Gridded Temperature generation using INSAT - Land Surface Temperature data and India Meteorological Department temperature data for Indian region

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Abstract: Gridded temperature generation is required in various domains of thematic applications such as crop growth simulation, forestry, hydrology and weather forecasting. The daily minimum and maximum gridded air temperature is generated for the Indian region using daily station-wise temperature data of 332 India Meteorological Department (IMD) ground stations. However, it is noted that there are many stations where temperature data is missing. In such cases, an attempt is made to generate accurate surface by estimating missing temperature of IMD stations data using various regression techniques. For this, Correlation Length Scale (CLS) is calculated using INSAT-3D and INSAT-3DR Land Surface Temperature (LST) satellite product. Neighbouring IMD stations data, which are falling within range of CLS radius, as well as respective satellite data are considered for estimating IMD station temperature using Linear Regression (LR) and Support Vector Regression (SVR) models. IMD stations temperature data values are estimated with indigenously developed weighted scheme given to LR and SVR. In order to validate the model and limit over fitting, Leave-One-Out Cross Validation (LOOCV) technique is used for April, August months for year 2017 and January month for year 2018 representing summer, monsoon and winter season respectively and corresponding results are reported in this paper. Root Mean Squared Percentage Error (RMSPE) values are used as measures for judging model goodness for various regression techniques. At the end, Thin Plate Spline (TPS) interpolation technique is used for gridded temperature generation. Deviation of temperature from actual temperature shows that TPS based gridded temperature with LST consideration performs better than without LST consideration.

1. Introduction

Weather data simulation involves simulation of the conditions of the atmosphere for a given location and time. Applications of weather simulation are in various areas viz. agriculture, forestry, marine, air traffic, electricity and gas companies. Majority of these applications rely on weather simulations to anticipate demand that is highly driven by weather. Gridded temperature field is required for optimum use of temperature for various models of crop-growth analysis, geology, hydrology and many more. This gave motivation to generate gridded temperature for Indian region. In this paper, two sources of temperature data are used, Surface Air Temperature from India Meteorological Department (IMD) weather stations and INSAT-LST Land Surface Temperature (LST) satellite data.

IMD stations measure surface air temperature from its non-uniformly distributed 332 ground stations daily at 2 m above ground. Sparse coverage of weather stations as well as missing measured data affect gridded temperature generation.

Another source for temperature data is INSAT satellite data, which provides Land Surface Temperature (LST). The advantage of satellite data is that it provides uniformly gridded LST data for the whole region of India. LST measured from satellite is also error-prone because various atmospheric factors such as dust particles, moisture and wind speed as well as electronic factors such as sensor degradation, which are very difficult to correct for, affect it.

Existing interpolation techniques viz. Inverse Weighted Regression (IDW), Kriging and Thin Plate Spline (TPS) are used for gridded temperature generation (Yang et al. 2004, Tiengrod and Wongseree 2013). These techniques interpolate values at unknown points using available information at known points and require large number of measured sample points. In order to generate gridded temperature using these techniques with increased number of sampling points, estimation of missing IMD stations data becomes an important step.

There are several methods to estimate surface air temperature for LST that are categorised into five groups, viz. Statistical, Empirical solar zenith angle, Energy balance, TVX and Neural Network approach (Shah et al. 2013). Shah et al. (2013) discuss these approaches and estimate minimum and maximum air temperature using MODIS data over Indo-Gangetic Plain with RMSE of 2.2% and 2.16% for NDVI-T_{min} and NDVI-T_{max} regression respectively where T_{max} and T_{min} are maximum and minimum surface air temperature.

In this paper, an attempt is made to estimate missing daily IMD surface air temperature data of 332 stations using measured IMD temperature data as well as available satellite based LST data using statistical methods. After estimation of missing temperature for IMD station data, the estimated temperature values as well as IMD measured temperature values are used to generate gridded temperature using Thin Plate Spline (TPS).

Indian Institute of Tropical Meteorology (IITM) at Pune has categorised India into seven homogeneous temperature regions based on the spatial and temporal variations of

surface air temperatures across India (Figure 1). These regions are East Coast (EC), North Central (NC), Interior Peninsula (IP), North East (NE), North West (NW), West Coast (WC) and Western Himalaya (WH). Regions WH, NW, NC and NE located in northern part of the country whereas WC, IP and EC located in the southern part of the country. In the end, Root Mean Squared Percentage Error (RMSPE) is calculated and estimation error of surface air temperature is compared region wise as well as for the whole country.

(source: www.tropmet.res.in)
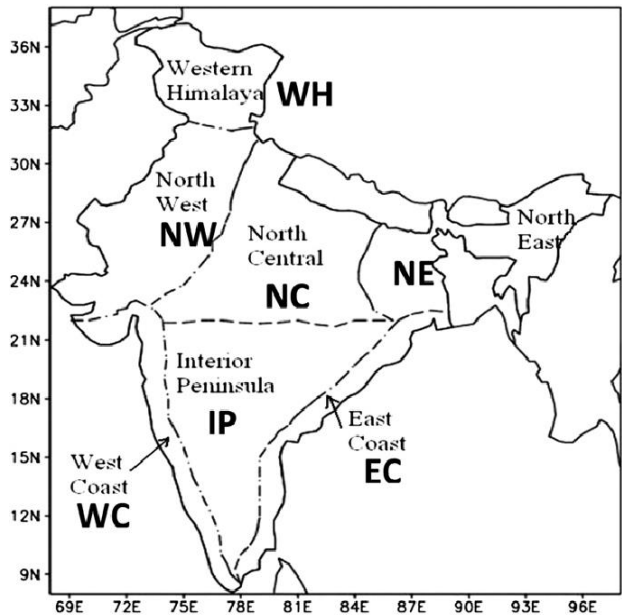
Figure 1: Seven homogeneous temperature regions of India. Regions WH, NW, NC and NE are located in northern India whereas WC, IP and EC are located in southern India

2. Data Used

In this study, daily minimum and maximum surface air temperature data provided by India Meteorological Department (IMD) and LST data of geostationary satellite INSAT-3D and INSAT-3DR are used for gridded temperature generation.

IMD provides daily weather data viz. maximum temperature, minimum temperature, relative humidity, rainfall etc. for its 332 ground based weather stations (IMD; www.imd.gov.in). Out of these weather parameters, maximum temperature and minimum temperature are considered in this study.

For satellite data, INSAT-3D and INSAT-3DR Land Surface Temperature (LST) L2B product Imager data is taken from Meteorological and Oceanographic Satellite Data Archival Centre (MOSDAC; www.mosdac.gov.in). INSAT-3DR is a geostationary satellite which is a repeated version of INSAT-3D. The location of INSAT-3D is 82-degree east and the location of INSAT-3DR is 74-degree east. INSAT-3D and INSAT-3DR provide data with temporal resolution of 15 minutes at spatial resolution of 4km when combined. INSAT-3D carries an improved Very High Resolution Radiometer (VHRR). INSAT-3D is

capable of capture data in six different wavelengths, viz. visible, shortwave infrared, middle infrared, water vapour and two bands in thermal infrared regions. Both INSAT-3D and INSAT-3DR LST products are generated using two thermal infrared bands of INSAT imager over India and come in form of Hierarchical Data Format (HDF). Both data products provided are processed by raw data extraction, radiometric corrections and geometric corrections by Meteorological and Oceanographic Satellite Data Archival Centre (MOSDAC).

3. Methodology

The main objective of the study is to estimate the missing IMD temperature values using satellite data that has its application in gridded temperature generation. In this paper, a methodology is developed for estimating missing temperature values and based on that, gridded temperature surface is generated. This methodology is carried out in three steps that are described below.

3.1 Processing INSAT-3D and INSAT-3DR data
INSAT-3D and 3DR provide Land Surface Temperature (LST) data in the form of Hierarchical Data Format (HDF) at temporal resolution of 15 minutes. From this, daily minimum and maximum LST is calculated in raster format. Both satellites data are used to improve quality of data in terms of temporal resolution.

LST data provided by satellite is in Kelvin (K) scale which is converted to Celsius (˚c) to make it compatible with IMD data. These daily temperature files are used further to calculate Correlation Length Scale (CLS) and for estimation of missing IMD stations data.

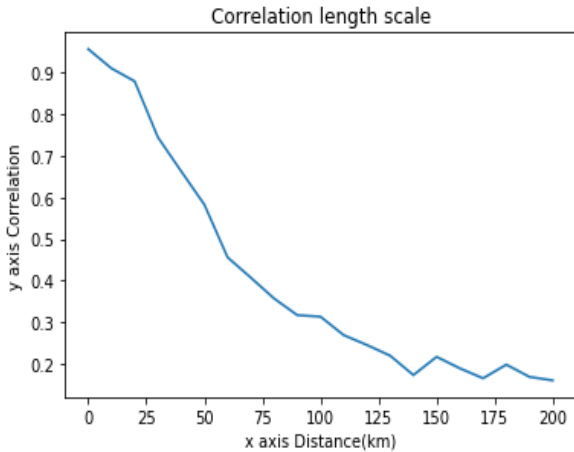### 3.2 Calculation of Correlation Length Scale (CLS)
As next step of methodology, CLS is calculated for each station. Satellite data is used to find correlation length scale as satellite data has synoptic spatial coverage as compared to IMD data. To calculate CLS, correlation is calculated based on last five days of maximum and minimum LST data at pixels corresponding to geographic location of an IMD station with stations falling under 200 km. These correlation values are then binned with an interval of 10 km. For each bin, the mean correlation is estimated and second-degree polynomial function is fitted to mean correlation values.

Further, CLS is defined as a distance at which the value of the function representing mean correlation fell below 1/e, where e ~ 2.73 (Srivastava et al. 2009). CLS varies for each IMD station. Figure 2 shows second-degree polynomial function fitted to mean correlation values for an IMD station.

3.3 Use of regression models to estimate missing IMD stations data
CLS is used to identify neighbouring influencing stations for missing IMD stations. Last five days of IMD stations data as well as corresponding satellite data which are falling within the radius of influence are considered for making regression model. Linear Regression (LR) and Support Vector Regression (SVR) are applied to estimate

air temperature at IMD stations. In regression models, missing temperature station's satellite data along with IMD data and neighbouring stations satellite data with IMD data for previous 'd' days are used for capturing temporal and spatial relationship between LST and IMD temperature data. For estimating IMD temperature value of a particular day, IMD temperature values of neighbouring stations and LST values for same day are also considered in model making. While generating regression model, IMD station data is considered as dependent variable whereas INSAT LST data is considered as independent variable.

Figure 2: Correlation Length Scale (CLS) of a sample IMD station

A)   Linear Regression (LR):

Linear regression is an approach to develop a linear model that depicts relationship between a scalar dependent variable and independent variables using training data. Simple linear regression equation is as shown below, (Cohen et al. 2003, Draper and Smith 1998).

$$y_i = w_0 + w_1 x_i + \varepsilon' \quad \dots\dots\dots\dots\dots\dots\dots\dots(1)$$

where, y_i = dependent variable
$\quad\quad x_i$ = independent variable
$\quad\quad w_0$ = intercept
$\quad\quad w_1$ = slope coefficient
$\quad\quad \varepsilon'$ = random error

B)   Support Vector Regression (SVR):

SVR uses a different optimization objective as compared to the ones used in linear regression. There are various properties associated with cost function which gives a good solution with lesser computation. The cost function involves using a kernel, which could be linear, polynomial, radial basis function (RBF) kernel or sigmoid kernel. SVR estimates equation coefficients by minimizing the cost function $f(w)$,

$$f(w) = \frac{1}{2} w^T w \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(2)$$

subject to: $\forall n \ |y_n - (x_n w + b)| \leq \varepsilon$

where, y_n = dependent variable
$\quad\quad x_i$ = independent variable
$\quad\quad w$ = weight vector
$\quad\quad w^T$ = transposed weight vector, and
$\quad\quad b, \varepsilon$ = bias and random error respectively.

With ε - incentive loss function, only the cost of samples that have residuals larger than ε is considered, while samples with smaller residuals have no effect on the regression. In this study, IMD stations data and satellite data used as training data to estimate missing IMD data using SVR with RBF kernel (Cohen et al. 2003, Draper and Smith 1998, Drucker et al. 1997).

In order to investigate the relationship between LST and IMD data, a weight based regression model is developed where for each sample; weights are assigned based on distance from missing temperature station and number of past days for which estimation is done. These weights are applied by varying polynomial order of weights. Distance weight and date weights are calculated to exploit spatial and temporal variations in temperature respectively.

$$distance\ weight = \left(\frac{CLS\ distance - x}{CLS\ distance}\right)^n \dots\dots\dots\dots\dots(3)$$

x = distance of sample point from missing temperature IMD station

$$date\ weight = \left(\frac{Total\ previous\ day - y}{Total\ previous\ day}\right)^n \dots\dots\dots\dots(4)$$

y = previous day from missing temperature day of IMD station.   For same day y=0, a day before missing temperature day y=1 and so on.

where, n = {1, 2, 3, 4} controls weights.

Maximum CLS distance is considered 200 km and total number of previous days affecting missing temperature day are taken as 5. Sum of distance weight and date weight is assigned to each corresponding sample point. Weighted Linear Regression and SVR are applied after assigning weights with varying degree i.e. n.

Performances of these regression techniques are evaluated by calculating Root Mean Squared Percentage Error (RMSPE) as measuring criteria (Nataliya et al. 2013). RMSPE is calculated by equation 5.

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(100.|p_i|)^2} \quad \dots\dots\dots\dots\dots\dots(5)$$

where $p_i = \frac{(t_i' - t_i)}{t_i}$
t_i' = predicted temperature
t_i = actual temperature

Leave-One-Out Cross-Validation (LOOCV) is used to estimate how accurately a predictive model will perform. It
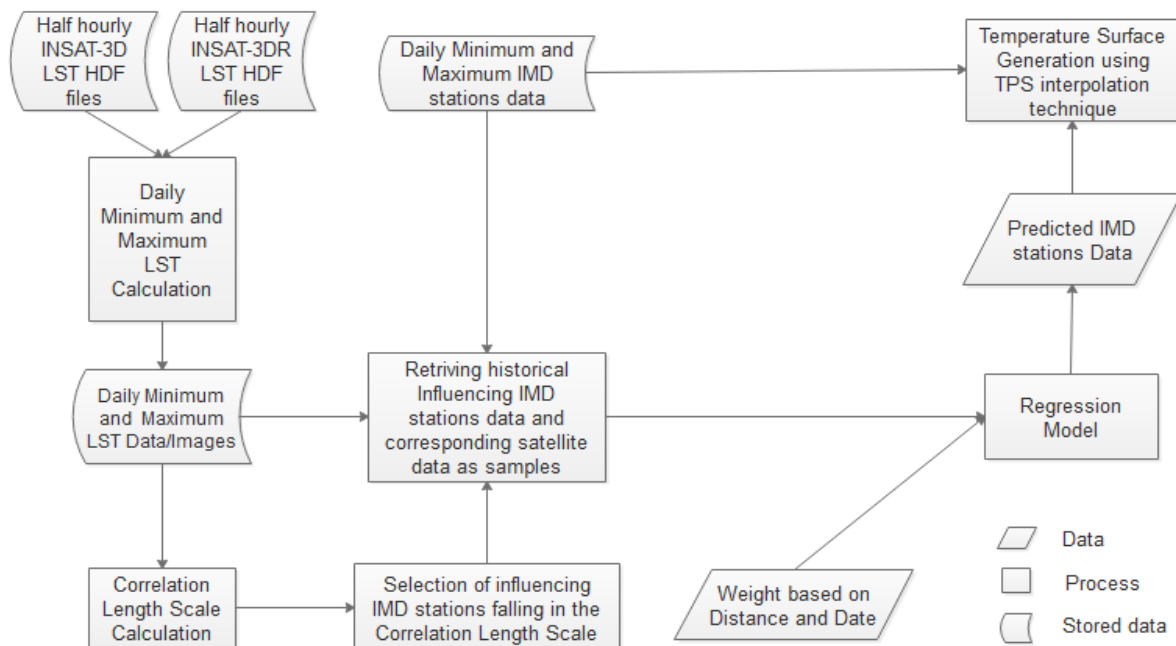
Figure 3: Flow diagram of proposed methodology

uses one observation as the validation set and remaining observation as a training set. In this paper, LOOCV is carried out by estimating temperature value of a station on a particular day while using other stations data as invariant. air temperature at IMD stations. A month-wise average RMSPE is reported for seven temperature homogeneous regions as well as Indian region.

In the end, TPS is applied to generate the gridded temperature for understanding effect on temperature interpolation without and with handling missing data as proposed. A flow diagram summarizing methodology is shown in Figure 3.

4. Results and Discussion

Performance of different regression techniques are compared by calculating Root Mean Square Percentage Error (RMSPE) in Leave One Out Cross-validation (LOOCV) manner for seasonal analysis. Seasonal analysis is carried out for seven temperature homogeneous regions in India namely, East Coast (EC), North Central (NC), Interior Peninsula (IP), North East (NE), North West (NW), West Coast (WC) and Western Himalaya (WH). April, August and January months data is used which represent summer, monsoon and winter seasons respectively. Results are computed up to four degree weighted linear and support vector regression methods to reduced model biasness towards nearest neighbour station with same day data. Various methods used in this study are summarized below in Table 1.

A)   Summer Season
For summer, daily maximum and minimum temperature data of April, 2017 is taken to analyze the performance of different regression techniques as shown in Table 2 and Table 3. Based on daily data, average RMSPE is calculated and reported region wise. In study, it is found that for almost all temperature homogeneous regions fourth-

degree polynomial weighted support vector regression gives best result. Results of regression methods for North Central (NC), East Coast (EC) and West Coast (WC) are seen to have less than other regions in summer. Lowest RMSPE for both maximum and minimum temperatures are reported for EC. In general, high RMSPE is noted for minimum temperature values over all regions as compared to maximum temperature values. North East (NE) and Western Himalaya (WH) show high RMSPE due to sparsity of stations in these regions and seasonal climatology.

Table 1: Various Regression techniques used in study with its abbreviations

AVG	Average of influencing IMD stations temperature data
LR	Simple Linear Regression
WLR	Weighted Linear Regression
WLR[n]	n - degree polynomial Weighted Linear Regression
SVR	Support Vector Regression
WSVR	Weighted Support Vector Regression
WSVR[n]	n - degree polynomial Weighted Support Vector Regression

B)   Monsoon Season
Daily minimum and maximum temperature data of August, 2017 is taken for study of monsoon season. Estimation error for whole country is nearly 5.58% for maximum temperature and 5.49% for minimum temperature. The estimation error for West Coast (WC) is 4.85% for maximum temperature and 5.25% is for minimum temperature. For East Coast (EC), RMSPE is 4.17% for maximum temperature and 4.29% for minimum temperature. For WH estimation error is 7.81% and 7.90% for maximum and minimum respectively, which is highest among all other regions. A 4.22% for maximum temperature and 3.83% for minimum temperature estimation error is noted for NW region. In most of the

temperature homogeneous regions fourth degree polynomial SVR estimation results best as shown in Table 4 and Table 5.

C) Winter season

Daily minimum and maximum temperature data of January, 2018 is used for winter season. Average RMSPE is calculated for different temperature homogeneous regions and for the whole country. It is noted that for WH region the results are not as good as other regions because of the winter climatology. WH region also performs worst in all seasons. The estimation error for East Coast (EC) is reported lowest in winter season i.e. 1.52% for maximum temperature and 3.55% for minimum temperature. For Indian region, estimation error is noted as 5.40% for maximum temperature and 11.97% for minimum temperature. Results for all regions are reported in Table 6 and Table 7.

Table 2: Average maximum temperature RMSPE for summer

	WH	NW	NC	NE	WC	EC	IP	INDIA
AVG	28.11	9.84	5.80	11.43	7.36	7.69	6.57	9.37
LR	18.09	7.59	4.99	9.04	5.99	6.44	5.70	7.34
SVR	22.83	7.99	4.70	9.58	6.04	5.38	5.78	7.69
WLR	17.17	6.77	4.38	8.30	5.24	5.76	5.03	6.63
WLR2	16.43	6.24	3.99	7.84	4.71	5.29	4.61	6.18
WLR3	15.87	5.89	3.73	7.54	4.35	4.97	4.34	5.88
WLR4	15.43	5.66	3.55	7.34	4.12	4.74	4.16	5.67
WSVR	18.13	6.19	3.46	7.85	3.99	3.51	4.82	6.11
WSVR2	17.07	5.63	2.98	7.09	3.28	2.96	4.52	5.59
WSVR3	16.34	5.26	2.73	6.52	2.84	2.57	4.37	5.24
WSVR4	15.91	5.00	2.53	6.11	2.55	2.30	4.24	5.00

Table 3: Average minimum temperature RMSPE for summer

	WH	NW	NC	NE	WC	EC	IP	INDIA
AVG	78.51	16.45	12.42	15.56	8.54	4.78	9.81	13.77
LR	47.62	11.82	9.51	12.52	6.41	4.11	7.53	10.16
SVR	55.58	12.44	9.45	13.01	6.18	3.51	8.11	10.67
WLR	44.62	10.93	8.55	11.38	5.79	3.64	6.86	9.32
WLR2	42.38	10.29	7.88	10.60	5.42	3.37	6.35	8.73
WLR3	40.85	9.85	7.45	10.08	5.18	3.20	6.03	8.34
WLR4	39.76	9.55	7.18	9.71	5.00	3.09	5.83	8.07
WSVR	43.58	10.39	7.36	10.65	4.55	2.70	6.26	8.61
WSVR2	41.00	9.53	6.35	9.75	3.99	2.44	5.70	7.88
WSVR3	39.03	8.89	5.67	8.95	3.53	2.24	5.34	7.33
WSVR4	37.43	8.40	5.22	8.35	3.29	2.11	5.07	6.93

Table 4: Average maximum temperature RMSPE for monsoon

	WH	NW	NC	NE	WC	EC	IP	INDIA
AVG	13.25	7.69	7.04	9.72	9.10	6.52	10.09	8.93
LR	10.23	6.40	6.49	8.25	8.07	6.31	9.44	7.82
SVR	11.04	6.35	5.63	8.79	7.73	5.27	9.50	7.87
WLR	9.63	5.99	5.93	7.69	7.26	5.95	8.58	7.24
WLR2	9.12	5.72	5.58	7.27	6.70	5.72	7.95	6.83
WLR3	8.71	5.52	5.34	6.99	6.29	5.56	7.52	6.54
WLR4	8.37	5.36	5.17	6.82	6.01	5.45	7.23	6.34
WSVR	9.15	5.28	4.39	7.23	6.23	4.64	8.45	6.66
WSVR2	8.54	4.83	3.92	6.62	5.80	4.42	8.14	6.23
WSVR3	8.17	4.46	3.62	6.12	5.43	4.26	7.87	5.87
WSVR4	7.81	4.22	3.46	5.78	4.85	4.17	7.57	5.58

Table 5: Average minimum temperature RMSPE for monsoon

	WH	NW	NC	NE	WC	EC	IP	INDIA
AVG	12.86	7.23	6.75	9.39	8.90	6.40	9.58	8.58
LR	10.37	6.47	6.45	8.22	8.41	6.20	8.29	7.61
SVR	11.08	6.08	5.88	8.29	7.63	5.34	8.83	7.56
WLR	9.81	6.05	5.98	7.62	7.51	5.94	7.69	7.07
WLR2	9.27	5.72	5.63	7.16	6.85	5.69	7.22	6.66
WLR3	8.80	5.47	5.41	6.86	6.41	5.49	6.86	6.36
WLR4	8.41	5.29	5.25	6.66	6.11	5.33	6.59	6.14
WSVR	9.35	4.97	4.46	6.84	6.35	4.80	7.74	6.42
WSVR2	8.68	4.46	3.95	6.32	6.00	4.56	7.49	6.02
WSVR3	8.25	4.10	3.68	5.95	5.66	4.39	7.27	5.73
WSVR4	7.90	3.83	3.44	5.71	5.25	4.29	7.03	5.49

Table 6: Average maximum temperature RMSPE for winter

	WH	NW	NC	NE	WC	EC	IP	INDIA
AVG	37.90	12.98	11.55	12.23	7.21	4.48	8.34	10.87
LR	24.60	9.45	8.52	8.90	5.92	3.84	6.25	7.99
SVR	28.13	9.27	8.41	9.22	4.91	3.50	7.70	8.32
WLR	23.03	8.77	7.74	7.89	5.13	3.37	5.55	7.24
WLR2	21.55	8.27	7.18	7.28	4.61	3.09	5.04	6.70
WLR3	20.43	7.92	6.78	6.89	4.28	2.90	4.70	6.34
WLR4	19.58	7.66	6.51	6.63	4.07	2.77	4.46	6.08
WSVR	23.95	7.62	6.37	7.16	3.64	2.30	6.07	6.64
WSVR2	23.08	7.03	5.57	6.45	3.07	1.88	5.45	6.07
WSVR3	22.34	6.59	5.07	5.95	2.68	1.65	5.01	5.67
WSVR4	21.74	6.27	4.78	5.57	2.32	1.52	4.78	5.40

Table 7: Average minimum temperature RMSPE for winter

|	WH	NW	NC	NE	WC	EC	IP	INDIA
AVG	204.23	36.96	34.09	28.09	17.76	11.31	19.80	25.42
LR	99.91	32.09	32.15	20.47	12.84	8.86	16.12	20.23
SVR	108.94	30.42	29.74	20.72	13.34	7.97	16.55	19.85
WLR	89.82	29.42	29.29	18.64	11.05	7.76	14.32	18.23
WLR2	85.69	27.28	27.07	17.33	9.91	6.99	13.06	16.79
WLR3	83.05	25.73	25.57	16.44	9.22	6.52	12.24	15.82
WLR4	81.06	24.61	24.53	15.79	8.78	6.22	11.70	15.15
WSVR	73.19	25.11	24.86	16.67	9.63	5.31	12.90	15.76
WSVR2	68.55	22.17	22.31	14.96	7.65	4.40	11.36	13.90
WSVR3	66.32	20.45	20.57	13.79	6.61	3.88	10.33	12.75
WSVR4	64.30	19.19	19.57	12.97	5.82	3.55	9.70	11.97

To understand effects of missing temperature data values on estimation over gridded temperature generation, thin plate spline interpolation is carried out using with and without estimating missing temperature values. Also, one station each from the seven temperature homogeneous regions is taken to study the deviation of estimated temperature from actual temperature. IMD stations viz. Srinagar, Amritsar, Agra, Shilong, Mangalore, Chennai and Hyderabad are selected from the regions WH, NW, NC, NE, WC, EC and IP respectively. Figures 4 to 9 show deviation of TPS Surface Air Temperature interpolation with and without estimation of missing IMD stations temperature data for minimum and maximum temperature for a sample day in summer, winter and monsoon seasons.
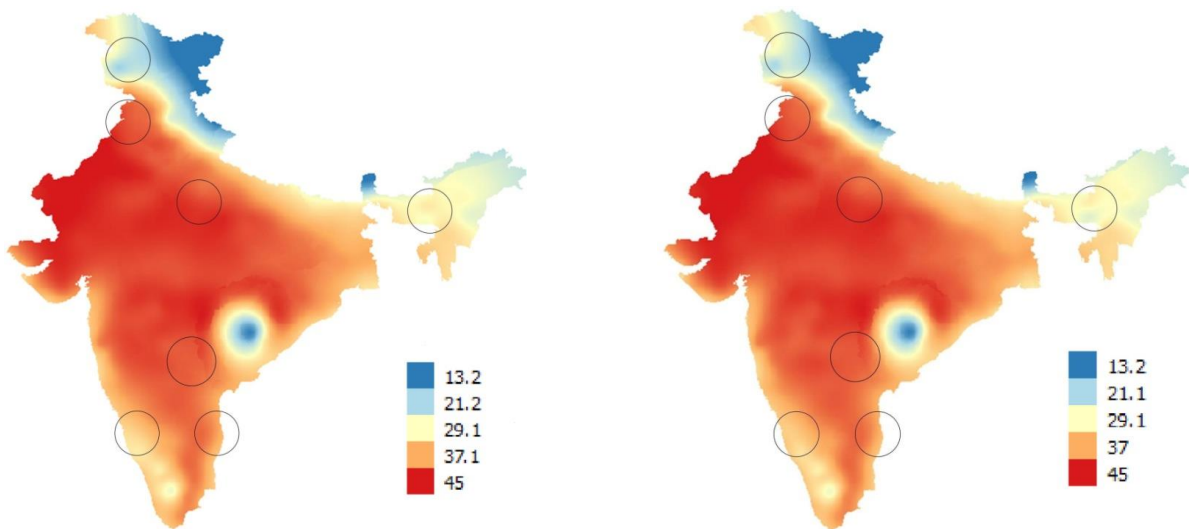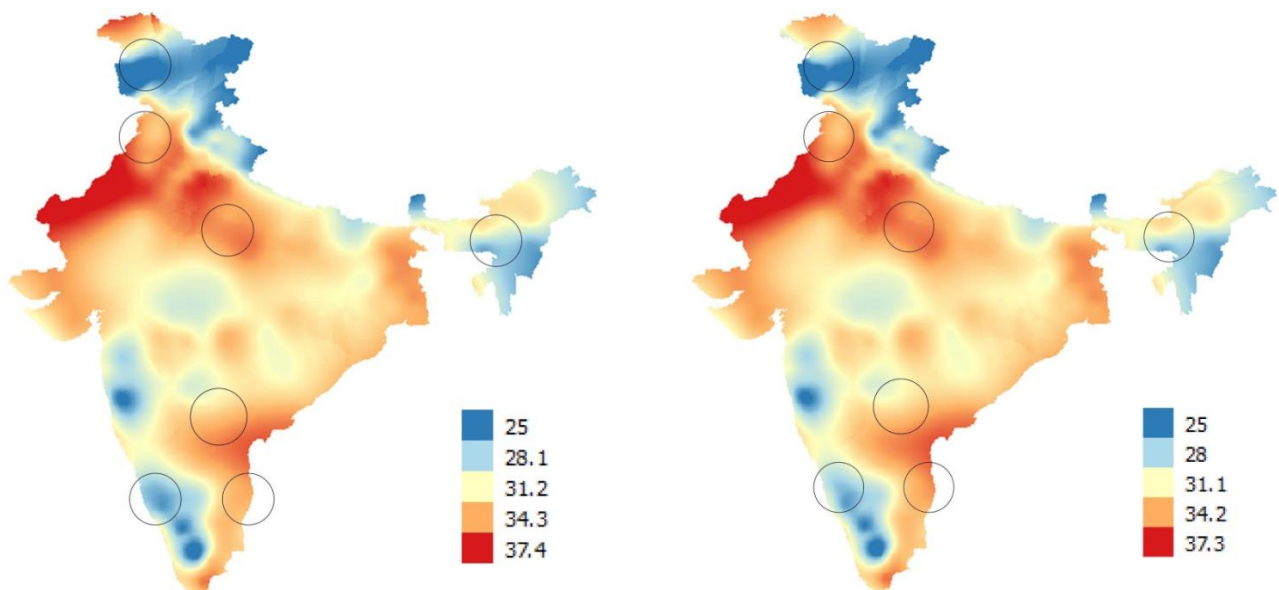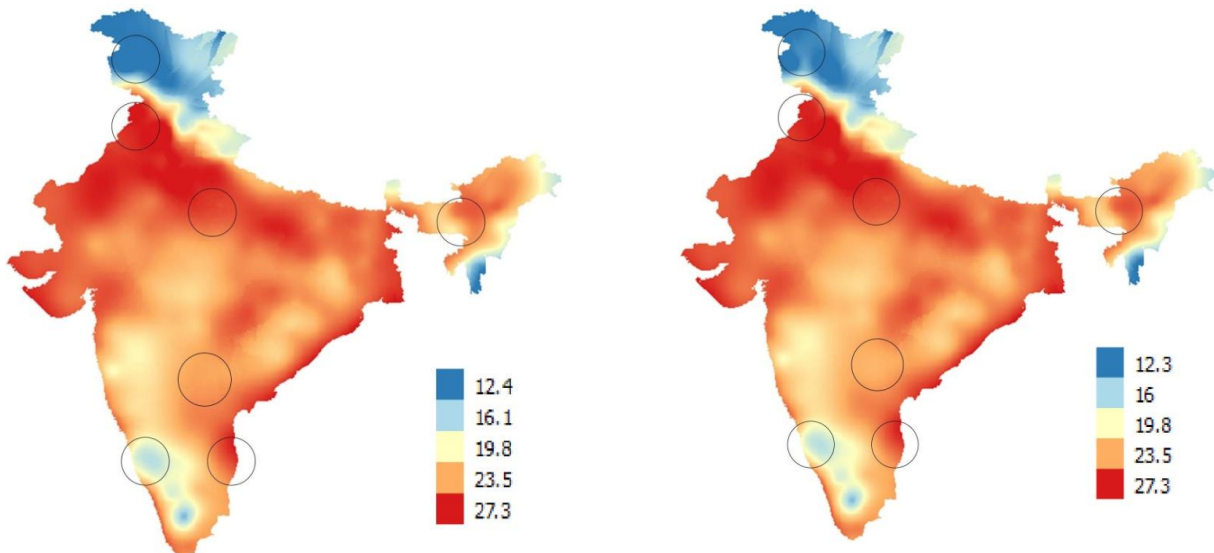
Figure 4: TPS interpolation of IMD stations Maximum Surface Air Temperature data for Summer (15 April); (a) With missing IMD stations data (Left), (b) After estimation of missing IMD stations data (Right)
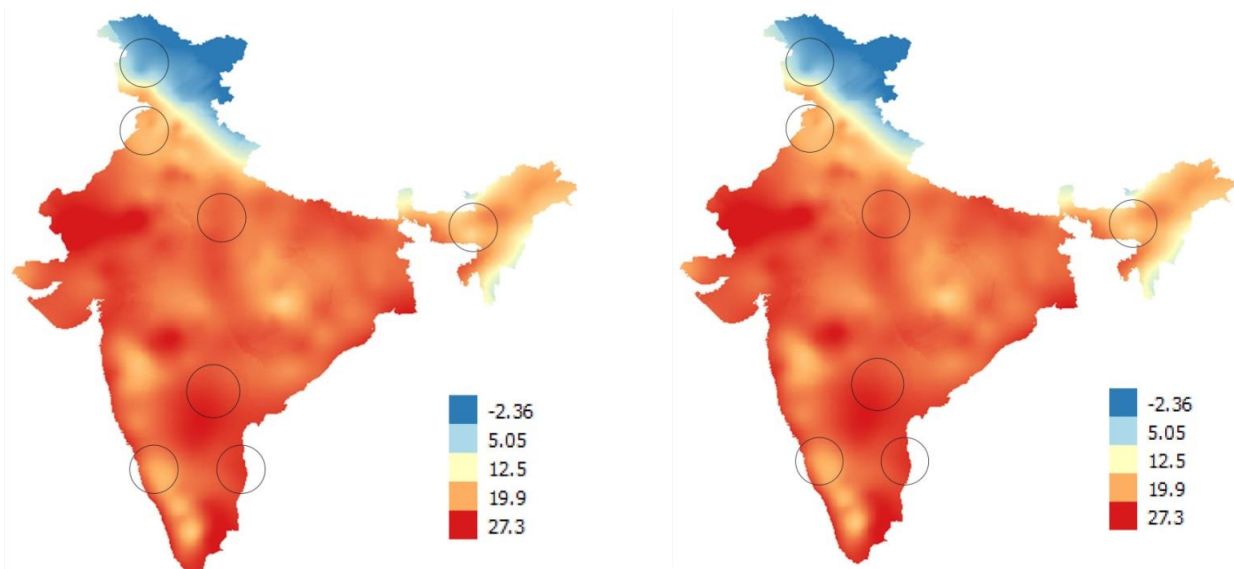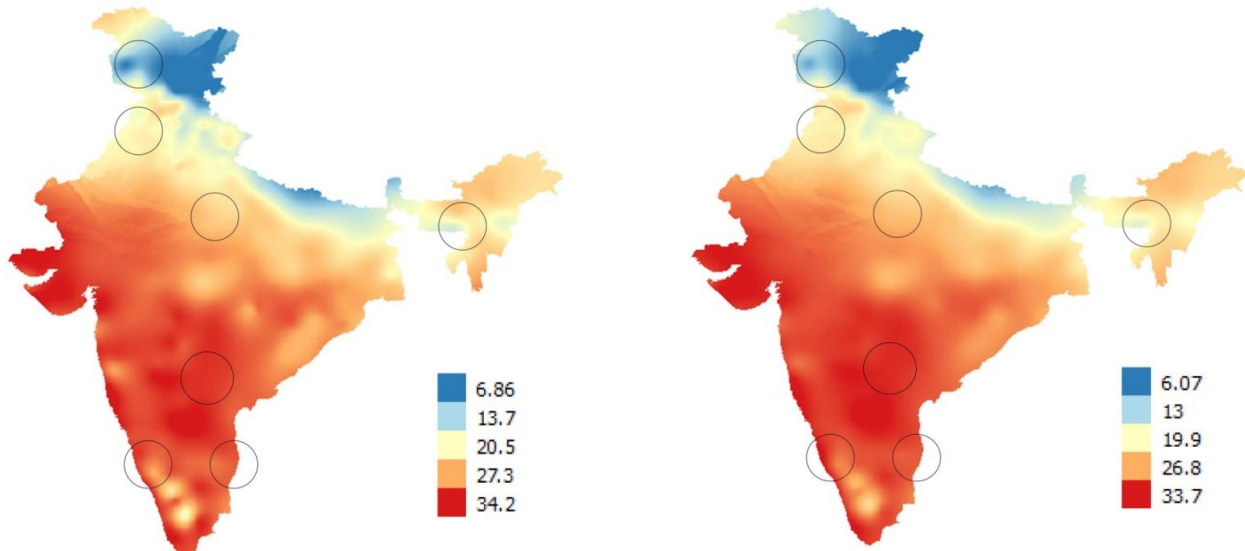

Figure 5: TPS interpolation of IMD stations Minimum Surface Air Temperature data for Summer (15 April); (a) With missing IMD stations data (Left), (b) After estimation of missing IMD stations data (Right)
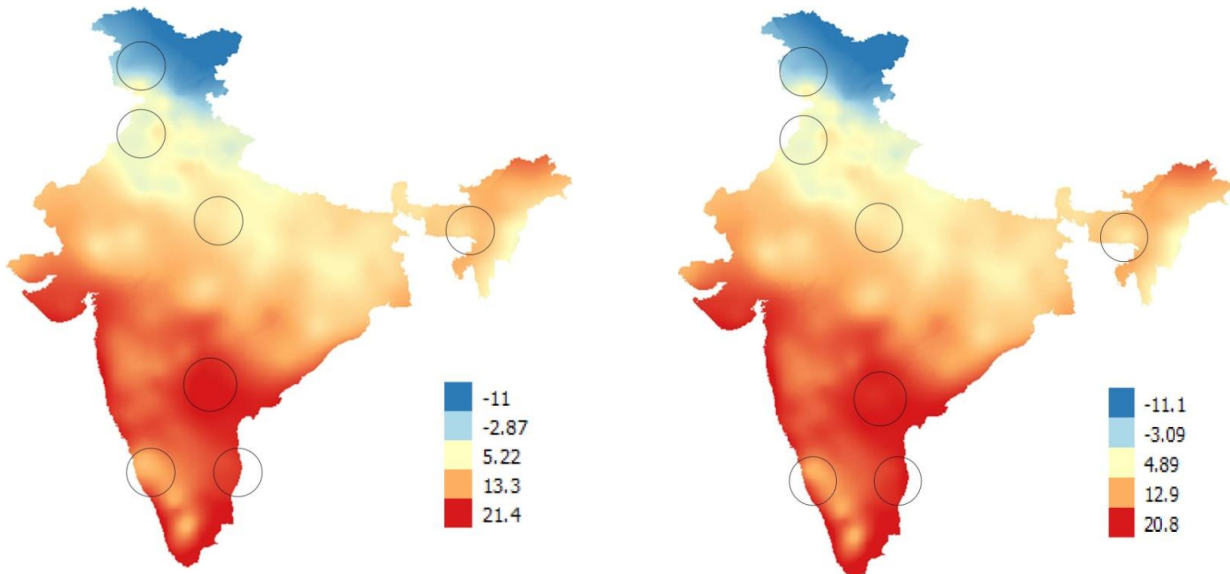

Figure 6: TPS interpolation of IMD stations Maximum Surface Air Temperature data for Monsoon (15 August); (a) With missing IMD stations data (Left), (b) After estimation of missing IMD stations data (Right)

Figure 7: TPS interpolation of IMD stations Minimum Surface Air Temperature data for Monsoon (15 August); (a) With missing IMD stations data (Left), (b) After estimation of missing IMD stations data (Right)

Figure 8: TPS interpolation of IMD stations Maximum Surface Air Temperature data for Winter (15 January); (a) With missing IMD stations data (Left), (b) After estimation of missing IMD stations data (Right)

Figure 9: TPS interpolation of IMD stations Minimum Surface Air Temperature data for Winter (15 January); (a) With missing IMD stations data (Left), (b) After estimation of missing IMD stations data (Right)

For almost all the regions, the results show that TPS temperature interpolation with LST consideration is closer to actual temperature than TPS temperature interpolation without LST consideration. The deviation of maximum and minimum temperature from actual temperature with and without LST consideration for a sample day for three seasons is reported in Tables 8 to 13.

Table 8: Deviation of Maximum Temperature from Actual Temperature with and without LST Consideration for Summer (15 April)

Station Name	Region	Actual temperature	TPS temperature interpolation without LST consideration	Deviation of temperature from actual temperature without LST consideration	TPS temperature interpolation with LST Consideration	Deviation of temperature from actual temperature with LST consideration
Srinagar	WH	27	21.47	5.53	24.68	2.32
Amritsar	NW	41.6	41.77	0.17	41.62	0.02
Agra	NC	43	43.03	0.03	42.95	0.05
Shilong	NE	23.4	29.34	5.94	26.45	3.05
Mangalore	WC	35.5	31.64	3.86	34.46	1.04
Chennai	EC	34.6	35.58	0.98	34.92	0.32
Hyderabad	IP	41.6	41.27	0.33	41.52	0.08

Table 9: Deviation of Minimum Temperature from Actual Temperature with and without LST Consideration for Summer (15 April)

Station Name	Region	Actual temperature	TPS temperature interpolation without LST consideration	Deviation of temperature from actual temperature without LST consideration	TPS temperature interpolation with LST Consideration	Deviation of temperature from actual temperature with LST consideration
Srinagar	WH	0	2.00	2.00	4.27	4.27
Amritsar	NW	17.8	18.97	1.17	18.53	0.73
Agra	NC	23.6	23.21	0.39	22.24	1.36
Shilong	NE	12.6	16.12	3.52	16.14	3.54
Mangalore	WC	25.6	24.65	0.95	24.56	1.04
Chennai	EC	26.3	26.03	0.27	26.11	0.19
Hyderabad	IP	25.9	25.80	0.1	24.96	0.94

Table 10: Deviation of Maximum Temperature from Actual Temperature with and without LST Consideration for Monsoon (15 August)

Station Name	Region	Actual temperature	TPS temperature interpolation without LST consideration	Deviation of temperature from actual temperature without LST consideration	TPS temperature interpolation with LST Consideration	Deviation of temperature from actual temperature with LST consideration
Srinagar	WH	27.6	19.79	7.81	24.45	3.15
Amritsar	NW	33.4	34.36	0.96	34.23	0.83
Agra	NC	36.8	35.04	1.76	35.69	1.11
Shilong	NE	25	27.77	2.77	27.96	2.96
Mangalore	WC	31.7	27.66	4.04	30.17	1.53
Chennai	EC	35.2	34.24	0.96	34.79	0.41
Hyderabad	IP	31.9	32.34	0.44	31.99	0.09

Table 11: Deviation of Minimum Temperature from Actual Temperature with and without LST Consideration for Monsson (15 August)

Station Name	Region	Actual temperature	TPS temperature interpolation without LST consideration	Deviation of temperature from actual temperature without LST consideration	TPS temperature interpolation with LST Consideration	Deviation of temperature from actual temperature with LST consideration
Srinagar	WH	16.3	11.13	5.17	14.02	2.28
Amritsar	NW	26.8	27.78	0.98	26.99	0.19
Agra	NC	26.4	26.56	0.16	26.57	0.17
Shilong	NE	14.7	21.98	7.28	22.92	8.22
Mangalore	WC	24.5	19.33	5.17	20.47	4.03
Chennai	EC	26.2	26.47	0.27	26.18	0.02
Hyderabad	IP	22.1	23.74	1.64	23.07	0.97

Table 12: Deviation of Maximum Temperature from Actual Temperature with and without LST Consideration for Winter (15 January)

Station Name	Region	Actual temperature	TPS temperature interpolation without LST consideration	Deviation of temperature from actual temperature without LST consideration	TPS temperature interpolation with LST Consideration	Deviation of temperature from actual temperature with LST consideration
Srinagar	WH	13.7	9.56	4.14	11.87	1.83
Amritsar	NW	22.3	9.77	12.53	21.48	0.82
Agra	NC	22.9	24.78	1.88	24.36	1.46
Shilong	NE	14.8	19.49	4.69	18.36	3.56
Mangalore	WC	35.9	32.54	3.36	34.47	1.43
Chennai	EC	30.7	31.11	0.41	30.63	0.07
Hyderabad	IP	33	33	0	32.87	0.13

Table 13: Deviation of Minimum Temperature from Actual Temperature with and without LST Consideration for Summer (15 January)

Station Name	Region	Actual temperature	TPS temperature interpolation without LST consideration	Deviation of temperature from actual temperature without LST consideration	TPS temperature interpolation with LST Consideration	Deviation of temperature from actual temperature with LST consideration
Srinagar	WH	-3.3	-5.67	2.37	-4.83	1.53
Amritsar	NW	1.2	3.51	2.31	3.91	2.71
Agra	NC	5.7	7.15	1.45	6.32	0.62
Shilong	NE	3.8	9.02	5.22	6.94	3.14
Mangalore	WC	20.5	14.04	6.46	18.23	2.27
Chennai	EC	22.2	19.82	2.38	21.51	0.69
Hyderabad	IP	18.8	20.05	1.25	19.59	0.79

Proposed methodology relies on quality of satellite data product to a large extent. Estimation from this methodology depends upon cloud free and clear sky environment as well as regional climatology. For current study, cloudy pixel handling is not performed on INSAT LST data. RMSPE for summer is low as compared to other seasons as winter season is affected by fog conditions for most of the India and monsoon season is cloudy.

5. Conclusions

This paper exploits the relationship between satellite derived LST and surface air temperature provided by IMD to estimate the missing IMD stations temperature data. This paper also reports performance of various regression techniques for estimation. Fourth degree polynomial regression performed best for most of the regions as well as for the whole country. RMSPE for WH region reported highest compared to other regions due to lack of stations and seasonal climatology. The southern part of India (WC, EC and IP) shows better accuracy as compared to northern part of India. The RMSPE reported for India is 5 and 6.93% for summer, 5.40 and 11.97% for winter and 5.58 and 5.49% for monsoon for maximum and minimum temperature respectively. At the end, the deviation of estimated temperature from actual temperature shows that,

TPS based gridded temperature with LST consideration is closer to actual temperature than TPS based gridded temperature without LST consideration.

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