Modeling of Temperature and Rainfall of West Bengal through Remote Sensing and GIS Techniques

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Abstract
This study proposes an empirical methodology for modeling and mapping of the seasonal air temperature and annual rainfall using remote sensing and GIS techniques. The study area is Gangetic West Bengal in the eastern India, where a number of weather systems occur throughout the year. Gangetic West Bengal is a region of strong heterogeneous surface with several weather disturbances. The land use/land cover, soil texture and digital elevation model are used as the independent variables for temperature modeling. Rainfall modeling is done using humidity, cloud cover, land use /land cover and relief of the study area. Standard deviation errors are evaluated after comparing the predicted and observed value of temperature and rainfall using real station observations of the area. Prediction of mean temperature for monsoon season is better than winter season. For better improvement distance from the coastline and seasonal wind pattern are stressed to be included as independent variables.

1. Introduction

Geographic information systems (GIS) and modeling are becoming powerful tools in agricultural research and natural resource management. Developing countries need an inexpensive and reliable method of spatial interpolation to make good for the lack of adequate number sampling stations for collecting data on the climatic variables that are necessary input for sound agricultural planning. Agricultural research seeks to evolve methods to deal with crop and soil variability, weather generators (computer applications that produce simulated weather data using climate profiles), and spatial interpolation, the estimation of the value of properties at unsampled sites within an area taking cue from the limited number of sampled points (Bouman et al., 1996). Especially in developing countries, there is a need for accurate and inexpensive quantitative approaches to spatial data acquisition and interpolation (Mallawaarachchi et al., 1996). Most data for environmental variables are collected from point sources. The value of an area between data points can be interpolated or modeled by fitting a suitable model to account for the expected variation. Interpolation approach for a given set of input data is especially true for areas such as mountainous regions, where data collection is sparse and measurements for given variables may differ significantly even at relatively reduced spatial scales (Collins and Bolstad, 1996).

Results of spatial interpolation and modeling contain a certain degree of error, and this error is sometimes measurable. The present study is undertaken with a view to providing suitable method in generating weather inputs over a large area using the limited number of stations of actual measurement. Reliable weather inputs when appropriately densified over a large region are paramount in spearheading agricultural development and hence propping the much needed food security of a developing country.

2. Study Area and Environmental Conditions

The study area is West Bengal in the eastern India. The study area corresponds to the LANDSAT-7 ETM+ imageries with path row numbers 138_43, 138_44, 138_45, 139_43, 139_44, 139_45, 140_43, 140_44 and 140_45. The region comprises with a semi-arid part in the west and south-west and relatively more moist and cool in the south and the east. Being the tail end of Chhotonagpur plateau, the terrain of the semi-arid part is more complex with higher elevation and permanent vegetation compared to the south and the eastern part of the study area. The region experiences four seasons having typical weather systems: monsoon (June through September) season, characterized by south-west monsoonal flow having a monsoon trough line through the region causing most of the annual rainfall; post-monsoon season (October through

November), being the transition season between the monsoonal flow and westerlies of winter season (December through February) in the upper levels, region experiences tropical storm on occasions; a part of the region, on the other hand, experiences the impact of western disturbances in winter; and frequent thunderstorm activity in the pre-monsoon season (March to May). Therefore, throughout the year, the study region experiences synoptic scale disturbances, such as monsoons and mesoscale weather systems leading to more complex patterns of climatic variables. This emphasizes the need for a better procedure to map the climatic variables in absence of dense network of observations.

3. Data Used

Different types of data sets are used for distribution map preparation of various climatic variables within the area.

- (i) Climate Research Unit (CRU) of East Anglia University, UK has developed a database of monthly gridded (0.5° x 0.5°) climate observations globally using various techniques (Mitchell and Jones, 2005) This data set contains nine climate variables, namely precipitation, daily mean temperature, monthly average daily minimum temperature, monthly average daily maximum temperature, diurnal temperature range, vapour pressure, cloud cover, wet day frequency and frost day frequency. Temperature and precipitation variables have been taken for our study.

- (ii) India meteorological department (IMD) has published monthly mean maximum & minimum temperature and monthly total rainfall of important stations (111) in India for the period 1901-2000. They have 677 automatic weather stations (AWS) and 1350 automatic rain gauge stations in India. Daily weather phenomena for 24 hour basis are also available from the website (http://www.imd.gov.in/). The IMD data sets are the real ground observation data set.

- (iii) One of the most widely used digital elevation model (DEM) data sources is the elevation information provided by the shuttle radar topography mission (SRTM) (Coltelli et al., 1996), but as with most other DEM sources, the SRTM data requires significant levels of pre-processing to ensure that there are no spurious artifacts in the data that would cause problems in later analysis such as pits, spikes and patches of no data (Dowding et al., 2004). In the case of the SRTM data, these patches of no data are filled, preferably with auxiliary sources of DEM data, like topographical maps. Both data sets used for our study.

- (iv) West Bengal soils sheets of National Bureau of Soil Survey (NBSS) and soil region map of national atlas & thematic mapping organization with different group of soil were used to generate soil texture map.

- (v) Optical bands with standard false color combination (SFCC) of LANDSAT 7 ETM+ satellite images were used to find out the land use/land cover classes in the study area. All other details of the variables, data spans along with the sources are given in the Table 1.

Table 1: Climate variables and topographical maps for spatial interpolation and modeling

Sl No	Average Climate Variables and other data sets	Scale/Data Resolution	Year / Range	Source
1	Mean Temperature, precipitation	30 minute	1901-2002	CRU TS 2.1; http://www.cru.uea.ac.uk
2	Monthly mean maximum & minimum temperature	Observed Station data	1901-2000	http://www.imd.gov.in
3	Topographical map	1:250000	1960	University of Texas Libraries, Austin
4		1:50000	1973-1980	Survey of India, Kolkata
5	LANDSAT-7, ETM+;	30 m	2000 – 2001	University of Maryland Institute for Advanced Computer Studies
6	National Atlas of India, Soil Region	1:2000000	1981	National Atlas & thematic Mapping Organisation, Department of Science and Technology, Govt. of India
7	Shuttle Radar Topography Mission (SRTM) data	3-arc seconds	2003	ftp://e0srp01u.ecs.nasa.gov

4. Spatial Interpolation

Interpolation techniques predict values for cells in a raster from a limited number of sample data points. It can be used to predict unknown values for any geographic point data: elevation, rainfall, chemical concentrations, noise levels, and so on. Interpolation methods can also be portrayed as "global" or "local" techniques. Global techniques (e.g. Inverse distance weighted averaging) fit a model through the prediction of variable over all points in the study area. Typically, global techniques do not accommodate local features well and are most often used for modeling long-range variations. Local techniques, such as splining, estimate values for an unsampled point from a specific number of neighboring points. Consequently, local anomalies can be accommodated without affecting the value of interpolation at other points on the surface (Burrough and McDonnell, 1998). Splining, for example, can be described as deterministic with a local stochastic component (Burrough and McDonnell, 1998). The ArcGIS and ERDAS IMAGINE software are used for spatial interpolation of the high resolution climate variables. CRU set is selected as a high resolution climate variable. Raster module of ArcGIS and ERDAS IMAGINE s/w are used to rectify the topographical map using the ground control points (GCPs) in the process of single image/map rectification. Geographical coordinate system and WGS84 datum and spheroid is used for this purpose. The vector modules of the two software- ArcGIS and ERDAS IMAGINE are used for creating a grid layer and a point layer for the entire study area. The climate variables like mean temperature and total rainfall data sets are introduced into the attribute table of the point layer. The monthly average and annual measurement of above climate variables are chosen for this purpose. The ArcGIS spatial analyst (ESRI, 1998) is used for spatial interpolation of the climate variables. A point data file and a covariate grid are used as inputs to the module. The program yields several output files: (i) a large residual file which is used to check for data errors; (ii) a file that contains an error covariance matrix of fitted surface coefficients; and (iii) an interpolated thematic map showing the distribution of the parameter. All the three interpolation methods, Inverse distance weighting, thin plate smoothing splines and kriging are used to interpolate the climate variables. After interpolation different sets of data (for all the months, seasons and annual) are generated to represent different climate variables spatially.

5. Modeling of Temperature and Rainfall

Spatially distributed estimates of temperature and rainfall are required as inputs to many environmental models. There is also an increasing demand for digital GIS-compatible maps of hydro-meteorological data (Daly et al., 2002). Hydro-meteorological data such as air temperature, humidity and rainfall are typically recorded at the ground level at a limited number of weather stations scattered over a region. Consequently, values have to be estimated at intermediate un-sampled locations in order to generate continuous surfaces for a whole area. In contrast to the methods described above, artificial neural networks (ANN) are particularly adept at handling massive amounts of data, dealing with complex nonlinear relationships, coping with non-normal and inter-correlated inputs, and allowing the incorporation of additional data and expert knowledge about a particular geographical domain within the estimation process (Bishop, 1995). ANNs are also able to select those values from a data set that have a large influence on the outcome, whilst giving little weight to other data. This robustness to redundant data could be used to incorporate flexibility about the number of stations and the number of covariate data sets that should be used on different days to form the best estimate of the temperature in a local area. Where it is appropriate, other types of data can also be incorporated into the ANN. ANNs can be used to estimate daily temperature with similar accuracy to the most sophisticated of the conventional methods, whilst requiring less stringent assumptions to be met about the data conditions (Rigol et al., 2001).

5.1 Modeling of Monthly Mean Temperature and Total Rainfall

Daily temperature data are relatively continuous and can often be estimated relatively accurately using data from only a small number of nearby stations and using a small number of environmental factors as covariates. After the inclusion of elevation as one covariate, including further covariates yielded only minor further overall improvements in the accuracy of estimations, although additional factors such as distance from the coast, distance from urban areas and local shelter did improve estimations locally for certain types of weather system (Jarvis and Stuart, 2001). In the atmosphere it is discovered that air temperature usually decreases with an increase in elevation through the troposphere. The decrease in temperature with elevation is called the environmental lapse rate of temperature *or* normal lapse rate of temperature. Recall that the normal lapse rate of temperature is the average lapse rate of temperature of 0.65° C / 100 meters. Average monthly soil temperature near the soil surface is calculated using equations developed by Parton (1984). The equations calculate maximum soil temperature as a function of the maximum air temperature and the canopy biomass (lower for high biomass) while the minimum soil temperature is a function of the minimum air temperature and canopy biomass (higher for higher biomass). The actual soil temperature used for decomposition and plant growth rate functions is the average of the minimum and maximum soil temperatures. Changes in soil temperature will lag behind the changes in air temperature if the difference in air temperature between months is greater than 2^0C. A variation of spatial air temperature is found between different land use/land cover categories on a diurnal basis and for all weather conditions (Eliasson and Svensson 2006). Altitude/elevation (Figure 1), land use/land covers (Figure 2) and soil textures (Figure 3) are used for modeling of temperature. The monthly and seasonal average means temperature is predicted in this modeling. The neural network approach is used to model the monthly and seasonal average means temperature. For this purpose hundreds of sample points are used as reference point. Existing climate data set of CRU is used as reference data set and tried to find out the average value of means temperature for all the month, January to December. Four equations are generated as the processes of temperature modeling are discussed in the following paragraph.

$$L\beta = \frac{\sum_{x,i} \frac{tix}{M}}{N}$$

Equation 1

$$S\gamma = \frac{\sum_{y,i} \frac{tiy}{M}}{N}$$

Equation 2

$$E\delta = \frac{\sum_{z,i} \frac{tiz}{M}}{N}$$

Equation 3

$$L\beta + S\gamma + E\delta = T$$

Equation 4

Where:
$\beta \propto x, i$; $\gamma \propto y, i$; $\delta \propto z, i$;
t= Observed temperature
x= Weight of land use/ land cover (33% to 40%)
y= Weight of soil texture (12% to 20%)
z= Weight of elevation (30% to 40%)
i= Month, January to December (1 – 12)
M= x + y + z
N= No of treatment sample point
T= Predicted temperature
L_β= Predicted temperature weight by land use
S_γ= Predicted temperature weight by soil
E_δ= Predicted temperature weight by elevation

In contrast, estimation of the pattern and amount of rainfall is a more complex task due to its discontinuous and quasi-stochastic nature in space and time. The added complexity of rainfall fields suggests that more factors may need to be included when data are interpolated in order to achieve acceptable accuracy. Altitude/elevation, land use/land cover, relative humidity and cloud cover are used for modeling of rainfall. The monthly total rainfall is predicted in this modeling. Five equations are generated as the processes of rainfall modeling are discussed in the following paragraph.

$$E\alpha = \frac{\sum_{a,i} \frac{ria}{f}}{N}$$

Equation 5

$$L\beta = \frac{\sum_{b,i} \frac{rib}{f}}{N}$$

Equation 6

$$H\gamma = \frac{\sum_{c,i} \frac{ric}{f}}{N}$$

Equation 7

$$C\delta = \frac{\sum_{d,i} \frac{rid}{f}}{N}$$

Equation 8

$$Ea + Lb + Rc + Cd = R$$

Equation 9

Where:
$\alpha \propto a, i$; $\beta \propto b, i$; $\gamma \propto c, i$; $\delta \propto d, i$
a= Weight of elevation (1% to 5%)
b= Weight of land use (1% to 5%)
c= Weight of relative humidity (2% to 35%)
d= Weight of cloud cover (5% to 55%)
f= a + b + c + d
N= Number of reference point
r= Observed rainfall
i = Month; January to December (1 - 12)
R= Predicted rainfall
E_α= Predicted rainfall weight by elevation
L_β= Predicted rainfall weight by land use
H_γ= Predicted rainfall weight by relative humidity
C_δ= Predicted rainfall weight by cloud cover

5.2 Weight Selection for the Climatic Parameters

We considered cent percent (100%) influence of those parameters for the prediction of monthly average temperature. We selected different weight values for different parameters and for each category of data set in model. Taking the example of land use, there were different types of land use / land cover classes and as such separate weight values were assigned for each and every class. A model calculation has been made to choose different weight for the parameters. First we chose the average temperature data set of January. Secondly we found out two points with similar characteristics except the elevation, as for example their relative height is 800 m and other characteristics like land use and soil texture are identical. The temperature was measured for both the places and we observed that it was not similar. Then we measured the difference of temperature emanating from the effect of elevation. We made numbers of measurement to find out the average weight value against elevation and it was almost forty percent (40%) of the average mean temperature. We made this calculation in point A and point B, which had been located at 86.33° E / 21.67° N and 87.17° E / 22.50° N. Soil texture type was 'sandy clay loam' and the land use type was 'forest' in both the points. The elevation of point A and B was 900m and 50m. The average mean annual temperature in point A was 24.7°C and B was 26.5°C. The total range of annual average mean temperature according to CRU 30 year's data set was 4.5°C and the temperature range of those points was 1.8°C, which is 40% of the total range. The same calculation process has done to choose the weight value for Land use and soil texture. We considered influence of soil texture as twenty percent (20%) while the influence of land use as forty percent (40%).

5.3 GIS Methodology for the Modeling

Using ERDAS IMAGINE and ArcGIS software, we created different raster layers for each parameters used for temperature modeling. SRTM data was use to generate DEM for the study area. There were some data gaps in the SRTM data set when we were used it to create the DEM. We had to use topographical maps in order to fill the data gaps. Using the 3-D analysis process the digital elevation model was generated from contours, which had been digitized from topographical maps. Finally, the elevation map had been generated as shown in Figure 1.

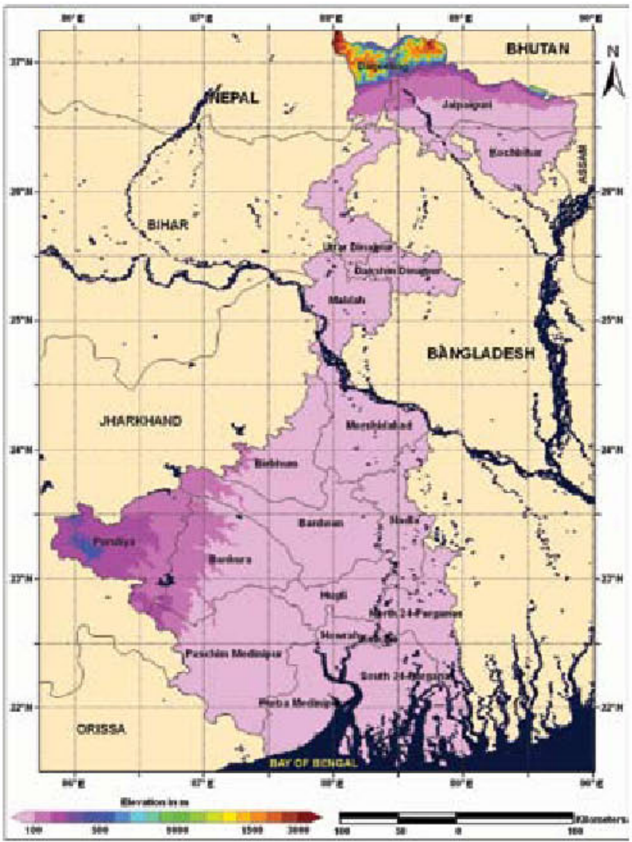

Figure 1: Digital elevation of the study area, generated from SRTM data and topographical maps

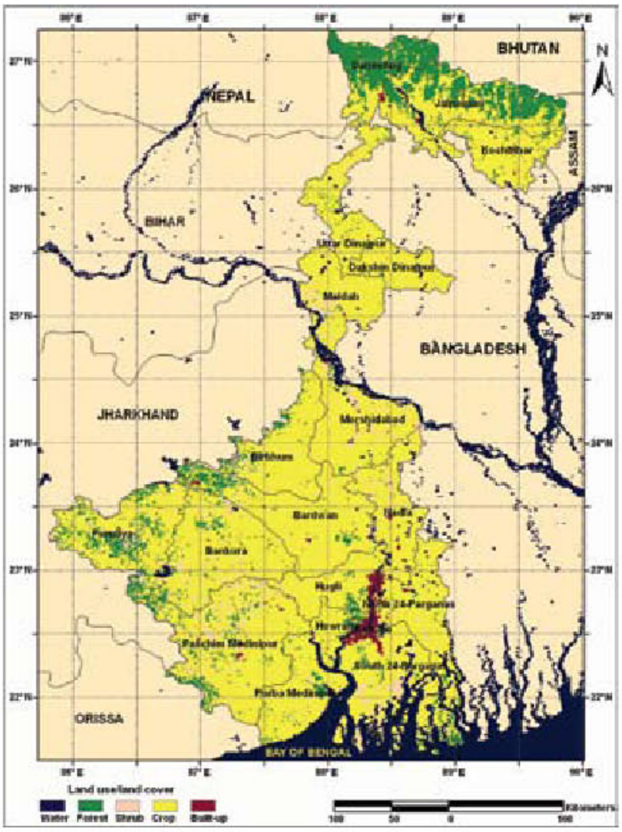

Figure 2: Land use/land cover of the study area, generated from LANDSAT-7, ETM+ satellite image

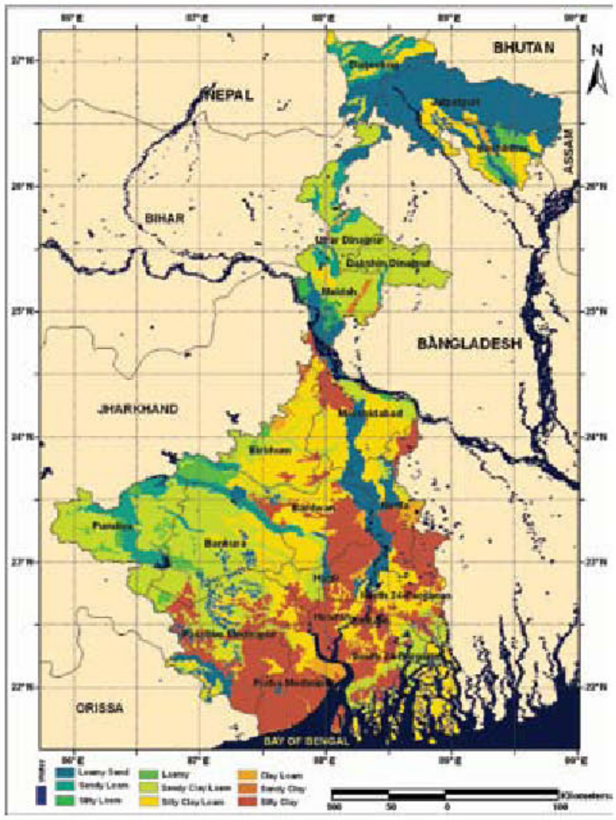

Figure 3: Soil texture of the Study area, generated from soil region map and NBSS soil sheets

It showed that the elevation of the eastern and southern parts of the study area were less than 100m while the northern parts were relatively more elevated (>1500m). The land use /land cover data set was generated from the digital image classification of LANDSAT, ETM+ satellite images. This classification was performed taking six classes, namely- water (Sea or inland water bodies), marshy land, forest land, shrub land (mixed or open), crop land (agricultural land) and built up area (Settlement or industries). The western part was relatively more heterogeneous having forested area, crop land and shrub land etc. as shown in Figure 2. Therefore the climatic variables patterns were expected to be more complex. From the tonal values of original SFCC imageries, land cover classes were selected and for classification a signature editor was created to supervise the computer software. Soil texture data set was generated by the process of digitization from soil region maps of the area. West Bengal soils sheet of national bureau of soil survey (NBSS), soil region map of national atlas & thematic mapping organization were used for this purpose. All the soils were categorized into nine (9) soil texture groups according to their characteristics, namely- loamy sand, sandy loam, silty loam, loamy sandy, clay loam, silty clay loam, clay loam, sandy clay, and silty clay. The southern part was relatively more heterogeneous then western and northern parts as shown in Figure 3. Then we formed a model by the model maker in the GIS environment using simple equation. Land use/land cover, soil texture and digital elevation model were used as input parameters for temperature modeling and Land use/land cover, digital elevation model, cloud cover and relative humidity for rainfall modeling. In the output, we developed a new raster layer with the predicted mean temperature and total rainfall. Figure 4 displayed predicted mean temperature of pre-monsoon season, where temperature varied spatially from 18° C (northern part) to 30° C (southern part) of West Bengal. Predicted total annual rainfall of West Bengal is displayed in Figure 5, where highest rainfall occurred in northern part (2800mm) and lowest rainfall (1400mm) in the south-west part.

6. Results and Discussion

Standard deviation errors were calculated for monthly mean temperature, seasonal mean temperature and annual mean temperature, displayed in Table 2. It revealed that percentage of area coverage was very less having standard deviation errors greater than 1.0, irrespective of the month or seasons. Hence it justified the applicability of the procedure used for predicting mean temperature. However, percentage of area coverage with standard error less than 1.0 was below 90% for winter seasons. Thus the prediction was relatively poor in the winter months, possibly due to lack of consideration of the impact of western disturbances. In winter season, extra-tropical disturbances (ETD) passes through the Himalayan region and while passing through the north of the study area, an induced low pressure system forms resulting sharp changes of temperature. The region also experienced little amount of rainfall. Such a disturbance is unlikely to be considered in the present model. Therefore in order to have a better prediction in winter month, principal wind pattern is to be considered as a parameter. It is again interesting to note that the prediction is relatively poor for the month of March compared to April and May, though March through May is considered to be pre-monsoon season. Usually, the impact of ETD, on occasions, extended up to the middle of March. Thus the same weather disturbance is expected to make the performance poor the prediction is better in monsoon season. Being synoptic phenomena, the entire study area gets affected by the system unlike mesoscale disturbances such as tropical storms in post-monsoon season or thunderstorms in pre-monsoon season. Being the transition period from the winter; both the pre-monsoon and post-monsoon seasons are susceptible for tropical storms. Standard deviation errors were calculated for monthly total rainfall and seasonal total rainfall, displayed in Table 3. It revealed that percentage of area coverage was very less having standard deviation errors greater than 10.0, irrespective of the month or seasons. Hence it justified the applicability of the procedure used for predicting total rainfall. However, percentage of area coverage with standard error less than 10.0 was below 75% for monsoon seasons. Thus the prediction was quite poor in the monsoon months, possibly due to lack of consideration of the impact of monsoonal uncertainty. In the summer monsoons the winds carried moisture from the Indian Ocean and bring heavy rains from June to September in this study region. The monsoon accounts for 80% of the rainfall in the study region. The summer monsoon consisted of alternating wet and dry events known as active and break period. During active periods, low pressure systems brought frequent thunderstorms and heavy rain, whereas break period looked typically bright and sunny. The timing and duration of active and break periods accounted for much of the year to year variation in the monsoon, dry years with frequent and long lived break.

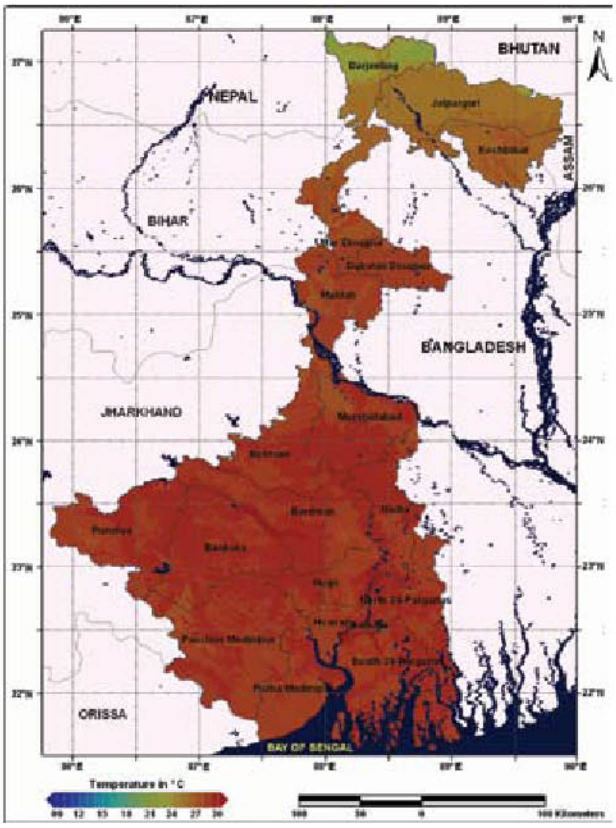

Figure: 4 Predicted mean temperature of pre-monsoon using 30 years CRU data set

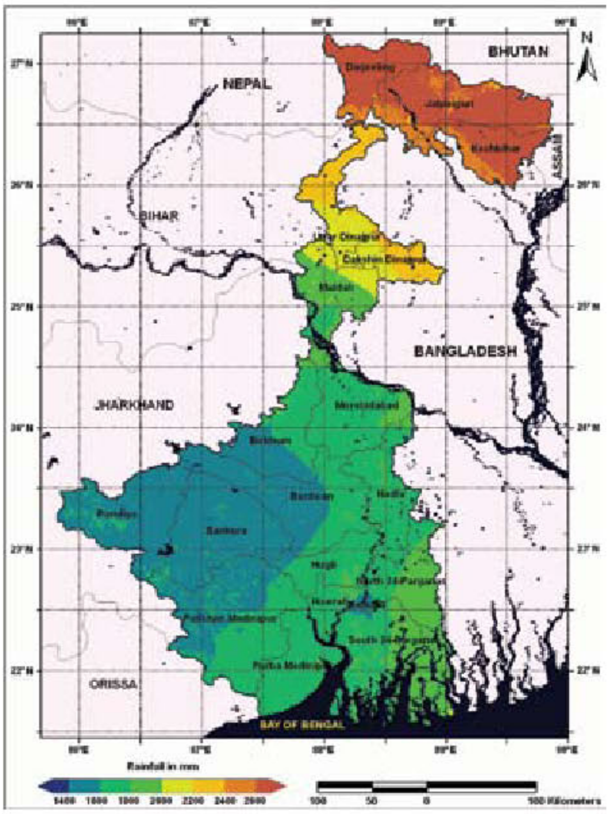

Figure 5: Predicted total annual rainfall of using 30 years CRU data set

Table 2: Standard deviation error estimation of predicted mean temperature using CRU 30-year's data set

Month	% of area coverage against Standard deviation error	
	α (0 – 1.0)	α (1.0- 2.0)
January	87.82	12.18
February	84.55	15.45
March	92.89	7.11
April	98.68	1.32
May	93.4	6.6
June	97.28	2.72
July	99.11	0.89
August	98.73	1.27
September	98.85	1.15
October	98.27	1.73
November	95.75	4.25
December	93.69	6.31
Pre-Monsoon	97.15	2.85
Monsoon	99.3	0.7
Post-Monsoon	97.68	2.34
Winter	89.67	10.33

Table 3: Standard deviation error estimation of predicted total rainfall using CRU-30 year's data set

Month	% of area coverage against Standard deviation error			
	α (0 – 10)	α (10 - 20)	α (20 – 30)	α (30 – 40)
January	100.0	0.0	0.0	0.0
February	93.0	7.0	0.0	0.0
March	98.3	1.7	0.0	0.0
April	75.7	24.3	0.0	0.0
May	71.2	26.8	2.0	0.0
June	54.3	38.1	4.3	3.3
July	61.0	25.7	8.5	4.8
August	53.3	28.7	13.4	4.6
September	55.4	26.8	13.4	4.4
October	62.5	25.8	8.5	3.1
November	88.5	11.5	0.0	0.0
December	100.0	0.0	0.0	0.0
Pre-Monsoon	80.7	17.6	1.7	0.0
Monsoon	57.0	29.8	8.9	4.3
Post-Monsoon	75.1	18.7	5.3	0.9
Winter	96.7	3.3	0.0	0.0

Table 4: Estimated vs observed weather stations mean temperature of Pre-monsoon

SL No	IMD Station	Observation	Predicted	SD Error
1	Asansol	28.5	28.6	0.07
2	Santiniketan	28.9	29	0.07
3	Krishnagar	28.5	28.5	0.00
4	Contai	28.6	28.5	0.07
5	Diamond Harbour	28.9	28.5	0.28
6	Bardwan	30.2	29.6	0.42
7	Digha	27.9	28.5	0.42
8	Dumdum	29.2	28.5	0.49
9	Alipur	29.6	28.5	0.78
10	Ulnberia	29	28.1	0.64
11	Bankura	30.5	29.2	0.92
12	Haldia	26.7	27.9	0.85
13	Medinipur	30.1	29.2	0.64
14	Purulia	28.7	29.8	0.78

The sudden cyclonic storm also led to uncertainty over the progress of the southwest monsoon in the eastern part of India. In addition to pre-monsoon thunderstorms, tropical storm also forms over the Bay of Bengal and cross through the region of interest. However the frequency is very less in pre-monsoon season (Lohar and Pal, 1995). On the other hand, tropical storm is more likely in the post-monsoon season. Since in the both seasons (pre-monsoon and post-monsoon) tropical storms cross the east coast and move inland, the distance of the coastline may be considered as one of the parameters in forming the model, so that further improvement of the prediction for the prediction for these seasons are expected. In case, the distance of the coastline is considered, it is likely that the predictions for monsoon months are expected to be improved further. Finally a comparison was performed between predicted pre-monsoon temperature and IMD (Indian Meteorological Department) weather station temperature, displayed in Table 4. The result showed less than 1.0 standard deviation error in all the 14 ground observation stations.

7. Conclusions

Under a specified solar irradiance and latitude, temperature depends on different variables on the Earth surface as well as the overlying atmospheric composition. For temperature modeling, we used only land use/land cover, soil texture and digital elevation model data set and elevation, land use/land cover, humidity and cloud cover for rainfall modeling. Expectedly some standard deviation errors are likely to crop up in our work. If we bring into play all other variables like distance from the sea, latitudinal location, continentality, solar radiation, permanent wind directions (trade wind, westerlies) and cloudiness factor, aspect etc, then the model may predict even more accurate result. As the result suggest, these three variables are likely to be major factors to control the temperature and four variables to control rainfall. We can run this model for calculating the mean monthly temperature and total rainfall for other areas as well provided the weightage of the parameters are calculated for respective area.

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