DISAGGREGATION OF MODIS LAND SURFACE TEMPERATURE IN URBAN AREAS USING IMPROVED THERMAL SHARPENING TECHNIQUES

3.1 INTRODUCTION

Remotely sensed thermal images are very useful in various applications like soil moisture estimation (Wang and Qu, 2009; Zhang et al., 2015), surface energy balance characterization (Kato and Yamaguchi, 2005; Weng, 2009; Liu et al., 2016), forest fire detection (Justice et al., 2002), urban heat estimation (Voogt and Oke, 2003; Rajasekar and Weng, 2009; Rasul et al., 2017; Zhou et al., 2019) and also for various agricultural applications (Kauffman et al., 2007; Nuruzzaman, 2015). Satellites having thermal sensors can detect LST images at different spatial and temporal resolution which acts as an input to study about the spatial and dynamic variability in LST (Julien and Sobrino, 2009; Yao et al., 2017, 2018). Various satellites with thermal sensors like AVHRR, MODIS, ASTER, Landsat TM/ETM+ and Landsat 8 Thermal Infrared Sensor (TIRS) have been used for retrieval of LST. The LST images with high spatial resolution are very limited and have low temporal resolution whereas LST images with high temporal resolution have very low spatial resolution. Due to the high heterogeneity in urban areas, low spatial resolution of LST images can lack some important information required for various urban applications. Hence, the demand for finer spatial resolution of LST data motivates for the development of downscaling techniques to increase the information content from the original LST image (Atkinson, 2013; Zhan et al., 2013).

Various statistical models like Distrad Method (Kustas et al., 2003; Eswar et al., 2016; Essa et al., 2012), Temperature Sharpening (Tsharp) algorithm (Agam et al., 2007a; Jeganathan et al., 2011), pixel block intensity modulation (PBIM) algorithm (Stathopoulou and Cartalis, 2009) were used for downscaling LST based on the correlation of LST with different visible, NIR and SWIR bands because of its availability at finer spatial resolution in various satellite data. The Distrad method is most commonly used for downscaling due to its simplicity, easy implementation and application. The original Distrad Model, based on the correlation between LST and NDVI (Kustas et al., 2003), was developed. Various researchers has used this method for downscaling LST over vegetated or natural land covers using relation of LST with NDVI, FVC and the results of this method provided reasonable accuracy (Jeganathan et al., 2011; Agam et al., 2007a, 2007b). Urban areas contain greater heterogeneity in land covers and the behaviour of LST pattern differs for different land covers. Therefore, NDVI cannot explain all the LST variations in urban regions (Essa et al., 2012; Bonafoni, 2016).

Stathopoulou and Cartalis (2009) used PBIM method to downscale AVHRR LST to the spatial resolution of Landsat TM data to study the SUHI effect and found that error in SUHI decreased from 2.4 ^{0}C as obtained from original AVHRR data to 0.94 ^{0}C from the downscaled image. Essa et al. (2012) studied the performance of Distrad thermal sharpening technique using different indices and impervious percentage for deriving LST over urban areas from Landsat 7 ETM+ data and the correlation of LST was found greater for impervious percentage than that with NDVI. Mukherjee et al. (2014) used five different regression techniques i.e. Distrad, Tsharp, Tsharp with local variant, LMSR and Pace regression for thermal sharpening of Landsat and MODIS thermal data using LST and NDVI relation over a heterogeneous region in India. They found these models to be suitable for agricultural and vegetated landscapes but not applicable to water bodies or sandy open areas.

Bonafoni (2016) used different regressive techniques to downscale MODIS LST and upscaled Landsat LST to 480, 240 and 120m for summer season over the urban area of Milan, Italy and found that RMSE was higher for MODIS than that of Landsat downscaled LST image. Eswar et al. (2016) used Distrad thermal sharpening technique with five different indices NDVI, FVC, NDWI, SAVI and MSAVI to downscale MODIS LST from 960 m to 120 m and compared with the Landsat 7 LST data at different sites in India and found that NDVI/FVC showed better result for wet areas whereas NDWI was found better for dry areas. Yang et al. (2017) used the multiple linear regression models to downscale the aggregated Landsat TIRS (360 m) image to 90 m using relation of LST with multiple scale factors in the area of mixed land covers and then compared with the Landsat LST. The result found was satisfactory with coefficient of determination of 0.87 and RMSE of 1.13 K. Mukherjee et al. (2017) studied the SUHI effect in Punjab by downscaling MODIS LST data to 250 m using the relation of LST and NDVI by LMSR and found increase in spatial variability in the downscaled image as compared to original image making it suitable for study of SUHI effect. Zhang et al. (2009) found that the correlation of LST with NDVI was weak but strong positive correlation with NDBI was observed in the cities.

Previous studies have compared the sensitivity of different indices for downscaling MODIS LST in agricultural region. The relation of LST with different indices varies with the type of land cover present in a region (Bala et al., 2018). Hence, the study performed on agricultural land may not be applicable for urban areas. Different urban areas are surrounded by different kind of natural land covers which may have influence on the downscaling of LST. Previous studies on downscaling of LST in urban areas that can be applicable to some urban areas but may not be applicable to some other urban areas with different kind of natural surroundings. Therefore, this study aims at the determination of the downscaling technique that can be applicable to most of the urban regions. Hence, it is necessary to determine the indices that are useful for downscaling LST in different urban areas. Therefore, the correlation of LST with different indices i.e. NDVI, EVI, NDBI, UI, NDWI, NDSI have been used in the present study for thermal sharpening of MODIS LST to Landsat 8 TIRS scale on four different urban areas of India i.e. Bikaner, Hyderabad, Vadodara and Varanasi using the Distrad thermal sharpening method. Different regions were selected based on the different type of natural land cover surrounding the urban region to study the effect of different SI in different region. The four major land covers are vegetation, urban, bare soil/sand and water. The relation of LST with the indices in a city is also influenced by the natural land cover within or outside the city. So, the selection of proper SI is also important for downscaling of LST. Therefore, the commonly used indices for the major land covers were used in the present study. Since, urban areas have mixed land covers and each MODIS pixels have greater heterogeneity, the index that was found most suitable was further used for disaggregation using robust regression methods i.e. LMSR and Bi-square regressions in order to improve the disaggregation of LST because of its lower sensitivity to the outliers.

3.2 STUDY AREA AND DATA USED

3.2.1 Study area

India consists of large variation in climates because of its vast size. The study areas were selected from different parts of India. Four different climatic types cover the largest part of India i.e. tropical wet and dry, sub-tropical arid, tropical semi-arid and humid subtropical. Climate of an area also depends on the type of natural land cover in any region. Four different cities each within different climatic zones were selected for the study i.e. Hyderabad, Bikaner, Vadodara and Varanasi as shown in Figure 3.1. The maps of the four cities are the fcc images obtained from Landsat 8 OLI data with the acquisition date of Bikaner – 22/02/2017, Vadodara – 03/03/2017, Varanasi – 21/02/2017 and Hyderabad – 19/02/2017.

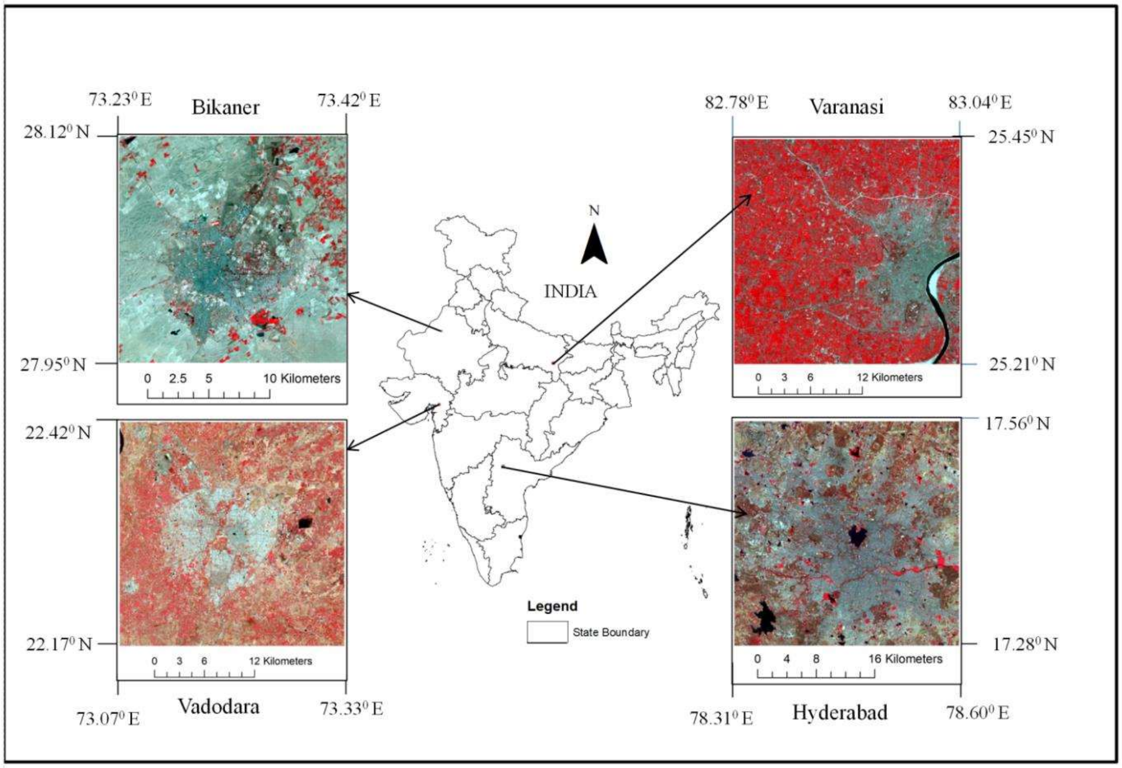

Figure 3.1. Location maps of study area

Hyderabad located in south east part of India, with coordinates 17.37 °N, 78.48 °E, covers an area of 650 km^2 and at an average elevation of 542 m. The city lies on small hills of pink and grey granite and consists of numerous lakes. Vadodara is located at 22.30°N, 73.19°E in western India at an elevation of 39 m with an area of 235 km^2. The city is located on the fertile plain between the Mahi and Narmada Rivers. Bikaner located in the north western part of India, with coordinates 28.01 °N, 73.31 °E, which covers an area of 155 km^2 and at an average elevation of 242 m. It is situated in the middle of the Thar desert. Varanasi is located in the northern part of India with coordinates 25.28 °N, 82.96 °E covers an area of 82.1 km^2 and at an average elevation of 80.71 m. It is situated at the bank of river Ganges. Different cities have different surrounding natural land covers.

3.2.2 Data used and image preprocessing

LST Higher-Level data products (Collection 1 Higher Level) and Landsat Level 1 Data products were obtained from the US Geological Survey website i.e. https://earthexplorer.usgs.gov/ for day time of winter season during 2017 for the four cities. Surface reflectance for visible and infrared band images were obtained from Collection 1 Higher Level Landsat data and thermal band images were obtained from Landsat Level 1 data. All the images acquired were taken during clear sky condition. Landsat Level 1 data products are radiometric, geometric and terrain corrected. Landsat Collection1 Higher Level products are also atmospheric corrected.

Table 3.1. Details about the satellite data acquired for the study

Cities	Landsat 8 OLI data		MODIS data (MOD11A2, MOD09A1)		Projection UTM WGS84
	Date	Path/Row	Composite Dates	Tiles	
Hyderabad	19/02/2017	144/48	18/02/2017 - 25/02/2017	h25v07	Zone - 44
Bikaner	22/02/2017	149/41	18/02/2017 - 25/02/2017	h24v06	Zone - 43
Vadodara	03/03/2017	148/45	26/02/2017 - 05/03/2017	h24v06	Zone - 43
Varanasi	21/02/2017	142/42	18/02/2017 - 25/02/2017	h25v06	Zone - 44

Therefore, LST (MOD11A2) and surface reflectance products (MOD09A1) of MODIS sensor aboard Terra satellite were downloaded for the same dates as that of Landsat 8 data for the four cities from the USGS LPDAAC website i.e. https://lpdaac.usgs.gov/. The data was acquired during clear sky conditions with similar atmospheric conditions and no rain occurred during the data acquisition period. This makes the MOD11A2 data suitable for the present study. All the MODIS images were reprojected and resampled using MODIS Reprojection Tool (MRT). Details of the satellite data acquired are shown in Table 3.1.

3.3 METHODOLOGY

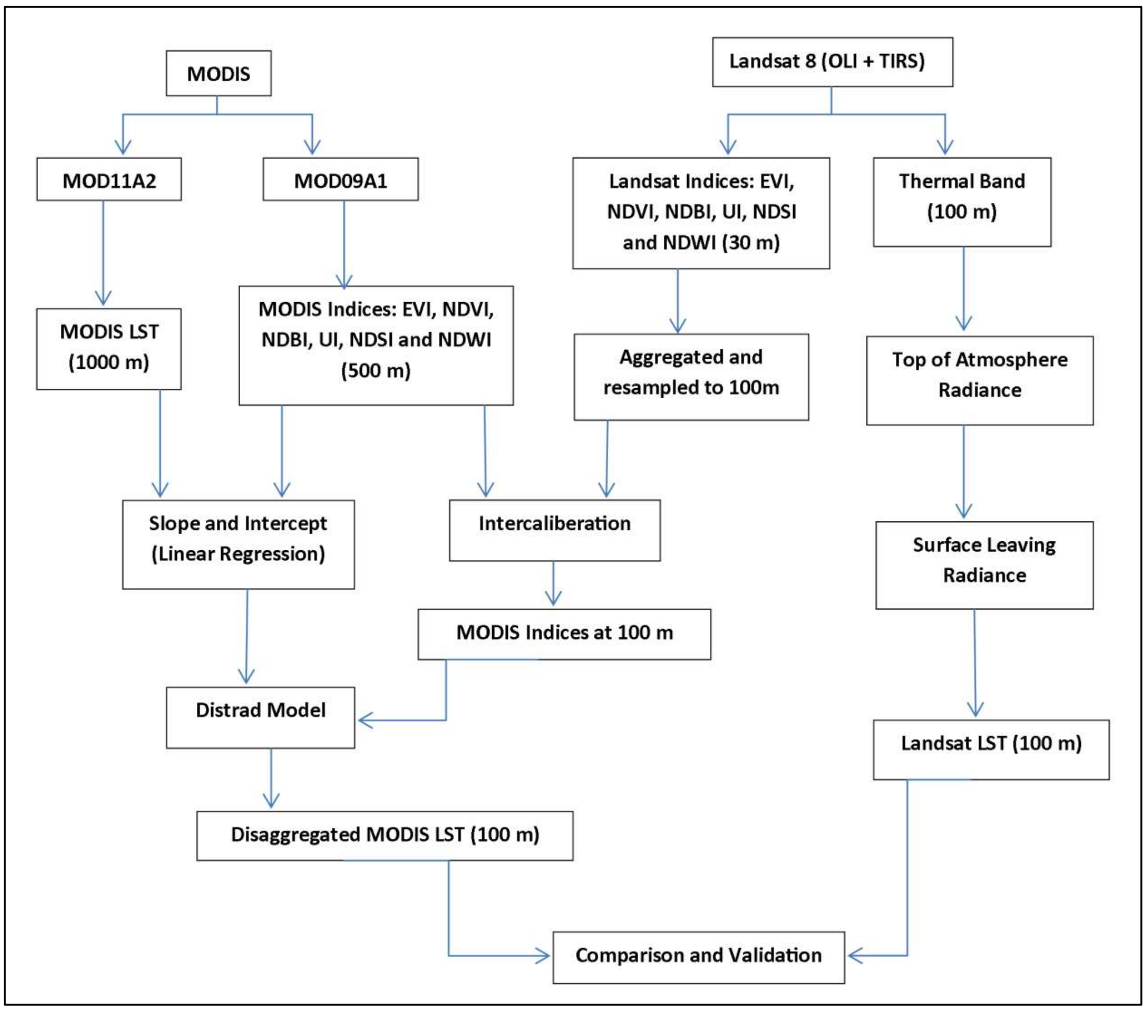

Figure 3.2. Research methodology (flow chart)

Various methods were involved in the disaggregation process which is presented in the flow chart shown in Figure 3.2. The different indices were computed from MODIS and Landsat 8 OLI images for inter-calibration. Indices from Landsat 8 were obtained at 30 m whereas MODIS indices were obtained at 500 m spatial resolution, so Landsat indices were first aggregated to 120 m and then resampled to 100 m to facilitate our inter-calibration process. MODIS LST was disaggregated using Distrad Model and compared with the Landsat LST. Further, LMSR and Bi-square regression models were used for downscaling of MODIS LST.

3.3.1 Calculation of spectral indices

Different indices were computed from the different visible and infra-red reflectance bands from the satellite data as shown in the Table 3.2. Here, ρ_n represents the reflectance of n^{th} band of Landsat or MODIS data respectively.

3.3.2 Inter-calibration of sensors

The indices obtained from MODIS were used for disaggregation to the spatial resolution of Landsat TIRS data (100 m). This disaggregation requires data from two different sensors, so sensor inter-calibration is required to convert fine resolution selected indices into its MODIS equivalent using linear regression as shown in Equation (3.1) and (3.2). (Steven et al., 2003)

$$SI_{MODIS} = a + b \times (SI_{agg\ Landsat}) \quad (3.1)$$

$$SI_{caliberated\ MODIS} = a + b \times (SI_{Landsat}) \quad (3.2)$$

Here, SI_{MODIS} is the original indices from MODIS data at 500 m spatial resolution. $SI_{agg\ Landsat}$ is the indices obtained after aggregation (17×17 pixels) to 510 m and then resampled to 500 m. From the linear regression, intercept and slope were obtained and denoted by a and b, respectively. $SI_{Landsat}$ is the original indices obtained from Landsat data. The values of slope, intercept and $SI_{Landsat}$ were used for estimation of the MODIS equivalent indices denoted by $SI_{caliberated\ MODIS}$ obtained at 100 m.

Table 3.2. Equations used for calculation of the selected indices

Selected Indices (SI)	Landsat 8 OLI	MODIS
NDVI	$\frac{\rho_5 - \rho_4}{\rho_5 + \rho_4}$	$\frac{\rho_2 - \rho_1}{\rho_2 + \rho_1}$
EVI	$2.5\frac{\rho_5 - \rho_4}{\rho_5 + 6\rho_4 - 7.5\rho_2 + 1}$	$2.5\frac{\rho_2 - \rho_1}{\rho_2 + 6\rho_1 - 7.5\rho_3 + 1}$
NDBI	$\frac{\rho_6 - \rho_5}{\rho_6 + \rho_5}$	$\frac{\rho_6 - \rho_2}{\rho_6 + \rho_2}$
UI	$\frac{\rho_7 - \rho_5}{\rho_7 + \rho_5}$	$\frac{\rho_7 - \rho_2}{\rho_7 + \rho_2}$
NDWI	$\frac{\rho_3 - \rho_5}{\rho_3 + \rho_5}$	$\frac{\rho_4 - \rho_2}{\rho_4 + \rho_2}$
NDSI	$\frac{\rho_7 - \rho_3}{\rho_7 + \rho_3}$	$\frac{\rho_7 - \rho_4}{\rho_7 + \rho_4}$

3.3.3 Thermal sharpening technique

The Distrad thermal sharpening technique was based on the correlation of LST with indices (Kustas et al., 2003; Eswar et al., 2016 and Essa et al., 2012). In the Distrad method, the linear least square fit was obtained between the coarse resolution LST and the indices selected to estimate the intercept and slope of the linear regression from Equation (3.3). Here, linear fit was preferred over polynomial fit because polynomial fit may result in some error due to the presence of outliers at high or low values of selected indices as given by Kustas et al. (2003) and Agam et al. (2007b).

$$LST_{CR} = c + d \times (SI_{CR}) \tag{3.3}$$

$$\Delta LST_{CR} = LST_{REF} - LST_{CR} \tag{3.4}$$

Here, SI_{CR} represents the indices selected at coarse spatial resolution and LST_{CR} represents the LST estimated from the satellite data at coarse spatial resolution. The parameters c and d are the intercept and slopes of the least square fit, respectively. ΔLST_{CR} is the residual obtained from calculated and estimated LST at coarse spatial resolution. LST_{REF} is the reference LST computed from the selected indices, intercept and slope determined from Equation (3.3). The disaggregated LST was obtained from the Equation (3.5).

$$LST_{FR} = c + d(SI_{FR}) + \Delta LST_{CR} \tag{3.5}$$

Here, SI_{FR} represents the fine resolution MODIS equivalent selected indices.

The regression parameters were estimated using ordinary least square regression (OLS) technique where sum of square residuals were minimized as shown in Equation (3.6)

$$MinSSR = \sum_{i=1}^{n} \left(LST_i - \left(c + d \times (SI)\right)\right)^2 \tag{3.6}$$

OLS regression is sensitive to outliers and interferes in the estimation of regression parameters. So, the regression must be modified to improve the relation of LST with the selected indices by reducing the influence of the outliers. Therefore, two different regression methods were used i.e. LMSR (Rousseeuw, 1984) and Bi-square regression where the OLS regression was replaced with the LMSR and Bi-square regression for estimation of the slope and intercept used to carry out the downscaling using Distrad Method. LMSR and Bi-square regression are robust algorithms and are less sensitive to outliers. In LMSR, Median of the square residuals was minimized to determine the regression parameters as shown in Equation (3.7)

$$MinMedSR = Median\left\{\left(LST_1 - \left(c + d(SI)\right)\right)^2, \left(LST_2 - \left(c + d(SI)\right)\right)^2 .... \quad \left(LST_n - \left(c + d(SI_n)\right)\right)^2\right\} \tag{3.7}$$

The Bi-square regression is a weighted regression technique in which the weighted sum of squares are minimised (Pati et al., 2016). The weight assigned to a data depends on its deviation from the fitted line. The data points with lower deviation were assigned greater weight values but points far from the fitted line were assigned very low or negligible weight values as shown by Equation (3.8).

$$W(x) = \begin{cases} \left(1 - \left(\frac{x}{6m}\right)^2\right)^2, & x < 6m \\ 0, & x \geq 6m \end{cases} \tag{3.8}$$

Where, W(x) is the weight provided to each data point, x is the residual value and m is the median of residuals.

3.3.4 Validation

Various methods were adopted to validate the results of downscaling for four different cities under present study. The original MODIS LST was also compared with Landsat LST at the same time to evaluate the performance of the downscaling techniques.

a) The downscaling of MODIS LST was performed for different indices in the four cities using the Distrad Model. RMSE and Bias were used to compare the disaggregated LST with original Landsat LST (Agam et al., 2007a, 2007 b; Eswar et al., 2016) and are shown by Equation (3.9) and (3.10).

$$RMSE = \left[n^{-1} \sum_{i=1}^{n} \left(T_{Disagg}^{MODIS}(i) - T_{Fine}^{Landsat}(i) \right)^{2} \right]^{\frac{1}{2}} \tag{3.9}$$

$$Bias = \left[n^{-1} \sum_{i=1}^{n} \left(T_{Disagg}^{MODIS}(i) - T_{Fine}^{Landsat}(i) \right) \right] \tag{3.10}$$

Here, each pixel in an image is denoted by i, n denotes total number of pixels in an image, T_{Disagg}^{MODIS} is the disaggregated MODIS LST to 100 m spatial resolution and $T_{Fine}^{Landsat}$ is the LST estimated from Landsat-8 TIRS data. By comparing these values for different indices, suitable index for downscaling was determined.

b) The index obtained was used for LMSR and Bi-square regression based downscaling and compared with the Distrad Model using RMSE and Bias. The similarity assessment was also performed on the downscaled MODIS LST with the coarse MODIS LST (Wald et al., 1997). The disaggregated LST was aggregated to its original coarse resolution. Then, the bias, coefficient of determination (R^2) and the difference in Standard Deviation (STD) were calculated for each downscaling method used for the four cities of study.

3.4 RESULTS AND DISCUSSION

3.4.1 Inter-calibration of Landsat and MODIS data

Table 3.3. The slope, intercept and R^2 determined for intercaliberation from MODIS to Landsat equivalent indices for Bikaner and Hyderabad

Indices	Bikaner			Hyderabad		
	Slope	Intercept	R^2	Slope	Intercept	R^2
NDVI	0.917	0.027	0.89	0.745	0.072	0.83
EVI	2.453	-0.008	0.84	0.850	0.027	0.86
NDBI	0.828	0.027	0.86	0.547	0.049	0.64
UI	0.882	0.005	0.85	0.651	0.003	0.66
NDSI	0.562	0.155	0.67	0.590	0.151	0.71
NDWI	0.877	0.059	0.84	0.733	-0.110	0.84

Table 3.4. The slope, intercept and R^2 determined for intercaliberation from MODIS to Landsat equivalent indices for Vadodara and Varanasi

Indices	Vadodara			Varanasi		
	Slope	Intercept	R^2	Slope	Intercept	R^2
NDVI	0.912	0.038	0.94	0.924	0.055	0.95
EVI	0.896	0.014	0.94	0.905	0.020	0.96
NDBI	0.834	0.027	0.87	0.968	0.016	0.94
UI	1.006	0.012	0.85	1.091	0.013	0.95
NDSI	0.795	0.076	0.70	1.589	-0.119	0.70
NDWI	1.695	-0.109	0.84	0.856	-0.088	0.94

The slope, intercept and R^2 determined for inter-calibration from MODIS to Landsat equivalent indices were shown in the Tables 3.3 and 3.4. The correlation of indices from MODIS and Landsat 8 images were found to be higher in Vadodara, Varanasi and Bikaner but lower in Hyderabad. The R^2 was found lower in Hyderabad due to the greater heterogeneity in the city as compared to other cities. Therefore, inter-calibration is a necessary step in downscaling of LST because correlation between indices of different satellites varies with the type of land cover present in a region.

3.4.2 LST downscaling using Distrad model with different indices

The comparison of six different indices used for disaggregation of MODIS LST to Landsat spatial resolution using Distrad Model was carried out. The LST error statistics were determined for comparison of original MODIS LST with reference Landsat LST and are shown in Table 3.5. Minimum error, maximum error, Bias and RMSE were also obtained from each downscaled and reference LST image and are shown in Tables 3.6 and 3.7 for the four cities.

Table 3.5. LST error statistics of original MODIS LST with reference Landsat LST

City	Min (K)	Max (K)	Bias (K)	RMSE (K)
Bikaner	-8.28	14.54	0.50	1.82
Hyderabad	-12.96	13.20	0.10	1.43
Vadodara	-10.60	10.52	-0.14	1.22
Varanasi	-13.19	5.60	-0.94	1.26

Table 3.6. LST error statistics of Bikaner and Hyderabad for downscaled LST using different indices

Indices	Bikaner				Hyderabad			
	Min (K)	Max (K)	Bias (K)	RMSE (K)	Min (K)	Max (K)	Bias (K)	RMSE (K)
EVI	- 8.90	22.74	- 0.04	1.65	- 13.90	15.52	- 0.11	1.40
NDVI	- 7.12	20.79	- 0.06	1.63	- 14.10	13.16	- 0.10	1.34
NDBI	- 7.77	12.27	- 0.09	1.54	- 13.99	12.07	- 0.10	1.24
UI	- 7.18	12.81	- 0.07	1.57	- 13.66	12.31	- 0.10	1.24
NDSI	- 15.46	14.35	- 0.07	1.63	- 13.66	11.37	- 0.01	1.28
NDWI	- 5.37	25.67	1.82	2.34	- 15.57	12.46	- 1.76	1.41

Table 3.7. LST error statistics of Vadodara and Varanasi for downscaled LST using different indices

Indices	Vadodara				Varanasi			
	Min (K)	Max (K)	Bias (K)	RMSE (K)	Min (K)	Max (K)	Bias (K)	RMSE (K)
EVI	- 10.37	10.36	- 0.14	1.21	- 8.91	9.02	- 0.17	1.23
NDVI	- 9.68	10.76	- 0.14	1.16	- 8.63	9.75	0.05	1.17
NDBI	- 7.64	7.01	- 0.13	1.10	- 7.27	5.77	0.05	1.03
UI	- 7.70	7.71	- 0.13	1.15	- 7.13	6.48	0.05	1.06
NDSI	- 8.28	9.97	- 0.14	1.19	- 18.42	13.85	5.45	5.11
NDWI	- 10.54	11.09	- 0.15	1.24	- 9.66	11.83	0.04	1.19

Comparing the error in downscaled MODIS LST and original MODIS LST with Landsat LST, it was found that all the indices, except NDWI, used in the present study improved the result. However, NDBI and UI were observed to show lower values of error as compared to other indices in the four cities. This is because of better correlation of LST with NDBI and UI as compared to other indices (Ogashawara and Bestos, 2012). Both the indices were found to show almost similar result. However, NDBI showed error values slightly lower than that of UI in four different cities. Hence, NDBI was observed to be the most suitable index for downscaling of LST in different urban areas. The original Distrad Model used relation of LST with NDVI for downscaling of LST but it was not found suitable for downscaling in urban areas.

Essa et al. (2012) used Distrad model for downscaling LST in urban areas using various indices and percent impervious. They concluded that percent impervious provided better downscaling result than the indices in an urban region with very high vegetation cover. The relation of LST with percent impervious was found good for regions where SUHI was formed and SUHI formation occurs in urban areas surrounded by vegetation. The presence of bare soil or sand which shows LST higher than urban built ups during day time results in absence of SUHI effect in such cities. In the present study, significant SUHI effect was formed only in Varanasi. Therefore, percent impervious cannot be used for downscaling in the other cities. Therefore, the use of NDBI in Distrad model can be applicable in different types of urban regions for downscaling LST with good result.

3.4.3 LST downscaling using different robust regression techniques

Further, the relation of MODIS LST with NDBI were used in LMSR and Bi-square regression for downscaling MODIS LST to the spatial resolution of 100 m and the downscaled LST was compared with the original Landsat LST. The error statistics were determined for the downscaled LST and the results were compared with the original Distrad Model as shown in Tables 3.8 and 3.9. The lower error was observed for downscaled LST using LMSR and Bi-square regression in the four cities. However, RMSE was found even lower by Bi-square regression technique.

Table 3.8. LST error statistics of Bikaner and Hyderabad for different downscaling methods

Methods	Bikaner				Hyderabad			
	Min (K)	Max (K)	Bias (K)	RMSE (K)	Min (K)	Max (K)	Bias (K)	RMSE (K)
Distrad	- 7.77	12.27	- 0.09	1.54	- 13.99	12.07	- 0.10	1.24
LMSR	- 5.72	10.03	- 0.06	1.32	- 10.84	10.49	- 0.08	1.21
Bi-Square	- 5.43	9.82	- 0.05	1.30	- 10.45	10.54	- 0.08	1.21

Table 3.9. LST error statistics of Vadodara and Varanasi for different downscaling methods

Methods	Vadodara				Varanasi			
	Min (K)	Max (K)	Bias (K)	RMSE (K)	Min (K)	Max (K)	Bias (K)	RMSE (K)
Distrad	- 7.64	7.01	- 0.13	1.10	- 7.27	5.77	0.05	1.03
LMSR	- 6.85	5.34	- 0.09	1.01	- 6.43	4.87	0.04	0.98
Bi-Square	-6.73	5.14	- 0.08	0.98	- 6.47	4.71	0.04	0.97

Table 3.10. Similarity assessment of downscaled MODIS LST with original MODIS LST for Bikaner and Hyderabad

Methods	Bikaner					Hyderabad				
	Mean (K)	Mean diff (K)	STD (K)	STD diff (K)	R^2	Mean (K)	Mean diff (K)	STD (K)	STD diff (K)	R^2
Reference LST	308.89	-	2.30	-	1	311.06	-	1.26	-	1
Distrad	308.88	0.01	2.39	0.09	0.902	311.04	0.02	1.30	0.04	0.938
LMSR	308.89	0	2.33	0.01	0.954	311.04	0.02	1.27	0.01	0.950
Bi-Square	308.89	0	2.32	0	0.960	311.05	0.01	1.27	0.01	0.953

The results of similarity assessment of downscaled MODIS with the original MODIS LST were shown in Table 3.10 and 3.11. The difference in mean and STD was almost negligible and the R^2 for the degraded MODIS LST and the original MODIS LST were found very high (> 0.94) while using LMSR and Bi-square methods for downscaling in the four cities. This indicates that the two methods improve the quality of downscaled LST images as compared to those obtained from Distrad Model

Table 3.11. Similarity assessment of downscaled MODIS LST with original MODIS LST for Vadodara and Varanasi

Methods	Vadodara					Varanasi				
	Mean (K)	Mean diff (K)	STD (K)	STD diff (K)	R^2	Mean (K)	Mean diff (K)	STD (K)	STD diff (K)	R^2
Reference LST	310.36	-	0.93	-	1	299.69	-	1.26	-	1
Distrad	310.31	0.05	0.98	0.05	0.947	299.77	0.08	1.21	0.05	0.953
LMSR	310.35	0.01	0.93	0	0.962	299.71	0.01	1.24	0.02	0.971
Bi-Square	310.36	0	0.93	0	0.963	299.71	0.01	1.26	0.01	0.980

Bonafoni S. (2016) used different regressive techniques to downscale MODIS LST to 120 m for different seasons and observed a minimum RMSE of 1.98 K. Yang et al. (2017) used the multiple linear regression model to downscale aggregated Landsat 8 image using relation of LST with multiple scale factors in area of mixed land covers and found satisfactory result with RMSE of 1.13 K. Mukherjee et al. (2014) used LMSR technique for downscaling LST in agricultural areas and found an improvement in the result as compared to the Distrad model. Qi et al. 2016 developed Geographical Statistical Model (GSM), Gao et al. 2012 developed a new DMS technique and Saavedra et al. 2017 proposed a new thermal sharpening method called TS2uRF for thermal sharpening for LST and the three studies were applicable for agricultural or forest areas. Our result also shows an improvement with LMSR and also Bi-square regression techniques over Distrad model in the four study sites. The bi-square regression technique used for downscaling shows the RMSE of 1.30 K, 1.21 K, 0.98 K and 0.97 K in Bikaner, Hyderabad, Vadodara and Varanasi respectively. Therefore, the method used in this study performed better than various previous studies and the result was also found applicable for four different study sites making this method suitable for widely different cities. The two robust regression techniques used in the present study are less sensitive to outliers which improve the relation of LST with NDBI in heterogeneous landscapes, thereby increasing its efficiency for downscaling of MODIS LST.

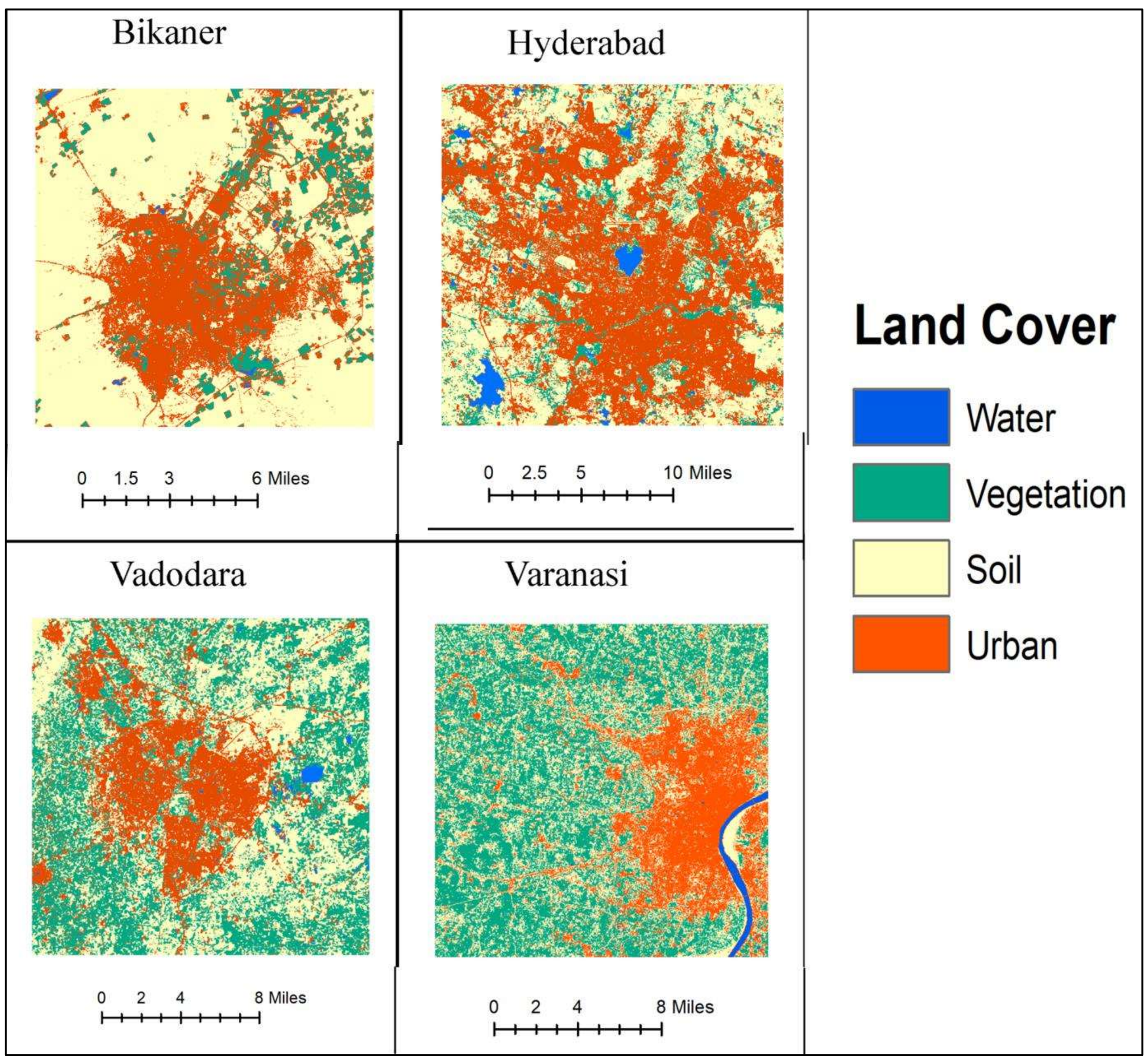

Figure 3.3. Classified map of Bikaner, Hyderabad, Vadodara and Varanasi

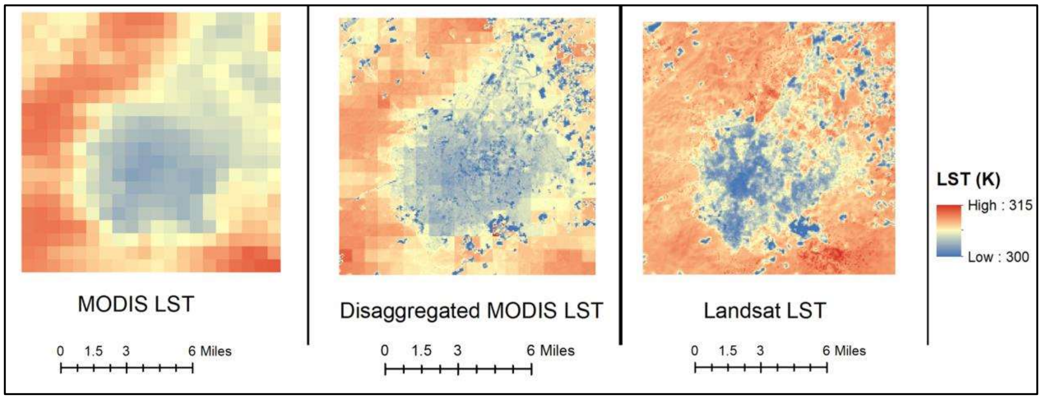

Figure 3.4. The original MODIS LST, Downscaled MODIS LST using Bi-square regression and reference Landsat LST of Bikaner

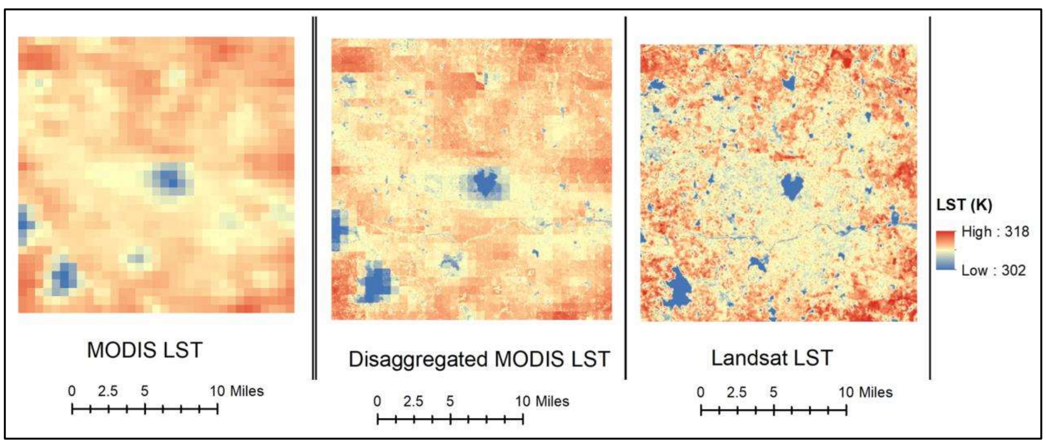

Figure 3.5. The original MODIS LST, Downscaled MODIS LST using Bi-square regression and reference Landsat LST of Hyderabad

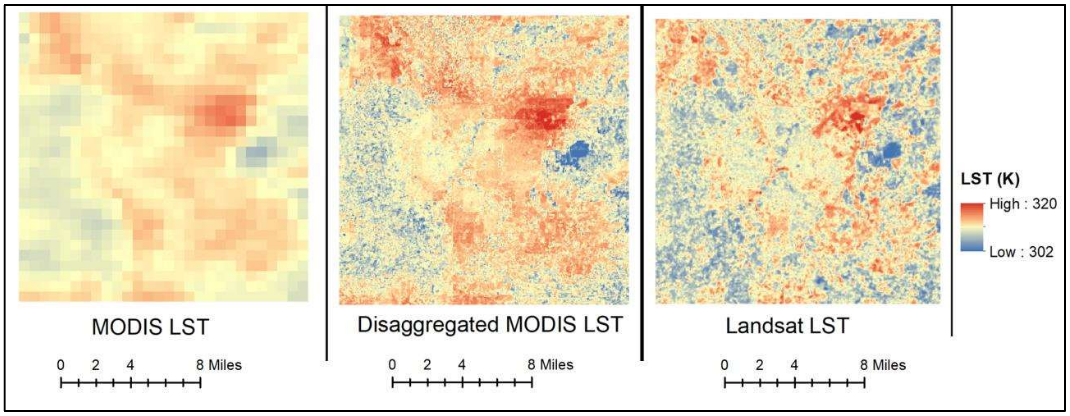

Figure 3.6. The original MODIS LST, Downscaled MODIS LST using Bi-square regression and reference Landsat LST of Vadodara

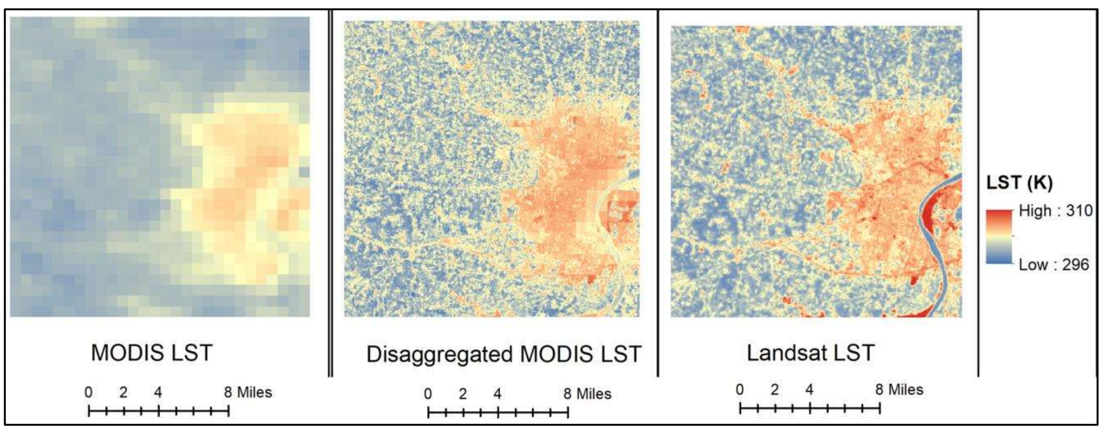

Figure 3.7. The original MODIS LST, Downscaled MODIS LST using Bi-square regression and reference Landsat LST of Varanasi

Figure 3.3 represents the land cover classification map of the four cities. Figures 3.4 – 3.7 represents the original MODIS LST, Downscaled MODIS LST and reference Landsat LST for Bikaner, Hyderabad, Vadodara and Varanasi, respectively. The disaggregated images were obtained using Bi-square regression technique. Urban heat sink (UHS) was observed in Bikaner due to the lower LST values in urban areas whereas higher temperatures were observed in the surrounding areas due to the presence of Thar Desert. In Hyderabad, waterbodies within the city showed lower LST values whereas bare regions and urban areas showed higher LST values. The urban areas near to the waterbody showed lower LST in the disaggregated LST image due to mixing of urban and water in a single MODIS pixel. In Vadodara, the lowest LST was observed due to the presence of waterbody and the highest LST was observed for the bare soil. The areas surrounding the urban areas consist of sparse vegetation due to the presence of agricultural land resulting in slightly lower temperatures than those in urban areas. SUHI was observed in Varanasi due to the presence of dense vegetation and waterbody surrounding the city. The dry river bed was found to show very high temperatures. The disaggregated LST showed higher LST values in waterbody as compared to the reference Landsat LST. This was due to the mixing of waterbody with urban in one MODIS pixel resulting in lowering of LST in disaggregated urban pixels and rising of LST in disaggregated water pixels. Hence, comparing the Disaggregated MODIS LST with the reference Landsat LST, it was observed that mixing of land covers with very high difference in LST in one pixel results in greater error in disaggregation of LST. The study shows acceptable accuracy for urban areas but greater error was observed for the waterbodies. Therefore, the methods used in the present study are not recommended for regions with large waterbodies or cities developed on islands.

3.5 CONCLUSION

The main objective of this study was to downscale the coarse spatial resolution (~ 930 m) LST image to finer spatial resolution (~ 100 m) for accurate mapping of LST in the urban areas. The study was performed over four different urban regions in India i.e. Bikaner, Hyderabad, Vadodara and Varanasi. Six different indices, namely EVI, NDVI, NDBI, UI, NDSI and NDWI were used for disaggregation of MODIS LST (960 m) to that of Landsat 8 (100 m) spatial resolution using Distrad Model and were compared for four different cities from different climatic zones in India. The disaggregated MODIS LST was compared with the original Landsat LST and the RMSE was found least for the downscaled LST image using NDBI in the study sites. Therefore, NDBI was found most suitable for downscaling of LST using Distrad Model as compared to other indices in urban areas. Therefore, the selection of proper indices for downscaling of LST is very important because the relation of LST was found different with different indices. The linear relation of LST with the most suitable index i.e. NDBI is also influenced by the outliers which can interfere with the final result. So, LMSR and Bi-square regressions were used to reduce the effect of outliers which resulted in improvement of downscaling of LST. From the error analysis, RMSE was observed to be lower for LMSR and Bi-square regression as compared to the Distrad Model resulting in improvement of downscaled MODIS LST in the four study sites. The similarity assessment of downscaled LST with original MODIS LST also revealed that the qualities of downscaled images were improved when using LMSR and Bi-square regression methods for downscaling. Therefore, the two robust regression techniques provided an improvement on downscaling of LST over Distrad Model. The improvement of downscaling observed for LST in four different cities in our present study reveals the potential of the LMSR and Bi-square regression models for accurate mapping of LST at fine resolution in the urban areas.

However, the methods used in the present study are not useful for the regions with large waterbodies or cities developed on islands. Further, use of ASTER derived LST can be used as an alternative for validation of MODIS downscaled LST image and also the development of a model could be done which can better explain LST in urban areas to improve accuracy of the downscaled LST (Jeganathan et al., 2011; Duan and Li., 2016).