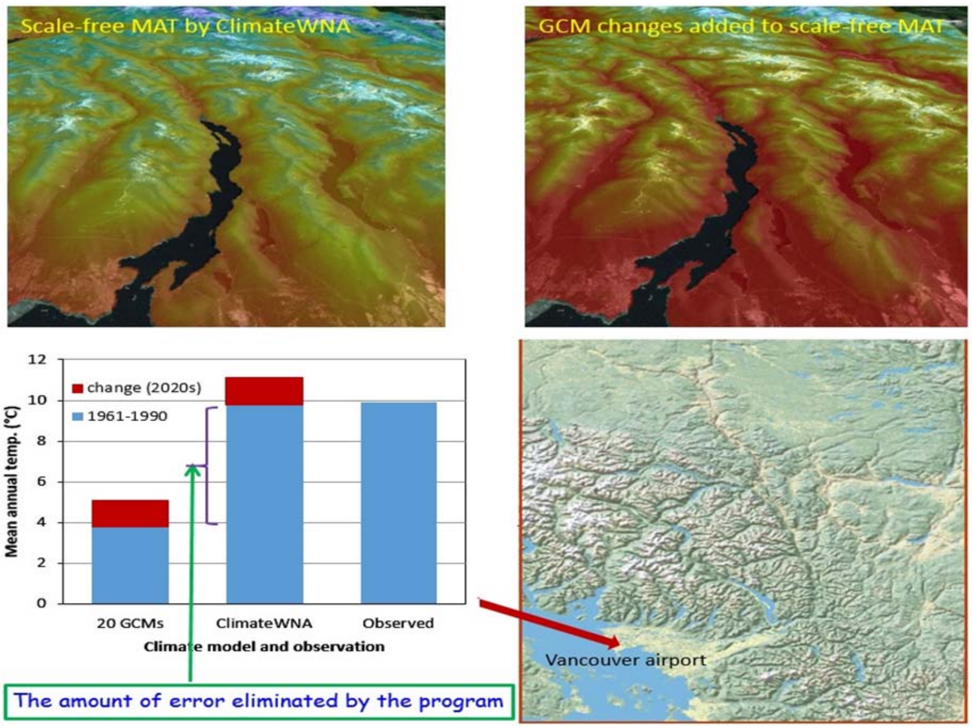

Figure 6: Delta method of downscaling where historical weather station data and GCM regional predictions used to project future seasonal and annual climate variables in BC, western North America and entire North America for the 1920s (Source ClimateWNA)

[NB: Climate WNA:It is a program to generate high-resolution climate data for climate change studies and applications in British Columbia and western North America. MAT acronym is used for mean annual temperature (in ^{0}C). Scale free climate data: To generate seamless geographical surfaces at high resolution, additional up-scaling techniques are required, effectively resulting in scale-free climate data]

a. Dynamic Downscaling

These downscaling techniques can be relatively simpler but involve high computation ability. For example, differences or anomalies between a future period and the present are calculated for each GCM grid cell, the anomalies are interpolated to a high resolution grid and the differences are added to observed climatology on the same high resolution grid (Tabor and Williams, 2010). An additional computation is usually employed for precipitation to scale modeled values so the changes are essentially converted to percent change that is consistent with observed values. Dynamical downscaling or regional climate modeling (RCM) also relies on output from GCM simulations. Output from GCM simulations is used to derive time-varying (for example, 6-hour) lateral (vertical profiles of temperature, humidity, wind) and surface (pressure and sea surface temperature) boundary conditions for a three-dimensional model domain that is selected to capture the important synoptic- and mesoscale atmospheric circulation features that determine the climatology of a region of interest. The 6-hour boundary conditions are assimilated along the four edges and surface (ocean) of the model domain and the RCM then simulates atmospheric circulation and surface interactions internally. Hence RCMs are comprehensive physical models, usually including the atmosphere and land surface components of the climate system, and containing representations of the important processes within the climate system (e.g., cloud, radiation, rainfall, soil hydrology). Many of these physical processes take place on much smaller spatial scales than the model grid and cannot be modelled and resolved explicitly. Their effects are taken into account using parametrizations, by which the process is represented by relationships between the areas or time averaged effect of such sub-grid scale processes and the large scale flow.

i. **Limitation Dynamical Downscaling:** The main drawback is its computational cost, of dynamical downscaling which still substantially limits the possible RCM resolution and length of the experiments produced, reducing the capability of RCMs to capture the frequency and, to a greater extent, the changes in frequency of extreme weather events. Although regional climate models in general can improve on the details of GCM simulations through dynamical downscaling over complex terrain, they cannot, for example, improve upon or make substantial changes to features of the large-scale circulation or SSTs produced by a GCM. This means that, for example, if the jet stream is incorrectly placed in a GCM, it also will be incorrectly placed in the RCM. RCM uses the output from GCMs so any misleading information in GCM would lead to incorrect information in RCM outputs.

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b. Statistical Downscaling: Statistical downscaling is one of the widely used downscaling methods since it is computational cheaper and fast. Statistical downscaling is a two-step process consisting of

1. The development of statistical relationships between local climate variables such as surface air temperature, precipitation and large scale predictors such as sea level pressure
2. The application of such relationships to the output of GCM experiment to simulate local climate characteristics in the future.

These statistical models can be applied to different GCMs and we can get an idea of uncertainty associated with it. In climate change studies one of the important questions is implication of global warming for a local climate. GCMs are unable to answer such question because of its coarser spatial resolution. The local climate is assumed to be a function of large-scale situation x, local effects l, and global characteristics g, and can be written as

$$y= f (x,l,g)$$

The formula is described by Stroch*et al*. (2000) and Benestad *et al.* (2008). In statistical downscaling it is important that there is a strong underlying physical mechanism that links the large and small scale climate, as the lack of a physical basis cannot preclude the possibility of weak or coincidental correlations. The small scale is known as predictand and large scale is known as predictor. The detailed description of these two will be discussed in details in next sub heading. In addition, statistical downscaling facilitates a "correction" to the simulations, so that the observations and the downscaled output can be regarded as directly comparable. In this type of downscaling statistical models can be optimized for the prediction of certain parameters at desired locations, as for instance specified by user. This makes the statistical model approach ideal for individuals. Before going to further details we will give a brief over view about predictors and predictand and its relationship

3.4.3.1 Predictors

As describe in the previous paragraph predictors are large scale variable describing circulation regime of the atmosphere. The predictors are also called response variable or independent variable in statistical regression equation. These are the inputs variable and can be written mathematically as

Predictand = *f*(Predictors)

Or

$y=f(x)$

In this relation there may be one predictor or a group of predictor. To select the predictor/s for statistical downscaling certain criteria should be followed,

a. They should have a strong physical relationship to the predictand.
b. They should be reliably represented by the reanalysis data or GCM.
c. Predictor and predictand relationship should be stationary.
d. Model representation
e. Description of change
f. Predictors should not be strongly correlated to each other.

3.4.3.2 Physical Relationship

The basis of statistical downscaling is the assumption that there is a close link between the large-scale predictor and the small-scale predictand, thus

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developing a strong relationship between them. Without the strong relationship between predictor and predictand the model output will not be reliable or it could generate unrealistic outputs.

3.4.3.3 Availably of the predictor in Reanalysis and GCM data

Most reliable source for the predictors are reanalysis and GCM data. From the middle of 19th century there are many sources of reanalysis data namely NCEP/NCAR, ERAINT, MERRA, JRA etc. The statistical model is established with the past small scale data (predictand) and past large scale data (predictor). It is convenient to choose those predictors from the reanalysis data which are also available in GCM output because for future prediction we have to rely only on GCM.

3.4.3.4 Stationary

Another important aspect to statistical downscaling is the issue of stationarity (Wilby, 1997). This means that the statistical relationship between the predictor and the predictand does not change over time. For example, if we consider vegetation over the land as local effect, then over time the amount of vegetation will remain constant.

3.4.3.5 Model representation

In statistical downscaling takes the predictor as a given, and it is therefore important that the predictor is simulated well by the models. In other words, if the predictor parameter is unrealistic in nature, then the statistical model that will develop will also went wrong. The question of the degree to which the predictor is representable also depends on time scale. Model result as well as observation equally play important role for model calibration. Large

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uncertainties in the gridded observations introduce difficulties in terms of model evaluations as well as in the matching of simulated traits to observed ones, thus leading to a weak relationship.

3.4.3.6 Description of changes

It is important that the predictor parameter responds to given perturbations in a similar way as the predictand, or the ESD results will not capture the changes. This can also be seen from the simple mathematical expression describing an ideal situation: $y = F(X)$. If this equation truly is representative, the equality implies that y and F(X) respond the same way (Benestad*et al.* 2008).

3.4.3.7 Predictors should be uncorrelated

The predictors or response variable should be independent of each other. They should be uncorrelated to each other. Principal component analysis (PCA; see the discussion on EOFs in the next chapters) can remould the data so that the input to the statistical model is orthogonal to each other. Nevertheless, if two input variables are correlated with the predictand during the calibration period, and only one responds to a climate change, then it is likely that the ESD will fail to provide a good indicator about a climate change. It is therefore important to have a good physical understanding.

There are few example to represent the circulation pattern over a large region e.g. geopotential height, ENSO (EL Nino southern oscillation), NAO (North Atlantic Oscillation) etc.

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3.4.3.8 Predictand

The predictand is the output data, typically the small-scale variable representing the temperature or rainfall at a weather/climate station. The predictand is also known as dependent variable or response variable. In equation 2 ‘y’ is predictand. In statistical downscaling role of predictand is equaled important to that of predictor. We often discuss about the importance and sensitivity of the predictor but the user should keep in mind the predictand have also an important impact in framing the statistical model. Statistical model will be more reliable if the predictand or observed data is high quality and available for longer time series. Predictand data can be used for daily and monthly time scale as per requirement for establishing the model.

There are different methods of statistical downscaling they are as follows.

a. Linear methods
b. Weather classification/Typing and
c. Weather generator

2. Linear methods

Establish linear relationships between predictor and predictand. Linear methods are very easy and widely used by statistical downscaling community, and they can be applied to a single predictor-predictand relation or spatial fields of predictors-predictands. The greatest constraint is the necessity of a normal distribution of the predictor and the predictand values, which means that it cannot be used to predict the distribution of daily rainfall because it is generally non-normal. These methods are mainly used for spatial downscaling technique.

3. Weather classifications/Typing

The predictand is predicted based on predictor. The states can be identifiable synoptic weather patterns or hidden, complex systems. The future atmospheric state, simulated by a GCM, is matched with its most similar historical atmospheric state. The selected historic atmospheric state then corresponds to a value or a class of values of the local variable, which are then replicated under the future atmospheric state. These methods are particularly well suited for downscaling non-normal distributions, such as daily rainfall. However, a large amount of observational daily data (e.g., 30 years of daily data for the region of interest) is required in order to evaluate all possible weather conditions. In addition, these methods are more computationally demanding in comparison to linear ones, due to the large amount of daily data analyzed and generated.

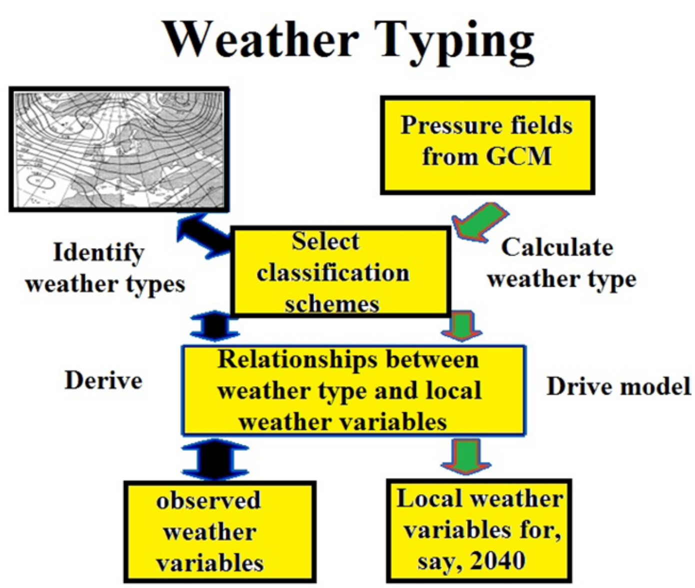

Figure 7: Schematic representation of the process of Weather Typing

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7 Weather generators

These statistical methods are typically used in temporal downscaling. For example, they are used to generate daily sequences of weather variables (e.g., daily precipitation, maximum and minimum temperature, humidity, etc.) that correspond to monthly or annual averages or amounts. Temporal downscaling is necessary for some impact models that require local spatial data at a daily resolution, which GCMs cannot reliably provide. Weather generators produce sequences of daily values, but since different weather sequences may be associated with a given set of, for example, monthly values, multiple sequences commonly are generated to be further used in impact models. Weather generators are data-intensive, require long sequences of daily data, and are sensitive to missing or erroneous data in the calibration set (Wilby et al., 2009). In addition, only some weather generators have the ability to account for the coherency among variables when multiple variables are predicted, e.g., to generate a daily sequence of insolation that matches the generated daily sequence of rainy and dry days.

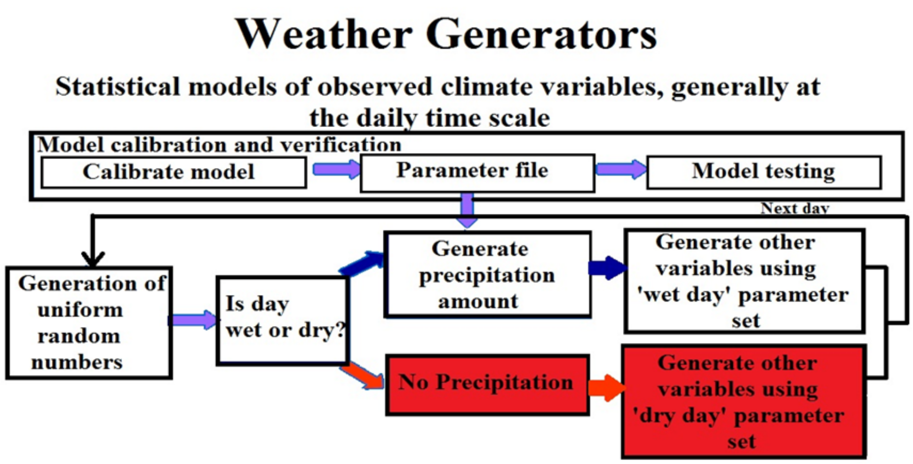

Figure 8: Schematic representation of the process of Weather generator

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8. Limitation of statistical downscaling

- The major weakness of statistical downscaling is the assumption that observed links between large-scale predictors and local predictands will persist in a changed climate.
- A problem when applying statistical downscaling techniques to daily values is that the observed autocorrelation between the weather at consecutive time steps is not necessarily reproduced. It is essential to reproduce this, a suitable method (e.g., weather generators; Katz and Parlange, 1996; Wilks, 1999) should be used.
- Statistical downscaling does not necessarily reproduce a physically sound relationship between different climate elements. Using a downscaling method based on weather classification for several predictands (e.g., Enke and Spekat, 1997) can minimize this problem.
- Successful statistical downscaling depends on long, reliable observational series of predictors and predictands.

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